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Dear Sir/Madam,

This letter is intended to clarify the purpose of the paper contained herein. It must be noted from the outset that the topic is not usual for a master's thesis as it is such that the paper would never be publishable. This is due to the fact that the paper attempts to design an experiment to test human behaviour under the conditions of the 'producer scrounger' game found in the biological social foraging literature. The paper should thus be seen as laying a foundation upon which future publishable work can be based.

The possibility of designing such an experiment was first discussed by Professor Don Ross (Dean of Commerce University of Cape Town) and Professor Luc-Alain Giraldeau (Department of Biological Sciences, UQAM, Canada) and I took on the task of the experimental design. The hope is that the paper is such that only minimal modification need be made before a revised version of the work can be submitted to the National Research Foundation and corresponding body in Canada as a grant application. We intend to run the experiment using both a South African and Canadian sample as soon as possible.

One point that must be noted is that the original intention was to include a simulation of the experiment in the paper done using custom software developed by Professor Glenn Harrision (Centre for the Economic Analysis of Risk, Georgia State University) that links Stata with a strategic game simulator, Gambit. This software enables Gambit to compute the quantal response equilibria of games with probabilistic payoffs. The probabilistic prizes are inputted into Stata and Gambit accesses this information as needed. This idea had to be abandoned however as, although the software is functional, the documentation that would allow it to be used by people who weren't part of the development team is still being developed. If this documentation arrives in time, it is planned to include this simulation as an appendix to the paper within.

Yours faithfully

George Etheredge

A Procedure to test Human Behaviour under 'Producer Scrounger' Conditions

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Abstract:

This paper examines the applicability of the 'producer scrounger' model, used in the biological literature to model social foraging, to human beings. It is argued that humans do find themselves in economically important situations that can be described by the producer scrounger dynamic. For this reason, an experimental procedure is designed in order to test human choice behaviour under the appropriate conditions. This experiment will be run at a later date and its primary goal is to test the impact of the provision of new information on choice under uncertainty.

Introduction

A keen bird watcher may notice a pattern exhibited by certain species of flocking birds when feeding, where one group of birds pecks at the ground searching for food while members of the other group watch and, at times, usurp some of the food found by the searching birds.

In biology, this type of situation is given formal representation by 'producer scrounger games' ("PS games", Barnard & Silby 1981). The pecking birds act as producers as they engage in a costly search to generate information regarding the location of food items in the patch on which the flock is currently foraging, and simultaneously generate information concerning the overall productivity of the food patch. This information is observable to the members of the group that are not producing. These are the scroungers, so called because they free-ride on the information, about the presence of food and the quality of the food patch, made available by producers. This information allows the scrounging birds to compete for and usurp some of the food found by the producing birds; and also gives an indication as to the relative profitability of the two strategies on the food patch as scrounging birds observe both their own and the producer payoffs. This is a game theoretic interaction: the dynamics of competition imply that the payoffs of both producers and scroungers depend on the proportion of the group producing or scrounging (Giraldeau & Caraco 1991, Giraldeau & Dubois 2008, Mottley & Giraldeau 1999). The foraging group generally reaches a Nash equilibrium under these conditions with stable numbers of producers and scroungers and, assuming uniform ability to compete for food, with equal payoffs to each strategy, for a food patch of given quality. The use of the strategies (producing and scrounging) does not appear to be phenotypically fixed, and over time and individual birds will change from producing to scrounging and vice versa whilst maintaining equilibrium frequencies, resulting in a mixed strategy Nash equilibrium (Giraldeau & Dubois 2008). There are two processes that could generate this equilibrium in birds. The first is a behavioural rule that would be specific to foraging birds and the second a group of neural processes responsible for calculating strategy

mixes. If the second possibility holds true, this has implications for the generalisability of the situation to other animals, including humans (Ross forthcoming).

PS games would be of interest to economists for the sake of their competitive dynamics and stability properties even if they were only encountered in avian populations. But of course the economist will wonder if they might arise among people. This question can be analyzed into three sub-questions:

- (1) Can PS game responses be induced in people in an experimental design?
- (2) Do people encounter situations usefully modelled by PS games 'in the wild'?
- (3) Would human PS game play in laboratory settings predict non-manipulated behavioural responses?

The primary aim of this paper is to present the design of an experimental procedure that can answer questions 1 and 3, and in the process of doing this provide some argument regarding the answer to question 2. The motivation for doing this is the hope that the answers to these questions will provide useful insight into human behaviour. In the PS game, this is most definitely the case. As illustrated in the biological PS model in section 2, producing is, in general, likely to be a more risky strategy than scrounging as the possibility that a producer receives a zero payoff in a given time period is greater than the possibility of a scrounger receiving a zero payoff as this only occurs with certainty when all producers come up empty handed. Producers however have a chance to obtain a higher payoff as they are able to feed from the time a food clump is discovered. Ignoring for the moment the information that producers generate, human behaviour in such a situation would be predicted by risk preference. However the presence of the information gives some indication as to which strategy may perform better on a given food patch and it is natural to think that humans would take account of this when deciding between the two strategies. Analysis of the data arising from an experimental PS game could therefore give some indication as to the relative importance of information over risk preference in explaining choice under uncertainty. Section 1 presents evidence that humans

do, in fact, find themselves in PS situations 'in the wild'. The situations examined here, namely decisions on the adoption of a new technology, decisions concerning investment in research and development and, most importantly, behaviour in asset markets are economically interesting in and of themselves. Here it is hoped that studying human behaviour under PS conditions may yield valuable insights into decision making in these situations. These factors attest to the usefulness of conducting a PS-type experiment with human subjects.

Pursuing the economic interest in PS games, this paper presents an experimental design to test human behaviour under PS conditions. The goal of the design process was to build an experiment that would yield economically interesting and tractable laboratory data within existing conceptual frameworks whilst staying as close as possible to the structure of the biological PS game. It is useful to clarify here the questions that the data arising from such an experiment would be used to answer. There are two main points here:

- (1) What is the impact of the provision of information on human behaviour under circumstances where choice would otherwise be predicted by risk preference?
- (2) Is the equilibrium that humans reach in PS situations similar to that reached by foraging birds?

The second question relates to the mechanism by which birds reach the Nash equilibrium strategy. The human equilibrium being similar to that attained by birds supports the hypothesis that Nash equilibrium is attained through general neural processes rather than a behavioural rule specific to foraging birds.

The rest of this paper proceeds as follows: section 1 provides a more detailed overview of the biological literature concerning PS games and briefly presents the most simple biological model of the interaction. This is necessary, as an understanding of much of the later analysis and design depends upon a sound basic understanding of the payoff structures and information dynamics in PS games. Additionally, this allows the reader to evaluate the claim that the final experiment is, in actual fact, a PS game. Section 2 provides a brief review of psychological and economic experiments that capture some elements of the PS

interaction and examines some situations where humans could plausibly be thought of as playing a PS game. Careful analysis of the similarities between PS and stock market games is conducted here as this appears to be the situation in which individual agents are most plausibly viewed as playing a PS game. Section 3 presents the basic experimental design and an argument that this design does indeed place humans in a PS situation. Section 4 discusses the more technical details of the experiment and presents simulations of the Nash equilibria implied by different values of key parameters and section 6 concludes and discusses useful extensions to the current project.

1: The PS game

The most effective way in which to illustrate the more detailed dynamics of the PS interaction is to examine a simple model of the phenomenon. This section examines the basic deterministic model presented by Giraldeau and Dubois (2008), and then discusses some of the key features of the interaction that it captures.

The foraging group numbers G individuals, with any member playing scrounger being able to detect the success of any individual producer. Food clumps contain a fixed number of food items, F , and the producer that finds the clump always receives a of the F items. This is known as the finder's advantage and, empirically arises from the producer being able to feed from the clump from the time it is discovered. The remaining $F-a$ items in the clump are shared between the producer and *all* of the scroungers, implying that each scrounger competes at all the clumps found by any producer. p represents the proportion of the group playing producer and thus $(1-p)$ the proportion playing scrounger. The total number of producers is given by pG and the total number of scroungers by $(1-p)G$. The $(1-p)G$ scroungers are assumed to arrive at clumps simultaneously, implying that competition for the resources in the clump is always between the producer and all of the scroungers. Payoffs are measured as energy intakes with I_p being the payoff to producing and I_s the payoff to scrounging. Energy intake for both types is calculated over the time interval, T .

If producers encounter food patches at constant rate λ (note that this implies that the model is deterministic), then the producer's energy intake after the interval T , is given by

$$I_P = \lambda T \left(a + \frac{F - a}{1 + (1 - p)G} \right)$$

and the scrounger's energy intake by

$$I_S = \lambda G p T \left(\frac{F - a}{1 + (1 - p)G} \right)$$

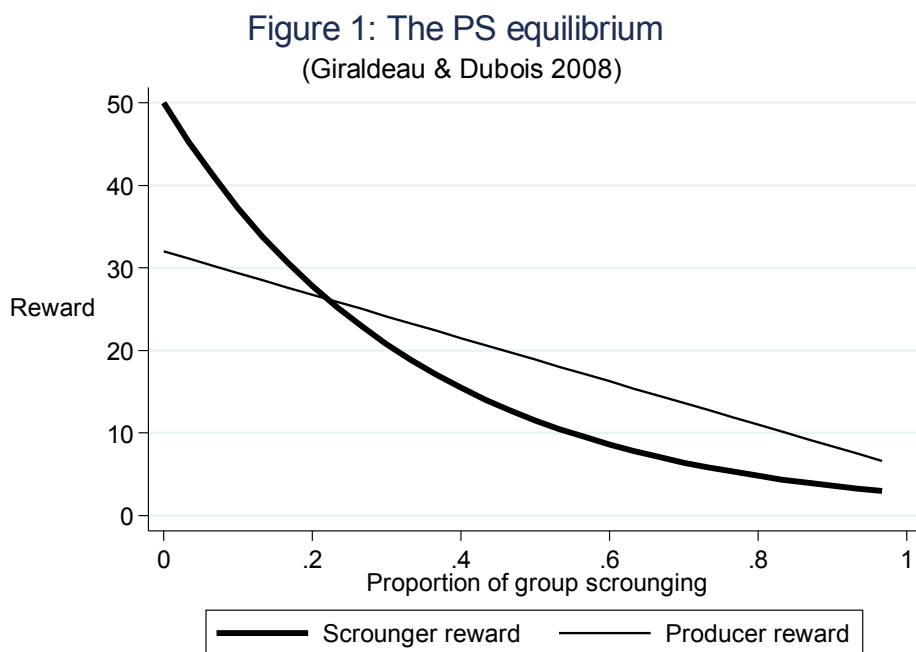
The producer's payoff is thus calculated as the number of patches found by the producer in question multiplied by the food the producer extracts per patch. Food per patch is calculated as the finder's share, a , plus the producer's share of the remaining $F - a$ food items in the clump. The $F - a$ items are shared between the one producer and the $(1 - p)G$ scroungers. The scrounger's payoff is calculated as the payoff per clump multiplied by the total number of clumps discovered by the Gp producers in the group. As the game modelled here is symmetric, the stable equilibrium frequency of producers is found by equating the producer and scrounger payoffs and solving for P . Thus the equilibrium frequency is given by

$$\hat{P} = \frac{a}{F} + \frac{1}{G}$$

The equilibrium frequency of producers in this model thus depends on the ratio of the finder's advantage to clump size and decreases with the number of individuals in the group. The primary extensions to this model found in the social foraging literature involve distributional assumptions for λ , and for the allocation of food to competing scroungers (hence making the game non-deterministic – see for example Giraldeau & Caraco, 1991). Despite the fact that the experimental design presented in section 3 is stochastic, the deterministic model presented above is sufficient to demonstrate the key features of the PS game. The primary goal of the design is to capture these features and as these are best illustrated by the simple deterministic model, the stochastic model is not presented here. Numerous biological experiments have been conducted in order to test the predictions of the PS model. While most of these confirm the model's predictions, they are plagued by problems of small sample size.

Two key characteristics of the PS game are illustrated by the model. The first is that the payoffs are frequency dependent. Producer payoffs are weakly negative frequency dependent on the number of scroungers due to the fact that producers share the remaining $F-a$ food items in a clump with all $(1-p)G$ scroungers. Fewer scroungers imply that competition for these food items is reduced and thus that each competitor can expect to obtain a greater share. Scrounger payoffs, on the other hand, are frequency dependent through two channels. Firstly, scrounger payoffs are increasing in the number of producers (implying negative frequency dependence to the number of scroungers) due to the multiplicative Gp term. Intuitively, more producers mean that scroungers have more opportunities to usurp resources and thus get a higher payoff. Secondly, scrounger payoffs are decreasing in the number of scroungers as they too must compete with every other scrounger for a share of the food clump. Although the model implies that both producer and scrounger payoffs are increasing in p , it must be noted that this is unlikely to be the case in reality. This is due to the fact that if there is any modicum of scarcity, λ will be a decreasing function of p and thus producer payoffs will be decreasing in p . Giraldeau and Dubois (2008) note that, in reality, producer payoffs can be an increasing, decreasing or constant function of the number of producers. In accordance with this reasoning, the graph below displays producer payoffs as decreasing in the number of producers as this is the most realistic situation but the experimental design assumes that producer payoffs are invariant to the number of producers as this is the simplest case.

Frequency dependence is a vital feature of the game as it creates the possibility that the reward functions for producers and scroungers will cross and cross once, thus generating a unique Nash equilibrium (or its complement in biological terms – a behaviourally stable strategy) for a given food patch. Figure 1 shows the reward curves to the strategies for a given food patch.



Here the horizontal axis measures the proportion of the group scrounging and the vertical axis the expected reward to playing each strategy. The thin line represents producer payoffs whilst the thick curve represents scrounger payoffs. The Nash equilibrium of the system is at the point of intersection of the two curves. The key here is that at this point, there is no possibility of profitable unilateral defection due to frequency dependence. Another point to note is that when the proportion of the group scrounging is equal to 1 (thus no individual is producing), all individuals receive a zero payoff as no information regarding the location of food clumps is produced.

One key aspect of the situation that the above model fails to capture is that scroungers free-ride off information produced regarding the overall quality of the food patch as well as off information regarding the presence of specific clumps of food (Giraldeau & Dubois 2008). The availability of this information suggests that scroungers will be better able to predict the more profitable strategy on the current food patch. The implication of this is that fewer producers, hence less information available to scroungers, will lower payoffs to scrounging, as scroungers will be less accurate in their assessment of the more profitable strategy. This dynamic is expanded upon below.

Another key aspect of the PS game is illustrated by the model, albeit subtly. This is that the two strategies are mutually exclusive (Giraldeau & Dubois 2008). This is

inferred from the fact that producer payoffs depend only upon the food clumps that they themselves find. Direct dependence of producer payoffs on the clumps found by other producers would indicate an ability to produce and scrounge simultaneously. This is an important point firstly for definitional purposes and secondly because it forces agents to make a dichotomous choice between the two alternatives. From a definitional point of view, if producers are able to compete for the resources found by other producers and search for food, the situation is classified as an information sharing game (Giraldeau & Dubois 2008). The mutual exclusivity of strategies is key to the interest that the situation holds for behavioural economists as, if individuals can choose both options simultaneously then very little can be learnt about preferences for one option over the other. In the bird case, there is some evidence for the mutual exclusivity of strategies, most notably the finding of Coolen, Giraldeau & Lavoie (2001) that head position in relation to a horizontal plane when foraging is a statistically efficient predictor of whether the individual is producing or scrounging.

The remainder of this paper abstracts away from resource based scrounging and focuses on the scrounging of information alone. It is useful at this stage to make explicit how this may generate relationships of frequency dependence based on the number of scroungers. As stated above, scroungers free ride firstly off information produced regarding the presence of food clumps within a food patch and secondly off information produced regarding the quality of the food patch as a whole. A higher proportion of scroungers implies firstly that information regarding the presence of specific food clumps is more likely to be outdated and, as the strategies are mutually exclusive and exhaustive, also implies a lower proportion of producers. This results in frequency dependence as scroungers are less able to ascertain which strategy is more profitable or whether the current foraging patch is close to exhaustion. Frequency dependence of producer payoffs on the number of scroungers arises as a result of the information produced as to the whereabouts of a specific food clump becoming outdated more rapidly.

As mentioned above, there are two possible mechanisms by which birds could reach and maintain NE strategies. The first possibility is that a simple behavioural rule is used. This could be something along the lines of:

1. If upon arriving at a new food patch there are fewer than P other birds present, play producer.
2. If, upon arriving at a new food patch there are more than P other birds present, play scrounger.

Such a rule would result in a similar NE to that observed in birds where the strategies are played at stable frequencies but individual birds alternate between producing and scrounging. Scrounging birds on food patch 1 would realise earlier that the patch was close to depletion and hence move to a new patch sooner than producing birds on patch 1. Hence, in accordance with the behavioural rule above, scroungers on patch 1 would be producers on patch 2 and producers on patch 1 would be scroungers on patch 2 and so on. The second possibility is that some form of neural process takes responsibility for the relevant strategic decisions. There is evidence to support this hypothesis in humans and monkeys where the neurons of the dorsolateral prefrontal cortex calculate strategy mixes (Lee, Conroy, McGreevy & Barraclough 2004; Lee, McGreevy & Barraclough 2005). The point here is that the type of learning model that captures this process can be conducted by any brain so long as it has a sufficient number of neurons (Ross, forthcoming). This suggests that if the second possibility is true then birds and humans should reach a similar equilibrium under PS conditions. Thus, if the two species do, in fact, reach similar equilibria this provides evidence for a neural mechanism being responsible for calculating strategy mixes in both birds and humans rather than a behavioural rule specific to foraging birds.

Note that implicit in the behavioural rule outlined above is the assumption that food patches are such that they have identical NE. This is unlikely to be the case however and thus some discussion about possible adaptive behaviour in order to reach NE in the case where P , the number of producers on a patch, is not equal to P^* , the optimum number of producers is offered here. The first possibility here is that with P producers, scrounger payoffs are low relative to producer payoffs indicating that more producers can be supported. In this case, scrounging birds, as they are able to observe the payoffs of all producers, will switch to producing until such a time as $P=P^*$ indicating that the payoffs to the two strategies are equal and that the system is in equilibrium. Note that scrounging payoffs being low relative to producer payoffs suggests that the

patch is such that λ , argued above to be one of the key determinants of producer payoffs, is still high and thus the patch is not close to depletion. The second possibility here is that producer payoffs are relatively low, implying that λ is low and the patch close to depletion. This will result in scrounger payoffs being low relative to producer payoffs as here relatively scarce food clumps are distributed amongst a relatively large number of scroungers. Producers however still receive a finders share. In this case, scrounging birds will fly off in search of other food patches and follow the behavioural rule outlined above. The implication of the above is that whenever scroungers observe their payoffs to be low relative to producer payoffs, they respond by searching for more productive food patches.

This examination of the PS game in biology is important as it draws attention to the key elements that must be captured in an experiment designed to test human behaviour under PS conditions.

2. PS and humans

This section is divided into two subsections. In section 2a, some psychological and economic experiments that capture elements of the PS dynamic are examined. The purpose of this is, firstly to provide some assurance that an experiment of the type described below does not already exist and, secondly to provide some indication as to how a true PS experiment may be set up. Section 2b is concerned with answering the second of the questions stated in the introduction: “do people encounter situations usefully modelled by PS games ‘in the wild’?” As argued above, an affirmative answer to this question greatly enhances the motivation for conducting such an experiment as it opens up the possibility that the results of the experiment will advance our understanding of human behaviour in these circumstances. The majority of this subsection is devoted to an analysis of the parallels between predicted behaviour in PS conditions and human behaviour in asset market games.

2a. Related experiments

The focus of this sub-section is on explaining an experiment conducted by Kameda & Nakanishi (2002, 2003) with the goal of examining human learning and population fitness in cultural and acultural conditions. This experiment is chosen as the focus as it successfully captures the impact of scroungers free-riding on information produced on the quality of a food patch. It comes short of fully representing the PS dynamic, however, as it generates no explicit linkage between the payoffs of producers and scroungers. In the bird situation, this link was created by the fact that the object of the information generated by producers, the food, is a rival resource. The Kameda & Nakanishi experiment thus captures the type of frequency dependence that the above PS model misses whilst missing the type that the above model captures. Both of these types are required in a design for human subjects.

Social learning can quite naturally be modelled as a PS interaction. In the cultural condition, meaning that the actions of others are observable, individuals who invest in learning act as producers, as the information generated by this process is observable to those that choose not to invest in learning – the scroungers. The scroungers' payoff improves when there are more producers as this implies more, and more reliable information in the system. This is an exact parallel to the bird case. More producers imply higher expected payoffs to scroungers as scroungers have more information by which to judge the relative profitability of the strategies on the current foraging patch. Furthermore, scroungers do not pay to receive this information.

In the cultural condition of the experiment, subjects played a game called 'where is the rabbit?' in which they were required to predict in which of two nests the rabbit currently resided. The rabbit moved a randomly determined amount of the time but subjects were told that it had a tendency to remain in the same place. Payment depended on the number of times that subjects successfully guessed the rabbit's location. The two strategies were accommodated by the option of using the 'rabbit search machine'. Doing so involved paying a cost but provided visual information to the subject choosing to use it that correctly identified the rabbit's location 67% of the time. This on its own does not constitute a producer strategy however as the information also needs to be observable to the members of the group not using the 'rabbit search machine'. This was done by making the cumulative earnings of a randomly determined

three out of the remaining five group members available every fifth period. Although this does not make the information generated by the search machine directly available to scroungers, it is assumed that it filters down through the payoff information provided implying that having more producers allows scroungers to better predict the location of the rabbit, thus raising their expected payoff. What must be noted here is that the other type of scrounging mentioned above where scroungers free-ride off information concerning the presence of individual food clumps is absent in this case.

Another experiment that resembles the PS game to an extent is used by Pietras & Hackenberg and Pietras, Locey & Hackenberg (2001, 2003) to study human choice between a risky and safe option when the goal is to meet a budget constraint. This situation closely resembles the more complex models of the PS game as, in these, birds are assumed to minimise the chance of failing to meet metabolic requirements (Giraldeau & Caraco 1991). Although Pietras & Hackenberg's is not a strictly game theoretic experiment, individuals engaged in a PS game face the same choice between risky and safe lotteries. This choice is mirrored in our design (with one notable complication).

Thus although it appears that no experiment directly testing behaviour under producer scrounger conditions has yet been developed there are some that capture certain elements of the interaction such as the information dynamics or the relative riskiness of the strategies.

2b. PS interactions in humans

This subsection is concerned with presenting cases in which humans can plausibly be modelled as playing a PS game. The majority of the section is devoted to a comparative analysis between PS games and interactions in asset markets. It is argued that the information dynamics occurring in PS games and asset markets are virtually identical and that both situations have the same payoff structure resembling that found in a 'chicken game' (see Dixit, Skeath & Riley 2009). In addition to this, several other situations are briefly discussed, namely the decision to adopt a new technology and the decision to invest in research and development in the pharmaceutical industry.

The role of public and private information in asset markets is well documented in the literature (see Anderson & Holt, 1997; Hung & Holt, 2001) and this results in the PS situation being almost identical to that in asset markets. To see this, consider a simplified view of a market where there are only two types of agent. Type 1 agents act only based on private information regarding the fundamental factors behind stock prices. While this information is generally reliable (or would be if not for the presence of type 2 agents), it is costly for the individual to obtain. Type 2 agents, on the other hand, act solely based on public information. In the market case, this is the information contained in stock prices. This information is freely available but is only reliable in cases where prices are strongly influenced by fundamentals. This implies that, if variation in prices is created by the demand of type 1 agents, this information will be a reliable indicator of value; whilst if the variation is due to type 2 agents, the information is less likely to be reliable.

The relationship between the above situation and PS games is already beginning to emerge. The type 1 agents, those that act on private information, are the producers in this case as they engage in a costly search for information and this information becomes available to others as a result of the type 1 agents' market decisions. Type 2 agents act as scroungers as they forego the costly search for information and base their decisions on freely available public information which is generated, in part at least, by the private information of type 1 agents. The relationship runs deeper than this however as this information dynamic and its impact on market volatility lead to similar relationships of frequency dependence as those observed in PS games. As public information is noisy, a large proportion of type 2 agents acting on this information will be likely to cause market volatility as the signal (information based on fundamentals) to noise (public information based on the actions of others) ratio decreases. For risk averse participants expected utility is, *ceteris paribus*, decreasing in market volatility; hence this implies negative frequency dependence. A higher proportion of type 2 agents decreases the utility of both type 1 and type 2 agents through increased market volatility. A compounding effect also occurs here: more type 2 agents imply that the likelihood of a type 2 agent basing decisions on the actions of another type 2 agent, as opposed to a type 1 agent increases, because participants do not know what type of agent they are

observing. This same dynamic is noted by Kameda & Nakanishi (2002, 2003) in their social learning experiment where a high proportion of scroungers decrease the overall quality of the information pool.

There is another similarity that may arise here if the producers' payoff function takes the appropriate shape. As noted by Giraldeau & Dubois (2008), an all producer equilibrium may be socially optimal if the producer payoff function is of the appropriate (plausible) shape. This is mirrored in asset markets. If everyone acts based on their own private information, market volatility is minimised as little information is lost to the market through scrounging implying that the market is more efficient. Such a point is not however robust to unilateral defection. In the PS game, a producer can improve his personal payoff by scrounging whilst in the stock market case a type 1 agent can improve his payoff by switching to type 2 and scrounging off the information produced by type 1 agents thus avoiding the costly information search. At such a point, all agents would realise this to be the case and switching would occur until the Nash equilibrium point was reached.

The situation where relatively few producers in the system decrease the overall quality of the information pool parallels that of an information cascade. This occurs in asset markets where participants ignore their own private information when choosing a strategy in favour of public information produced by the actions of others. This results in the private information of all cascading agents being lost to the market and hence, reduced efficiency (Anderson & Holt, 1997; Hung & Holt, 2001). In laboratory settings, cascading behaviour is usually tested by asking subjects to 'guess' which of two urns a ball was pulled out of. Each urn contains balls of two colours but at different frequencies. In each period of these experiments, subjects are told about the proportion of balls of each colour in the urn being used for the trial and are then allowed to select a ball from the urn in use. The colour of this ball represents the subjects' private information. Following this process, subjects sequentially announce their 'guesses' as to which urn the ball was drawn from to the rest of the group. Here subjects can either base their decision on their own private information or, for all but the first subject to announce a guess, base their decision upon the prediction of previous group members. If subjects take the second option and there was initially a pattern of conformity in

decisions, a cascade may occur. This negatively affects payoffs. To see this, consider the case (taken from Anderson & Holt, 1997) where urn A (in use) contains two red balls for each white while urn B (not in use) contains two white balls for each red. In a situation where each subject bases their guess on private information, subjects who are required to make their decision later may have a better idea about the nature of other player's private information. If a large proportion of other subjects guess B, the subject in question may believe that this indicates that more of the group drew white balls than red, in accordance with the distribution in urn A. This dynamic does not arise in the case of a cascade however as all decisions other than that of the first subject are based upon the decision of the first subject. This implies that subjects who announce their guess later have a lower chance of guessing the correct urn as they effectively only have one other subject's guess to rely on. This in turn will lower expected payouts if these are conditional on guessing the correct urn.

Relating this back to the PS game, in a situation where there is a greater proportion of scroungers than producers, all individuals have less information upon which to base decisions as in the case of a cascade. This means that neither type of bird is able to accurately assess the profitability of the strategies for the current resource patch. This increases the chance of sub-optimal play.

The close parallel between asset markets and PS situations further justifies the decision to conduct a PS game experiment with human subjects as optimal policy in asset markets is a highly controversial topic in economics. The insights into human behaviour that such an experiment could offer would advance our understanding of asset markets and thus have direct, practical, not to mention academic, value.

One does not need to look too hard to find other areas in which humans find themselves in conditions that may plausibly be described as similar to those of the PS game. Consider, for example, the decision to adopt a new technology. Conley & Udry (2008) examine the decision of farmers in Ghana to abandon traditional crops in favour of growing pineapples for export. As noted by Evenson & Westphal (1995), the characteristics of a new technology are often not transparent to the prospective user. This implies that an investment in learning about the technology is generally associated

with its adoption. The prospective pineapple farmer has two options when it comes to learning about this technology. The first is to make the costly investment himself through research and, inevitably, experimentation and the second is to observe the methods of other farmers who are experimenting with the crop. Here experimenting farmers act as producers and observing farmers act as scroungers. Frequency dependence also occurs in this case. Having more producers experimenting with the technology will increase the quality of the information pool as this increases the chances of finding new, improved methods for cultivation. Having more scroungers, on the other hand, will likely result in a slow pace of innovation for the same reason. It seems reasonable to assume that this dynamic may occur with any new technology after the first user has adopted it. That this is a PS situation is reinforced by work by Walden & Browne (2002) describing the occurrence of information cascades in the adoption of new technologies.

A third case where the PS dynamic appears to be at play is in the decision firms face between developing new products through conducting research and development and producing generic copies of pre-existing products. This is perhaps most clearly illustrated with reference to the pharmaceutical industry. For simplicity assume that each firm must choose to produce either only new drugs or only generic drugs. The firms that choose to produce new drugs are the producers as these can only be developed through a costly research process. These costs are however compensated for by the finder's advantage which, in this case, is the profits that producing firms can make by producing a patent protected drug. Firms that choose to produce generics, on the other hand, are scroungers as they free ride off the expensive research conducted by producing firms. Here again, an argument can be made for payoffs being frequency dependent. If there is a proliferation of scrounging firms, competition in the market for the generic drugs that these firms produce will likely be high. While this may be advantageous to society as a whole, it likely limits the profitability of the scrounging firms. Producers, if others are rare, may feel it less important to develop new drugs as there is a lower chance that a rival will produce the same drug first. This dynamic relies upon some common information in the R&D process however. This analysis leads to the well known general conclusion on research and development – firms must be adequately incentivised through the prospect of increased future profits if they are to

conduct research (Levin, Klevorick, Nelson & Winter 1987). What is interesting about the analysis, however, is that this incentive, acting through a patent, mirrors the finder's advantage in the PS model above. In order to increase the equilibrium frequency of producers, the finder's advantage must be increased (Di Bitetti & Janson 2001).

The above analysis presents three cases where humans could be modelled as playing a PS game 'in the wild'. The most striking similarities here are found in the case of asset markets where the information and payoff dynamics are almost identical (one difference is that scrounging may be the more risky strategy in asset markets). Whilst the other two cases definitely bear some resemblance to PS games, the link may not be as useful here. The reason for this is that decisions to adopt new technologies and decisions to invest in R&D are typically the domain of corporations rather than individual agents. As argued above, the fact that PS situations naturally occur in human interactions provides the motivation to design and conduct and experiment testing human behaviour under these conditions.

3. Experimental design

This section presents the basic design of an experiment to test human behaviour under PS conditions. Some of the more detailed elements of the design are left to section 4 as these will be determined by a computer simulation of the experiment. First the basic design of the experiment is explained. Following this, the design is compared to the PS game to confirm that it captures the key intuitions. This is a necessary step as the design employed is fairly abstract. Lastly, the experimental procedure is examined, with this section covering topics such as the necessity of practice rounds, subject selection and the importance of conducting an independent elicitation of risk preference.

The basic procedure is best explained by examining the process that subjects are put through in each round of the experiment. Here a round refers to the number of periods (the number of times the choice between producing and scrounging is presented to subjects) played on a specific resource patch. As is explained below, the lotteries that correspond with producing define a resource patch. The process is the same in all rounds so any differences across rounds are due to the payoffs used.

In each period, subjects will be required to make a choice between two options: A and B . Here A corresponds to producing and B to scrounging. Subjects will be presented this choice on a computer screen and do not observe the mechanics that determine payoffs. A choice of A corresponds with a random process determining which of two lotteries will actually be played whilst a choice of B corresponds with a lottery scaled to account for frequency dependence.

The lotteries faced by subjects choosing A differ depending on whether the subject's previous choice was A or B . Consider a subject choosing A in period 1. This corresponds with the lottery, L^A . Contained in this lottery are two sub-lotteries of different types; a lucky lottery (L^{a^L}) and an unlucky lottery (L^{a^U}). Which of these types of lottery a subject choosing A will end up playing is determined randomly with each lottery occurring with a 50% chance. Furthermore, the lottery allocated to the player here determines the player's type (lucky - a^L and unlucky - a^U) which is fixed as long as the subject continues to play A . Thus a^L players play lottery L^{a^L} whilst a^U subjects play lottery L^{a^U} . L^{a^L} stochastically dominates L^{a^U} , hence the classification as lucky and unlucky.

Both of the A lotteries have five prizes that occur with equal probabilities. Note that the payoffs of the A lotteries represent the resource patch on which the group is currently foraging. This leads to the natural interpretation of a round of the experiment as the time spent foraging on a specific patch. The process for determining the actual prizes used is discussed in section 4. Subjects playing A in the first period will keep their a^L/a^U classification for all consecutive periods in which they choose A . This means that in these periods, subjects do not play the compound lottery L^A as this could lead to reclassification. Rather subjects play whichever of (a^L, a^U) corresponds with their type. This dynamic holds for any subject choosing A for the first time. In order to be reclassified, subjects choosing A in the previous round must switch to B and then back to A . This results in reclassification through the play of lottery L^A . In short, any subject choosing A at $t=1$ and any subject playing A at $t=g$ that played B at $t=g-1$ is classified through playing lottery L^A whilst any subject playing A at $t=g$ that played A at $t=g-1$ plays whichever of (a^L, a^U) corresponds with their type. As noted above, this process is

the same in all rounds. What changes from round to round are the prizes associated with the A lotteries.

The process determining the payoffs to strategy B is far simpler. A choice of B results in a simple lottery, L^B , that is stochastically dominated by L^{aL} but stochastically dominates L^{aU} . One complication here is that the prizes in the B lottery are scaled in order to impose negative frequency dependence to the number of scroungers. The scaling equation used is

$$P^B = P^R \left(Y - \left(\frac{Z}{XN} \right) \right) \quad \text{if } S < G$$

$$P^B = 0 \quad \text{if } S = G$$

with P^B being the payoff received by the subject playing B , P^R the 'raw', unscaled B payoff, Y being a constant, X determining the slope of the curve, N being group size, S being the number of subjects playing B and G being the total number of subjects. $Z=S-1$. The Y and X parameters allow for the B payoff curve to be adjusted in order to accommodate various quantal response equilibria (QRE). This scaling also implies that payoffs are zero if the entire group play B . The frequency of B players at which the prize is equal to the minimum motivating amount is within the QRE region for each set of A lotteries (hence each round) and is elaborated upon in section 4. The A lotteries and B lotteries are set such that L^{aL} stochastically dominates L^B which stochastically dominates L^{aU} . There is no relationship of stochastic dominance between L^A and L^B however.

At end of each period, players are presented with information about the payoffs of some other players. The nature of the information received is determined by the player's choice in the period. Players playing B observe the payoffs of all subjects playing A in addition to their own payoff. They are also told how many other subjects chose B . It is likely that this information is available to scrounging birds in the biological version of the game. As these birds are present at every food clump, they will observe producer payoffs and, as all scroungers compete at each clump simultaneously, it is likely that they will have some idea as to how many other birds are scrounging. Subjects

choosing A on the other hand receive information about the payoffs of a number of other A players as well as the number of subjects playing B . The exact number of other payoffs that each A player sees has a potentially strong impact on the way subjects play the game. If too many payoffs are observable, the game could become one where players optimise by trying to predict the expected value of the L^A . If too few then the frequency dependence of A payoffs is less likely to hold. For this reason, this amount is varied over experimental rounds. The exact proportions can only be determined with reference to a simulation of the experiment. The procedure for doing so is discussed in section 4. It is likely that producers observe the number of scroungers in the group due to competing for resources simultaneously. Furthermore, producers will have some idea as to the number of birds feeding off the current patch. This gives an indication as to how depleted the resource patch is. There being many birds feeding on the patch implies that the level of depletion is still low. If, on the other hand, there are relatively few birds on the patch, the implication is that the patch is close to exhaustion and thus scroungers (as they have better information regarding patch quality) have flown off in search of greener pastures.

Providing A players with information on the payoffs of some other A players is necessary as this creates the possibility for these players to recognise that there are in fact two payoff structures within L^A . Although this may appear to violate the assumption that the two strategies are mutually exclusive, there are two factors that serve to mitigate this worry. The first of these is that, in reality, producing birds will likely have some indication of the success of proximate producers. This could be indicated through the behaviour of scrounging birds upon arrival at a newly discovered resource patch. Secondly, as argued above, the economic interest in the mutual exclusivity of strategies stems from the implication that birds must make a dichotomous choice between producing and scrounging, thus revealing some information regarding their preference for one option over the other. The payoffs, both in terms of information and actual reward, to the strategies are sufficiently different under this design to ensure that this is still a meaningful choice. Consider first the information available to B players: as B players observe the payoffs of all A players there is a greater likelihood of them observing both L^{aL} and L^{aU} payoffs. A players receive no direct information regarding B payoffs and thus even if they do observe A payoffs of both types, they are only able to

compare these with B payoffs by actually playing B . In addition to this, the monetary rewards associated with the two options will be sufficiently different as, although there is no relationship of stochastic dominance between L^A and L^B , L^{aU} is stochastically dominated by L^B which is stochastically dominated by L^{aL} . As A players will receive a payoff from a lottery that either stochastically dominates or is dominated by L^B , the actual rewards associated with their choices are such that the choice is still meaningful.

Examination of the payoff structures implied by this game illustrate that this is, in fact, a PS game. Payoffs in terms of expected values are presented in figure 2. Here the B payoff curve is drawn in such a way that it incorporates the scaling that generates frequency dependence. The A lottery payoff curves are drawn horizontal as the information mechanism that generates frequency dependence is a result of subjects' decisions within the experiment.

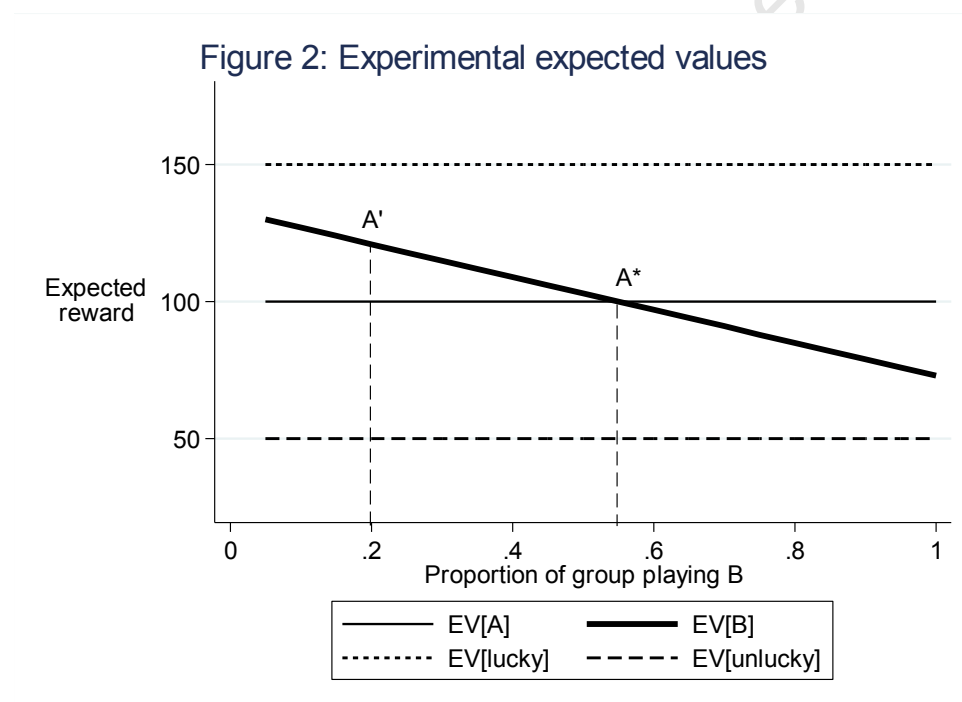


Figure two makes it clear that the payoff structure in the experimental design is very similar to that found in the PS game. The main difference is that here the B option payoff curve is linear. This is simply a result of the scaling function used and has no impact on the nature of the game. Although there is not an explicit cost to producing in this design, there is a probabilistic one. This results from the compound nature of the L^A lottery. At

the expected value equilibrium, a risk averse subject will still prefer to play B indicating that there is a cost to producing.

Another point that arises from examination of figure two is that in this game subjects maximise their payoff by correctly predicting the number of other subjects that will switch strategy when the system is out of equilibrium. For example, if at the end of period 1, the system is at A' , any subject playing A can improve their expected payoff by switching to B on the condition that fewer than A^*-A' subjects switch to B . If more than A^*-A' subjects switch, the system ends up at the right of the equilibrium point and the subjects' optimal action would have been to continue playing A . This will hold for all cases where the system is not in equilibrium. The key to success thus lies in predicting how many subjects are likely to switch to the more profitable strategy at current levels of producing and scrounging.

As noted above, the experimental design may initially appear to be fairly far removed from theoretical discussion of the PS game. A closer examination of the elements of the design shows that the key features of the game are however captured. The key features of the game were identified as being the negative frequency dependence of scrounger payoffs on the number of scroungers, the free-riding of scroungers off information produced by producers and the mutual exclusivity of strategies. As explained previously, although the experimental design may at first appear to violate the requirement that the strategies be mutually exclusive, this is in fact not the case as although A players do receive information on the payoffs of some other A players, the choice between playing A and B is still meaningful. That the choice between A and B be meaningful was argued to be the most economically interesting aspect arising from the mutual exclusivity of strategies. The negative frequency dependence of scrounger payoffs to the number of scroungers is generated by the scaling equation presented above. The fact that this is generated artificially in this design whilst it occurs naturally in foraging birds is immaterial. The importance of negative frequency dependence is that it allows the reward curves to producing and scrounging to cross and cross once thus generating a unique mixed strategy NE, represented by A^* in figure 2. Lastly, the design allows scroungers to free ride off costly information generated by producers. This is achieved by making the payoffs of *all* A players available to B players

at the end of each period. As B players receive information on all A payoffs whilst A players receive information on only a subset of other A payoffs, there is a far higher chance of B players observing payoffs of both lucky and unlucky A players. Furthermore, this information is far more valuable to B players as they are able to compare the payoffs to the two options as they receive some information regarding the profitability of playing B , namely their own payoff. The cost to A players of generating this information is in this case probabilistic due to the compound nature of the A lottery. Thus, although the design presented above may initially appear to be too far removed from a pure PS game, all of the important elements of the interaction are captured.

As one of the primary objectives of this experiment is to assess the impact that the provision of new information has on choice that would otherwise be predicted by risk preference, it is necessary to conduct an experiment eliciting risk preference in each experimental group. This will be done by means of a multiple price list (MPL) method (see: Holt & Laury 2002). In this, subjects are presented with a choice between two different binary lotteries. Table 1 illustrates the nature of choices that subjects are offered in this treatment. Note that subjects do not see the final column listing the difference in expected value.

Table 1: An MPL

Option S (safe)					Option R (risky)					
Row	p	Rand	p	Rand	Row	p	Rand	p	Rand	EV^S-EV^R
1	0.1	88	0.9	53	1	0.1	132	0.9	22	23
2	0.2	88	0.8	53	2	0.2	132	0.8	22	16
3	0.3	88	0.7	53	3	0.3	132	0.7	22	8
4	0.4	88	0.6	53	4	0.4	132	0.6	22	1
5	0.5	88	0.5	53	5	0.5	132	0.5	22	-7
6	0.6	88	0.4	53	6	0.6	132	0.4	22	-14
7	0.7	88	0.3	53	7	0.7	132	0.3	22	-22
8	0.8	88	0.2	53	8	0.8	132	0.2	22	-29
9	0.9	88	0.1	53	9	0.9	132	0.1	22	-37
10	1	88	0	53	10	1	132	0	22	-44

In each row, subjects are required to select either option S or option R. Option R is risky in the sense that the variance in payoffs is greater than that of option S up to row ten. For each option, the chance of receiving the higher outcome increases as the row number increases with the higher outcome being certain in row 10. The final column presents the difference in expected values between the two lotteries. As, in row 1, the expected value of S is far greater than that of A, all but the most risk affine agents will choose S. In row 10 however, the higher payoff is certain and thus all subjects would be expected to select option R. This implies that the typical subject will switch from S to R at some row. The point at which this switch occurs is the key to determining risk preference. As a first pass, subjects switching before row 5 are risk affine as here the expected value of the safe option is still greater than that of the risky option indicating that some utility is gained through bearing this risk. Subjects switching on or after row 5 are risk averse as this implies that the expected value of the risky option must exceed that of the safe option to compensate for the loss in utility due to the increased variance of R option payouts. Note that the MPL presented above is weighted toward risk aversion as there are only four risk affine choices but five risk averse choices. This makes for more precise estimation of risk preference in the risk averse domain.

Beyond being able to test whether a subject is risk affine or risk averse, an MPL allows for the calculation of more specific measures of risk aversion if appropriate assumptions are made concerning subjects utility functions. Consider for example the constant relative risk aversion (CRRA) function below:

$$\frac{x^{1-r}}{1-r}$$

Here x is the lottery prize and r the coefficient of risk aversion with $r > 0$ indicating risk aversion, $r = 0$ risk neutrality and $r < 0$ risk affination. This structure enables the calculation of an upper and lower bound of the coefficient of risk aversion. Assume that a subject plays S for the first seven rows and switches to R on the eighth. This implies a lower bound to r of

$$0.7 \left(\frac{88^{1-r}}{1-r} \right) + 0.3 \left(\frac{53^{1-r}}{1-r} \right) = 0.7 \left(\frac{132^{1-r}}{1-r} \right) + 0.3 \left(\frac{22^{1-r}}{1-r} \right) \Leftrightarrow r \approx 1.07$$

and an upper bound of

$$0.8 \left(\frac{88^{1-r}}{1-r} \right) + 0.2 \left(\frac{53^{1-r}}{1-r} \right) = 0.8 \left(\frac{132^{1-r}}{1-r} \right) + 0.2 \left(\frac{22^{1-r}}{1-r} \right) \Leftrightarrow r \approx 1.53$$

The range in which the coefficients are estimated can be narrowed by presenting subjects with multiple MPLs designed such that the implied coefficients of risk aversion overlap to an extent. Four such MPLs are used in this design and they are presented in Appendix 1. In MPL tests, subject payment is determined by random selection of one of the lists, following this, a row on the selected list is chosen at random. The subject's choice is then recorded and some form of random number generator (a ten sided die for example) is then used to determine whether the subject receives the high or the low payout. Important here is that this leads the subject to act in each choice as if the current choice was for payment as each choice is paid out with equal probability. This gives some assurance that subjects will reveal their true risk preference. In addition to this, lottery payouts are set such that the expected value of the experiment (assuming moderate risk aversion on average) is equal to the minimum motivating hourly amount for the intended sample.

This independent elicitation of risk preference will allow the impacts of risk preference and the provision of information to be estimated separately in econometric analysis.

The remainder of this section discusses the procedure of the experiment and various miscellaneous details such as subject choice and experimental conditions. The most important issue here is having an extended practice period. The reason for this is that, as such an experiment has not been conducted before, there is no way to judge how long it will take subjects to reach equilibrium for a given set of A lotteries and thus no way to determine how many periods an experimental round should contain. A long practice round will provide assurance that subjects know the game and understand its

dynamics. This allows for the length, in periods, of the main experimental rounds to be arbitrarily set at 20. The practice round will be played for hypothetical stakes similar to those used in the main rounds and be paid at the minimum motivating amount for the sample.

The experimental sessions will be run in South Africa and Canada simultaneously as this provides a point of comparison. The obvious choice of experimental subject in this case would appear to be students. This is problematic however as the experiment aims to test the impact of new information on risky choice. Students are likely to be far more sensitive to the presence of new information as the university environment is one where the main purpose is (in theory) to learn, hence to process and act upon new information. This dynamic is undesirable as it greatly limits the external validity of the trial. For this reason, it was decided to draw the sample from fluent English speaking individuals living in Cape Town in the Western Cape Province of South Africa having completed at least twelve years of schooling (Matric). The same process will be used to obtain the Canadian sample however it must be noted that a far lower proportion of the Canadian population will be excluded by the education condition. The condition that the subjects be educated ensures firstly that the South African and Canadian samples can be compared (as the level of education in the Canadian population is considerably higher than in the South African population) and secondly that subjects will be able to understand the experimental tasks with relative ease. It must be noted here that sampling from this educated portion of the South African population implies that the sample will not be representative of the population as a whole.

The importance of providing meaningful incentives to subjects in an experimental task of this sort is well documented (Friedman & Sunder 1994). For this reason, it was necessary to calculate a minimum motivating hourly amount for the sample described above. This was done by taking the average hourly wage of employed individuals working in the Western Cape with at least a Matric qualification (from the National Income Dynamics Survey (NIDS 2008)) and adjusting this for inflation. The resulting minimum motivating hourly amount is R65,00. In order to calculate the corresponding amount for the Canadian sample, this amount was converted into

Canadian dollars and then adjusted to account for differences in purchasing power. The resulting minimum hourly motivating amount for the Canadian sample is \$C 16,00.

The probabilistic and frequency dependent payoffs used in the design necessitate that the main experimental task be computer based. For this reason, it was decided to conduct the risk preference elicitation procedure on the computer as well. There is no disadvantage to this as most subjects will likely have some experience with using computers due to the education requirement. Individual work stations will be separated by barriers to ensure that the actions of other subjects are not directly observable.

Upon arrival, each subject will be seated at an individual workstation. A welcome presentation will then be given by the lead experimenter outlining the main goals of the experimental task and requesting that subjects sign the consent form provided. Following this, subjects will be instructed on how to complete the MPL task and proceed to do this. After payments for the risk elicitation have been determined, subjects will be given instructions regarding the main task. These will be limited and give no indication as to the payoff structure behind the choices. Subjects will however be told that some information will be received at the end of each period depending on which choice was made. Following this, subjects will complete the extended practice round. As noted before, this round is played for hypothetical stakes and paid out at the minimum motivating rate. When this is completed, the paid rounds of the main task will be played. The method of determining payment here is very similar to that for the MPL described above. At the conclusion of the experiment, subjects will draw a random number that will determine which round payment is to be based on and then draw another random number determining which period in that round they will be paid for. Whatever the subject earned in this period is his payoff for the main task. As with the MPL task, this helps to ensure that subjects treat each decision as if it were for payment. Subjects will only receive their payouts at the end of the experimental session.

4. Technical details

This section attempts to resolve some of the more technical aspects of the above design. Most notably, it explains the process of conducting a computerised simulation of the experiment and presents simulated results for different values of key parameters on the assumption that subjects play to the NE point. The specific prizes used for the A lotteries will be based upon this simulation in order to provide for sufficient variation in the position of the equilibrium position. In addition to this, the specific prizes used for the lotteries in the MPL task are presented here. Both of these exercises require certain assumptions about subjects' utility functions. It is assumed that these are of the CRRA form described above and that the average subject is moderately risk averse (r between 0.4 and 0.5).

This assumption of risk aversion allows for the expected value of the MPL task to be set at the minimum motivating amount for our moderately risk averse subject. This of course assumes that this task and its instructions will take an hour to complete. This is justified by the fact that the sample is educated and that the task is fairly simple. The lotteries for this task are chosen such that firstly the expected value is equal to the minimum motivating amount under the assumption of risk aversion and secondly that the CRRA coefficients can be estimated within relatively precise intervals namely (0.32 – 0.42), (0.42 – 0.54), (0.54 – 0.61) and (0.61 – 0.68) for the risk aversion domain. The actual lotteries used, with S indexing the first column and R the second and $i=1,2,3,4$ indexing the lottery set number, are (S1: 110, 66; R1: 175,18), (S2: 88, 53; R2: 132, 22), (S3: 31, 20; R3: 49, 4) and (S4: 26, 22; R4: 44, 11). The tables to be used are contained in Appendix 1 along with the corresponding coefficients of risk aversion.

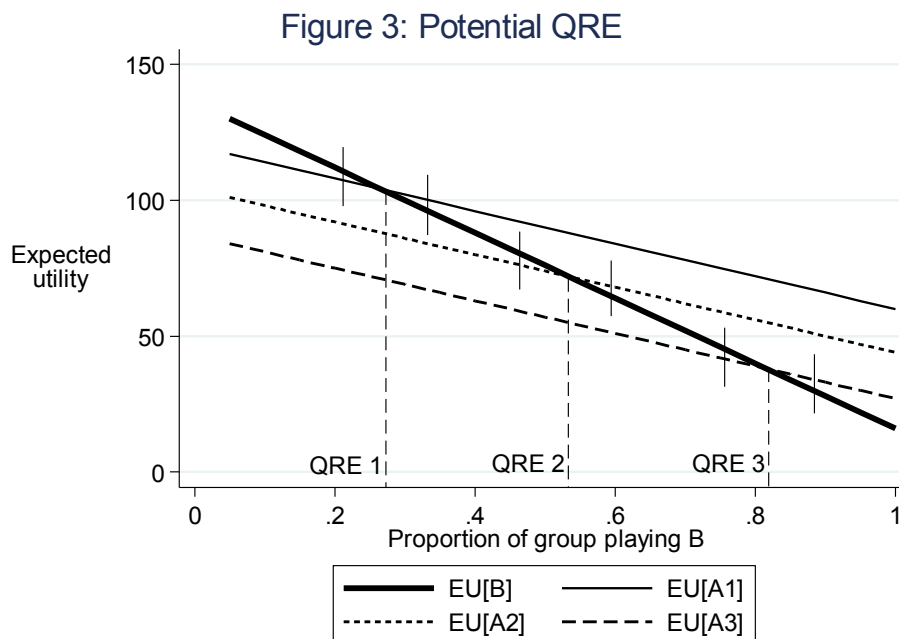
Three aspects of the experimental design can only be determined by simulating the experiment. These are the exact payoffs to the lucky and unlucky A lotteries, the amount of information provided to producers and the robustness of the design to different assumptions about maximising behaviour. This simulation will be conducted using custom software developed by Professor Glenn Harrison at the Centre for the Economic Analysis of Risk at Georgia State University. Although the software is functional, the documentation explaining how it is used is still in development and, for

this reason this section discusses the process of simulating the experiment and the motivation for doing so. In addition to this, some simulations of various Nash equilibria are presented.

The software in question enables Gambit (a strategic game simulator) to run designs where payoffs are probabilistic rather than deterministic. This is done by linking Gambit and Stata. Lottery prizes and data are inputted in to Stata and the custom software causes Gambit to call on Stata for this information when it is needed. From this, Gambit is able to compute the relative quantal response equilibria.

Figure 3 makes clear the importance of choosing lottery prizes such that the quantal response regions are sufficiently far apart. This amounts to a condition that the design has statistical power. The figure illustrates potential QRE for three different combinations of A lottery payoffs. In addition to using A lottery payoffs to move the QRE region, this could also be done by adjusting the X and Y parameters of the scaling equation presented above as these control the height and slope of the curve. This would need to be done in such a way as to be sure that the minimum motivating amount payoff remained inside the QRE region.

In the figure, the curves labelled EU [A1], EU [A2] and EU [A3] give the expected utilities for differing variances of the L^A lottery. The expected value of this lottery is constant across these scenarios. A1 is the case where the prizes in lottery L^{aU} are relatively close to those in L^{aL} reflecting that the expected utility of the risk averse agent is relatively high in this case. A3 represents the case where the difference in payoffs is large and A2 lies between the two. The fact that these curves are linear reflects the assumption that A players utilities are linearly increasing in the amount of private information available. One of the purposes of simulating the experiment is to determine if this assumption is justified. EU[B] is the expected utility from playing the B option. The QRE regions for A1, A2 and A3 are given by the vertical lines around the points QRE 1, 2 and 3 respectively.

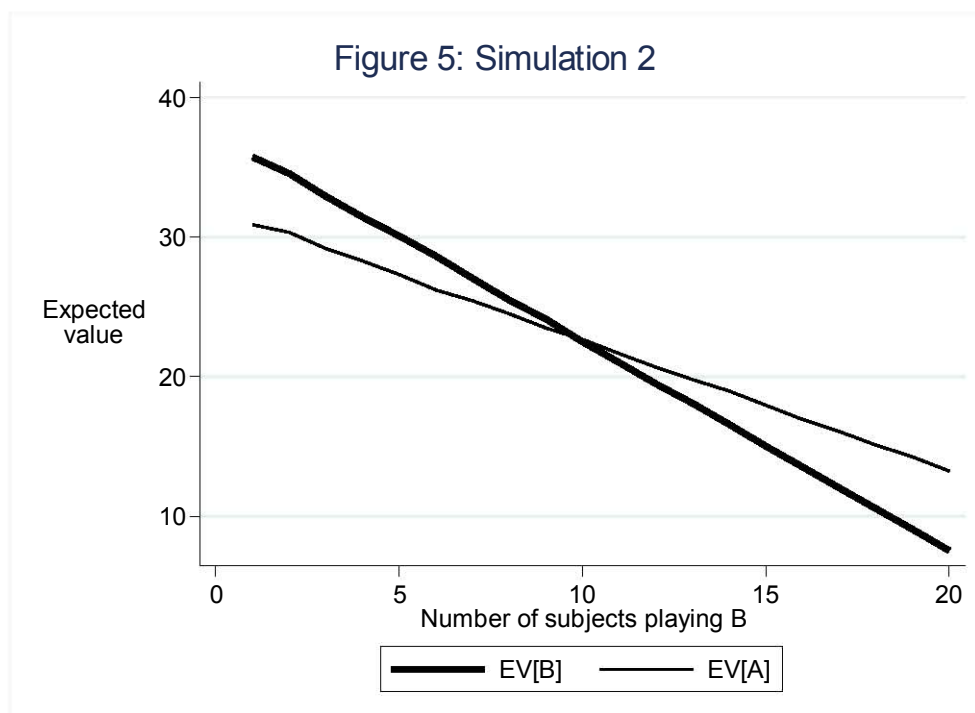
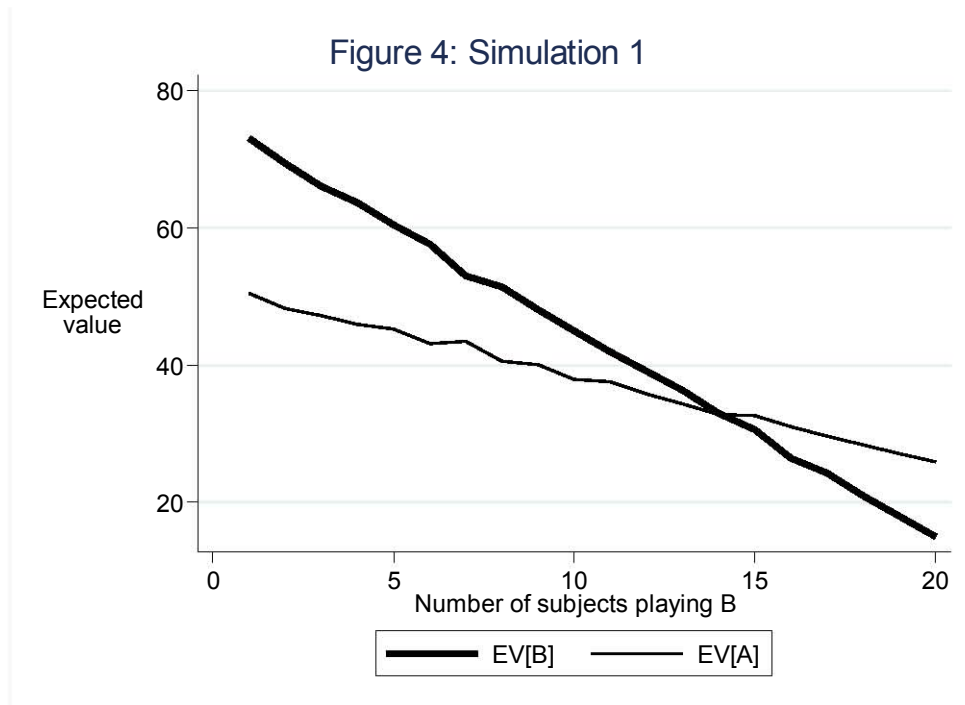


The payoffs to the A lotteries must be such that three conditions are satisfied. Firstly, the QRE region for each set of payoffs must not be too large. This has implications for the power of the experiment. If individual QRE regions are too dispersed, the case that subjects are approximating best response behaviour is weakened. The second condition is that the QRE for the various A payoffs show sufficient variation. This is effectively a condition that the payoffs must be such that the equilibrium frequencies of A and B are sufficiently different that equilibrium play under each set of payoffs is not approximated by equilibrium play under any other set. The third condition is that the expected value of L^A be equal to R65,00 at the point where the moderately risk averse agent is indifferent between playing A and B.

The B payoffs are calculated according to the scaling equation above. These will be such that the scaled value of B is equal to R65,00 within the QRE regions.

Although Gambit is necessary in order to determine the QRE associated with a given set of lotteries, it is still informative to examine simulations of the Nash equilibria. The QRE region will, after all, contain the Nash equilibrium point. Figures 4, 5 and 6 illustrate simulated Nash equilibria for three sets of lotteries and for different parameters of the scaling equation. These simulation were performed in Excel and required the assumption that A lottery expected values decline linearly as less

information is available. The expected values of the *A* lotteries are thus scaled with the same scaling equation as presented above but with different values of *X* and *Y* to the *B* lotteries.



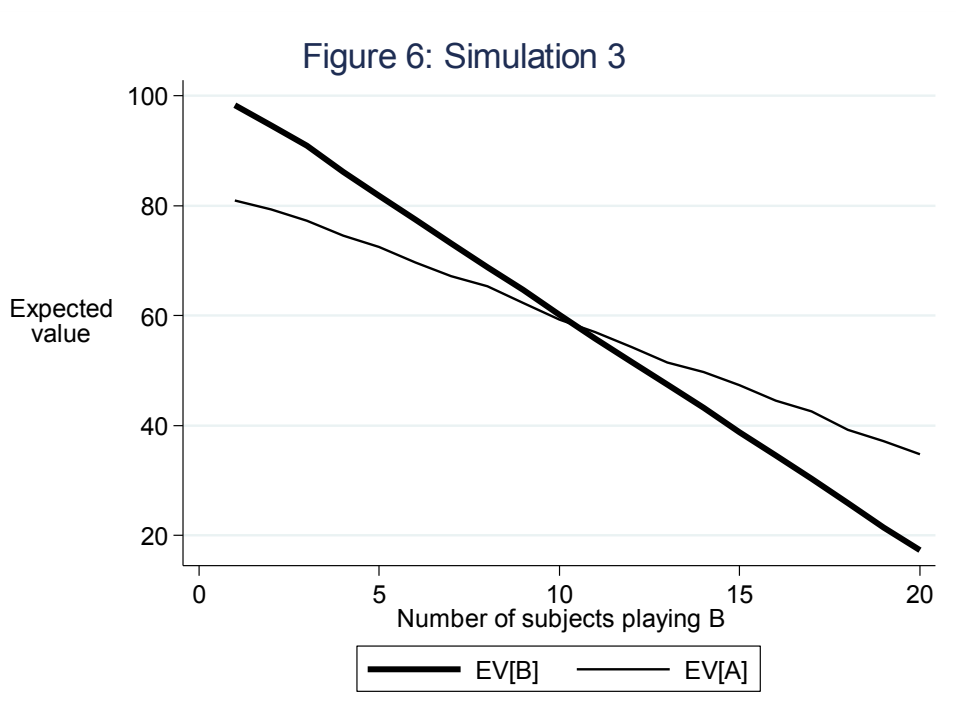


Table 2: Simulated lottery prizes

Figure 4	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5
Prizes L^{aL}	0	190	240	290	340	0	180	185	190	195
Prizes L^{aU}	0	80	90	100	110					
Figure 5										
Prizes L^{aL}	100	110	120	130	140	65	70	75	80	85
Prizes L^{aU}	20	30	40	50	60					
Figure 6										
Prizes L^{aL}	150	250	350	450	550	150	150	180	180	200
Prizes L^{aU}	50	60	70	80	90					

Table 2 provides information on the L^{aL} , L^{aU} and L^B prizes used in each simulation. In all cases, prizes occurred with equal probability of 0.2. In addition to this, the scaling parameters used for the A lotteries (given in the form (X, Y)) were $(5, 0.35)$, $(4.25, 0.4)$ and $(4.25, 0.2)$ for the simulations shown in figures 4, 5 and 6 respectively. In the same order, the B lotteries were scaled by $(2, 0.4)$, $(2.5, 0.5)$ and $(2, 0.6)$. The results presented in the figures constitute the average A and B payouts for 100 observations at each number of scroungers. This simulation is informative for two reasons. Firstly, it illustrates how the Nash equilibria (in expected values) can be adjusted by altering the

scaling parameters and in the case of simulation 3, shows the appropriate magnitude of the raw lottery payouts.

5. Conclusions and extensions

The aim of this paper, as stated in the introduction, was to design an experiment for human subjects that mirrored the producer scrounger dynamic that occurs in foraging birds. The motivation for doing this stems from the close parallels between the PS dynamic and various economically relevant human situations. Here it was argued that the stock markets in particular can be described by PS dynamics.

The primary questions that this experiment aims to answer are:

- (1) What is the impact of the provision of information on human behaviour under circumstances where choice would otherwise be predicted by risk preference?
- (2) Is the equilibrium that humans reach in PS situations similar to that reached by foraging birds?

The answer to the first of these questions potentially has an impact on the modelling of bounded rationality. If it turns out that the provision of new information plays a large part in explaining choice that would otherwise be predicted by risk preference then it follows that individuals should be more willing to pay costs associated with acquiring this information. An affirmative answer to the second question would give some evidence toward the hypothesis that the PS equilibrium in birds is a result of neural processes rather than a non-generalising decision rule.

An obvious extension to the current project, assuming that humans were found to behave like birds under PS conditions, would be to build a model of human behaviour in these circumstances. This would involve adapting the biological models of the phenomenon to a greater or lesser extent. The main tension that arises when attempting to apply these models directly to humans is that there is no direct parallel to the form of frequency dependence that occurs

in foraging birds as a result of direct competition for resources. In the paper it was hypothesized that if the interaction was viewed in terms of information dynamics then this form of frequency dependence would be captured. There is no assurance however that it could be modelled in the same manner as resource based frequency dependence is in formal models of bird behaviour under these conditions. The invention of such a model would allow for the use of empirical data to search for areas in which humans play this game.

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Appendix 1:MPL Tables:Table 1:

<u>Option S (safe)</u>					<u>Option R (risky)</u>						
Row	p	Rand	p	Rand	Row	p	Rand	p	Rand	EV^S- EV^R	r
1	0.1	110	0.9	66	1	0.1	175	0.9	18	37	-1.57
2	0.2	110	0.8	66	2	0.2	175	0.8	18	25	-0.87
3	0.3	110	0.7	66	3	0.3	175	0.7	18	14	-0.43
4	0.4	110	0.6	66	4	0.4	175	0.6	18	3	-0.07
5	0.5	110	0.5	66	5	0.5	175	0.5	18	-9	0.24
6	0.6	110	0.4	66	6	0.6	175	0.4	18	-20	0.54
7	0.7	110	0.3	66	7	0.7	175	0.3	18	-32	0.87
8	0.8	110	0.2	66	8	0.8	175	0.2	18	-43	1.25
9	0.9	110	0.1	66	9	0.9	175	0.1	18	-54	1.80
10	1	110	0	66	10	1	175	0	18	-66	7.02

Table 2:

<u>Option S (safe)</u>					<u>Option R (risky)</u>						
Row	p	Rand	p	Rand	Row	p	Rand	p	Rand	EV^S- EV^R	r
1	0.1	88	0.9	53	1	0.1	132	0.9	22	23	-1.73
2	0.2	88	0.8	53	2	0.2	132	0.8	22	16	-0.95
3	0.3	88	0.7	53	3	0.3	132	0.7	22	8	-0.45
4	0.4	88	0.6	53	4	0.4	132	0.6	22	1	-0.04
5	0.5	88	0.5	53	5	0.5	132	0.5	22	-7	0.32
6	0.6	88	0.4	53	6	0.6	132	0.4	22	-14	0.68
7	0.7	88	0.3	53	7	0.7	132	0.3	22	-22	1.07
8	0.8	88	0.2	53	8	0.8	132	0.2	22	-29	1.53
9	0.9	88	0.1	53	9	0.9	132	0.1	22	-37	2.20
10	1	88	0	53	10	1	132	0	22	-44	8.84

Table 3:

Option S (safe)					Option R (risky)						
Row	p	Rand	p	Rand	Row	p	Rand	p	Rand	EV^S- EV^R	r
1	0.1	31	0.9	20	1	0.1	49	0.9	4	12	-1.79
2	0.2	31	0.8	20	2	0.2	49	0.8	4	9	-1.06
3	0.3	31	0.7	20	3	0.3	49	0.7	4	6	-0.59
4	0.4	31	0.6	20	4	0.4	49	0.6	4	2	-0.22
5	0.5	31	0.5	20	5	0.5	49	0.5	4	-1	0.11
6	0.6	31	0.4	20	6	0.6	49	0.4	4	-4	0.42
7	0.7	31	0.3	20	7	0.7	49	0.3	4	-8	0.75
8	0.8	31	0.2	20	8	0.8	49	0.2	4	-11	1.13
9	0.9	31	0.1	20	9	0.9	49	0.1	4	-14	1.67
10	1	31	0	20	10	1	49	0	4	-18	9.51

Table 4:

Option S (safe)					Option R (risky)						
Row	p	Rand	p	Rand	Row	p	Rand	p	Rand	EV^S- EV^R	r
1	0.1	26	0.9	22	1	0.1	44	0.9	11	8	-2.3
2	0.2	26	0.8	22	2	0.2	44	0.8	11	5	-1.21
3	0.3	26	0.7	22	3	0.3	44	0.7	11	2	-0.49
4	0.4	26	0.6	22	4	0.4	44	0.6	11	0	0.09
5	0.5	26	0.5	22	5	0.5	44	0.5	11	-3	0.61
6	0.6	26	0.4	22	6	0.6	44	0.4	11	-6	1.13
7	0.7	26	0.3	22	7	0.7	44	0.3	11	-9	1.68
8	0.8	26	0.2	22	8	0.8	44	0.2	11	-12	9.71
9	0.9	26	0.1	22	9	0.9	44	0.1	11	-15	9.64
10	1	26	0	22	10	1	44	0	11	-18	15.52