The Advantage of Resource Queues over Spot Resource Markets: Decision Coordination in Experiments under Resource Uncertainty

Miguel A. Fonseca, Alexander Pfaff, and Daniel Osgood

Farmers have to make key decisions, such as which crops to plant or whether to prepare the soil, before knowing how much water they will get. They face losses if they make costly decisions but do not receive water, and they may forego profits if they receive water without being prepared. We consider the coordination of farmers' decisions, such as which crops to plant or whether to prepare the soil when farmers must divide an uncertain water supply. We compare *ex-ante* queues (pre-decision) to an *ex-post* spot market (post-decision & post-rain) in experiments in rural Brazil and a university in England. Queues have greater coordination success than does the spot market.

Key words: queue, decision-making under uncertainty, coordination, experiments, field.

JEL codes: C92, C93, D02.

Introduction

Consider a set of farmers who must share an uncertain quantity of naturally supplied water. Before rain falls, each farmer must make several decisions, the returns of which depend upon obtaining water; for example, whether to purchase expensive seeds and fertilizers or to prepare the land for planting at all. Such decisions can be financially consequential. Direct losses can be incurred if crops fail when water is scarce, while the foregone profits can be significant when water is plentiful but not used.

Under uncertainty, such choices are difficult even when farmers act independently. Choices become more challenging when water is shared. Indeed, there exists real potential for coordination failure. If expected water supply is low, then few farmers should plant – but if farmers do not know what other farmers are doing, each may expect to obtain water and may plant seeds with high water requirements. On the other hand, it could occur that none plant out of fear that water would be scarce. Both scenarios are inefficient in the sense of expected loss from aggregate decisions not matched by water supplies.

Within this familiar setting, information concerning either water supply or water demand could substantially affect farmer choice (Bryant et al. 1993; Willis and Whittlesey 1998; Cai and Rosengrant 2004; Sunding et al. 2000; Moreno et al. 2005). The importance of such information implies a critical role for institutional design and establishes a value from defining rights to water, markets for those rights, and markets for water (Burness and Quirk 1979; Dinar and Letey 1991). This was first acknowledged by Coman (1911) in the first article published in the *American Economic Review*. Despite such longstanding awareness, however, water allocation and decisions under uncertainty remain "unsettled" (see Ostrom 2011, discussing Coman 1911). Identifying efficient coordinating institutions still has great value, which inspires our current efforts.

One common institution is a queue, where farmers are allocated water in sequence from the start of the queue until the water is gone. Frequently, water cannot be transferred

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post-allocation, although in some cases spot markets do allow farmers to sell water to each other after overall quantity is known (Howitt 1998; Olmstead et al. 1997; Brozovic et al. 2002) and informal annual leases of rights between farmers occur (Cristi 2007; Skees and Akssel 2005). One common basis for this type of allocation is appropriative water rights, which are common within the western United States (as noted by Burness and Quirk 1979; Berck and Lipow 1994; Libecap 2011). Much prior study of queues compares their allocative efficiency to that of equal share allocations, focusing on issues of infrastructure, transaction costs, and risk aversion (Burness and Quirk 1979; Libecap 2011; Lefebvre et al. 2012). We focus on the coordination of farmers' pre-rainfall decisions. Specifically, we ask whether a water queue alone could be more efficient than a post-rain spot water market in helping farmers to coordinate decisions whose returns depend on an uncertain water supply.

Should we expect queues to improve decision coordination? In theory (Small, Osgood, and Pfaff 2009), forward-looking individuals facing an *ex-post* spot market for their water might not only figure out the most efficient crop choice in the aggregate, but also somehow coordinate their expectations about each others' decisions. This may not be likely, but it is still possible.

Yet coordination of *ex-ante* decisions in such a manner seems like an immense challenge because, unlike an *ex-ante* queue, an *ex-post* market provides useful information on scarcity only after crop choices are made and rain has fallen. Thus, in theory (Berck and Lipow 1994; Freebairn and Quiggin 2006; Small, Osgood, and Pfaff 2009), *ex-ante* queues for water rights can raise *ex-ante* decision efficiency. Although Freebairn and Quiggin (2006) claim that *ex-ante* and *ex-post* markets could perform all of the same functions, they do not address the importance of the many pre-rainfall farmer decisions which we focus on. Small, Osgood, and Pfaff (2009), in contrast, focus precisely on *ex-ante* versus *ex-post* institutions' coordination of *ex-ante* decisions. In particular, *ex-ante* queues provide differentiated probabilities of receiving water according to which queue slot the actor holds. Earlier slots have a greater chance, which is common knowledge. This should improve the coordination, between farmers, of their *ex-ante* (pre-rainfall) decisions. Thus, it should be more likely that crop water demands are proportional to expected water supply.

Ultimately, whether a queue helps to coordinate decisions is an empirical question. Yet empirically examining institutions to answer this question requires both queues and spot markets in numerous comparable settings where resource uncertainties can be appropriately quantified; this seems exceptionally unlikely. Similarly, it is highly unlikely that researchers would receive permission to vary any actual local water-allocation institutions in a systematic way for research purposes.

Experiments are another option, where a researcher controls the uncertainty faced by participants – who also face financial incentives that are structured to imitate farmers' actual decision problems (for agriculture see, e.g. Binswanger 1981; for natural-resources management see, e.g. Cason and Gangadharan 2004 on auctions).[1] The most relevant experiment of which we are aware is that of Lefebvre et al. (2012), which studies profits with security-differentiated water rights (mimicking the essence of a queue) versus non-differentiated, equal share rights. The differentiated rights are seen to have profit and risk-management benefits relative to the non-differentiated rights.

We use our experiments to answer a different question, however. Instead of the queue (differentiation) versus share (equality) debate in which transaction costs and infrastructure are important, we study the coordination of pre-rainfall farmer choice, which Lefebvre et al. do not consider. While the related study included markets both before and after the resource quantity was known, we test how alternate mechanisms help decision-making, specifically designing the treatments to have information and trading mechanisms either before or after resource revelation.

[1] Our work is relevant to experimental studies of auction structures for emissions trading (see, e.g. Cason and Plott 1996, Mestelman et al. 1997, Godby et al. 1998). In such experiments, emissions-permit auctions are often framed as markets for an uncertain resource that is necessary in production, much like in our water-allocation context. In the emissions-permit work, auction structures are evaluated for efficiency considering variation in auction timing, for instance, as well as in permit banking. Some work is done in a deterministic setting, while some has featured uncertainty, but all of the models with closed-form solutions have had only risk-neutral actors. Comparisons of performance involve multiple benchmarks (price and quantity stability, efficient pricing, complete use of permits) but do not address the coordination of decisions, which is our focus here. As coordination can be relevant to emissions trading, this may extend the relevance of our work comparing allocation in *ex-post* resource spot markets to *ex-ante* queue institutions.

With this motivation, we compare three water institutions using controlled experiments: two water queues established before crop choice, which is before resource realization (rainfall), and a spot market in which the market allocation of water occurs after both crop choice and rainfall. In one queue, farmers are allocated their places in the queue. In the other queue, each farmer purchases a queue place in an auction. For each of these two queues, after knowing her/his place, each farmer chooses between a more costly crop, one that is higher in both yield and water demand, and a cheaper and lower-yield crop that is less water-demanding. Then, once nature has determined the total water supply, water units are allocated in sequence to the farmers as per their queue places.

In the spot water market, farmers choose between crops under greater uncertainty about effective water availability because each farmer faces the same chance of obtaining the resource; that is, farmers lack the differentiation provided by a place in queue. Once the water supply is known, farmers purchase units at auction. The most direct analog to this is an annual water auction conducted by a centralized authority. Yet from the bidder's perspective, it is not important who supplies the water. Thus, our type of *ex-post* spot-market is consistent with various forms of existing spot markets with many sellers.

We employ both laboratory and 'artefactual' field experiments (Harrison and List 2004). Most experiments to date have been conducted at universities with undergraduate participants. However, there is a growing recognition of the importance of using field subjects as participants, whether in abstract experiments or natural settings (Levitt and List 2009; Herberich et al. 2009). Our field subjects were taken from the state of Ceará, in Northeast Brazil, where farmers face the issue we are considering, that is, they are subject to seasonal-to-interannual climate shocks, in particular associated with ENSO, that affect crop outcomes. Our lab subjects are undergraduates from the University of Exeter. Having subjects from both the field and the lab provides a robustness test and a window on lab versus field differences.

We find that each queue outperforms the post-decision, post-resource-realization market for coordinating pre-rainfall choices and, thus also outperforms the market in terms of efficiency. Both queues permit participants to capture a greater share of total possible earnings. Both queues also have fewer large deviations than does the spot market; this is from efficiently balancing aggregate decisions with the expected supply of water. Interestingly, we find little or no difference between the two queues, that is, between when players bid for queue places versus being in an exogenously assigned queue, despite the added complexity from the bidding for queue places. We also find that the individual choices appear to reflect an understanding of the intended incentives within the game, although there is somewhat greater variability in the behavior observed in the Brazilian field subject pool than was observed within the subject pool consisting of university undergraduates.

The remainder of the article is organized as follows. Section 2 lays out the theory from which we derive predictions to be tested in our experiments. Section 3 details the experimental design and our procedures. Section 4 discusses our results, and section 5 concludes.

Theory

Let $j = \{1, 2, 3, 4, 5\}$ denote a set of risk-neutral players. Each player must make binary decisions such as pre-rainfall crop choices: $t_j = 1$(higher yield but more resource-demanding); or $t_j = 0$ (lower yield but less required resources). Payoffs are a function of t_j, as well as the availability of the resource. Let $w = \{0, 1, 2, 3, 4, 5\}$ denote the possible total supply levels of the resource, and let $g(w)$ denote a probability distribution over w. We consider three types of probability distributions (figure 1): certainty (six versions, one for each of the six resource levels); a uniform distribution (assigning 1/6 chance to each of the six resource levels); and geometric distribution, assigning probabilities 0.339 to $w = 0$, 0.238 to $w = 1$, 0.167 to $w = 2$, 0.117 to $w = 3$, 0.082 to $w = 4$, and 0.057 to $w = 5$.

For the higher-yield crop to pay off, a unit of the resource is required (a complement to the crop-choice decision, which had to be taken before the total resource quantity was realized). Let w_j be an indicator for whether player j obtained a unit of resource (i.e. $w_j = 1$) or not ($w_j = 0$). The payoff function is: if $t_j = 1$ and $w_j = 1$, 80; if $t_j = 1$ and $w_j = 0$, −40; if $t_j = 0$ and $w_j = 1$, 40; and if $t_j = 0$ and $w_j = 0$, 0. That a farmer suffers a loss given $t_j = 1$ and $w_j = 0$ is due to this crop's cost. If the lower-yield crop is chosen, no loss is incurred without a unit of the

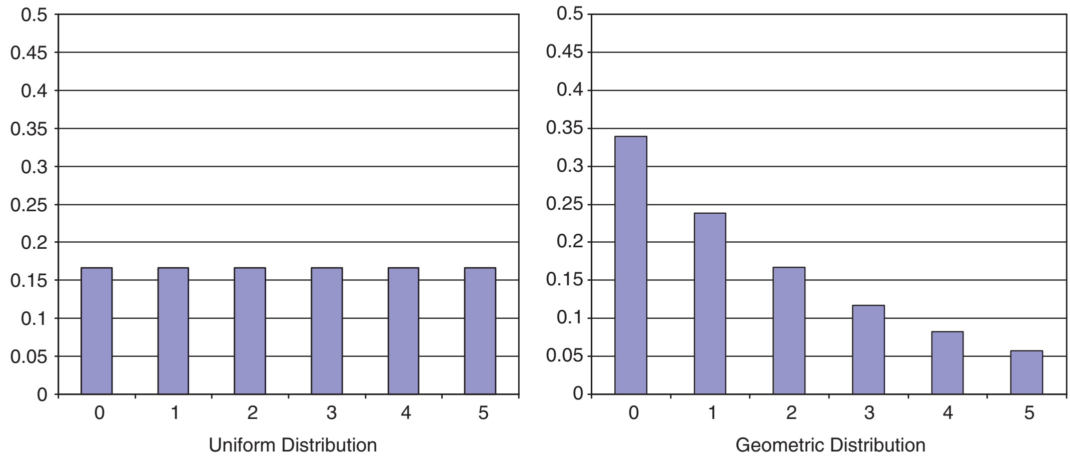

Figure 1. Probability distribution over outcomes of *w*

resource. Yet the profit given a resource unit is lower. Below, we consider the equilibria of three allocation institutions.

Queue Before (QB) decision and resource realization

Here the allocation of the resource proceeds along a queue, and places in the queue q_j are randomly assigned. Let $prob\ (w_j = 1|q_j)$ denote the probability of player j obtaining a resource unit $(w_j = 1)$ given his place in queue q_j. Given that conditional probability, the crop choice will depend on the place in queue. Players will choose a high-yield crop if the expected value is higher than that of choosing a low-yield crop. Both expectations depend upon the chance of obtaining a resource unit. Thus, the farmer should choose the crop with a higher yield that is also more resource intensive if:

$$(1) \quad prob(w_j = 1|q_j)\bullet(80) + (1 - prob(w_j = 1|q_j))\bullet(-40) > prob(w_j = 1|q_j)\bullet(40).$$

Players higher in the queue will choose high-yield crops more often. One should be indifferent between the crops if $prob\ (w_j = 1|q_j) = 1/2$, that is, the chance of obtaining a resource unit is 50%. The implications for the crop choice are in table 1, which provides the values of $prob\ (w_j = 1|q_j)$ by queue placement for each probability distribution we consider, as well as the implied decision.

Under uniform distribution, the first two players in the queue should choose the high yield with certainty. The third player should be indifferent, while the fourth and fifth should choose a low-yield crop. Under the geometric distribution, only the first place has a chance of obtaining a unit of the resource that is higher than $1/2$. Hence, only that player should choose the high-yield crop.

Market Before (MB) decision and resource realization

Here, queue places go to the highest bidder in a sequential first-price auction.[2] We start by bidding for the first place in the queue. The highest bidder wins and pays the bid price. Given a tie, the place is randomly allocated to one of the highest bidders, who then pays the bid price. After the first place in queue is allocated, the winner is then excluded from the subsequent auctions and the remaining bidders bid for the second place. The process continues for all the queue places.

Therefore, MB is a six-stage game, with five bidding stages, then the choice of crop type. Hence, a strategy consists of $< b_j^1, b_j^2, b_j^3, b_j^4, b_j^5; t_j >$, where b_j^k is the bid player that j makes for the k^{th} place in the queue. We restrict our attention to subgame-perfect equilibria. The subgame-perfect equilibrium is $<$ *v(1)-v(5), v(2)-v(5), v(3)-v(5), v(4)-v(5), 0;* $t_j >$. Equilibrium bids for each place in the queue should be the expected value of that place, minus the value of obtaining fifth place.

Consider the choice of crop. Players already know their queue places by then, thus this stage

[2] We felt this would be the easiest mechanism for subjects to understand.

Table 1. Equilibrium Queue-Place Prices & Crop-Type Decisions by Place (MB Treatment)

	Uniform Distribution				Geometric Distribution			
Queue Place	Prob. w = 1	Prob. High Yield	Value	Bid	Prob. w = 1	Prob. High Yield	Value	Bid
1	0.83	1	60.13	53.33	0.66	1	39.44	37.04
2	0.67	1	40.13	33.33	0.42	0	17.04	14.64
3	0.50	0.5	20.13	13.33	0.26	0	10.36	7.96
4	0.33	0	13.47	6.67	0.14	0	5.68	3.28
5	0.17	0	6.8	0.00	0.06	0	2.40	0.00

functions like the fixed queue (QB). Crop decisions are governed by the same rule (although the payoffs are lower here, since players pay for queue places). As in QB, the optimal choice will depend on queue place. No matter the probability distribution, the fourth and fifth places in queue will choose low yield. Knowing those decisions, we can calculate the value of each place in the queue for each probability distribution and, as a result, the optimal bids for those queue places. Consider the auction for the fifth place. Given as many places as bidders, only one player bids for last place, so the equilibrium bid is $b_j^5 = 0$. We can compute the value or expected payoff for having this place, given that high-yield crops are never optimal: $v(5) = prob\ (w_j = 1|q_j = 5)\bullet 40$.

Now consider the auction for the fourth place in queue. A player will never bid more than $v(4)$ - $v(5)$, since losing the bidding for fourth and earning $v(5)$ in fifth place would be better than bidding more and winning the fourth place. From there, it is clear that no player should bid more than $v(q)$ - $v(5)$ for any queue place $q < 5$. We can apply the expected payoffs expressions above for each queue place and the probability distribution to calculate the value for each place and, by implication, the most one should bid for a queue place. Table 1 displays the probability of receiving water for each queue place and each probability distribution, the crop decision that it implies, the value or the expected payoff from that place combined with that crop choice, and, finally, the equilibrium bids for each of the queue places that depend upon all of the preceding information.

A note is warranted concerning risk neutrality (assumed in the literature on which we build). Purchasing a place in the queue is equivalent to purchasing the right to choose between two lotteries that differ in expected value and variance, by queue place. For $prob(w_j = 1) > 0.5$, moving down the queue means a high-yield crop has a lower expected value and higher variance, that is, a higher average return and less risk of being higher in the queue. However, where $prob(w_j = 1) < 0.5$, there is a tradeoff between risk and expected return. Lower places have a lower expected return, but also have a lower variance. If risk aversion matters, then we should see a sharper drop in the prices from the first to second place in the queue, as it is a dominant strategy to bid the value of one's queue place net of the value of having fifth place.[3] Note that we randomly assigned people to institutions. Thus, risk aversion should not affect our queues-versus-spot-markets comparisons.

Market After (MA) decision and resource realization

Here, a spot market allocates water after the crop choice and the resolution of uncertainty. Players choose crops based on expectations of aggregate rainfall, as well as of all the others' choices. Then resource units are realized and sold in a sequential first-price auction, starting with the first unit of the resource. The highest bidder wins the auction and pays that price. In the event of a tie, the resource unit is allocated randomly to one of the highest bidders, who pays that price. After the resource unit is allocated, the winner is excluded from the subsequent auctions and the remaining farmers bid for the second unit. The bidding continues until all of the units are allocated.

[3] There is longstanding debate, from early auction experiments (Cox, Smith and Walker 1988) onward, about whether risk aversion matters in lab experiments. Rabin 2000, e.g. shows that if experimental subjects were to reject low-stake gambles it would imply absurdly high coefficients of risk aversion, as illustrated by this example. "Suppose that, from any initial wealth level, a person turns down gambles where she loses $100 or gains $110, each with 50% probability. Then, she will turn down 50-50 bets of losing $1,000 or gaining *any* sum of money," (p.1282). Nevertheless, we feel this caveat is worthy of mention, and one benefit of randomly assigning participants to treatments is that large differences in risk aversion should not drive our results.

Hence, MA is a six-stage game with a crop-yield decision and then five bidding stages. A strategy is $< t_j; b_j^1, b_j^2, b_j^3, b_j^4, b_j^5 >$, where b_j^k is the bid player j makes for the k^{th} resource unit. We restrict our analysis to subgame-perfect equilibria, working from the bidding equilibria, after crop choice and resource realization, back to the choice of crop. This is relatively complicated even as summarized here, as optimal crop choice depends on decisions by others. In particular, equilibria require players to form consistent beliefs about each other's actions in the auction, and to use those beliefs in the crop-decision stage, where they should select a probability distribution over t_j. We expect this institution to underperform because coordinating such beliefs is very hard.

Here we examine the resource spot market following crop choice and resource realization. Let T represent the total number of players choosing the high-yield crop. If $T > w$, that is, if more players choose the high-yield crop than the number of resource units that were later supplied by nature, then the equilibrium price of each resource unit is 80. Even for the last resource unit, there will be at least two players who opt for the higher-yield crop, and thus have the maximum valuation of 80. There are two possible equilibria: one bids the maximum amount, or all shade the maximum amount by ε. Either way, no player can improve by changing his action. Thus, equilibrium prices are either 80 or 80-ε. By backward induction, it is clear that there will always be excess demand for all of the other resource units, and thus all units will be sold for 80.

If $T \leq w$, the price for the first T units will be $40 + \varepsilon$, and 40 for the remaining units. To see why, consider the auction for the final unit. All bidders have a valuation of 40, as they did not invest, so in the equilibrium at least one player bids 40. This logic applies up to the T^{th} unit. For that unit, there will be one bidder who has invested and has a valuation of 80 who will win the auction by bidding $40 + \varepsilon$. It would not make sense for the unit sold prior to that to sell for more, as investors can wait to outbid non-investors. Thus, all previous units will sell for $40 + \varepsilon$ as well.

Turning to the crop-choice stage, we consider payoffs for higher-yield and lower-yield farmers given the resource auction just described, noting that the crop decision takes as an input not the actual level of resource units that is supplied, but only the expected number. Also, each individual's crop decision will be made conditional on the expectation of all others' decisions.

Considering crop choice, if $t_j = 1$ and $T \leq E(w)$, that is, the total number of high-yield crops is relatively low and the resource will be less scarce, then one can expect to successfully bid for a resource unit at 40 and net 40 from earning 80. If $t_j = 1$ and $T > E(w)$, the resource will be scarce and one successfully bids for a resource unit at 80 and nets 0, or obtains −40 without a resource unit. If $t_j = 0$ and $T \leq E(w)$, one either successfully bids at 40, netting 0, or obtains 0 without the resource. If $t_j = 0$ and $T > E(w)$, then the resource will be scarce and one can expect to obtain 0 without a unit.

Now we consider how T is determined. Consider $w = 0$. As low-yield crops earn 0 while high-yield crops earn −40, it is a Nash equilibrium for all players to plant low-yield crops. For $w = 5$, high yield earns 80 and low yield earns 40, so the unique Nash equilibrium is for all high yields. For $0 < w < 5$, one might or might not get the resource whether one picked high yield or not (linking to the expected payoff calculations above, either $T \leq E(w)$ or $T > E(w)$ may be obtained).

In this setting, multiple asymmetric equilibria exist in which $T = E(w)$, that is, the aggregate choice of high-yield crops is efficient. That is, $E(w)$ of the players are expected by all to select higher-yield crops, while all the others are expected not to do so. While it is unclear how the expectations arise, taking them as a starting point, a player expected to plant high yield, who in fact does, will obtain a resource unit for a price of 40, netting 40. By planting low-yield seeds, he would obtain 0, and so should not deviate. A player not expected to plant high yield, and who does not, would receive a payoff of zero with certainty. Planting high-yield seeds while assuming that the others expected to plant high-yield crops would result in a resource unit with some probability, netting zero, or not, netting −40. Thus, the expected payoff from deviating is strictly negative.

An alternative is symmetric mixed strategy Nash equilibrium, that is, all the identical players choose high-yield crops with the same probability. Details of the equilibrium merely depend on $E(w)$. If the number of units is certain, a mixed-strategy prediction only varies with the available units. Thus, for zero resource units, $p = 0$; for one resource unit, $p = 0.25$; for two resource units, $p = 0.51$; for three resource units, $p = 0.76$; for four resource units, $p = 0.96$; and for the case of as many units as players, or five resource units, $p = 1$, that is, all players would pick high-yield crops with certainty. Under uncertainty with uniform distribution, the probability of choosing high-yield crops is 0.85; with a geometric distribution that probability is 0.3, reflecting the higher scarcity (see online appendix).

Experimental Methods

Each session had 10 or 15 participants. The Brazilian sessions took place in an internet cafe in the town center of Limoeiro do Norte, in the rural agricultural Jaguaribe Valley in the state of Ceará, in the semi-arid and relatively poor Northeast region. The room had 15 networked computers that were physically separated. We ran 23 sessions in June 2007 with 310 subjects. The average payment for participation was $R17.15 ($8.73); the average daily salary in the area is $R18.15 ($10.47). The U.K. sessions took place in the FEELE laboratory at the University of Exeter; we ran eight sessions there in the fall of 2007 and spring of 2008. The average payment for participation was £8.78 ($17.40.) A total of 90 subjects participated. We ran the sessions in both locations with the software toolbox z-Tree (Fischbacher 2007).

The Brazilian subject pool consisted of students from the local polytechnic institute and employees from local government agencies recruited through fliers in their work or study places. Most students were not full-time, and were children of local farmers who worked within irrigated areas, so they had the desired agricultural background for our sessions, as well as the requisite literacy. Subjects had never taken part in an experiment and no individual was in more than one session. The United Kingdom subjects consisted of undergraduates from a wide range of subjects, recruited via email. This is the typical subject pool used in the large majority of experimental-economics research.

Experimenters assigned each participant a booth. Instructions were distributed and read aloud by the experimenter. The subjects then spent between 5 and 10 minutes re-reading instructions, and they had the opportunity to ask questions. Communication between the subjects, however, was not allowed at any point during sessions. Two trial rounds took place before the experiment in order to facilitate full comprehension. The outcomes of the trial had no impact upon the subjects' payments.

The instructions informed each participant that he/she was in a group of five people (none of the participants knew with whom they were playing, however) and that each of the people in the group had to choose between one of the two options presented, labeled A and B. The payoff that each option yielded depended on one's possession of a unit of the resource. The probability of a given total number of resource units being available in each period was shown to the participants on the screen. If a subject chose A and had obtained a unit of the resource, he would get a payoff of 80 'points'; otherwise, he would get a payoff of −40 from option A. If a subject chose B and obtained a resource unit, he would get a payoff of 40; if he had not obtained a resource unit, his payoff from B would be zero. To avoid losses, subjects were endowed with 120 'points' in every period. The experiment consisted of 30 periods. At the end of each period, subjects learned the total resources in that period and the prices that resulted. Subjects were matched with the same others within each period. Subjects were paid on the basis of four randomly selected rounds to minimize income effects. That is, we wanted to avoid the likelihood that subjects would change their behavior at later stages of the experiment due to having already accumulated earnings.

The three institutions described above were the main treatment, and thus we compare the choices in MA, MB, and QB institutions. The second treatment was the probability distribution over the available resource units. We broke each experiment down into three 10-period blocks. In periods 1 to 10, the number of available units was known with certainty. In periods 11 to 20, we imposed a uniform distribution over 0 through 5 with a 1/6 chance of each outcome. In the last 10 periods, we imposed a geometric distribution over 0 through 5, so the probability of there being 0, 1, 2, 3, 4, or 5 resource units was 33.9%, 23.8%, 16.7%, 11.7%, 8.2%, and 5.7%, respectively. This implies a high degree of scarcity. Distributions were available on screen in each period and the experimenter publicly announced both these changes. It is important to note that our within-subjects design raises the issue of disentangling probability distributions' effects from learning.

Results and Discussion

We start this section by comparing the queue institutions with the spot market using two performance metrics: the frequency of aggregate deviations from efficient crop choice given the (certain or expected) level of resources, and the 'earnings losses', that is, the share of total potential earnings not realized. Next, we compare the queues to each other. Then we conclude by examining individual behavior.

Queues Before (QB, MB) vs. Market After (MA)

We conjecture that a spot market would have a greater potential to generate inefficiencies (e.g. all the players might plant high-yield crops even though the expected water was insufficient) given the challenge of coordinating expectations while making all the decisions simultaneously. We note that design choices somewhat limited the potential for large deviations from efficiency. For instance, our groups are relatively small. In addition, one probability distribution has a high degree of scarcity, while another distribution has two efficient high-yield choices. Still, we start by comparing the larger deviations from (expected) resources in the total high-yield-crop choice.

Inefficiency Frequency

Table 2 shows total higher-yield-crop choices as deviations from risk-neutral predictions (combining Brazil and UK). Negative columns indicate a high-yield total lower than expected resources, while positive columns indicate the opposite. The institutions do affect deviations, as the queues always differ from the market in their distributions of the fractions for each deviation. All pair-wise comparisons of fraction distributions between market and a queue (all uncertainty conditions) yielded statistically significant differences at the 1% level using a Pearson χ^2 test.[4]

We also ranked institutions in terms of coordination failure. We can compare, for instance, the frequency of cases in which the deviation is greater than one in absolute value. For MA in periods 1-10 with a known resource supply, looking across the top row of the table that fraction is 24%, which is statistically significantly different from both the MB treatment ($p = 0.04$) and QB ($p = 0.01$). We find no statistical difference between the two queue treatments, and pooling all the data from both queue treatments also differs from the market in this fashion ($p < 0.01$).

In rounds 21–30, high scarcity makes it unlikely to have too many low-yield choices relative to the already low risk-neutral prediction, and thus the significant large deviations are on the higher side, that is, too many high-yield crop choices than are efficient, in aggregate. Adding up all of the deviations with magnitudes above one yields 29% of the observations in MA, which is statistically different from the MB treatment ($p = 0.09$), although it is not different from the QB even at the 10% level ($p = 0.12$). We find no difference between the two queues in terms of frequency of deviations from efficiency, and when we pool their data, we see that the queues as a whole differ from MA ($p = 0.07$). Thus, when we can expect large deviations from efficiency, queues have fewer large deviations than does a market.

In rounds 11–20, the prediction for total high-yield choices is actually *either* 2 or 3. For such a broader prediction, clearly table 2 is going to indicate smaller deviations. Still, as an alternative, we can test the rate of the exactly efficient coordination success, that is, the zero column in table 2. The MB scenario has a significantly higher success rate than MA ($p = 0.08$), while QB does not.

Earnings Loss

We measure earnings loss as a 'shortfall fraction' (i.e. 1 is the ratio of the total payoffs to the *ex-ante* maximum possible earnings). Maximum earnings arise when *X* units of the resource (recall that these are certain resource amounts for rounds 1-10, but are expected values for rounds 11-30) are matched by *X* high-yield choices (that could be any *X* people for the resource market, while for either resource queue that would be *X* people who are at the front of the resource queue). These maximum earnings arise from avoiding the direct losses of 40 from choosing a higher yield, but then failing to obtain water, as well as the foregone profits of 40 from choosing a low yield then receiving water (note that under the geometric distribution, direct losses from an excess high-yield choice were the main source of losses). We compute total and maximum earnings for each group, then subtract their ratio from one,

[4] Within periods 1-10: QB = MA, Pearson $\chi^2(4) = 352.31$, $p < 0.0001$; MB = MA, Pearson $\chi^2(7) = 335.84$, $p < 0.0001$. We use Pearson χ^2 as opposed to Fisher's exact test, as our sample size (in terms of independent groups, as well as choices) exceeds the relevant threshold of n above 40. Further, the expected frequency for each contingency is larger than one for all possible cases (see Sheskin 2011, page 646, for a methodological discussion). Within periods 11-20: QB = MA, Pearson $\chi^2(4) = 66.38$, $p < 0.0001$; MB = MA, Pearson $\chi^2(4) = 153.81$, $p < 0.0001$. Also, within periods 21–30: QB = MA, Pearson $\chi^2(5) = 98.92$, $p < 0.0001$; MB = MA, Pearson $\chi^2(5) = 153.52$, $p < 0.0001$.

Table 2. Deviations of High-Yield Totals from Expected Resource Units (in fractions of groups)

Periods	Treatment	−4	−3	−2	−1	0	+1	+2	+3	+4
1-10	*MA*	0.00	0.02	0.13	0.27	0.30	0.18	0.07	0.02	0.00
	MB	0.00	0.00	0.02	0.16	0.65	0.13	0.03	0.00	0.00
	QB	0.00	0.01	0.02	0.24	0.57	0.15	0.01	0.00	0.00
11-20	*MA*	0.00	0.00	0.03	0.13	0.64	0.19	0.01	0.00	0.00
	MB	0.00	0.00	0.01	0.13	0.82	0.04	0.00	0.00	0.00
	QB	0.00	0.00	0.02	0.15	0.72	0.09	0.01	0.00	0.00
21-30	*MA*	0.00	0.00	0.00	0.09	0.28	0.34	0.23	0.05	0.01
	MB	0.00	0.00	0.00	0.18	0.40	0.28	0.13	0.00	0.00
	QB	0.00	0.00	0.00	0.10	0.41	0.34	0.13	0.03	0.00

and round the value of the total of such 'earnings losses'. Anything that lowers efficiency raises this metric (and thus will have a positive sign in table 3). To explain the earnings losses for each group, we run OLS regressions using treatment dummies, as well as interactions with those treatment dummies, as shown in table 3. For most of the columns in table 3, we consider a round-group as an observation, which allows us to test for learning. We then cluster standard errors by the group, given our fixed matching.

We find the highest level of earnings loss in the MA treatment (omitted treatment is QB), that is the *ex-post* spot resource market, in regression (1), which does not control for the uncertainty conditions (MA = MB: $F(1, 79) = 171.38$, $p < 0.00001$), and regression (2) controlling for uncertainty conditions (MA = MB : $F(1, 79) = 171.23$, $p < 0.00001$). These results are confirmed in (1*) and (2*), as a strong robustness test averaging across rounds.[5] In (2), and (2*), we see a significant detrimental effect on earnings from the geometric condition. Regression (3) unpacks this effect by allowing for interaction effects between uncertainty conditions and institutions. When water availability follows a uniform distribution, earnings loss is lower for both queues (significant only for QB), but higher for MA (Unif x MA = Unif x MB: $F(1, 79) = 28.31$, $p < 0.01$; Geom x MA = Geom x MB: $F(1, 79) = 56.30$, $p < 0.01$). For a geometric distribution of the uncertain water availability, the earnings loss rises for MA and QB, but falls in MB (Geom x MA = Geom x MB: $F(1, 79) = 56.30$, $p < 0.00001$). Regression (4) considers subject pools, lab versus field. We see a small but significant difference in earnings loss under certain water availability scenarios, with more earnings loss in the Brazilian subject pool, but we do not see this in uncertainty cases. Augmenting regression (2) to test for learning yields no significant results within either regression (5) or regression (6); that is, whether modeling potential learning across rounds in an information condition using a time trend (linear by round), or a dummy variable for the last five rounds. In short, examining the deviations from efficiency suggests that the queues coordinate *ex-ante* decisions better than a spot market.

Comparing Queue Options (QB vs. MB)

Our queue institutions differ in levels of complexity. One option is a simple pre-determined queue (QB), while the other is a more complex institution where players must make purchases within a market for queue places (MB). We conjecture that due to its simplicity, the QB might function better than the MB. We compare these queues in terms of both coordination failure and earnings.

Inefficiency Frequency

We see little difference between the queues in terms of crop-choice deviations in table 2. Formally, they do differ in distribution across deviation sizes; that is, driven by the fact that one distribution seems to have a greater variance–rather than because it features a different mean. We confirmed this by means of Pearson

[5] Specifically, we use the group's average for the 10 rounds within an information condition as a single observation for the (2*) column. Extending this dimension, we use a group average for all 30 rounds, that is, all information conditions, as a single observation for the (1*) column.

Table 3. Earnings Losses (1 − Earnings Ratio; Ratio = actual earnings/maximum total)

	(1)	(1*)	(2)	(2*)	(3)	(4)	(5)	(6)
MA	0.200***	0.200***	0.200***	0.200***	0.085***	0.219***	0.200***	0.200***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.029)	(0.024)	(0.018)	(0.018)
MB	−0.039*	−0.039*	−0.039*	−0.039*	−0.007	−0.060***	−0.039*	−0.039*
	(0.022)	(0.022)	(0.022)	(0.022)	(0.034)	(0.018)	(0.022)	(0.022)
Unif			−0.002	−0.002	−0.044***	−0.002	−0.029	−0.012
			(0.015)	(0.016)	(0.016)	(0.015)	(0.031)	(0.021)
Geom			0.128***	0.128***	0.069***	0.128***	0.104***	0.119***
			(0.018)	(0.018)	(0.019)	(0.018)	(0.033)	(0.023)
Unif x MB					−0.043			
					(0.031)			
Unif x MA					0.146***			
					(0.028)			
Geom x MB					−0.052*			
					(0.030)			
Geom x MA					0.200***			
					(0.030)			
Brazil						0.067***		
						(0.025)		
MB x Brazil						0.038		
						(0.030)		
MA x Brazil						−0.023		
						(0.032)		
Trend							−0.005	
							(0.004)	
TrendxUnif							0.005	
							(0.004)	
TrendxGeom							0.004	
							(0.004)	
End								−0.021
								(0.019)
End x Unif								0.019
								(0.020)
End x Geom								0.018
								(0.021)
Constant	0.151***	0.151***	0.109***	0.109***	0.142***	0.055**	0.139***	0.119***
	(0.016)	(0.016)	(0.019)	(0.019)	(0.018)	(0.021)	(0.029)	(0.021)
N	2,400	80	2,400	240	2,400	2,400	2,400	2,400
R-squared	0.21	0.69	0.28	0.58	0.32	0.30	0.28	0.28

Computed '*ex-ante*', using the expected resource levels that players could base decisions upon.
Robust standard errors clustered at group level in parentheses.
*** significant at 1%; ** significant at 5%; * significant at 10%.

χ^2 tests, one for each of these information conditions.[6]

When we focus on substantial deviations (2 units or more) from modeling predictions, we do not find statistically significant differences between the QB and the MB queue treatments. In periods 1–10 and 21–30, the fractions of larger deviations are not distinguishable (though the fraction is higher for MB in periods 1–10, but higher for QB in periods 21–30). For periods 11–20, that is, comparing exact successes, MB is higher but is not statistically significantly higher.

Earnings Loss

Given that our prior supposition was that the QB might do better in coordinating decisions due to its simplicity, perhaps it is surprising that in table 3 we see a small yet statistically significant gain in efficiency from an MB relative to QB. This leads us to ask

[6] That is the case within periods 1–10 ($QB = MB$, Pearson $\chi^2(6) = 48.14$, $p < 0.01$), it is also true for a uniform distribution ($QB = MB$, Pearson $\chi^2(4) = 46.58$, $p < 0.01$) and, finally, true under a geometric distribution, that is, with higher scarcity ($QB = MB$, Pearson $\chi^2(4) = 50.43$, $p < 0.01$).

why. Regression (3) provides one clue: there is no difference under certainty or under a uniform uncertainty distribution; rather, it is with a geometric uncertainty distribution that the queue with purchased rights outperforms the simpler QB queue. That may not come as a surprise: as seen within table 2, for this higher-resource-scarcity situation, most of the errors are over-investment in high-yield crops. The MB scenario, in which queue places already have up-front costs, might discourage players from incurring the additional up-front costs of choosing the high-yield crop.

Another explanation could be that purchasing queue places raises the attention to payoff consequences and thus efficiency–though that should apply to a uniform distribution as well. Yet another speculative explanation concerns 'sorting'; for example aggressive (or less risk-averse) types bid high for places and choose the higher yield, while less aggressive (or more risk-averse) types land lower in queues and choose low yields. Such sorting could avoid the more timid types choosing low yield when at the front of the queue, and the bold types from choosing high yield when at the back of it (we do not have data on individual risk attitudes to test for effects of risk aversion). Such sorting is not possible in QB, although it should also apply to the uniform distribution. In short, we find little or no consistent difference between when subjects bid for queue places and when queue places are exogenously assigned, despite the added complexity of bidding.

Individual Behavior

We now turn to individual behavior. This analysis allows us to test particular point predictions generated by theory, and permits us to explore individual heterogeneity, especially when we analyze data from the field data as opposed to the laboratory.

Crop Choice

We look at the crop choices by institution, followed by the bidding behavior in the queue-place and water-unit auctions.

Crop Choice in Queues

Table 4 shows OLS estimates of the frequencies with which subjects in queue treatments chose the high-yield crop, alongside an indication of the model prediction for risk-neutral actors (denoted "RN Prediction") for the rounds where there was uncertainty about water availability. All of the predictions are binary, that is the model's probability of picking high yield is either 1 or 0, except for the third place under a uniform distribution; that prediction is 0.5–the third place in the queue should pick the high yield half of the time, given that the expected number of units of the resource is 2.5. Each row has its own distinct prediction, plus two samples for testing it, QB and MB. Unlike for the columns in table 2, we treat the fractions in these cells as independent (and within each cell asterisks indicate significant differences from the predicted probabilities).

Using F-tests, we examine whether the overall decision frequencies differ from the model predictions. With three exceptions, all of these sets of decisions do differ from their queue-place-distribution predictions; following the logic of 4.2.2, those three exceptions are all investments that do not get made in the institution when the queue places are bought.[7] We also jointly test whether the observed frequencies for each queue equally place the predicted frequencies. For a uniform distribution (periods 11–20), this means testing $P1 - 1 = P2 - 1 = P3 - 0.5 = P4 = P5 = 0$. We reject this for both the queues (for QB: $F(5, 29) = 36.98$, $p < 0.00001$; for MB: $F(5, 20) = 19.88$, $p < 0.00001$). For the geometric distribution (periods 21–30), the joint hypothesis is instead $P1 - 1 = P2 = P3 = P4 = P5 = 0$, and again we reject for both the queues (for QB: $F(5, 29) = 69.24$, $p < 0.00001$; for MB: $F(5, 20) = 70.74$, $p < 0.00001$). Thus, the behavior does not exactly match the theory for either queue. However, the lower shares of high-yield choices for each place in rounds 21–30 reflect greater scarcity, as do the falling frequencies of high-yield choices across the places for each queue and distribution.

Crop Choice in Spot Market

Table 5 compares high-yield choices in the market (MA) to symmetric mixed strategies. Aggregating across the two subject pools, under certainty the fraction of high-yield crops is not significantly different from the predictions for one or two resource units. For $w = 3$, 4, 5, however, high-yield crop choices are significantly less frequent than the model predicted, by roughly 25%. Lower

[7] MB institution for periods 11–20: $P3 - 1 = 0$, $F(1, 20) = 2.32$, $p = 0.14$; $P5 = 0$, $t = 1.70$, $p = 0.11$; MB institution for periods 21–30: $P5 = 0$, $t = 1.70$, $p = 0.10$.

Table 4. Fraction of High-Yield Crop Choice by Queue Place (QB, MB Treatments)

Period	Dep. var.: crop choice	QB	MB	RN Prediction
11-20	*P*1	0.883***	0.924***	1.00
		(0.024)	(0.026)	
	*P*2	0.700***	0.805***	1.00
		(0.037)	(0.045)	
	*P*3	0.427***	0.410***	0.50
		(0.042)	(0.059)	
	*P*4	0.150***	0.120***	0.00
		(0.026)	(0.026)	
	*P*5	0.173***	0.019	0.00
		(0.029)	(0.011)	
	N	1500	1050	
	R-squared	0.64	0.74	
21-30	*P*1	0.763***	0.719***	1.00
		(0.032)	(0.053)	
	*P*2	0.417***	0.419***	0.00
		(0.043)	(0.062)	
	*P*3	0.183***	0.186***	0.00
		(0.037)	(0.056)	
	*P*4	0.103***	0.029	0.00
		(0.022)	(0.017)	
	*P*5	0.100***	0.019	0.00
		(0.024)	(0.011)	
	N	1500	1050	
	R-squared	0.52	0.53	

Clustered standard errors in parentheses.
*** significant at 1%; ** significant at 5%; * significant at 10%.

Table 5. Spot Market, Fraction Who Choose High-yield Crops by Expected Resource Units

PERIODS	1-10					11-20	21-30
E(w)	1	2	3	4	5	2.5	1
Prediction	0.25	0.51	0.76	0.96	1.00	0.85	0.30
Aggregate	0.35	0.48	0.52***	0.71***	0.75***	0.51***	0.38
UK	0.28	0.40	0.40	0.90	0.92	0.50	0.30
Brazil	0.37	0.48	0.52	0.63	0.72	0.51	0.40

***: 1%; **: 5%; *: 10% - significance levels of 1-sided Proportion Test.
Aggregate row is tested (1-sample test) for equal proportion against Prediction.
The Brazil row is tested (2-sample test) for equal proportion against U.K. sample.

frequencies of high-yield also occur for the uniform distribution–but not for geometric, where high-yield frequency is above prediction but not significantly so ($p = 0.17$, OSPT). We also see no significant difference between the high-yield choices for 2 or 3 units with certainty versus when facing the uniform distribution (where the expected units of resources is 2.5), or for choices with 1 certain unit versus when facing the geometric (expected resource units of 1.0). We find no subject pool differences (though comparisons are limited by the smaller United Kingdom sample).

Bidding

Having looked at the decisions of primary interest, that is, the frequency of crop choices, we now turn our attention to bidding behavior, starting with behavior in the queue. In the queue auction (MB), the place prices convey players' perceptions of the value of each place. Table 6 presents uncertainty cases (periods 11–30), plus one useful result for the case of certainty. Under certainty, a place is worth 80 if a resource unit is available, but zero otherwise. Thus, there should be no fall in price by queue place, as long as the resource is available. Under uncertainty, the value of a place depends on the probability of obtaining a resource unit (i.e. it falls by place). Under a uniform distribution case, the risk-neutral equilibrium prices are 53.33 for the first place in the queue, 33.33 for the second, 13.33 for the third, 6.67 for the fourth, and 0.00 for the fifth. Corresponding price predictions under the geometric distribution case are 37.04, 14.64, 7.96, 3.28, and 0.00 respectively, for the first to fifth places.

The OLS regressions in table 6 explain queue prices using a set of dummy variables (P2, P3, P4, P5) indicating the queue place being auctioned. *Unif* and *Geom* are dummies for the two uncertainty conditions. *Brazil* is a dummy variable for the Brazilian subject pool. *Trend* is a linear time trend in an uncertainty block, while *End* is a dummy for the last five periods of any block. As a robustness check we consider an augmentation of our basic empirical models using individual characteristics. We include the age of participants, a dummy variable for gender, a set of dummy variables for educational attainment (distinguishing between technical, high school, and basic education), a dummy variable for Brazilian full-time university students, and finally a set of dummy variables for employment type (farmer, irrigation technician, other occupation, and unemployed). The omitted category is United Kingdom university students.

The main finding is that prices decline as one moves down the queue. We identify two potential explanations: falling competition, and rising uncertainty. Prior work suggests that the auctions for lower queue places, with fewer bidders, will produce less aggressive bidding (more 'shading' of bids to gain more surplus).[8] Support for this is found in regression (1) for periods 1–10, which considers only periods when resource units were known to be available. As expected from prior experimental evidence, but not from theory, prices of places decline as we move down the queue.

For the rest of table 6, the second explanation enters as well, as these place prices should also reflect lower chances of obtaining a resource unit as we move down the queue. Regression (2) shows that queue prices fall with place in a non-linear fashion. Regression (3) shows that the decline is even more accentuated under the geometric condition, at least for the first three queue places. Regression (3*) re-estimates regression (3), adding the individual characteristics, and it confirms that the core results are robust to their inclusion (note also that we find a negative and significant coefficient for *Male*, as well as positive and significant coefficients for the dummy variables for high school and primary school education; a joint test of equality of these coefficients to zero is rejected at the 1% level ($F(9, 18) = 4.31$, $p < 0.01$).[9] Through a series of F-tests, we test whether the average price for any given queue place equals the predicted price. Under both the uniform and geometric conditions, for all queue places, prices significantly exceed theoretical predictions.[10] We find no systematic subject pool differences (regression 4) but, in this case, we do find some evidence of learning across rounds, in that the prices decline over the course of the experiment.

In the resource spot market (MA), prices should reflect scarcity. Indeed, they should be related to the ratio of high-yield choices to resources. If the number of participants who choose high-yield is higher than the number of realized resource units, the resource is scarce and its equilibrium price is 80. If there are more resource units than players who choose high-yield crops, then those who chose high-yield crops should pay 41, while all the others players should pay 40. The OLS regressions in table 7 explain resource prices using a dummy (*Over*) for whether total high-yield choices are above resource units, as well as a set of dummy variables (*P2, P3, P4, P5*) indicating the resource unit at auction. *Brazil* is a dummy for that subject pool. *Trend* is a linear time trend within any uncertainty block, while *End* is a dummy for the last five periods of any block.

We again test for robustness to the addition of individual characteristics, augmenting (2) in (2*) with little effect on coefficients or significance for *Over* or places. Regarding the

[8] Dufwenberg and Gneezy (2001) analyze the effect of the number of competitors in Bertrand markets where subjects repeatedly interact in fixed pairings. They find that Bertrand duopolies are significantly less competitive than 3-firm and 4-firm markets (see Normann 2008 for a review).

[9] Here and in table 7, results are also robust to interacting characteristics with the queue places.

[10] Regression (3), first considering uniform distribution tests. Constant = 53.33: $F(1, 20) = 37.76$, $p < 0.00001$; *Constant + P2* = 33.33: $F(1, 20) = 73.80$, $p < 0.00001$; *Constant + P2 + P3* = 13.33: $F(1, 20) = 11.13$, $p = 0.0033$; *Constant + P2 + P3 + P4* = 6.67: $F(1, 20) = 17.32$, $p = 0.0005$.
Next considering geometric distribution tests: *Constant + Geom* = 37.04: $F(1, 20) = 15.05$, $p = 0.0009$; *Constant + P2 + Geom + Geom x P2* = 14.64: $F(1, 20) = 21.24$, $p = 0.0002$; *Constant + P2 + P3 + Geom + Geom x P2 + Geom x P3* = 7.96: $F(1, 20) = 2.42$, $p = 0.1358$; *Constant + P2 + P3 + P4 + Geom + Geom x P2 + Geom x P3 + Geom x P4* = 3.28: $F(1, 20) = 73.29$, $p < 0.00001$.

Table 6. Explaining Average Queue-Place Prices (MB treatment, U.K. and Brazil)

	(1)	(2)	(3)	(3*)	(4)	(5)	(6)
P2	−9.310***	−11.895***	−7.448***	−7.114***	−10.200***	−7.448***	−7.448***
	(1.835)	(1.805)	(1.178)	(1.351)	(1.583)	(1.179)	(1.179)
P3	−25.434***	−36.074***	−29.748***	−28.739***	−34.267***	−29.748***	−29.748***
	(3.236)	(3.349)	(3.609)	(3.760)	(4.081)	(3.611)	(3.611)
P4	−52.232***	−56.020***	−56.482***	−54.176***	−59.714***	−56.474***	−56.482***
	(3.498)	(3.460)	(2.834)	(3.192)	(4.612)	(2.829)	(2.832)
P5	−76.314	−63.883***	−70.357***	−69.448***	−64.283***	−70.365***	−70.358***
	(1.048)	(3.917)	(2.771)	(3.335)	(5.405)	(2.779)	(2.776)
Geom			−12.948***	−12.510***	−18.033***	−16.816***	−14.575***
			(2.995)	(3.017)	(5.322)	(4.222)	(3.481)
Geom x P2			−9.895***	−8.466***	−8.333*	−8.895***	−8.895***
			(2.657)	(2.664)	(4.475)	(2.658)	(2.658)
Geom x P3			−12.652**	−12.530**	−5.200	−12.652**	−12.652**
			(4.647)	(4.510)	(9.683)	(4.650)	(4.650)
Geom x P4			0.982	−0.589	14.048**	0.974	0.982
			(4.477)	(4.392)	(6.513)	(4.486)	(4.484)
Geom x P5			12.948***	12.640***	18.033***	12.955***	12.948***
			(2.995)	(2.942)	(5.322)	(2.986)	(2.990)
Brazil					8.503		
					(6.180)		
Brazil x P2					3.853*		
					(2.131)		
Brazil x P3					6.327		
					(6.321)		
Brazil x P4					4.401		
					(5.774)		
Brazil x P5					−8.503		
					(6.180)		
Brazil x Geom					7.120		
					(6.359)		
Brazil x Geom x P2					−0.787		
					(5.542)		
Brazil x Geom x P3					−10.433		
					(10.913)		
Brazil x Geom x P4					−18.168**		
					(8.267)		
Brazil x Geom x P5					−7.120		
					(6.359)		
Trend						−1.616***	
						(0.242)	
Trend x Geom						0.703*	
						(0.370)	
End							−8.133***
							(1.345)
End x Geom							3.255*
							(1.861)
Constant	76.314***	63.883***	70.357***	57.560***	64.283***	79.245***	74.424***
	(1.048)	(3.917)	(2.771)	(15.047)	(5.405)	(2.010)	(2.437)
Indv. Characteristics	No	No	No	Yes	No	No	No
N	1,050	2,100	2,100	1,900	2,100	2,100	2,100
R-squared	0.61	0.57	0.63	0.66	0.66	0.65	0.64

Column (1): Rounds 1–10 with known resource levels, and when w > 0, to study prices with fewer bidders.
Columns (2)-(6): Rounds 11–30 with uncertainty; the chance of obtaining a resource unit falls with place.
Group-clustered standard errors in parentheses: ***, **, *: significant at 1%, 5%, 10% levels, respectively.

Table 7. Explaining Average Resource-Unit Prices (MA treatment, U.K. and Brazil)

Resource Price	(1)	(2)	(2*)	(3)	(4)	(5)
Over	26.415***	10.991***	10.340***	13.772***	10.995***	10.991***
	(1.802)	(1.749)	(1.498)	(3.205)	(1.749)	(1.745)
P2		−8.098***	−7.734***	−8.301***	−8.094***	−8.098***
		(1.148)	(1.251)	(2.276)	(1.147)	(1.151)
P3		−19.953***	−19.200***	−15.216***	−19.929***	−19.954***
		(1.972)	(2.170)	(3.910)	(1.955)	(1.966)
P4		−31.410***	−31.024***	−24.743***	−31.381***	−31.411***
		(2.744)	(2.748)	(5.395)	(2.717)	(2.736)
P5		−65.829***	−66.374***	−59.813***	−65.815***	−65.829***
		(2.595)	(2.492)	(5.130)	(2.587)	(2.600)
Over x P2		5.846***	6.227***	9.072***	5.861***	5.845***
		(1.325)	(1.568)	(2.763)	(1.330)	(1.335)
Over x P3		15.103***	15.885***	16.894***	15.105***	15.100***
		(2.531)	(3.098)	(4.518)	(2.515)	(2.553)
Over x P4		26.839***	26.882***	28.885***	26.907***	26.830***
		(4.691)	(6.218)	(6.492)	(4.698)	(4.712)
Brazil				7.465		
				(5.911)		
Brazil x P2				0.248		
				(2.635)		
Brazil x P3				−5.862		
				(4.491)		
Brazil x P4				−8.257		
				(6.191)		
Brazil x P5				−7.465		
				(5.911)		
Brazil x Over				−3.523		
				(3.820)		
Brazil x Over x P2				−3.898		
				(3.239)		
Brazil x Over x P3				−5.543		
				(6.234)		
Brazil x Over x P4				−13.212		
				(13.381)		
Trend					−0.109	
					(0.322)	
End						0.043
						(1.358)
Constant	49.179***	65.829***	55.200***	59.813***	66.433***	65.808***
	(2.502)	(2.595)	(7.868)	(5.130)	(3.303)	(2.845)
Indv. Characteristics	No	No	Yes	No	No	No
Observations	1,972	1,972	1,972	1,972	1,972	1,972
R-squared	0.13	0.46	0.49	0.46	0.46	0.46

Robust standard errors (group clustered) in parentheses: ***, **, *: significant at 1%, 5%, 10% levels, respectively.
Column (6): over = 0; Column (7): over = 1.

characteristics, the coefficients on male, basic education, and farmer are positive and significant. A joint test of equality to zero for all of the coefficients is rejected at the 5% level ($F(9, 28) = 2.48, p = 0.032$).

Regression (1) shows that, as expected, prices are higher with too many high-yield crop choices, although they are still significantly below the equilibrium of 80 ($Constant + Over = 80$: $F(1, 28) = 8.22$, $p = 0.0078$). The constant is slightly but significantly above the predicted price for those who chose lower yield ($Constant = 40$: $F(1, 28) = 13.46$, $p = 0.001$). Much like in the auction for queue places, we observe a competitive effect, in that the resource units auctioned off later sell for less. This result is true irrespective of whether there are excess high-yield choices or not, although it is significantly weaker when there are excess high-yield choices, as seen in the interactions of *Over* with the places. We find neither subject pool differences nor any evidence supporting learning.

Discussion

It is important to place our findings within the context of ongoing debates about water allocation. Burness and Quirk (1979) showed that when there are differentiated claims to water usage based on seniority, inefficiencies arise due to junior appropriators underinvesting in diversion capacity. This is reiterated by Libecap (2011), who argues that holders of junior claims to water may bear a large downside risk – worse than for water shares – if differentiated claims are for specific amounts. Such results are driven by homogeneous production functions: if farmers with identical functions have differentiated instead of identical water access, then they invest in different capacity levels, leading to outcomes that are inferior to the case where all agents know they have equal shares of water.

In our setting, initially identical farmers end up being heterogeneous due to their crop choices. Such critical *ex-ante* choices imply that they no longer have homogeneous production functions at the point when water is allocated. This more fundamental differentiation has implications that differ from those of differentiated water access in prior work. In fact, this differentiation suggests potential gains from differentiated water access, as it considers the complexities of coordinating those choices. Specifically, differentiated water access in a queue helps to coordinate efficient choices, in that the number of farmers investing in crops who actually possess a high water need is consistent with the expected water. In short, once we allow for *ex-ante* crop choices that differentiate farmers' production functions, we should use differentiated water access to achieve efficiency within those crop choices.

In this setting, we might expect inefficiency from announcing equal claims on the water. Indeed, it is efficient to have some of the farmers invest in crops that have higher water requirements, but there are no signals that coordinate farmers' expectations of each other concerning who will invest. Thus, each might guess that the others will not invest, leading all to invest, with the consequence of a significant efficiency loss. Alternatively, each might guess that others will invest, so nobody invests. This new complexity, which stems from having to coordinate ex-ante choices, changes one's views on access. Differentiated access in queues can generate efficiency when junior rights holders (those towards the end of the queue) hedge against the risk of not obtaining any water by selecting a low-yield, low-risk crop, even while those closer to the queue's front choose higher-yield crops.

Other recent experimental evidence also fails to support Burness and Quirk's proposition. For example, Lefebvre et al. (2012) compare markets with senior and junior rights to markets with non-differentiated rights, and find that such differentiation leads to better risk management, in that subjects are able to trade off profit variance against expected profits. Inspired by a recent regulatory change in Spain, Garrido (2007) also studies the impacts of allowing trading between senior and junior water rights holders. Allowing junior holders to purchase rights from senior holders yields Pareto improvements. Differentiated water rights as considered in such work reflect the essential features of our *ex-ante* queue (QB), in that senior claimants have priority in water allocation after quantities are realized. Our *ex-post* spot market (MA) has some analogies with non-differentiated or equal share allocations since all farmers have equal bidding rights to the natural water supplies, as if they received equal shares and were allowed to trade. Thus, in finding that *ex-ante* queues (QB, MB) outperform the *ex-post* spot market (MA), we are, to some extent, finding that rights queues outperform equal share allocations – in terms of guidance provided for critical decisions. That said, the questions being addressed are different, and this analogy can only be taken so far.

Conclusion

We considered agricultural decisions that are made under resource uncertainty in experiments with subjects from two quite distinct backgrounds: a university in the United Kingdom, and a rural setting in Northeastern Brazil. To study the coordination of agricultural decisions under varied appropriative irrigation rights, we compared a queue, which provides *pre-decision* differentiation in the chance of receiving the necessary resource, to a resource market after the decision and the resource quantity are known. We considered two versions of the appropriative rights queue institution, one with all the places in the queue exogenously (and randomly) assigned, and one with an auction of the water rights.

The results support our conjecture that a queue's *ex-ante* information permits the queues to out-coordinate a spot water market. Our main result, robust across our quite different subject pools, is that decisions are coordinated more efficiently in the queues. A market for water rights, before decisions are made in advance of rain, is more efficient than a water market after rainfall: fewer large deviations from efficiency occur, and a higher fraction of the potential earnings is realized.

The advantage of resource queues over spot markets concerns two types of uncertainty, environmental and strategic. Concerning environmental uncertainty, a queue transforms the shared probability of a given total resource level into individualized probabilities of obtaining resources that vary with queue place. Then, those most likely to get the water can plant crops that depend on it, which is efficient. Per strategic uncertainty, with the queue a farmer no longer needs to concern himself with whether the others will also plant the higher-yield crop. In contrast, competition for resources in the spot resource market will depend upon what others do, and the market lacks any differentiated probabilities that could be a basis for belief coordination.

Such results also have implications for actual institutional designs within agriculture. For instance, following upon the theme of environmental uncertainty, research about climate change and in particular adaptation has often focused on forecasts without extensive consideration of the local institutional setting into which they enter. Our results show that the value of such natural-science output can depend critically on the social or institutional setting, for example, if water access is equal or is differentiated. Following the theme of strategic uncertainty, we made a case for differentiated water access by broadening the decision setting to include choices that not only must be made before farmers know water availability, but may also need to be coordinated.

Regarding further research, to allow for large deviations from efficiency when coordination fails, two design shifts could help. First, we could increase the groups' sizes such that coordinating actions becomes harder. Second, we could select probability distributions whose means are farther from their endpoints, in the sense that more than one person should select the higher-yield crops in order to achieve efficient allocation, unlike in our current case of geometric distributions.

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