PRIVATE COSTS FOR ENVIRONMENTAL GOODS PROVISION IN A DEVELOPMENT CONTEXT: LAB AND FIELD TESTS OF A NOVEL COST-REVEALING MECHANISM

Samuel D. Bell (sam.bell@oregonstate.edu)

Applied Economics Department, Oregon State University

Selected Paper[1] prepared for presentation at the 2017 Agriculture & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30 – August 1, 2017.

[1] Thanks go to Kelsey Jack for providing input on mechanism design, and to Bill Schulze for guidance on experimental procedures. I am grateful for financial support from Kenneth L. Robinson endowment. Specific thanks to Mwape Chibale for excellent field work assistance.

Abstract

This paper presents and evaluates a novel cost-revealing extension to the Becker-DeGroot-Marschak (BDM) mechanism, termed the Random Quantity Mechanism (RQM), and reports on the first field implementation of the RQM in a payments for environmental services (PES) setting. I examine the performance of the RQM in a laboratory experiment with induced costs, and utilize the RQM in a field setting to estimate the willingness to accept payment for agroforestry tree planting, an impure public good that has private benefits and positive externalities, by smallholder farmers in Zambia. The RQM in principle allows for the non-parametric estimation of individual cost curves and supply, and identification of the distribution of cost types and functional forms. It provides exogenous variation in contract terms that enables, with a sufficiently large sample size, exploration of the effect of opportunity costs and performance incentives on contract outcomes. I present the determinants of willingness to accept (WTA) payments for tree planting, construct supply curves derived from WTA, and report on performance under the contract. The results show that the RQM is incentive compatible, that decision-making within the mechanism is efficient, and that it holds potential as a field research tool for estimating WTA across intensive margins, and, with sufficiently large sample size, exploring the impact of WTA and incentive premiums on contract performance.

1. Introduction

The procurement of goods and services for which markets are absent or functioning poorly can be achieved by price-setting mechanisms such as auctions. When private costs of provision are heterogeneous and information asymmetries exist between the principle and the agent, such mechanisms can reveal limited information on the distribution of reservation prices or willingness to accept payments for goods or services. In this paper, using an economic laboratory experiment, I empirically evaluate the performance of a novel cost-revealing extension to the Becker-DeGroot-Marschak (BDM) mechanism, termed the Random Quantity Mechanism (RQM). Similar to the BDM, the RQM provides quasi-experimental variation in treatment, precise estimates of minimum willingness to accept, random variation in contract terms (conditional on satisfying minimum WTA), and allows for direct non-parametric estimation of supply and cost structures. When implemented in a field setting, these features in principle can enable the estimation of heterogeneous treatment effects, and may help to isolate the impact of incentives and selection on contract performance.

Smallholder farmers, forest communities and other land managers in developing nations have the potential to make a significant contribution toward combating climate through changes in land-use management such as agroforestry and reforestation. In Zambia, where the field study is set, the potential for reforestation and afforestation is high. According to Zomer et al. (2008) there is the potential in Zambia to sequester over a billion tons of CO2 equivalent on the 74,000 square kilometers of land eligible for carbon offsets. Revenue from terrestrial carbon offsets sold through compliance and voluntary carbon markets, and other such ‘payments for environmental services’ (PES), can help to unlock this potential by providing subsidies for improved land management practices. Landholders, however, may have heterogeneous opportunity costs that are difficult for policy makers and conservation agents to observe. These information asymmetries will decrease the cost-effectiveness of PES initiatives. Approaches to revealing the information that private agents have about their own costs can increase the effectiveness of resources earmarked for public goods such as climate change mitigation from land-use, and inform international climate policy on Land-Use, Land-Use Change and Forestry (LULUCF) and REDD+.

Knowledge of landholders’ private costs also helps to address concerns over the additionality of incentives for the provision of environmental goods. The term additionality is used, particularly in climate change policy discussions, to denote the extent to which there is a direct causal relationship between incentive payments and the land-use activities that result in carbon offsets. If these activities would have been undertaken without the incentive payment, they are deemed non-additional. This binary definition is too crude a measure for environmental services that are incremental, and can be provided across a range of different levels. This is the case for terrestrial offsets, where landholders often have a choice over, for example, the quantity of agricultural land on which to practice low-till, or the number of trees to plant in a reforestation program.

The issues of information asymmetries (adverse selection) and additionality present incentive design and contracting challenges for conservation agents who are tasked with maximizing environmental benefits from a fixed budget. Three broad approaches to help limit information asymmetries and improve the efficiency of PES designs are available: collect information on landholder characteristics that are expected to be correlated with landholders' private costs; use procurement auctions to allocate contracts; offer screening contracts that are tailored to the distribution of private costs (Ferraro, 2008).

The first option is relatively simple where high-quality data is readily available, however in contexts where information on landholder characteristics is difficult to obtain, such as in developing nations, this approach can be costly. Moreover, this approach is very reliant on the strength of correlations between observable characteristics and private costs. Particularly in cases where market failures are present, observable characteristics may be a poor measure of the true shadow cost of compliance further limiting the effectiveness of this method. Procurement auctions are market based allocation mechanisms that have been used extensively in environmental policy. The third option requires the conservation agent to gain a better understanding of the general functional form and distribution of landholder opportunity costs. With this information the conservation agent can limit adverse selection by creating an optimal menu of contracts designed for the different cost types of the target population. This serves to alleviate concerns over additionality, as contracts are designed so that a landholder would never be better of with a contract designed for another cost type, and improves the efficiency of PES. To be effective in sorting farmer types screening contracts necessarily incur deadweight loss.

This paper presents estimates of smallholder willingness to accept (WTA) payment for the provision of environmental goods (tree planting) based on a quasi-experiment implemented in Zambia. The RQM enables estimation of WTA across a range of quantities for each participant, and thus reveal individual cost curves for the provision of these goods. Information on the function forms of cost curves and their distribution revealed by the RQM can be used to design screening contracts (Guiterras, 2011). I also present evidence from the field on the marginal effect on contract outcomes from incentive payments above the minimum participation constraints using random variation in the contract terms. This research also makes a practical methodological contribution to PES and similar settings by demonstrating a field application of the RQM.

The paper is organized as follows. Section two develops theoretical predictions and properties of the RQM in its standard form, and for a variation used in the field. Section three presents the induced-cost laboratory experiment and section four presents the field RQM study on tree planting with smallholder farmers. Section five concludes with a discussion of the main results.

2. Random Quantity Mechanism theory

In this section I describe the RQM in detail and develop theoretical predictions of quantity offer behavior within this mechanism, and describe a modified version used in the field study. The RQM is incentive compatible within the expected utility framework adopted here, and capable of eliciting point estimates of the private cost of production or service provision. The analysis is restricted to expected utility as the BDM, the value-revealing counterpart to the RQM, is not always incentive compatible outside of this framework (see Horowitz 2006, Karni and Safra 1987).

Standard form (fixed production determined by draw)

The RQM works as follows: an individual is offered a transfer (total payment) for supplying a good or service, and asked to respond with the maximum quantity of the good or service that she is willing to supply for that transfer amount. A random quantity is then drawn from a predetermined distribution that encompasses possible quantity offer values. If the drawn quantity is less than or equal to the quantity the individual offered to supply, then she receives a contract with terms specified by the transfer and *drawn* quantity. Otherwise, no contract is awarded and her profits are zero. If she is awarded a contract, she must produce no less than the drawn quantity in order to be eligible for the fixed transfer payment. In this case, her profit is the transfer less the costs of producing the drawn quantity.

Under the maintained assumption that total private costs are weakly increasing in quantity, the intuition behind the incentive compatibility of this mechanism is straightforward. The dominant strategy for the individual, faced with uncertainty in the quantity required by the contract, is to state the maximum quantity for which their total private costs are no greater than the transfer[2]. Or equivalently, when costs are non-decreasing, to state the maximum quantity that would result in a non-negative profit should that quantity be drawn. This strategy maximizes her chances of receiving a contract that would meet or exceed her total costs of production, and excludes the possibility of receiving a contract in which the transfer is smaller than her costs.

More formally, let:

T	= the transfer (total payment) offered under the contract;
Q	= the quantity offered for the contract transfer;
R	= the random quantity draw, required by the contract;
$F()$	= the quantity distribution from which R is drawn;
Y_o	= initial income;
$C(Q)$	= the private cost of producing Q units;
$U(Y)$	= utility, a function of money income including the net value of the contract;

If $R \leq Q$ then the individual receives a contract at (R, T) and her utility is $U(Y_o + T - C(R)) \geq U(Y_o + T - C(Q))$ under the assumption that $C'(Q) \geq 0$ and $U'(Y)>0$. In an expected utility framework, the optimal quantity offer solves:

$$\max_Q \int_0^Q U\big(Y_0 + T - C(x)\big)dF(x) + U(Y_0)(1 - F(Q))$$

The first term describes expected payoff for random quantities R less than or equal to the offer Q, and the second term describes the expected payoff for a randomly drawn quantity greater than the offer (Q). In our experimental setting, a predetermined value will limit the maximum offer that participants may submit.

First order conditions define the optimal offer Q^*, which satisfies:

$$U\big(Y_0 + T - C(Q^*)\big) - U(Y) = 0$$

[2] In the case that total payment equals total private cost for a specific quantity, q, the optimal solution is not unique as q and q-1 result in the same expected payoff.

$$T = C(Q^*)$$

The optimal offer is where total costs equal the contract transfer.

In a discrete production setting, where units of the good are not infinitely divisible, individuals maximize expected utility by offering Q^* such that $C(Q^*) \leq T$ and $C(Q^*+1) > T$. In the continuous output scenario, the RQM provides accurate point estimates of private costs (the minimum WTA payment for producing the offered quantity), while in the discrete case it provides a bounded estimate of private costs. This bounded estimate is defined as the difference between the transfer and the true cost of the offered quantity and is at maximum the marginal cost of the unit Q^*+1.

These results are reliant on a number of assumptions. As Horowitz (2006) and others have pointed out, if the independence axiom of von Neumann-Morgenstern preferences is violated then individuals may not maximize expected utility and the RQM will no longer be incentive compatible. The participant must also believe that her responses will not affect future contract terms. If this does not hold then she may tend to understate her quantity offers, thereby overstating her minimum WTA, in order to increase future transfers or lower the quantity values available for the random draw.

Providing each individual with a menu of contract transfers, instead of a single transfer, can extend the RQM. For each transfer, the individual responds with the maximum quantity she is willing to produce. A random transfer is then drawn from the menu of transfers, and a random quantity is drawn for that transfer, as before. This random selection of the transfer is explained to participants. Since there is only one contract transfer chosen from the menu, and it is selected randomly, incentive compatibility is theoretically maintained under this generalization. This approach provides the opportunity to select transfer values to reveal multiple point estimates along the individual's cost curve. This feature is of relevance in field applications of the RQM as it allows the researcher to identify, under some theoretical assumptions, the distribution of cost curve types when applied to a representative sample of the population of interest.

Although the multi-unit RQM is incentive-compatible in theory, it is an empirical question whether it has this property in practice. The laboratory experiment reported on in this paper tests the incentive compatibility of the multi-unit RQM in a pure induced-cost setting. The results demonstrate that the RQM is incentive-compatible and cost revealing in this setting.

Partial fulfillment form (unit price and maximum quantity determined by draw)

The optimal quantity offer is a function of the structure of the contract. In the standard form (above) the landholder must produce at least the full quantity drawn in order to be eligible for the transfer payment. There is no pro-rated payment for partial fulfillment of the contract. If instead I allow a pro-rated transfer payment for partial fulfillment of the required contract quantity (determined by the drawn quantity) then the dominant quantity offer strategy for the landholder may deviate from $C(Q^*) = T$. Intuitively, we expect that expanding the individual's choice set will (weakly) increase their expected utility.

In the partial fulfillment form, the agent is faced with an additional decision dimension – how much to produce given the terms of the contract– which leads to a dual optimization problem a) profit maximization, in which she must determine optimal supply, q*, for possible transfers and quantity draws (together defining marginal revenue) and b) utility maximization, by determining the optimal offer, Q*, for any given transfer and quantity draw by using the optimal profit function resulting from (a). In the analysis that follows I continue to maintain the assumptions that C(q)>0, C'(q)>0 and C''(q)>0.

Under this scenario, the utility derived from a contract is as follows:

$U\left(Y_0 + \frac{T}{R}q - C(q)\right)$ where $q \leq R$

The key distinction here is that instead of production (q) being equal to the quantity draw, production is now only limited above by the randomly drawn quantity (R) required by the contract, conditional on $Q \geq R$.

The optimal supply (q*) for a given T and R solves the profit maximization problem:

$$\max_q \pi\text{:}\ {}^{T}\!/_{R}\, q - C(q)$$

$$\text{subject to: } q \leq R \text{ to satisfy } {}^{T}\!/_{R}\ q\ \leq T$$

First order conditions define the optimal q^* for a given T and R, satisfying:

$$ {}^{T}\!/_{R} \geq C'(q^*) \qquad (1)$$

With equality if $q^* < R$ (or q* = R in one special case elaborated on below), and inequality when optimal supply is greater than the draw so actual supply is constrained at R ($i.e.\, q_R^* = R$)[3]. This results in optimal profit $\pi^*(T, R, q^*|Q)$ as a function of T, which is exogenous, and R, which exogenous and bounded above by the offer (Q), the choice over which requires a utility optimization problem.

The optimal profit resulting from first maximization problem, $\pi^*(T, R, q^*)$, is an input in the utility maximization problem, in which the optimal offer (Q*) under an expected utility framework solves:

$$\max_{Q} \int_0^Q U(Y_0 + \ \pi^*) dF(x) + U(Y_0)(1 - F(Q))$$

The first order condition defines the optimal Q^* for a given T, satisfying:

$$U(Y_0 + \pi^*) - U(Y) = \ 0$$

$$\text{and therefore; } \ \pi^*(Q^*) = \ 0 \qquad (2)$$

Optimality conditions (1) and (2) result in either a) T/R = C'(q*) at R = Q*, or b) T/R > C'(q_R*) and q_R* < q* such that T/R q_R* = T and therefore q_R* = R. Given the maintained assumption that the cost function is convex, it is possible to show that $d\pi^*/dR \ \leq 0$, with a strict inequality holding when the cost function is strictly convex (unless there are no fixed costs, in which case min(π^*)=0). This means that optimal profit for any drawn quantity R, where R < Q, is larger (or no smaller where there are no fixed costs) than optimal profit for R = Q, and optimal profit for R > Q is smaller (no larger, without fixed costs) than at Q. This property along with the optimality conditions (1) and (2) are sufficient to define the optimal Q* and q* for a given cost function C(q).

In the following I derive optimal offers Q*(T, R, C(q)) and supply q*(T, R) for strictly convex cost functions with and without fixed costs. As $d\pi^*/dR \ \leq 0$ it is sufficient to examine the case where R = Q* (the 'worst case' quantity draw in terms of realized profit) in demonstrating optimality.

[3] I use q_R* to denote the supply when the drawn quantity, R, is binding (i.e. q_R* = R), and q* (without a subscript) to denote supply that is not constrained by the draw.

a) Properties of the RQM for a convex cost function with fixed costs (see figure 1).

> ***Proposition one**: Q^* is defined by $T = C(Q^*)$ and $q_R^* = R$ in the region where $T \leq T_m$ where T_m is defined by $T_m - C'(Q_m)Q_m = 0$, and $T_m = C(Q_m)$*

For the critical case of R = Q* (and all R < Q*) the *unconstrained* optimal supply would equate marginal revenue with marginal cost, $T/R = C'(q^*)$, but for $T < T_m$ marginal costs are strictly smaller than marginal revenue for all $R \leq Q^*$ and given $C''(q) > 0$ we know that supply is constrained by the draw ($q^* > R$) and therefore $q_R^* = R$. Hence, when $T < T_m$ we have $q_R^* = R$ for all $R \leq Q^*$ and $\pi^*(Q^*) = 0$ at R = Q* given that Q* is defined by T = C(Q*) in the proposition.

If Q* is not the optimal offer, then there is a $Q^{**} \neq Q^*$ such that expected utility is greater at Q** than Q*. If $Q^* < Q^{**} \leq Q_m$ then $C(Q^{**}) > T$, and profit is negative when R=Q** thus contradicting (2). Similarly, if $Q^{**} < Q^* \leq Q_m$ then $C(Q^{**}) < T$ and this also contradicts optimality condition (2). Condition (1) shows that $q^* > q_T^*$ as marginal revenue is greater than marginal costs for all $T < T_m$, so R = q* and when R = Q** profit, given as T/R q* - C(q*), is equal to $(T/Q^{**})Q^{**} - C(Q^{**}) < 0$.

Therefore by contradiction proposition one holds and T = C(Q*) for $T < T_m$.

Proposition 1 shows that, when there are fixed costs of production, the optimal quantity offers in the range of transfers $T < T_m$ are equivalent to the optimal offers within the standard RQM, and offers in this range are cost revealing.

> ***Proposition two**: Q^* is defined by $T - C'(Q_m)Q^* = 0$ for all $T > T_m$ where T_m and Q_m are defined by $T_m - C'(Q_m)Q_m = 0$, and $T_m = C(Q_m)$*

$T - C'(Q_m)Q = 0$ is a ray from the origin with a slope equal to marginal cost at quantity equal to Q_m, which is the quantity at which point marginal costs first begin to exceed average costs, and (equivalently) where average cost is at a minimum. Any offer Q* as defined above satisfies (1) at the critical point (when the draw, R , is equal to Q*) only where T/R = C'(q*) and that q* is single valued at Q_m, for all $T > T_m$ and R = Q* as a direct result of the definition of Q*. When R = Q* profit is maximal at zero for $q^* = Q_m$

If Q* is not the optimal offer, then there is a $Q^{**} \neq Q^*$ such that expected utility is greater at Q** than at Q*. If Q* < Q** (for example, Q_3 in Figure 1) then for R = Q** there is no level of production for which profit is positive or zero, as T/R = MR < MC at all q, therefore Q* < Q** does not satisfy condition (2) of the dual optimization problem. If instead Q** < Q* (e.g. Q_1 or Q_2 in figure 1) then for R = Q** it follows that MR = T/Q** > T/Q_m and also that MR = C'(q**) > C'(q*) = C'(Q_m). Hence, q** > q* and since C''(.) > 0 we know that the cost of production of all but the last unit of q** is less than the MR, which is T/Q**, so profit is positive and therefore does not satisfy condition (2).

Therefore by contradiction proposition two holds and the optimal offer is defined by $T - C'(Q_m)Q^* = 0$ for all T > T_m

Supply function

The supply function in this cost scenario is given by the following:

$$q^* = \begin{cases} R & \quad if\ T \leq\ T_m\ and\ R \leq Q^* \\ R & if\ T\ >\ T_m;\ T/R\ \geq C'(R); and\ \ R \leq Q^* \\ C'^{-1}(T/R) & if\ T\ >\ T_m;\ T/R\ \leq C'(R); and\ \ R \leq Q^* \end{cases}$$

b) Properties of the RQM for a convex cost function *without* fixed costs (see figure 2).

> ***Proposition three****: Q* is defined by T – C'(0)Q* ≥ 0 for all T, and q* ≥ 0 with equality only when R >= T/C'(0).*

This is similar to the case of proposition two, above, in that the optimal offers follow a ray from the origin that is tangential to the cost curve at the point of lowest average cost. In the case of fixed costs, this point of tangency occurs at some T_m > 0, while here (no fixed costs) this point of tangency is at the origin. The point of departure from proposition two is that here there are no fixed costs so $\pi^* = 0$ at q = 0 and therefore the producer is no worse off from quantity offers greater than those on the ray as they can always produce nothing without penalty if the drawn quantity exceeds the value defined by the ray (i.e. Q* ≥ R > T/C'(0)).

If Q* is not the optimal offer then there is some Q** < Q* = T/C'(0) (i.e. the minimum Q* that satisfies the proposition above) such that expected utility at Q** is higher than at Q* (e.g. see Q2 in Figure 2). If Q** < Q* then T/R > C'(0) at R = Q** < Q* and there exists a q** > 0 such that

T/R = C'(q**) as C''(q) > 0. At q** average costs are smaller than marginal costs, C(q**)/q** < C'(q**) as the cost function is convex and C(0) = 0, while AR=MR = C'(q**) for all q** units, hence $\pi^* = (AR - AC)q^{**} > 0$ and this does not satisfy condition (2).

If Q** > T/C'(0) were not an optimal offer then it would not maximize expected utility for a given T. Any positive production at Q** would incur negative profits for any drawn quantity given by Q** ≥ R > T/C'(0) because T/R < C(q**)/q** when q** > 0 as a direct result of our assumptions on the cost function (C(0) = 0, C'(q) > 0, C''(q) > 0). However, when Q** ≥ R > T/C'(0), q=0 is always feasible and satisfies conditions (1) and (2) so any Q** > T/C'(0) is an optimal quantity offer under the maintained assumptions on cost structures.

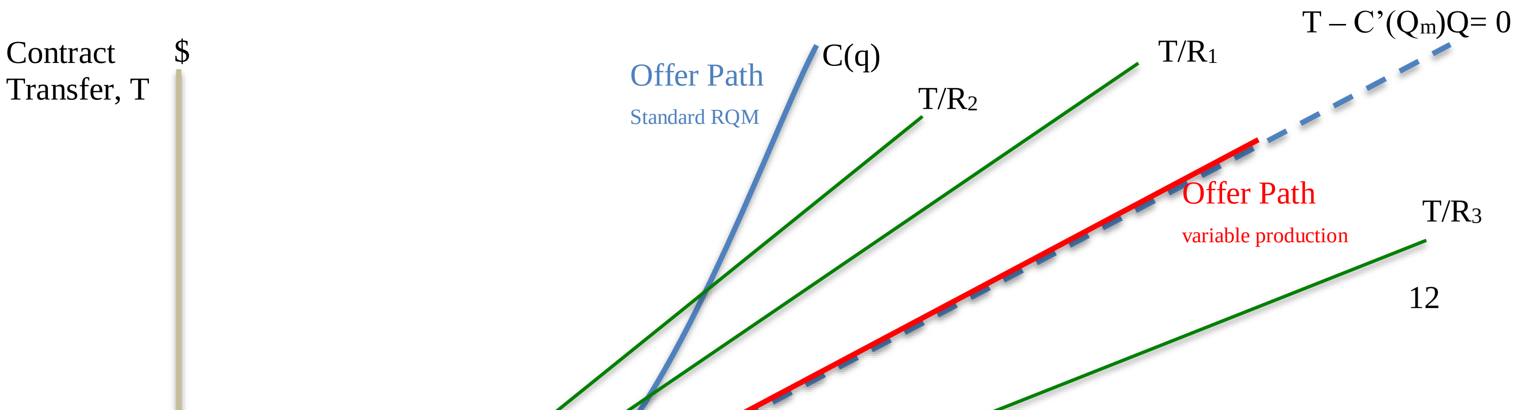
Therefore by contradiction proposition three holds.

Supply Function

The supply function in this cost scenario is given by the following:

$$q^* = \begin{cases} C'^{-1}(T/R) & if\ T > T_m;\ T/R \leq C'(R); and\ R \leq Q^* \\ 0 & otherwise \end{cases}$$

Figure 1. RQM Offers with fixed costs of production



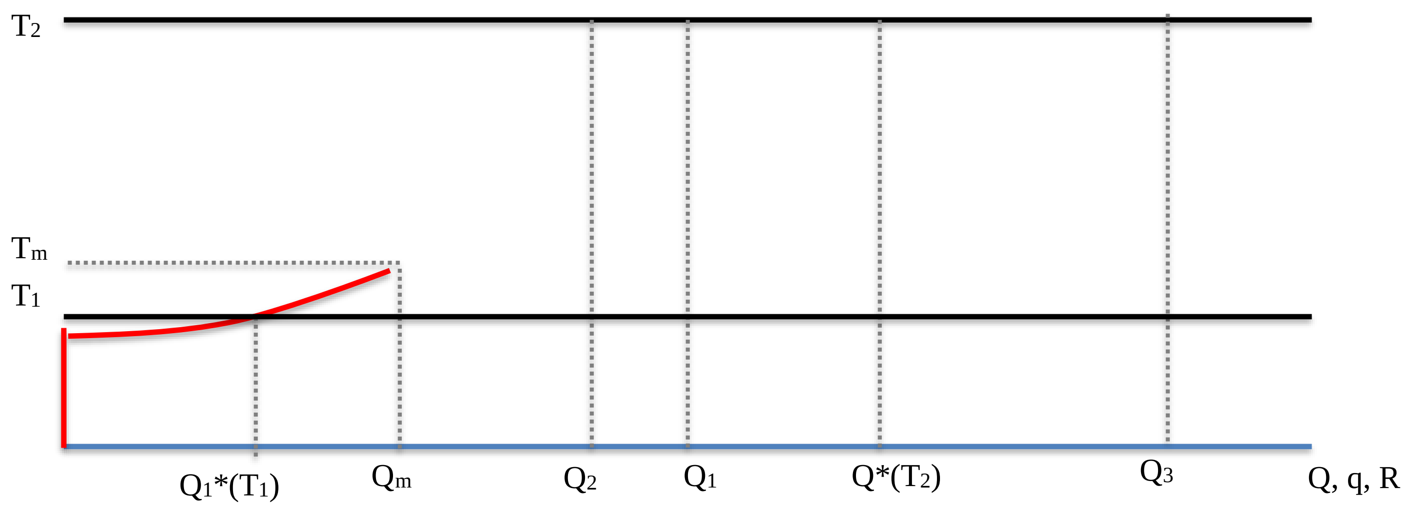
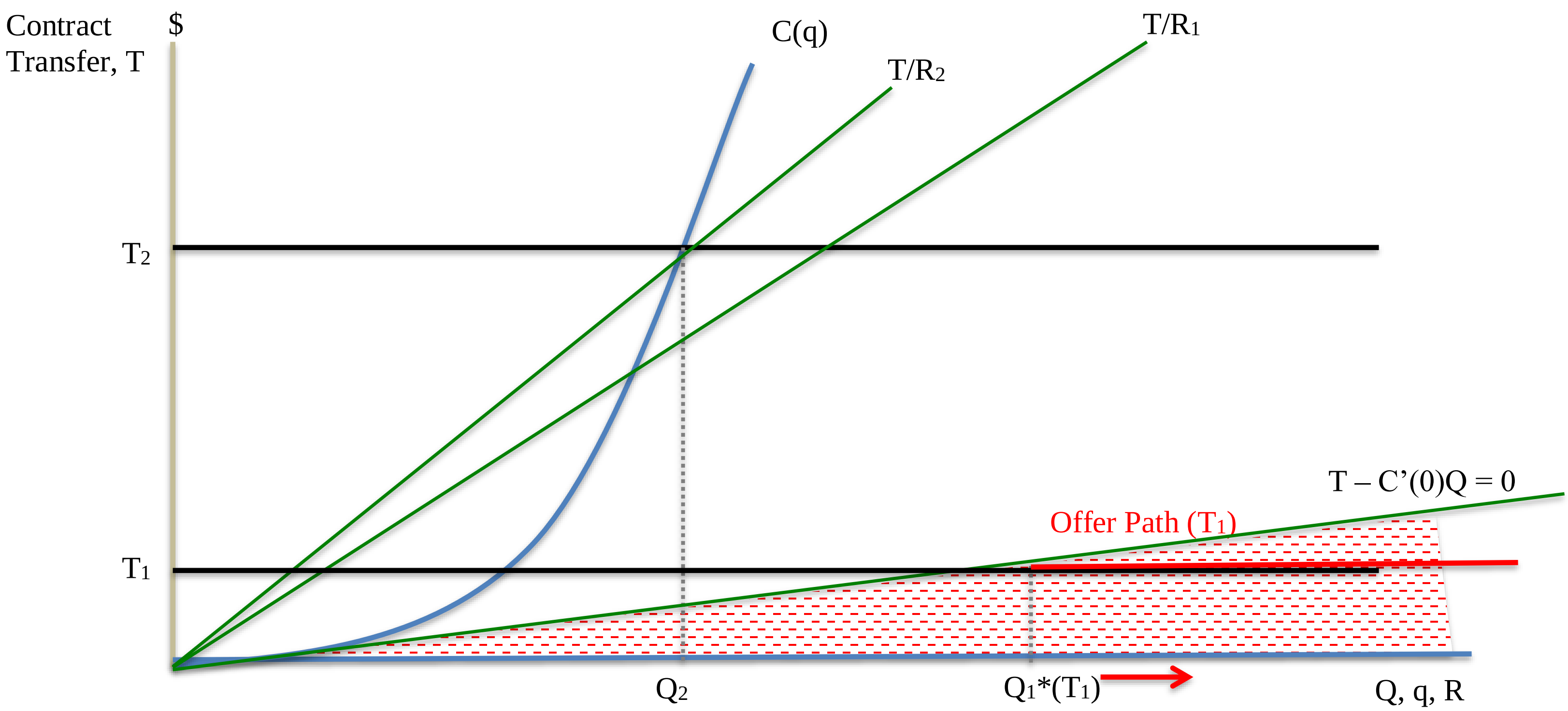


Figure 2. RQM Offers without fixed costs of production.



While the RQM implemented with contracts that allow for partial fulfillment does not reveal the full cost curve, it has some interesting features. It is able to identify the minimum unit price at which the agent will produce a positive quantity (of some practical interest), and may approximate the expected quantity produced at that price depending on the calibration of the transfers. It also reveals the cost curve directly in the lower cost region (when $T \leq C(\tilde{x})$), and based on realized production it may in theory reveal the marginal cost under some conditions.

The dual optimization necessary to determine the dominant strategy when transfer payments are pro-rated by partial fulfillment potentially imposes a significant cognitive burden on the decision maker. Under both versions of contract design the RQM is reliant on respondents having good knowledge about their private costs, or at least better information than the principle (otherwise there is no information asymmetry present, just uncertainty). Without knowing the 'true' underlying functional form of landholders in this field experiment it is not possible to test which decision strategy landholders are using, and this could be an area of future research.

3. Laboratory experiment

3.1 Setting and Data

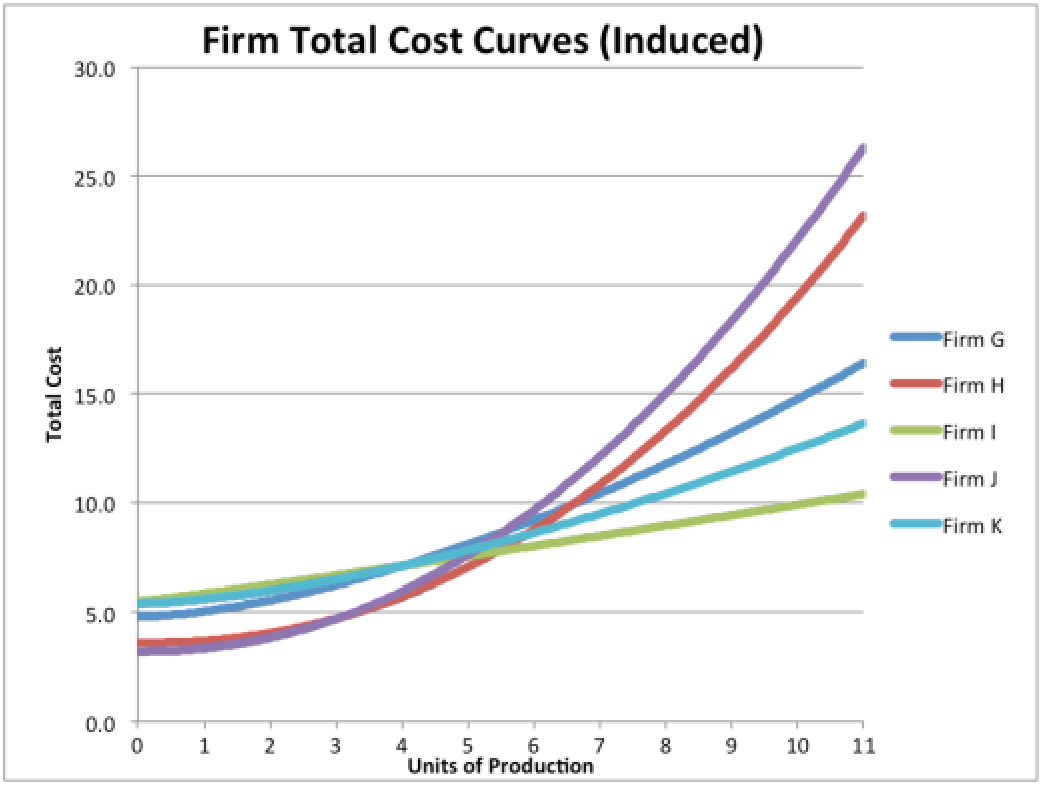
This experiment is designed to provide a test of the reliability and incentive compatibility of the RQM mechanism, using an induced value framework in a controlled laboratory setting. Experimental sessions were conducted in the Laboratory for Experimental Economics and Decision Research (LEEDR) at Cornell University, Ithaca. The subjects (N=21), recruited from the student population at Cornell, were 21 years old on average and 38% were female. Subjects sat at individual cubicles each with a computer display and keyboard, and received written and verbal instructions. Subjects were permitted to ask questions of the experiment administrator, but were not allowed to communicate with each other. A session lasted approximately 45 minutes, with average earnings of $34 and the guaranteed minimum earnings level ($5) was not binding for any participant.

Each session implemented five sets of induced total costs for five fictional firms that produce a single fictional good in discrete quantities. Production at the firms was limited to between 1 and 10 units inclusive, and total cost schedules unique to each firm listed the total costs of production for all possible output levels (e.g. Firm G in Table 1). The total cost schedule for each firm was generated by a power function of the general form $TC = a + bQ^d$, where TC is total cost, a is fixed cost, and b and d are parameters defining variable costs. Firms' total cost curves are shown in Figure 3.

Table 1: Example of firm cost schedule

	FIRM G - Total Cost Schedule									
UNITS of GOOD	1	2	3	4	5	6	7	8	9	10
TOTAL COST of PRODUCTION	$5.05	$5.56	$6.25	$7.10	$8.08	$9.20	$10.42	$11.76	$13.21	$14.75

Figure 3: Firm total induced cost curves



Notes: Parameters {*a*, *b*, *d*} for each firm are as follows {Firm G: 4.8, 0.25, 1.6; Firm H: 3.6, 0.1, 2.2; Firm I: 5.5, 0.35, 1.1; Firm J: 3.2, 0.15, 2.1; Firm K: 5.4, 0.2, 1.55}.

Subjects were provided with a sequence of three contracts with varying transfer values specific for each of the five firms. Possible transfers for each firm were randomly selected in advance from the unit-cost ranges within each firm-specific total cost schedule; nine for firms {G, H, I, K} and three for firm J. The values of the possible transfers are summarized in Table 2.

The transfer presented to each subject for a specific firm-contract pair was randomly selected from the three possible values listed below, apart from firm J in which the payment in each contract was fixed. For example, a subject would be presented with a random selection from {$7.40, $8.28, $10.14} as a total payment for contract 2 in Firm G. The order of firms presented to each subject was randomized, as was the order of contracts for each firm, so as to avoid possible order effects.

Table 2. Summary of possible transfer values

Contract #	Optimal Offer	Firm G	Firm H	Firm I	Firm J	Firm K
1	**Q1**	$5.46	$3.76	$6.14		$5.82
	Q2	$6.13	$4.60	$6.26		$6.42
	Q3	$6.31	$5.58	$6.92	$4.77	$6.81
2	**Q4**	$7.40	$6.16	$7.42		$7.57
	Q5	$8.28	$7.09	$7.76	$9.65	$8.41
	Q6	$10.14	$9.23	$8.02		$9.16
3	**Q7**	$11.64	$12.56	$8.68	$12.85	$10.10
	Q8	$12.06	$16.15	$9.39		$10.82
	Q9	$14.63	$18.61	$9.61		$12.41

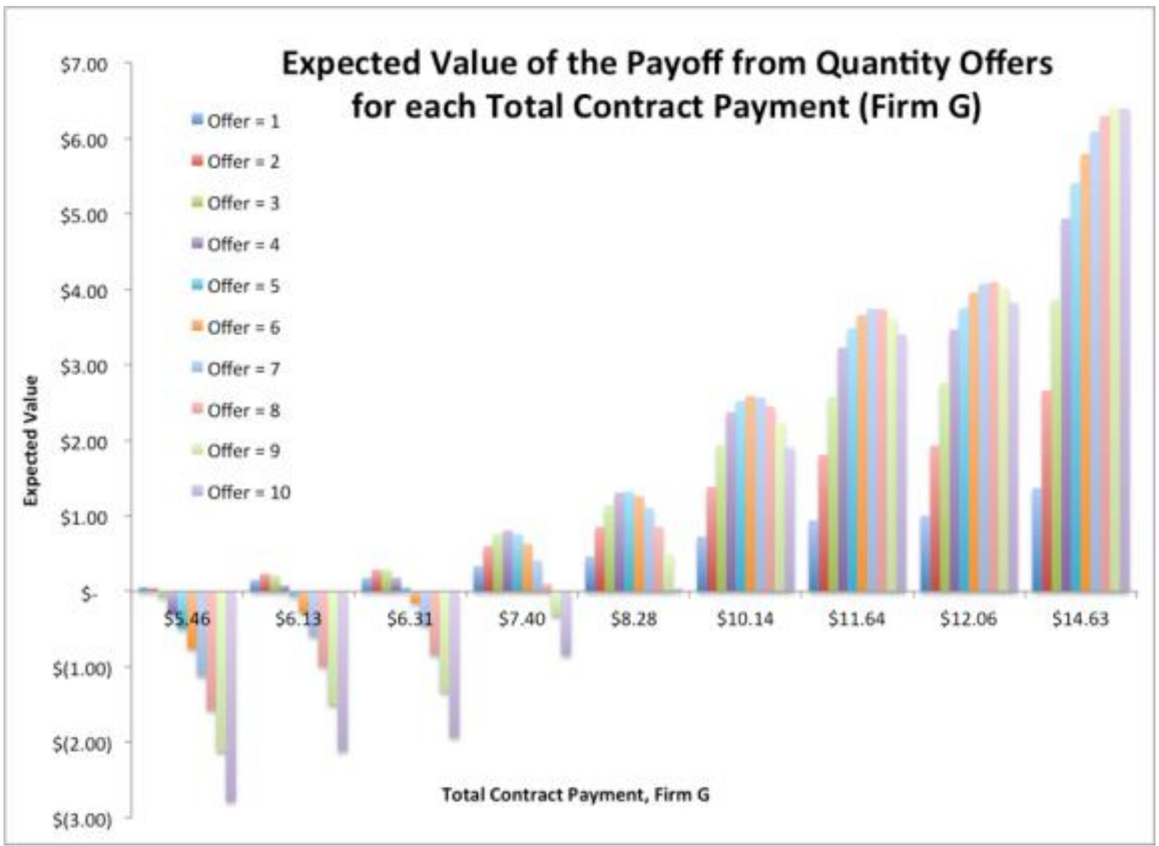
In each round, subjects were provided the firm's Total Cost Schedule and were presented with a transfer value randomly selected from the set of values within each firm-contract pair listed in Table 2. A prompt on the same screen asked subjects to submit the maximum number of units they would be willing to produce for that payment based on the information provided in the firm's total cost. After being offered a single opportunity to change their offer in each round, they would progress to the next offer round and a new contract. All three contracts for a firm were completed before subjects were presented with a new firm.

Once all 15 offer rounds were completed, market clearing was undertaken for the five firms. A single contract from each firm was implemented by drawing a single ball (without replacement) from the set {1, 2, 3}. As in the offer rounds, the sequence of firm presentation for each market clearing was random, so that each contract draw would apply across the range of firms according to the firm randomly selected for each subject. This random presentation was not necessary for mechanism function, however it reduced the variance of the total cost of the experiment given that a limited number of sessions were implemented.

Following the contract draw, the quantity required for the transfer was randomly determined by having a volunteer draw from a bag of marked balls. If the drawn quantity was less than or equal to the subject's offered quantity for that total contract payment the contract would be awarded. For awarded contracts, subjects would receive the difference between the total contract payment and the (induced) cost of producing the drawn quantity, otherwise they would receive zero compensation. Note that for sub-optimal offers, the costs of production could be higher than the total contract payment and the difference would be subtracted from the subject's cumulative profits.

No further feedback on performance – directly linking decisions to payoff outcomes – was provided to subjects after the practice round, and market clearing occurred following the completion of the full set of 15 offer rounds. Irwin et. al. (1998) found that steep payoff schedules improve decision-making when subjects must search for the optimal bid, but they found no evidence that payoff schedule shape had any effect on optimizing behavior when subjects were able to compute the optimal bid from the initial information provided. The RQM is a similar decision task to the BDM, and therefore expected to be similarly cognitively transparent. The experimental instructions combined with the practice round were expected to be sufficient for subjects to compute the optimal strategy, and this is supported by the experimental results. The expected payoff structure for Firm G is provided in Figure 4.

Figure 4: Expected value payoff functions for each total contract payment

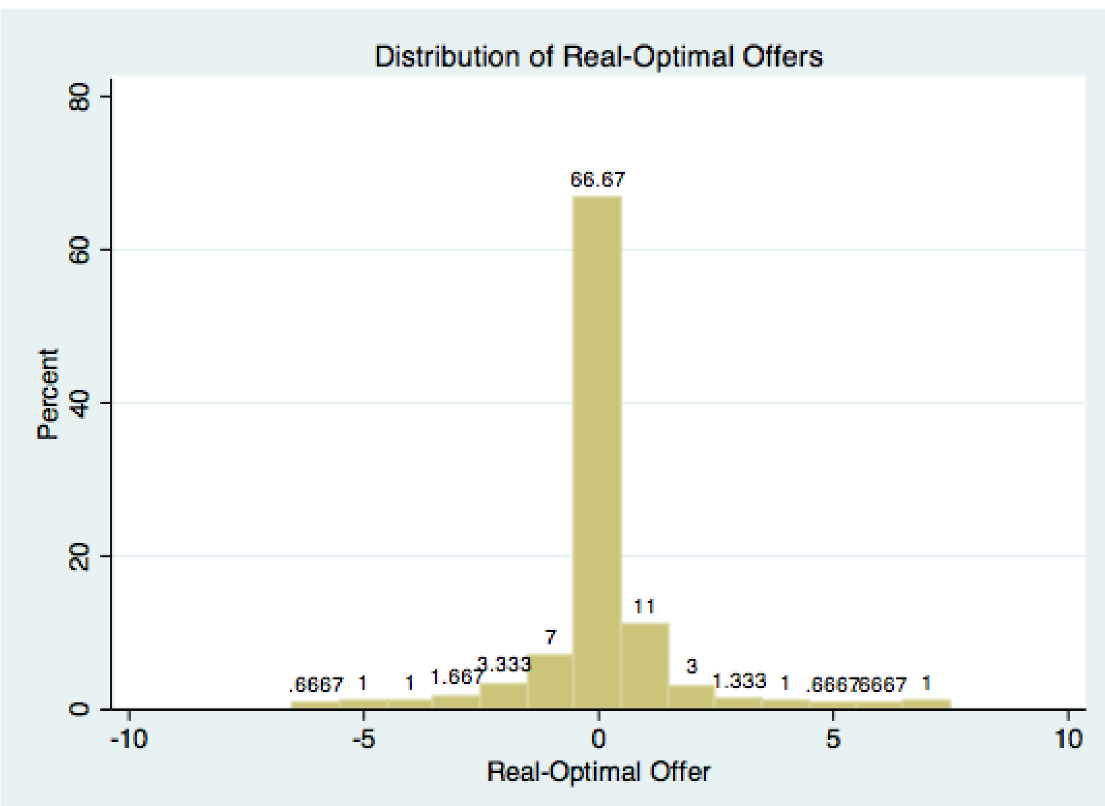


3.2 Results

RQM offers in relation to optimal offers

The distribution of real-minus-optimal ("Real–Optimal") offers is shown in Figure 5, pooled across subjects and production decisions, and in Figure 6, pooled across production offers for each subject. Differences of zero indicate that the real offer was optimal. Of the 300 offer decisions pooled across individuals, 66.7% were strictly optimal. The histograms in Figure 6 show the difference in each subject's real offer and the optimal offer for each transfer value, pooled across offer rounds. The patterns suggest that there is a divergence in subject cognition or decision strategies. Random bidding strategies in this experiment will result in real-optimal offer values evenly distributed between negative eight and nine[4]. This is due to the high degree of uniformity of optimal offers[5] resulting from the experimental design. It therefore seems likely that those subjects with relatively few optimal offers who also did not have an even distribution of real minus optimal offers were not employing random offer strategies. It can be seen in Figure 7 that the distribution of real offers was skewed to the right or left of the set of possible offers for those individuals with fewer optimal offers. This is evident in subjects 1, 7, 10 and others to a lesser degree.

Figure 5: Distribution of the difference in real and optimal offers



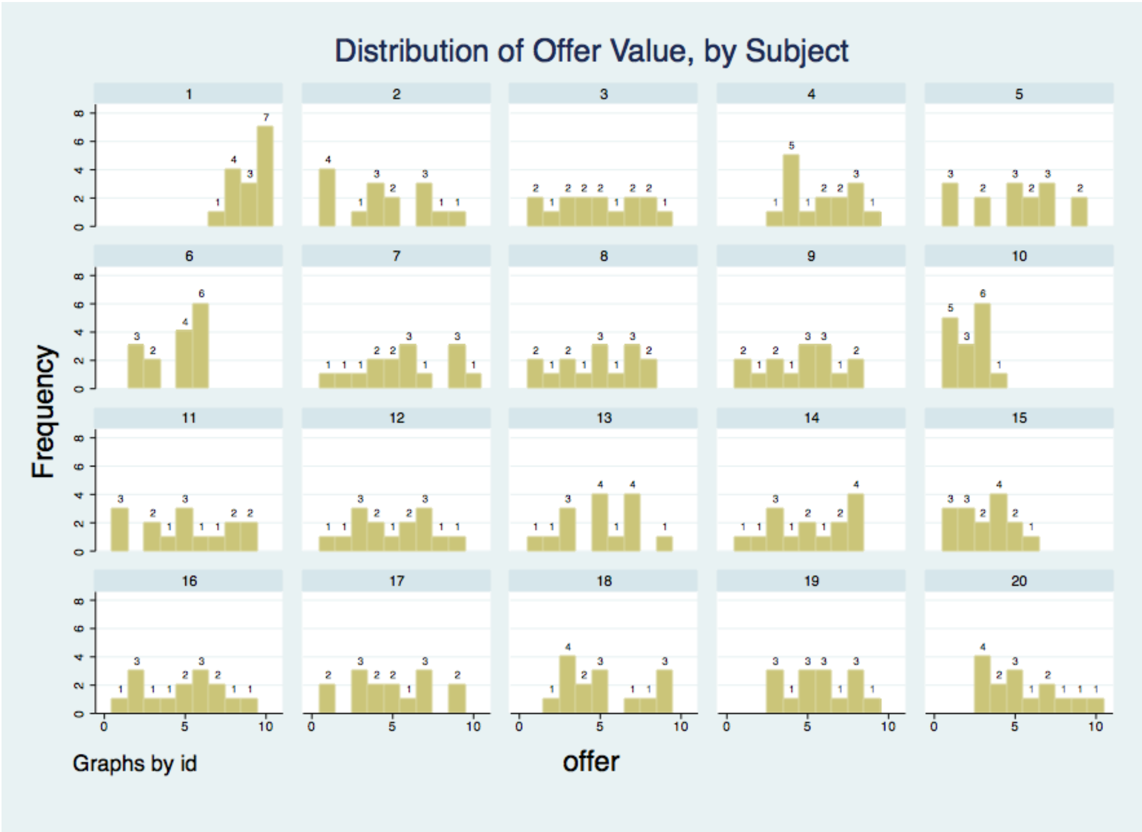
[4] This range is not symmetrical around zero as the possible offer range was {1,…,10} while the range of optimum offers was {1,…,9}

[5] The three total payment values for Firm J generate the only non-uniformity across this distribution.

Figure 6: Distribution of the difference in real and optimal offers, by subject

While it is not possible to determine the motivations or decision strategies applied by individuals, there are at least two candidate motivations that could explain offer distributions that are skewed right or left. A subject may believe the goal to be 'winning contracts', and in order to maximize their chances of achieving this they offer high numbers, resulting in offers skewed to the right of the possible range. Alternatively, she may calculate the net payments resulting from lower *draws*, for a given total contract payment, and believe that by offering a lower draw she is therefore ensuring a higher profit. These approaches could result from one or both of the following factors: the initial information and practice round provided may have not been sufficient to ensure cognition; reward saliency and payoff dominance were not achieved (Smith 1982). Nevertheless, most participants appeared to have understood the information and in the field where private costs are very salient this may be less of a concern.

Figure 7: Distribution of offer value, by subject



There were 39 unique contract transfers presented across the five firms (see Table 2). Three of these transfers are for Firm J, to which all subjects responded (*n*=20) [6]. The remaining 36 transfers come from the sets of nine possible total contract payments for the remaining four firms. Each participant responded to a third of these 36 – one randomly selected from each contract-firm pair listed in Table 2 – resulting in treatment responses ranging between *n*=3 and *n*=9. The coefficients of indicator variables for the 39 transfer values regressed on real offers, when applied to a pooled dataset across the whole sample, provide estimates of the average real offers that can be used for comparisons with the optimal offers for each transfer and firm. I use robust standard errors clustered at the individual level here, and where appropriate elsewhere in the analysis, due to the non-independence resulting from the presence of multiple offers from each individual. Additionally, as there is no feedback after the start of the offer rounds, corrections for learning are not warranted nor applied in the analysis that follows.

[6] One subject was dropped from the analysis, as 13 of their offers were 10 units and the remaining two offers were 7 and 9.

Table 3: Mean quantity offers

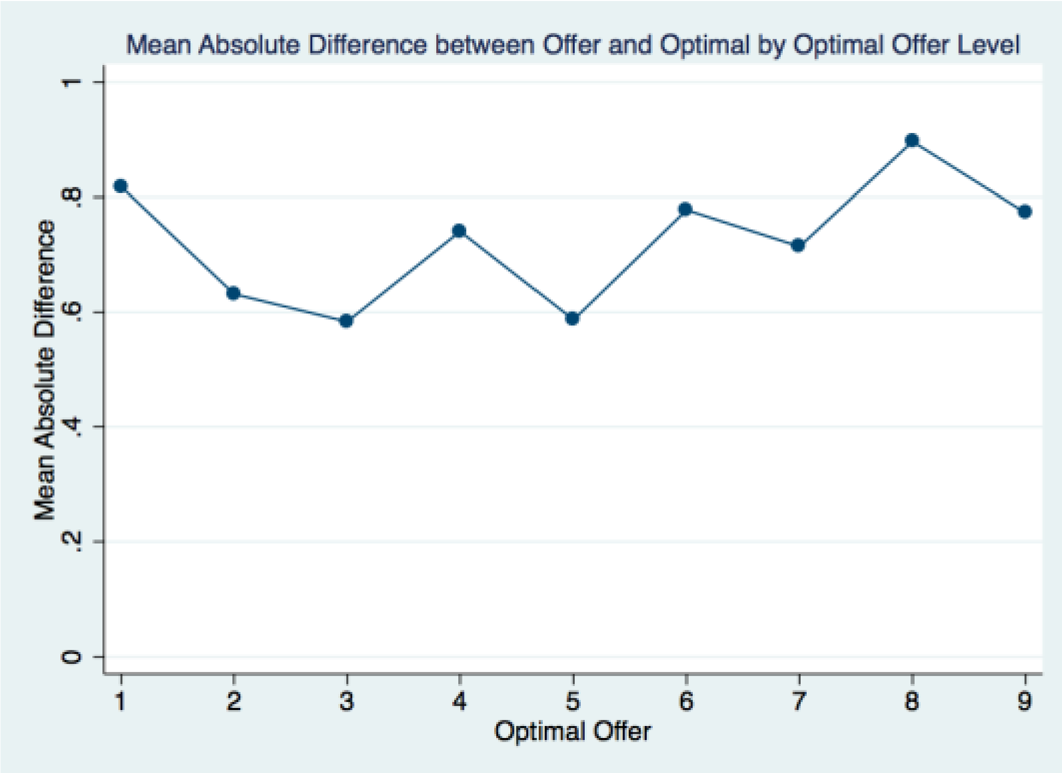
Optimal Quantity Offer	Firm G	Firm H	Firm I	Firm J	Firm K	Weighted Mean (G-K)
1	2.00	1.82	1.43		2.00	1.82
2	2.43*	2.00	2.50		2.20	2.32
3	2.80	3.00	3.78	3.15	3.38	3.25
4	4.00	4.71	5.29		4.25	4.59
5	5.29	4.71	5.17	5.25	5.17	5.15
6	5.88	5.50	5.29		6.00	5.67
7	7.00	7.33	7.60	6.55	7.11	6.94
8	7.14	7.44	7.14		7.83	7.38
9	9.5*	9.00	7.88		7.80	8.41

Notes: * Indicates a mean offer that is statistically different than optimal at the 10% confidence level.
For each of the Firm J estimates, *n*=20; for each of the estimates for other firms, *n* varies between 3 and 9 according to the specific estimate.

Table 3 summarizes the estimates of mean offers for each unique treatment. None of the 39 estimates are statistically different from the optimal offer at the 5% confidence level, however if the confidence levels are weakened slightly (10% level) two of the estimates are statistically different to the optimal value. These results suggest that the RQM is incentive compatible and approximately cost revealing - which I explore further in the next section.

To examine individual accuracy the mean absolute difference between optimal offer and real offer is plotted in Figure 8 by optimal offer value pooled across firms and rounds. We see that, for each optimal offer level, mean real offers pooled across treatments were less than one unit different than optimal. This provides further evidence that the RQM is incentive compatible and approximately cost revealing. The next section evaluates the efficiency of the RQM, both from an aggregate and individual standpoint.

Figure 8: Mean absolute difference between real and optimal offers



Efficiency of decision-making in the RQM

The expected value of the payoff for offers in each treatment provides us a metric for evaluating the efficiency of the RQM. I examine the aggregate and individual-level efficiency of the RQM in terms of expected value of the payoff from real offers compared to the maximum expected value of payoff in the treatment.

Payoff functions in this experiment are quasi-quadratic, and truncated at 1 and 10 due to the set of available offer quantities. As can be seen in Figure 3, the penalty for deviating from the theoretically predicted individually optimal offer can be very small for small deviations. For example, offering 8 units in Firm G for a total contract payment of $11.76 results in a reduction in the expected value of the payoff of less than $0.01 when compared to the maximum possible expected payoff (for the optimal offer of 7). Though Irwin et al (1998) find that flatter payoff structures (and therefore more trivial penalties for sub-optimal bidding) do not make ‘sloppy bidding’ more likely in a setting where the mechanism is transparent, such as the BDM, in the following evaluation of the efficiency of the RQM I allow for small degree of decision-making error in identifying the quantity that results in maximal expected payoffs when defining the optimal offers. I define this expected payoff error margin as follows. When examining efficiency on the aggregate level, real offers for a given treatment are considered optimal if they result in expected payoffs that are different to the maximum expected payoffs by less than 2.5% of the range[7] of the expected payoffs for that treatment. Individual decision-making in the experiment is considered optimal if the sum of expected payoffs for all offers made by a given individual is less than 2.5% below the sum of the maximal expected payoffs for those same treatments.

Applying this efficiency criterion, 79% of the offers (*n* = 300) in the experiment resulted in optimal expected payoffs for their respective treatments. The percentage of optimal offers by firm ranged from 72 – 100%. This high proportion indicates that decision making in the RQM results in expected payoffs very close to the maximum. Recalling the heterogeneity of individual offers shown in Figures 5 and 6 above, it is worthwhile to evaluate the performance of individual subjects using our current efficiency metric. The offers of 17 of the 20 subjects (85%) resulted in expected payoffs within 2.5% of the maximum expected payoff for the set of treatments that were randomly assigned to them. The three subjects who did not meet this threshold had expected payoff values that were 90%, 70% and 64% of the maximum total expected payoff for the treatments they were assigned. Given the relatively small penalties for small departures from the optimal offer in each treatment, the offers from these three subjects were far from optimal relative to the remaining subjects in the group.

Cost revelation and mechanism performance

The preceding analysis provides strong evidence that the RQM is an individually incentive-compatible mechanism. In this section, I extend the analysis to evaluate empirically the theoretically demonstrated cost-revealing attribute of the RQM. This feature is of potential value in situations where markets are not functioning efficiently or are absent, such as in the supply of environmental services, where price signals are not available or do not reflect true marginal costs. The multi-transfer application of the RQM is of particular interest in this context, as it provides estimates at a sequence of points along the cost curve and thus allows for estimation of the cost structure.

[7] The range is the appropriate reference value as it is an accurate measure of the difference between the best and worst potential outcome for a given treatment, the latter of which can be negative.

The induced cost structures allow us to empirically test the cost-revealing feature directly. I use two approaches that provide statistical measures of this in the analysis that follows. First, I compare parameter estimates based on the real offer data to estimates based on optimal offer values for the randomly assigned experimental treatments. The degree to which these estimates match provides an indication of the optimality of decision-making in the RQM. Second, I compare parameter estimates based on the real offer data (as before) to those resulting from continuous cost data that has been generated by the induced cost functions. This approach differs from the first as it models the underlying cost curve directly, while in the former approach the cost function parameter estimates resulting from optimal offers will always be to the left of the true underlying cost curve. This second approach tests more directly whether the RQM reveals the underlying cost structure that drives individual decision-making, and may better represent implementations in a field setting where the distribution and form of cost structures are the objective of study.

Induced costs in the experiment were generated by five power functions, one for each firm. As power functions are non-linear in parameters, and not amenable to simple transformations resulting in a linear in parameters form, I instead use a quadratic functional form to estimate cost curves so as to avail the use of linear methods. Using a functional form for estimation that is different to that which generated the cost structures may be a better representation of real applications given that in general the 'true' functional form will not be known. The function to be estimated for each firm is given by

$$c_j = b_0 + b_1 x_j + b_2 {x_j}^2 + \upsilon_i + \varepsilon_{ij}$$

where c is total private costs, x is the quantity offer, errors are distributed $\varepsilon_{ij} \sim n(0, \sigma_\varepsilon^2)$, υ_i is a subject-specific time invariant error and there are j transfer-quantity observations per individual (j=3). The idiosyncratic error term (ε_{ij}) in this setting represents not only the subject's error in determining the correct offer[8], but cost function specification error, while υ_i is formally fixed in the panel fixed effects model used here. I estimate the fixed-effects model using robust standard errors clustered at the individual level to address possible heteroscedasticity and correlation of individual-level responses resulting from multiple observations per individual.

[8] Possibly exacerbated in non-induced cost settings where respondents may not know their opportunity costs with precision.

Table 4 lists the parameters of the power function generating the induced cost for each firm, as a reference. Table 5 reports the parameters for each firm of the quadratic model in separate regressions using the experimental offers and the optimal offers that are predicted by theory. Goodness of fit as measured by R^2 is high and two of the three coefficients in our experimental models are statistically different from zero in all cases (with the exception of Firm J) suggesting a good fit for all models. The optimal offer model for Firm J is over-specified as there are three parameters to be estimated and only three unique data points - the transfer-offer pairs (compared to nine for each of the other firms), so while these estimates are included in Table 5 for completeness, comparisons to this Firm J optimal offer model are not made in the analysis that follows as the estimated coefficients are unreliable.

Table 4: Induced Cost Power Functions for firms ($\boldsymbol{c = L + sx^m}$)

Parameters	Firm G	Firm H	Firm I	Firm J	Firm K
Constant (L)	4.8	3.6	5.5	3.2	5.4
Coefficient (s)	0.25	0.1	0.35	0.15	0.2
Power (m)	1.6	2.2	1.1	2.1	1.55

The three parameters of the experimental model were jointly tested as equal to their scalar[9] counterpart parameters in the optimal offer regression. Due to limited degrees of freedom, this comparison was undertaken using a fixed effects regression on the experimental data[10] without robust standard errors clustered at the individual level, though robust standard errors with clustering are reported in Table 5. Given that the standard errors are larger with robust clustered errors, and that point estimates do not change, joint tests of significance based on standard errors without robustness adjustments or clustering are conservative. The joint tests show that parameters resulting from experimental data are not statistically different than their optimal offer counterparts, and based on these data the I cannot reject the hypothesis that these models are indistinguishable. This provides further empirical support to the theoretical results of the RQM and suggests that regression estimates across multiple transfer-offer pairs may be able to provide information on the structure of private costs.

[9] These coefficients are not treated as random variables given that these are simulated data generated from non-stochastic processes.

[10] Adjustments for robust standard error clustered at the individual level were not appropriate for the optimal offers as these data were simulated and non-stochastic.

Table 5: Quadratic Form Fixed-Effects Results (Real & Optimal Offers)

	Firm G		Firm H		Firm I		Firm J		Firm K	
	Experimental	Optimal	Experimental	Optimal	Experimental	Optimal	Experimental	Optimal (øø)	Experimental	Optimal
Offer	-0.0238	0.260**	0.725**	-0.626***	0.555**	0.364***	2.187*	4.120	0.502*	0.354***
	(0.352)		(0.250)		(0.166)		(0.855)		(0.227)	
Offer^2	0.196***	0.0873***	0.0432	0.253***	-0.00624	0.00894**	-0.00859	-0.210	0.0322	0.0441***
	(0.0323)		(0.0236)		(0.0149)		(0.0892)		(0.0213)	
Constant	3.081***	5.080***	4.030***	4.418***	5.193***	5.706***	-1.564	-5.700	4.939***	5.439***
	(0.752)		(0.514)		(0.361)		(1.725)		(0.468)	
P-Value joint test (ø)	0.099		0.36		0.48		0.04*		0.45	
R-sq	0.935	0.989	0.933	0.993	0.845	0.992	0.887	1.000	0.899	0.998
N	60	60	60	60	60	60	60	60	60	60
Standard errors in parentheses										
* p<0.05	** p<0.01	*** p<0.001								

Notes:
ø Firm J estimation on optimal offer data is over-specified with the quadratic as there are only three independent data points and three independent variables. Estimates and joint test P-value are listed for completeness, but have little meaningful interpretation.
øø Joint test of the parameters from the real offer data compared with the point estimates of coefficients from optimal offer panel data. Robust clustered standard errors were not used in the joint test as this limits the degrees of freedom and results in an over-specified test. Standard errors are smaller when robust clustered errors adjustments are not applied, so this test is a conservative measure of significance compared to the robust clustered model used in the analysis.

Two other approaches to comparing experimental and theoretically optimal responses, involving pooling the two sources of offer data, provide opportunities to cross-validate the results presented in Table 5. I compare coefficients between the two groups by applying a chow-test – the null hypothesis that each pair of coefficients between the two groups are jointly equal – using a seemingly unrelated regression, as well as by jointly testing the significance of a group indicator variable included as a constant and interacted with quadratic terms in a nested regression model. Robust standard errors clustered at the individual level are used in both approaches, however neither test can be undertaken using a panel fixed-effects model so fixed (time-invariant) effects (υ_i) each individual are not included. The results are consistent across tests, but not consistent across firms. Both tests of Firm G suggested that there is a difference in at least one of the quadratic coefficients between the two groups (SUR Chow-test: p=0.0029, nested F-test: p=0.048), while for each of the other three firms the results were not significant, with p-values ranging between 0.14 and 0.23, suggesting that the two cost models are not distinguishable. The small sample size in this experiment could be a factor in either of these results.

I have demonstrated that the relationship between contract payments and quantity offers based on induced costs in the RQM can be modeled using a quadratic function that reasonably maps the offers predicted by theory. I next evaluate if the RQM is cost revealing. Simulated data generated by the induced cost power functions is used to determine coefficient point estimates for a quadratic form that models induced cost structure[11]. The resulting coefficients enable direct comparison with the coefficients estimates of our experimental model. For reasons outlined previously, the preferred model in this experimental setting is the fixed effects panel model using the within estimator. Joint tests that include all of the coefficients of our FE quadratic model with robust standard errors clustered at the individual level are not possible as the degrees of freedom remaining after estimation are not sufficient for the four necessary restrictions used by the joint test. I therefore do not apply robust-clustered standard error adjustments for the joint test. Given that coefficient estimates are not affected by these adjustments, and that the cluster-robust standard errors are larger than the unadjusted standard errors, the test results reported below are conservative as they are more sensitive to differences in the coefficient between the experimental model and induced cost model. The joint tests for each firm (with the exception of Firm J) show that we cannot reject the hypothesis that the parameters of the two models are the same (Firm G, p-value=0.3938; Firm H, p-value=0.1437; Firm I, p-value=0.5469; Firm J, p-value=0.0193; Firm K, p-value=0.6548).

[11] Cost data were generated between quantities of 0 and 11 using increments of 0.05 for a total of 221 observations for each power function. The estimated quadratic model fit these data well (R^2 >0.99).

Figure 9: Fixed effects quadratic model and real cost curve (Firm G)

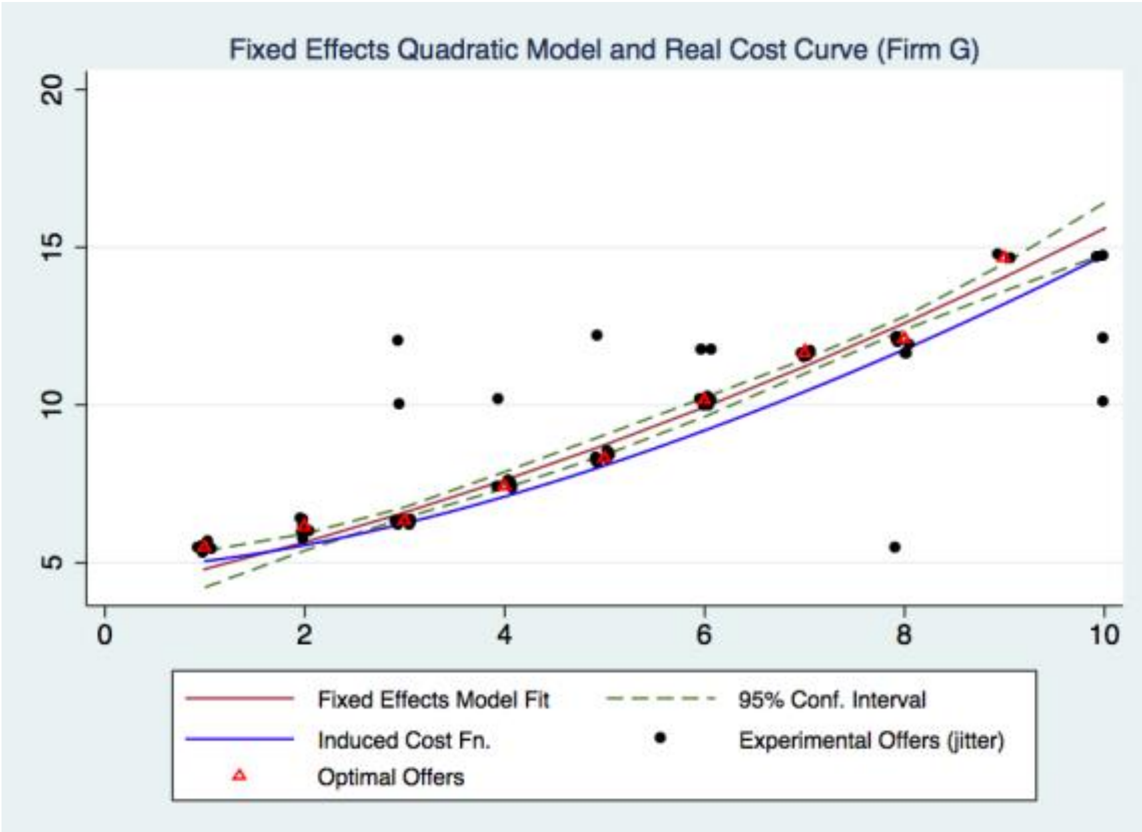


Figure 10: Estimated marginal cost (real offers) versus marginal induced cost

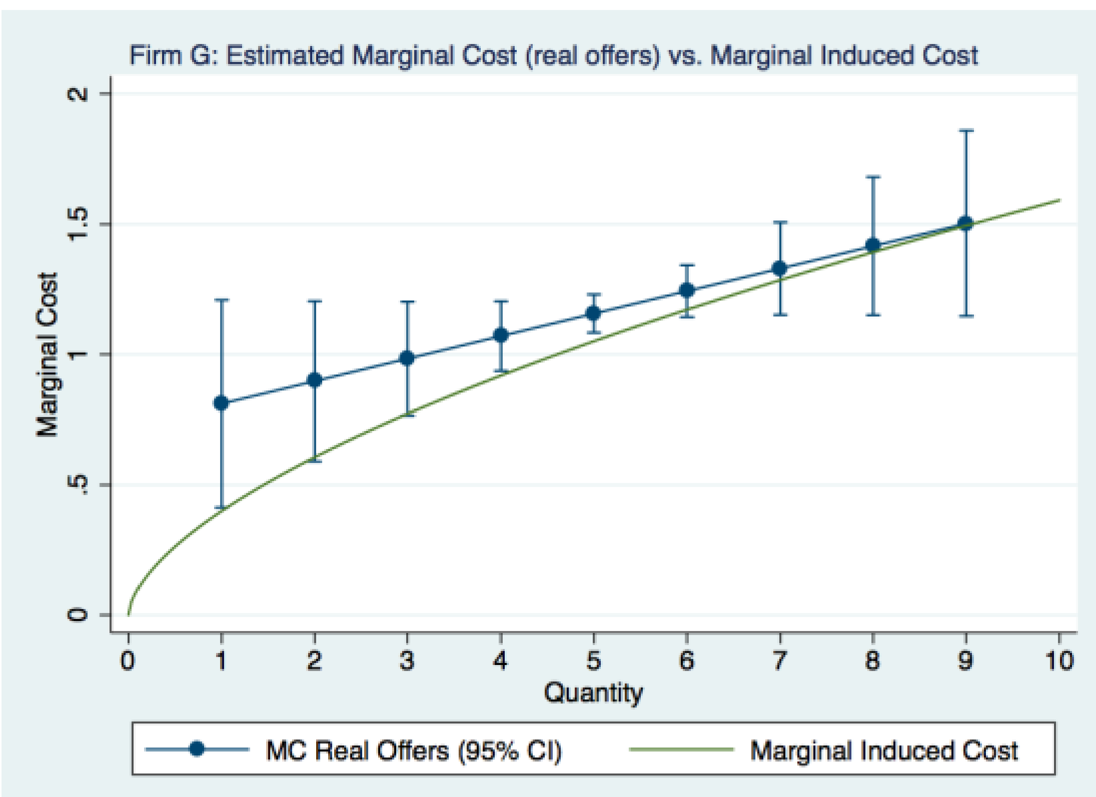


Figure 9 shows both the estimated model and the induced cost curve power function for Firm G. Figure 10 shows the marginal costs derived from the estimated model and the marginal induced costs. The estimated model closely matches the induced cost function as can be seen in the two figures, providing further evidence that the multi-unit RQM can be effective at revealing cost structures.

4. Field Experiment

4.1 Setting and data

Study Setting

Agroforestry tree planting initiatives have been implemented in Zambia for more than a decade (e.g. The Conservation Farming Unit), however smallholder adoption and persistence with these practices in many areas has been low even though inputs and training are often fully subsidized. At the time that the data were collected[12] agroforestry tree planting had been promoted in the study area by a number of NGOs as part of a suite of conservation agriculture practices. Faidherbia also grows natively in these areas and can be found most commonly on alluvial soils near streams and riverbeds, but sparsely elsewhere. Almost a third of study participants reported the presence of Faidherbia in their fields[13], while evidence from a related study in 2011 shows that only around 10 percent of households had Faidherbia planted on their fields in a neighboring district (Jack et al, 2014).

The study area has a bimodal rainfall pattern characterized by a single wet season followed by a dry season in which there is no significant precipitation. Most agriculture is rain fed in these areas, so smallholder farmers are highly dependent on the rainfall patterns for their cropping needs. Successful intercropping propagation of the species requires inputs (seeds and seedling bags) and specific techniques including scarification of the seeds and the establishment of a raised nursery that requires the construction of a makeshift stand.

[12] October/November of 2010
[13] The survey question made no distinction between naturally occurring trees and farmer planted, but field officers reported limited intercrop planting of Faidherbia. Moreover, visual inspection of satellite imagery of the fields that participants selected for planting showed few pre-existing trees present.

Study sample

Landholders (n = 223) in the Mambwe district of Eastern Province, Zambia, were invited to participate in information sessions on tree planting in coordination with ongoing activities of a new tree planting program run by a local NGO. Information sessions were conducted at public meeting areas within villages at specified times in cohorts ranging from 34 and 53. Sessions lasted approximately three hours and included an introduction to the program, an explanation of the process through which contract terms were generated (the RQM), presentation of skits that provided simulated examples of this process, as well as training on optimum tree planting and management practices by experienced local extension staff knowledgeable in these practices.

4.2 Methods

Experimental procedure

Each session also included contracting through the Random Quantity Mechanism in which tree quantity planting commitments were elicited for a non-varying sequence of five total contract transfer payments [20, 40, 70, 100, 140] in '000 Zambian Kwacha (approximately 4,700 ZMK:USD). The field implementation of the RQM worked as follows*:* participants were informed of the range of contract transfers before being called one at a time to begin the RQM contracting process. The participant was asked to provide the maximum number of trees they would be willing to plant, manage and keep alive for one year for each of the five contract transfer values. After each response, the enumerator confirmed with the landholder the number of trees they were willing to offer at that specific price. Once tree quantity responses were provided and confirmed for each of the five contract transfers, the enumerator would review with the participant the tree quantity responses for each transfer for final confirmation.

Following this final confirmation, the landholder was asked to randomly draw one ball out of two opaque containers. The first container held one ball for each of the contract transfers from the pre-defined range. This draw determined the transfer value of the contract. The second container that the respondent drew from contained a ball for each of the tree quantities determined from a pre-determined set of positive values [12, 25, 37, 50, 75] not known to participants. This draw determined the quantity required under the contract. The drawn quantity and transfer are the treatments in this experiment, and the draw procedure used ensures that treatments were allocated randomly amongst participants.

If the tree quantity drawn was less than or equal to the maximum quantity offered by the landholder, a contract was offered to the landholder. In all other cases, a contract was not offered. Once the transfer draw was complete a landholder could no longer change their responses, and contracts could not be offered where random transfer/quantity pairs did not meet a respondent's participation constraint, as determined by their responses. A signed copy of the contract was provided to the participant and another provided to the implementing NGO.

Implementation and data collection

Following the contracting session, the landholder was then asked demographic and land-use questions in a short survey. Landholders who were not offered a contract were also asked if they would have accepted the contract on the selected terms. Once the survey session was complete, respondents were directed to an area with refreshments that was separate from the waiting area for those yet to participate in the RQM and survey. This served to safeguard the integrity of the process and limit information from participants being passed on to those waiting to participate.

Following the completion of all information sessions, the partner NGO established and maintained seedling nurseries until the start of the wet season, at which point seedlings were distributed to landholders at their homes according to contract terms. Landholders were again informed of the contract terms and had the opportunity to ask questions. The NGO partner staff provided periodic extension support to the farmers through the course of the year. In order to receive the first contract payment, landholders had to transplant the contracted number of seedlings in their fields. Transplanting involves transporting the seedlings to their selected plot of land (often a significant distance from their home), preparing the land and planting the seedlings. All contracted landholders met the transplanting target required by the contract at the end of the wet season when field visits were made. At the end of the year an extension staff member and an enumerator monitored the number of surviving trees with the landholder in order to determine contract performance and payments, which were made once the landholder signed to confirm tree survival rates and resulting payment. The remaining contract transfer payment was pro-rated based on the number of trees surviving compared to the number stipulated in the contract.

4.3. Results

Contracting within the RQM

Approximately 60% of the 220 landholders that participated in individual contracting sessions to allocate individual-specific contracts specifying the transfer value and number of trees received contracts. Descriptive statistics of the respondents' characteristics are in Appendix A.

Mean quantity offers for each transfer value are displayed in Table 6. Column 3 shows the mean across the sample, while columns 2 and 1 provides means for those awarded contracts and those not, respectively. Two mechanistic features of the experiment are evident here, the first is an inevitable result of the RQM and the second is an artifact of the experimental design. In order to maintain incentive compatibility, the contract allocation rule of the RQM is that quantity offers must be no less than quantity draws for a contract to be awarded; you will never receive a contract requiring a higher quantity than you were willing to produce for that transfer. While the quantity and transfer treatments (draws) are randomly assigned, the probability of receiving a contract increases with the quantity offer (across the range of predetermined quantity draws)[14]. Moreover, to enable direct comparability of quantity draws across contracts the set of quantity treatments was predetermined in the experimental design; a recipient drew a ball from the same set of five quantity values irrespective of which transfer value treatment they were assigned.

These two features can be seen clearly in Table 6. Firstly, comparing mean offers across any transfer value row it is evident that mean offers for those contracted are consistently lower than those not allocated a contract (and the population mean is between these two values). This pattern is a natural result of the RQM[15]. Secondly, we can see that the proportion of respondents allocated a contract increases with increasing transfer values. This is a result of using a fixed set of quantity treatments. Quantity offers increase with increasing transfers, and therefore the probability of drawing a quantity lower than the offer increases also. While not relevant for WTA estimates, these two features become important when investigating outcomes because they result in sorting of WTA by treatment dimensions thus confounding identification.

[14] Recipients are not informed of the predetermined quantity values available in the draw to maintain incentive compatibility.

[15] With the exception of two trivial cases in which no one, or everyone, is allocated a contract.

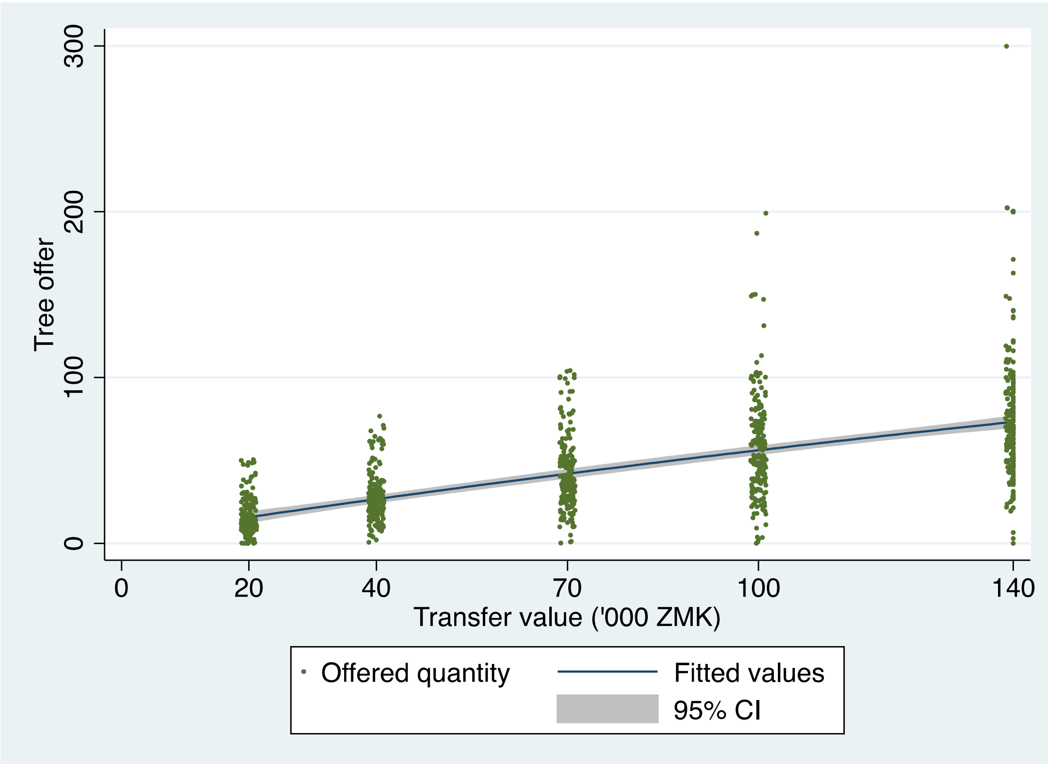
Table 6. Mean Quantity Offers

Transfer (ZMK)	**Not Awarded contract** (1)	**Awarded contract** (2)	**All RQM participants** (3)
20,000	14.19	22.50	15.54
	[7.12]	[8.67]	[7.9]
# obs	31	6	37
40,000	19.61	45.29	30.53
	[6.21]	[21.97]	[19.63]
# obs	23	17	40
70,000	28.13	46.35	39.40
	[12.19]	[22.03]	[20.75]
# obs	16	26	42
100,000	31.58	65.34	58.11
	[19.87]	[30.9]	[31.95]
# obs	7	38	45
140,000	39.14	73.37	68.04
	[26.46]	[25.13]	[28]
# obs	7	38	45
Total	22.40	59.34	44.40
	[14.66]	[29.04]	[30.28]
# obs	89	131	220

Notes: Mean quantity offers (trees) with standard deviations in brackets followed by # observations.

The distribution of quantity offers can be seen in Figure 11. The positive relationship between the offer and the transfer value is highly statistically significant. Including a range of control variables changes the scale of the price-specific coefficients minimally, but not the significance (see appendix B for regression results). \

Figure 11: Distribution of tree quantity offers



Notes: Marker locations include random noise to increase visibility. The offers from one respondent are outliers and are omitted from this figure.

Survival expectations

In order to have a rough measure of landholder tree survival expectations, respondents were asked how many trees would survive until the next wet season if they planted 20 this season and managed them well. Landholder expectations over survival are important as these can provide an indication of whether farmer effort has a causal impact on outcomes. Low expectations of survival might lead to landholders investing no effort into meeting contract terms. On the other hand, high expectations of survival may suggest that a landholder underestimates the true level of work required to keep trees alive. It is unclear ex-ante the likely net effect of expectations in this context. In this study, landholders had reasonably high[16] expectations about the survival rate of 20 well-managed trees (mean 16, s.d. 4). Results from a regression on household and agricultural characteristics on survival expectations are presented in Table 7. Significant determinants of survival expectations include the respondent being female (-), land that is on an

[16] Relative to rates implied by actual survival outcomes.

area that is seasonally inundated called a dambo (+), the household supplying casual labor to other farmers "ganyu" (-), their membership of comaco - a local conservation organization (+) and the number of months in a year that their household did not have enough food to eat (+). The directions of these covariates conform broadly to our expectations.

Table 7 Determinants of Tree Survival Expectations

survival	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
hhsizeadult	-.2048174	.1565846	-1.31	0.193	-.5138066	.1041718
female	-1.355653	.6019335	-2.25	0.026	-2.543452	-.1678547
femalehh	-.2492557	.8069669	-0.31	0.758	-1.841648	1.343136
trees	.7540972	.5991988	1.26	0.210	-.4283051	1.9365
soilqual	-.0239478	.362106	-0.07	0.947	-.7384935	.6905979
croparea	.4544533	.2909177	1.56	0.120	-.1196162	1.028523
dambo	.8583218	.3438332	2.50	0.013	.1798339	1.53681
comaco	1.346933	.5196222	2.59	0.010	.3215597	2.372306
dunavant	1.018889	.6361872	1.60	0.111	-.2365028	2.27428
hungryMonths	.3806442	.1782962	2.13	0.034	.0288113	.7324771
ganyu	-1.502866	.5955679	-2.52	0.012	-2.678104	-.3276291
crafts	-.522595	.6646263	-0.79	0.433	-1.834106	.7889156
sellfood	-.4909173	.5302253	-0.93	0.356	-1.537214	.5553792
_cons	15.39118	1.133098	13.58	0.000	13.15523	17.62713

Notes: Linear regression with robust standard errors. Dependent variable is the landholder's expected number of surviving trees after one year if they planted 20 and managed them well. N = 193 due to missing responses from some participants.

Determinants of WTA

To determine the degree to which survival expectations and respondent characteristics determine WTA, I regress quantity offers on survival expectations and other characteristics while controlling for the transfer values. Expectations of survival are interesting as they may affect effort under the contract, which in turn is likely to influence survival outcomes. As noted earlier, the effect on outcomes of survival expectations is ambiguous ex-ante. Strong correlations between observable characteristics and WTA suggest the possibility of contract targeting based on observables. Effective targeting on observables is also reliant on the predictive ability of WTA on outcomes, which is explored further below.

We see in Table 8 that survival expectations are positively and statistically significantly correlated with quantity offers (column 1), and the coefficient is increasing in magnitude with the transfer value. Including respondent characteristics (column 2) changes the scale of the coefficient on survival expectations (and interaction terms) minimally, but it is no longer statistically significant. This is perhaps to be expected given that many of these characteristics affect survival expectations as we have seen in Table 7 above.

Respondent gender and gender of household head have opposite signs and their effect on quantity offers is marginally and highly statistically significant respectively. While many factors may influence quantity offer patterns, fulfilling the contract primarily relies on household provision of land and labor and therefore we would expect that characteristics related to labor and land availability (and value of the outside option) may be influential. We do not see consistent evidence for this in relevant covariates (such as the number of adult household members), and the opposite signs on the coefficients for female and female headed are difficult to interpret through a labor or land constraint lens. I speculate that intra-household decision-making dynamics may be an important underlying cause for the different signs of these two coefficients. Respondents who are not household heads (whether female or male) might be inclined to be more conservative in their quantity offers when they are not able to confer with the household head, when compared to a respondent who is the head of the household. Invites to participate were targeted at the household head, but the household head status of the respondent was not confirmed explicitly at the time of the survey. These two characteristics combined may therefore present an incomplete proxy for household head status (amongst women only), which would provide some possible intuition behind the gender parameter estimates. Other individual factors with a statistically significant positive effect on the quantity offer are selling crafts and selling food for income generation, and months of the year in which hunger is a problem.

Table 8 Determinants of quantity offers (inversely proportional to WTA)

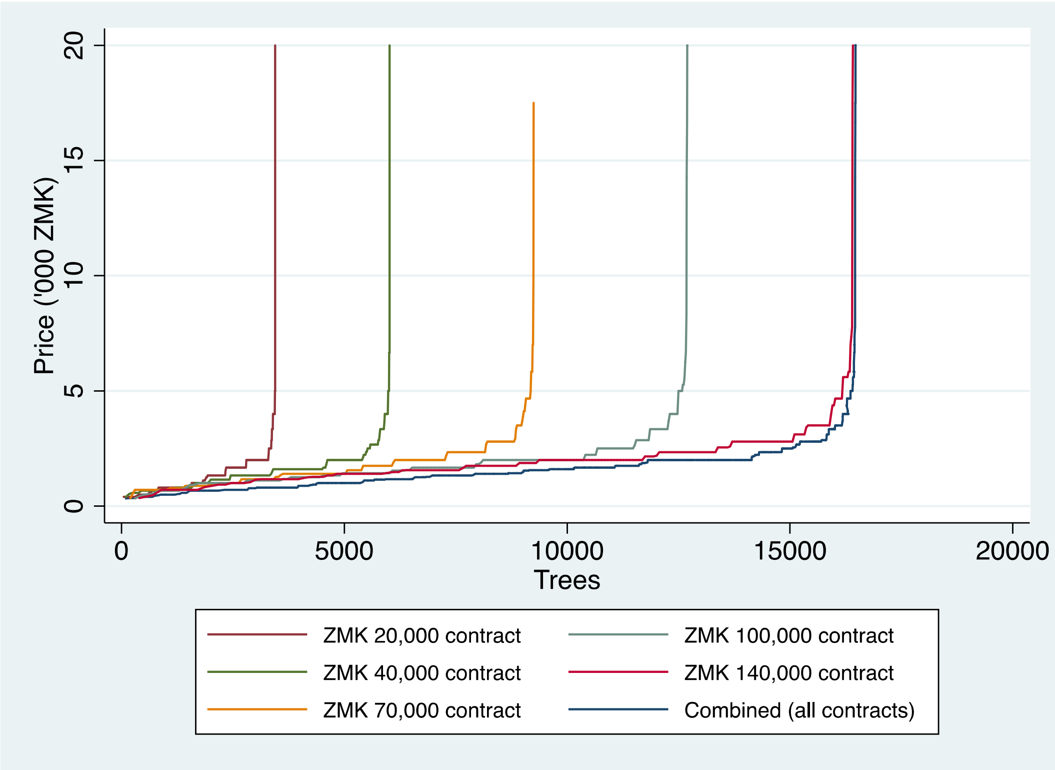
	(1)	(2)
Transfer = 40,000	9.412***	7.992***
	[2.810]	[3.099]
Transfer = 70,000	22.15***	24.81***
	[5.898]	[7.185]
Transfer = 100,000	28.77***	32.58***
	[7.017]	[8.649]
Transfer = 140,000	36.55***	35.59***
	[9.228]	[11.08]
Survival expectations (x/20)	0.541***	0.488*
	[0.135]	[0.284]
Survival exp.*40,000 Transfer	0.141	0.211
	[0.158]	[0.176]
Survival exp.*70,000 Transfer	0.275	0.0841
	[0.336]	[0.408]
Survival exp.*100,000 Transfer	0.850**	0.588
	[0.428]	[0.520]
Survival exp.*140,000 Transfer	1.413**	1.443**
	[0.574]	[0.682]
# adult household members		0.868
		[0.943]
Respondent is female		-5.684*
		[3.228]
Female headed household		15.02***
		[5.661]
Has Msangu trees on fields		-2.889
		[3.323]
Soil qual. (poor/aver/good=0/1/2)		1.176
		[2.042]
Cropped area (ha)		-2.169
		[1.533]
Crops wetlands		-1.386
		[1.926]
Membership (comaco)		5.164
		[4.291]
Membership (dunavant)		-2.525
		[4.055]
Months without adequate food		1.676*
		[0.873]
Supply casual labor		-4.031
		[3.448]
Sells crafts for income		7.586*
		[4.345]
Sells food for income		8.232**
		[3.393]
Constant	7.365***	-0.666
	[2.031]	[7.583]
# observations	1055	965

Notes: Panel regression with quantity offers as the dependent variable, showing coefficients and robust standard errors clustered at the individual level. Column 1 show direct effects of transfer dummies (omitted category is 20,000), survival, and all interactions, while column 2 also includes respondent characteristics. *, **, *** denote significance at 10%, 5% and 1%, respectively.

Aggregate supply

The experimental design and RQM allow direct measurement of revealed WTA and enable non-parametric estimation of individual and aggregate supply curves. In Figure 12 average prices implied by the quantity offer-transfer pairs (five per respondent) are plotted against offers to construct an approximate aggregate supply curve[17]. Prices (WTA on a per tree basis) in the offer-transfer pairs from this sample range from 333 to 20,000 ZMK (approximately USD 0.07 to 4.25), and supply appears to reach a maximum at approximately 16,500 trees, or an average 75 trees per respondent. This apparent maximum threshold is at least partly an artifact of the fixed transfer range in this experimental design, though may be related to land constraints also. Evidence for the latter is seen in offer patterns for some respondents that appear to flatten out towards the upper range of transfer values. Twenty-five per cent of the sample reported total land available of 1 hectare or less, which is enough land to plant 100 trees at the recommended spacing.

Figure 12 Revealed Aggregate Supply

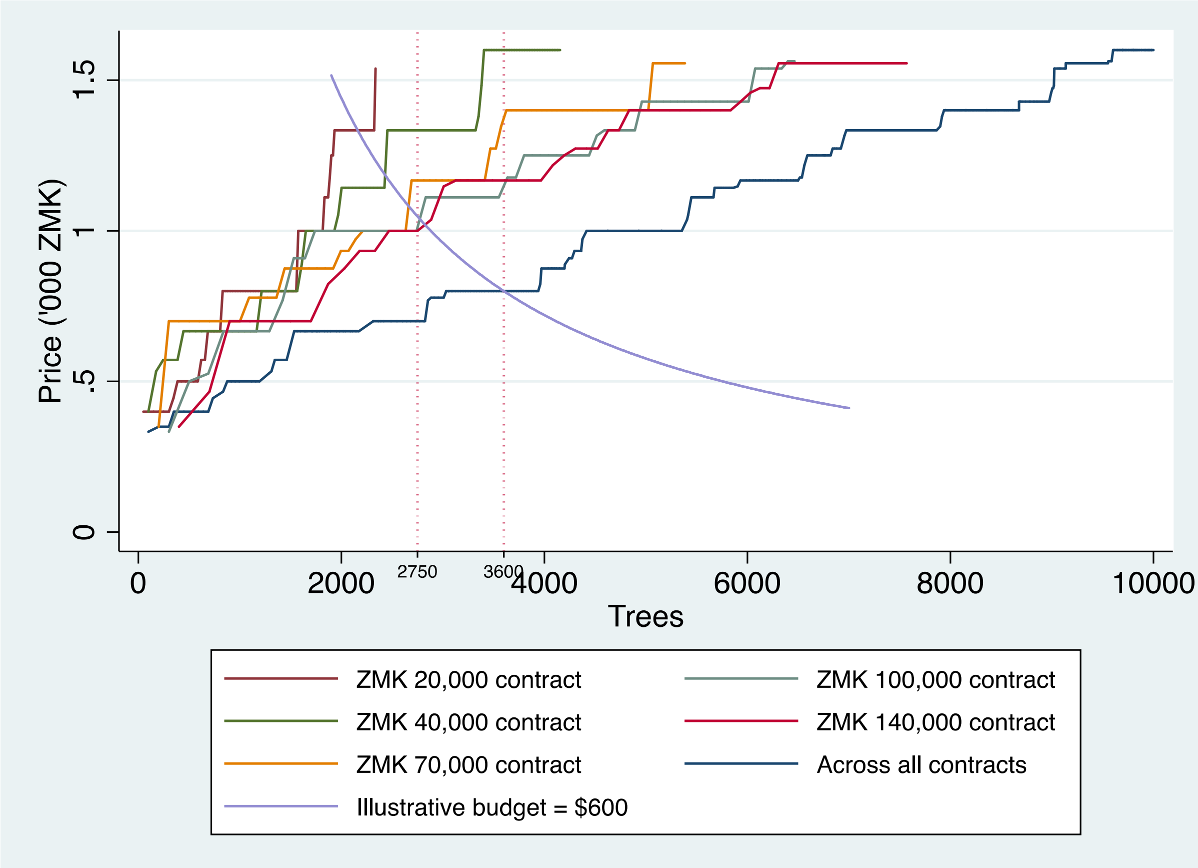


[17] This is constructed using discontinuous average costs derived from a discrete set of transfer values. A supply curve derived from a continuous range of transfers and offers (or equivalently marginal cost) would fall below the curve depicted here (assuming non-negative marginal cost of supply).

Figure 13 provides a detail view of the same aggregate supply curve produced by restricting the quantity to 10,000 trees or less, as well as the constituent supply curves for each of the five transfer values available. Also depicted is an illustrative budget constraint set at $600 that could, for example, represent an NGO's available funds for tree payments in a selected area. This figure provides a useful demonstration of the benefit derived from eliciting multiple WTA values from each individual when modeling supply. Aggregate supply curves constructed from a single transfer value, as shown here, tend to underestimate supply that incorporates changes in production along intensive margins (i.e. individual supply response). The 'combined' aggregate supply curve indicates that around 850 more trees (31%) could be supplied for $600 compared to a supply curve constructed from WTA estimates from the 140,000 transfer value[18]. The degree of underestimation will be larger the greater the heterogeneity of opportunity costs and the greater the elasticity of individual supply. Moreover, with a finite population the maximum aggregate supply will be a function of the largest contract value that is used. This can be seen in Figure 12, which shows the full range of the combined aggregate supply and each contract specific version.

[18] 2750 trees supplied at a price of $0.21 and total expenditure of $572.92 (due to discrete WTA measures) under the 140,000 contract aggregate supply curve, versus 3600 at a price of $0.17 and $600 total expenditure for combined aggregate supply.

Figure 13 Detail of aggregate supply curves and illustrative budget.



Balance across treatments

Randomization of contract quantity and transfer terms allocated to each respondent (treatment assignment) was undertaken by asking respondents to draw a ball from bags that contained a fixed set of quantity and transfer values. Randomization is important as it helps to avoid bias in the treatment allocation. Before discussing tree survival outcomes across treatments I check that the randomization was successful. Table 9 presents the results of linear regressions of respondent characteristics on treatment dummies. The first and sixth columns show the mean and standard errors of the omitted category for the 12 tree quantity draw and transfer draw of 20,000 ZMK respectively, and coefficient estimates for each of the other treatment categories are provided in columns 2 – 5 (quantity draw) and columns 7 - 10 (transfer draw). Respondent characteristics in each treatment are generally well balanced. No coefficients were statistically different from the reference treatment at a level of 0.05, however there were some differences that are marginally statistically significant ($p < 0.10$). Household size, soil quality, COMACO membership, provision of casual labor and selling food had no statistically significant differences between treatments, while each of the other characteristics had marginal differences in one or more treatment categories. These differences are not expected to systematically bias results given their marginal significance and, more importantly, the reliability of the randomization procedure. Nevertheless, I include these variables as controls in the multivariate analysis below in order to isolate the potential influence of these factors on contract performance outcomes.

Table 9: Summary statistics and coefficients of quantity draw and transfer draw treatments

	Q = 12 Mean [SD]	**Q = 25**	**Q = 37**	**Q = 50**	**Q = 75**	**T = 20,000 Mean [SD]**	**T = 40,000**	**T = 70,000**	**T = 100,000**	**T = 140,000**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Survival expectations (x/20)	16.171	0.409	-0.222	0.052	-1.534*	15.514	0.153	-0.255	0.694	1.582*
	[3.483]	[0.753]	[0.868]	[0.707]	[0.888]	[4.538]	[0.988]	[0.936]	[0.957]	[0.874]
Household size	2.659	0.32	0.011	0.598	0.488	2.917	0.11	0.158	0.083	-0.388
	[1.679]	[0.347]	[0.336]	[0.372]	[0.407]	[1.500]	[0.408]	[0.316]	[0.394]	[0.313]
Respondent age	36.777	2.003	4.213	1.335	3.005	39.389	0.665	-0.662	1.685	-4.683*
	[13.102]	[2.592]	[2.724]	[2.774]	[3.060]	[12.532]	[2.967]	[2.970]	[2.796]	[2.701]
Respondent gender (female)	0.367	0.133	0.193*	0.022	0.09	0.486	0.039	-0.034	-0.058	-0.064
	[0.487]	[0.100]	[0.099]	[0.108]	[0.110]	[0.507]	[0.115]	[0.114]	[0.107]	[0.112]
Female headed household	0.163	-0.061	0.170*	0.031	0.079	0.222	-0.012	-0.103	-0.004	0.028
	[0.373]	[0.069]	[0.087]	[0.085]	[0.092]	[0.422]	[0.097]	[0.086]	[0.090]	[0.096]
Soil quality (0-2)	1.169	0.014	-0.081	0.002	-0.052	1.081	-0.107	0.232	0.126	0.039
	[0.656]	[0.137]	[0.134]	[0.157]	[0.150]	[0.722]	[0.166]	[0.147]	[0.154]	[0.154]
Membership (comaco)	0.265	0.155	0.035	-0.015	0.163	0.243	0.157	0.162	0.114	0.001
	[0.446]	[0.095]	[0.091]	[0.097]	[0.106]	[0.435]	[0.106]	[0.105]	[0.096]	[0.096]
Membership (dunavant)	0.224	0.016	-0.004	0.026	-0.139*	0.189	-0.039	0.025	0.061	0.033
	[0.422]	[0.086]	[0.085]	[0.095]	[0.077]	[0.397]	[0.087]	[0.091]	[0.088]	[0.090]
Months without adequate food	2.396	0.064	0.588*	0.131	0.289	2.432	-0.007	0.311	0.514	-0.045
	[1.439]	[0.332]	[0.325]	[0.343]	[0.361]	[1.676]	[0.385]	[0.381]	[0.357]	[0.373]
Supply casual labor (0-1)	0.265	0.015	0.035	0.04	0.192*	0.297	0.003	0.179	-0.047	-0.031
	[0.446]	[0.091]	[0.091]	[0.101]	[0.106]	[0.463]	[0.106]	[0.109]	[0.096]	[0.101]
Sells food for income (0-1)	0.388	0.072	0.012	-0.054	-0.102	0.378	-0.078	0.074	-0.003	0.022
	[0.492]	[0.100]	[0.099]	[0.106]	[0.105]	[0.492]	[0.109]	[0.112]	[0.104]	[0.109]
# observations	49	50	50	36	35	37	40	42	56	45

Notes: Columns 1 and 6 show the omitted category for the minimum quantity draw and minimum transfer draws respectively. Other columns display the coefficients and standard errors from a linear regression of each covariate on the treatment dummies, with robust standard errors.
*, **, *** denote significance at 10%, 5% and 1%, respectively.

Determinants of contract performance (tree survival)

To investigate the degree to which various factors determine respondent performance under the contract, I regress tree survival data collected a year later on contract quantity and value, respondent offers (WTA), a constructed proportion variable ("premium") representing the extent that contract value exceeds WTA, and survival expectations. I use a negative binomial (NB) model for this analysis as NB does not rely on normally distributed data and is well suited to count data such as tree survival. The NB model is more flexible than the commonly used poisson model, and it is appropriate in conditions of over dispersion. The high incidence of zeros in our outcome measure (surviving trees) and a mean outcome substantially lower than the variance indicate dispersion is present and hence the NB model is a good choice for these data.

The experimental design results in treatment pairs spanning the range of possible combinations of the quantity draw {12, 25, 37, 50, 75} and transfer values {20000, 40000, 70000, 100000, 140000}, the latter providing our WTA measure in an inversely proportional relationship. Contracts are allocated according to the randomly selected price-quantity pairs, conditional on the landholders offer. The RQM serves to reveal the landholders WTA payment for tree planting across a range of quantities, and by design the composition of WTA values are endogenous to the random draw results, as discussed earlier. As is evident in Table 6, mean offers increase with increasing transfer values, and mean offers of those awarded contracts increase with increasing quantity draws.

Table 10 presents negative binomial regression results of tree survival on a selection of key variables (such as transfer drawn, quantity drawn, quantity offer, survival expectations), and a range of control variables across a number of model specifications. The left panel presents treat the treated (TT) while the right panel presents intention to treat (ITT) where non-contracted respondents are assumed to have zero surviving trees. Columns 1-5 and 8-12 provide the same sequence of five regression models, the former restricted to respondents who received contracts (i.e. TT) and the latter on the full sample (i.e. ITT). Columns 6 and 7 present results from regressions that are only applicable to the contracted subsample.

Table 10 Determinants of Tree Survival

	TREAT THE TREATED							INTENTION TO TREAT				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Contract transfer treatments (USD)	0.0498***	0.0514***	0.0716***	0.123***	0.135**	0.0466**	0.0573***	0.111***	0.0796***	0.1000***	0.251***	0.225***
{4.2, 8.3, 14.6, 20.8, 29.2}	[0.0171]	[0.0188]	[0.0243]	[0.0468]	[0.0537]	[0.0183]	[0.0220]	[0.0203]	[0.0257]	[0.0243]	[0.0476]	[0.0473]
Contract quantity treatments	-0.0277***	-0.0271***	-0.0372***	-0.0337***	-0.0444***			-0.0503***	-0.0546***	-0.0679***	-0.0645***	-0.0743***
{12, 25, 37, 50, 75}	[0.0101]	[0.0101]	[0.0141]	[0.0115]	[0.0153]			[0.0117]	[0.0123]	[0.00968]	[0.0107]	[0.00973]
Offered quantity		-0.00138	-0.00517	0.0283	0.0208	-0.0106**	-0.0152**		0.0201***	0.0125	0.0963***	0.0686***
(proportional to 1/WTA)		[0.00496]	[0.00495]	[0.0196]	[0.0210]	[0.00485]	[0.00588]		[0.00767]	[0.00821]	[0.0228]	[0.0200]
Contract transfer * Offered quant.				-0.00151	-0.00130						-0.00419***	-0.00303***
				[0.000946]	[0.00101]						[0.00105]	[0.000989]
Survival expectations			-0.103*		-0.114*		-0.0919*			-0.102**		-0.114**
(# trees alive after 1yr if 20 planted)			[0.0550]		[0.0589]		[0.0542]			[0.0492]		[0.0559]
Premium (=[offer-draw]/offer)						1.504**	1.766**					
						[0.610]	[0.699]					
Constant	0.961**	0.992**	2.343**	-0.106	1.664	0.183	1.665	0.227	-0.0601	1.896	-2.413***	0.631
	[0.376]	[0.382]	[1.111]	[0.742]	[1.235]	[0.411]	[1.185]	[0.392]	[0.415]	[1.165]	[0.829]	[1.394]
Individual Controls	No	No	Yes	No	Yes	No	Yes	No	No	Yes	No	Yes
# observations	219	219	214	219	214	219	214	219	219	202	219	202

Notes: Negative binomial regressions on contracted subpopulation (treat the treated) and full sample (intention to treat). Survey weighting used to correct for unbalanced allocation to transfer draw strata. One outlier omitted (with 60 surviving trees). *, **, *** denote significance at 10%, 5% and 1%, respectively.

The coefficients on the contract terms (transfer draw and quantity draw treatments) have consistently significant impacts on tree survival and of a similar magnitude across regression models in both ITT and TT, so are fairly robust to model specification. The number of surviving trees is increasing in the contract transfer value and decreasing in quantity stipulated in the contract. Awarded contracts with the largest transfer result in 1.2 – 3.4 additional trees surviving one year after planting when compared to contracts with the smallest transfer, depending on the model specification. Contracts in the largest quantity treatment result in 2 – 3.9 fewer surviving trees compared to the smallest quantity treatment. The magnitude of the coefficients on the two treatment variables is consistently larger in the ITT as compared to TT (e.g. the coefficient on transfer is 0.0796 in column 7 compared to 0.0514 in column 2) as the former includes the effect of treatments on the probability of receiving a contract, as well as the direct effect on survival for contracted respondents.

The first model specification (columns 1 and 6) only includes contract quantity and transfer terms (treatments) as a useful comparison point for other model specifications. We are interested in, among other things, finding evidence of the effect of WTA on survival – controlling for contract terms, do lower cost farmers perform better? The offered quantity variable sheds light on this relationship as it provides a direct inversely proportional measure of WTA; WTA decreases as offered quantity increases. A lower WTA (i.e. higher offer) indicates lower opportunity costs of managing trees.

The coefficient on the quantity offer is negative and not significant in TT (column 2) but highly significant and positive in ITT (column 6). The TT result may indicate that WTA has little identifiable impact on survival, while the significant ITT coefficient likely reflects the allocation rule of the RQM – those with higher offers are more likely to receive contracts. The impact of WTA on outcomes may affect the efficiency of screening contracts. Guiterras et al (2013) further explore the use of screening contracts for REDD+ with forest communities using this study context as an example. Columns 3 and 8 add survival expectations (expected number of trees surviving after a year if 20 are planted and managed well) to the model specification and other household characteristics as controls. Survival expectations have a statistically significant negative effect on survival, and do not markedly change coefficients on existing variables (transfer, quantity and offer) or their significance in the treat the treated analysis. Survival is significant and of a similar magnitude in the ITT analysis, however the magnitude and significance of the quantity offer parameter has decreased. As noted earlier, the impact of survival expectations is difficult to interpret but expectations could influence survival through selection effects (quantity offer, which affects the probability of being contracted, is increasing with survival expectations, and the magnitude of this effect increases with transfer value), through effort devoted to keeping trees alive, or through a combination of these and other factors. The magnitude of the survival expectation parameter is similar to that of either of the treatment parameters (across the experimentally determined ranges) so landholder expectations appear to be influential.

The endogeneity of landholder WTA composition along the two dimensions of treatment parameters (quantity and transfer) make identification of the effect of WTA on outcomes difficult without a large sample size. It is not clear whether the lack of statistical significance of the quantity offer in column 1 is a result of a small sample size or simply indicates no correlative relationship. As noted, amongst those contracted mean quantity draws increase with increasing offers as a direct result of the experimental design. Including an interaction between the quantity offer and contract transfer parameters in the model (columns 4, 5 and 9, 10) helps to separate the impact on contract performance that is driven by correlations with quantity draws resulting from the experimental design from the underlying direct impact of WTA on survival, if it exists. In this model specification the direct effect of WTA (Offered quantity) on survival is positive – as WTA decreases (lower opportunity costs) the number of surviving trees increases – but is not statistically significant in TT, while the interaction terms is negative and also not significant. In the ITT analysis both terms are of the same sign as in TT but larger in magnitude and highly significant, likely resulting from the effect of offers on the probability of contract allocation. Including the survival expectations and controls in the model (columns 5 and 10) does not alter the WTA parameter estimates greatly.

To examine the possible impact of contract payments that are above minimum WTA on tree survival outcomes I construct a variable, ‘Premium’, which seeks to provide a consistent measure of the degree to which average per-tree payments (i.e. tree unit prices) exceed average per-tree WTA. *Premium* is equal to the proportion of the quantity offer that remains after subtracting the quantity draw, and is intended to offer some comparability across the range of quantity offers and draws. To illustrate this, imagine two respondents who offer 24 and 74 and who draw quantities 12 and 37 respectively. The value of *premium* for these two individuals is the same, irrespective of their drawn transfer. In column 2' I regress tree survival on the premium parameter while controlling for the transfer value and quantity offer (WTA). We see that the premium is 1.504 and statistically significant. In column 3' survival expectations and individual controls are included in the specification, resulting in a statistically significant estimate of 1.766 on the premium parameter. Consistent with our expectations this suggests that the degree to which average per-tree payments are above average per-tree WTA positively affects survival, when controlling for quantity offer (WTA) and the direct effect of the transfer value.

5. Discussion

The Random Quantity Mechanism, a novel extension of the BDM, has a number of features that make it potentially useful in field research applications such as Payment for Environmental Services where there are information asymmetries that can limit the efficiency of traditional contracting. It provides quasi-experimental variation in treatment (drawn quantity and transfer values), precise estimates of minimum willingness to accept, random variation in contract terms (conditional on satisfying minimum WTA), and allows for direct non-parametric estimation of supply. When used in a field setting, these features in principle allow for the estimation of heterogeneous treatment effects, and can help to isolate the impact of incentives and selection on contract performance.

In an expected utility framework the mechanism is theoretically incentive compatible; the weakly dominant strategy for the participant is to offer the maximum quantity whose cost of production is no more than the transfer. I find in a laboratory setting that 66.7% of quantity offers made in response to contract transfer values in an induced cost experimental setting were exactly optimal, and the mean absolute difference between respondent and optimal offers was less than one. The expected value of the payoff for respondent offers provides a measure of decision-making efficiency within the RQM. Allowing for a small margin of error in finding the optimal expected payoff, 79% of the offer decisions pooled across participants were found to be optimal, while the offers of 17 of the 20 participants had optimal expected payoffs for the contract terms they received. The three participants who did not meet the efficiency criterion fell short of the maximum expected payoff by 10%, 30%, and 36%. With the exception of these three respondents, the above results suggest the mechanism is incentive compatible. A larger sample size would help to strengthen this analysis and more clearly identify potentially anomalous quantity offer decisions.

Information asymmetries in non-market goods and services, such as climate change mitigation by smallholder farmers, often present a barrier for policy makers and other agents interested in stimulating supply in order to realize positive externalities or address market failures. I implement the Random Quantity Mechanism in a field setting to examine cost structures for the provision of environmental goods and the determinants of WTA. The multi-transfer experimental design allows for non-parametric estimation of individual and aggregate supply curves that could be used by policy makers to examine the effect of subsidies and similar policy instruments on the provision of non-market goods and services, and conservation agents to predict supply for a given budget and evaluate cost-effectiveness compared to substitute environmental goods that could be used to achieve similar goals (e.g. pollution abatement through other mechanisms).

The RQM is shown to be feasible to implement in a field setting, and when used in a multi-transfer design can provide rich data on minimum WTA across intensive margins enabling construction of individual supply curves. In order to elicit revealed, rather than hypothetical, WTA information it is necessary to implement real contracts for goods or services in the RQM. Under these conditions, the RQM reveals minimum WTA while also generating (constrained) random variation in the effective average price paid (through randomization of quantity draws) and guaranteeing participation constraints are met. While this in principle provides the opportunity to examine the effect of WTA on contract performance, controlling for contract terms, and the impact of payments that exceed minimum WTA on contract performance, controlling for WTA, the allocation rule that ensures participation constraints are met creates endogeneity in the composition of landholders' WTA along the quantity dimension for those that are contracted. Similarly, the composition of landholders' WTA is endogenous to the transfer dimension resulting from the multi-transfer design. In other words, selection for low-cost farmers in contract allocation is increasing in the quantity draw and decreasing in the transfer. These features are an inevitable result of the design, and present difficulties when looking to examine contract performance and WTA relationships. When pooling data across the two dimensions of treatment in the multi-transfer design, the two features serve to confound identification of the effects of WTA, and payments above minimum WTA, on contract performance. Identification of these relationships would be improved with larger sample sizes.

Landholders in our sample offer to supply from 0 to 400 trees for a fixed set of contract values ranging from \$4.2 to \$29.2 (USD). This provides a direct measure of WTA payment for the provision of tree planting. I find gender to be an important factor in landholder's WTA for tree planting. Female respondents have higher WTA (coefficient on quantity offer is -5.7, p=0.078), and respondents from households headed by women have lower WTA (coefficient on offer is 15.0, p=0.008). This divergent response may partly relate to intra-household decision-making patterns, wherein non-household heads may be more conservative in their quantity offers when compared to household heads. The two gender characteristics that I have data for, above, may together form a proxy for household head status (but only amongst women respondents), thus contributing to the divergence seen here if decision-making authority is a factor in quantity offers. I also find that food sales (8.23, p=0.015) and craft sales (7.59, p=0.081) as a source of income generation affects WTA. These results highlight the need for consideration of gender access and distributional effects for programs that seek to promote tree planting to smallholders in Zambia.

Expectations over tree survival may be important as these can provide an indication as to whether farmer effort has a causal impact on outcomes. Survival expectations have a significant negative impact on WTA, and a marginally significant impact when controlling for other individual characteristics. The impact of survival expectations on

WTA is increasing in the transfer value, with coefficients on the quantity offer ranging from approximately 0.5 to 1.95 for each extra tree expected to survive out of 20 planted. Survival expectation are themselves a function of individual characteristics; female respondents and those respondents supplying casual piecework had lower expectations of survival, while farming seasonally inundated land, membership of a conservation organization, and the number of months in which the household faced hunger all had positive coefficients.

The incentive compatibility of the RQM ensures that the quantity offered for each transfer value is a direct measure of minimum willingness-to-accept payment for the provision of goods or services. As I show theoretically, when contracts provide pro-rated payments for partial contract fulfillment this result only holds in certain circumstances. I use average prices and quantity offer data to construct an aggregate supply curve across the sample and an aggregate supply curve based on quantity offers for each transfer value independently. Supply here is based on quantity commitments under a pro-rata contract payment scheme, and therefore the accuracy of the constructed supply curve is affected by the degree to which the RQM as implemented performs similarly to the standard case in which payment is not pro-rated on partial fulfillment. Our data cannot rule out the partial fulfillment RQM behavior nor confirm that quantity offers conform to the standard RQM scenario.

I use a hypothetical NGO budget of $600 for tree planting incentives with the constructed supply curves to illustrate a fixed-budget scenario in which I calculate market clearing price and quantity, and to highlight one of the advantages of the multi-transfer design. At a per-tree price of 800 ZMK (approximately $0.17) our sample population would offer to supply 3,600 trees, and the NGO would spend its entire $600 budget on incentives. If instead the largest transfer value (140,000 ZMK) was the only transfer implemented, the resulting aggregate supply curve would have indicated market clearing at a price of 1,000 ZMK (approximately $0.21) and 2,750 trees, with NGO expenditure at $572.92[19].

[19] Average prices and quantity offers are not continuous, and for the purposes of supply I consider the offers indivisible. Therefore this is the closest single offer that would satisfy the NGO budget constraint.

Tree survival data that was collected one year following contracting is used to explore the impact of WTA on contract performance outcomes. Contract quantity and transfer are highly statistically significant, and have a negative and positive effect on tree survival respectively. I do not find evidence that WTA significantly affects the number of surviving trees, when controlling for contract terms in our sample. Contract payments that are above the minimum WTA[20], however, do increase tree survival outcomes, controlling for WTA. Surviving trees increase by 1.5 when the contract quantity, as a proportion of the quantity offer, decreases from one to zero. I also find that expectations of tree survival, selling crafts, being a contract cotton farmer, and supplying casual farm labor decrease the number of surviving trees statistically significantly (casual labor) or marginally significantly, but respondent gender and a female head of household have do not have significant effects on survival.

The next increment on the supply curve is 2850 trees at a price of 1,037 ZMK resulting in $623.30 in total costs. This is still well short of the 3,600 trees in the combined aggregate supply.

[20] A proportional measure was constructed to enable consistent comparison across quantity offers and draws.

APPENDICES

A: Sample Summary Statistics

variable	mean	variance	min	max
female	.4590909	.2485524	0	1
age	38.82381	170.3455	18	72
hhsizeadult	2.905213	2.998597	1	12
educ	5.814815	8.752746	0	12
femalehh	.2095238	.1657815	0	1
soilqual	1.146919	.467009	0	2
trees	.2892157	.2057717	0	1
survival	15.98104	16.01482	0	20
croparea	5.419194	12.24395	.5	28
totalarea	7.491784	25.96945	0	31
useganyu	.4947917	.2502335	0	1
maize	2.561364	2.718024	0	10
beans	.1568182	.3336659	0	5
tobacco	.15	.250455	0	4
cotton	1.728409	3.627548	0	15
dambo	.3329545	.4312947	0	4
chickens	7.022727	87.16509	0	60
goats	.5181818	6.055174	0	30
pigs	1.931818	14.26741	0	25
cows	.3818182	6.851352	0	28
sellfood	.3818182	.2362478	0	1
sellbeer	.1227273	.1077633	0	1
ganyu	.3136364	.2154645	0	1
crafts	.2136364	.1681487	0	1
shop	.0590909	.0556498	0	1
remit	.05	.0475432	0	1
dunavant	.2090909	.1655224	0	1
cargill	.1272727	.1111754	0	1
comaco	.3318182	.2219166	0	1

B: Regression results for quantity offers ('bid')

```
. xtreg bid i.price##c.survival educ female croparea ganyu hungryMonths sellfood, vce(robust)

Random-effects GLS regression                   Number of obs      =       920
Group variable: id                              Number of groups   =       184

R-sq:  within  = 0.6942                         Obs per group: min =         5
       between = 0.1422                                        avg =       5.0
       overall = 0.4642                                        max =         5

                                                Wald chi2(15)      =    877.36
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 184 clusters in id)
```

bid	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
price						
40	9.319546	2.647844	3.52	0.000	4.129867	14.50923
70	15.29867	4.225838	3.62	0.000	7.016182	23.58116
100	23.96773	6.226866	3.85	0.000	11.76329	36.17216
140	33.50905	8.915967	3.76	0.000	16.03408	50.98403
survival	.5819684	.2027112	2.87	0.004	.1846618	.9792749
price#c.survival						
40	.1319475	.1559548	0.85	0.398	-.1737183	.4376134
70	.6426323	.262616	2.45	0.014	.1279143	1.15735
100	1.079845	.4240459	2.55	0.011	.2487305	1.91096
140	1.511857	.6004584	2.52	0.012	.3349803	2.688734
educ	-1.25426	.5148552	-2.44	0.015	-2.263358	-.2451625
female	-8.878142	3.386815	-2.62	0.009	-15.51618	-2.240107
croparea	-.7207556	.3391326	-2.13	0.034	-1.385443	-.0560679
ganyu	-5.181344	3.249545	-1.59	0.111	-11.55034	1.187647
hungryMonths	1.417344	.8963384	1.58	0.114	-.3394465	3.174135
sellfood	5.582334	3.254168	1.72	0.086	-.795719	11.96039
_cons	17.52029	7.234156	2.42	0.015	3.341602	31.69897

Notes: Prices are in '000 Zambian Kwacha (4,700:1 USD). Price = 20 is the omitted case. Female, ganyu (piecework), and sellfood are binary indicators (1=yes). Variable hungryMonths is the sum of months in a year that the respondent's household did not have enough food to eat.

REFERENCES

Ashraf, N., Berry, J., & Shapiro, J. M. (2010). Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia. *American Economic Review*, *100*, 2383-2413.

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral science*, *9*(3), 226-232.

Ferraro, P. J. (2008). Asymmetric information and contract design for payments for environmental services. *Ecological Economics*, *65*(4), 810-821.

Guiterras, R.P., Jack, B.K., Oliva, P. and Bell, S.D., (2011) Additionality in developing countries: Optimal contracts for avoided deforestation. Unpublished AERE conference paper.

Horowitz, J. K. (2006). The Becker-DeGroot-Marschak mechanism is not necessarily incentive compatible, even for non-random goods. *Economics Letters*, *93*(1), 6-11.

Irwin, J. R., McClelland, G., McKee, M., Schulze, W. D., & Norden, N. E. (1998). Payoff dominance vs. cognitive transparency in decision making. *Economic Inquiry*, *36*(2), 272-285.

Jack, B. K., Leimona, B., & Ferraro, P. J. (2009). A revealed preference approach to estimating supply curves for ecosystem services: use of auctions to set payments for soil erosion control in Indonesia. *Conservation Biology*, *23*(2), 359-367.

Jack, B. K., Oliva, P., Bell, S. D., Walker, E., Severen, C., (2014). Uncertainty, self-selection and the design of subsidies: Evidence from Zambia. *Unpublished Working paper*.

Karni, E., & Safra, Z. (1987). " Preference reversal" and the observability of preferences by experimental methods. *Econometrica: Journal of the Econometric Society*, 675-685.

Pattanayak, S. K., Wunder, S., & Ferraro, P. J. (2010). Show me the money: Do payments supply environmental services in developing countries?. *Review of Environmental Economics and Policy*, *4*(2), 254-274.

Smith, V. L. (1982). Microeconomic systems as an experimental science. *The American Economic Review*, *72*(5), 923-955.

Zomer, R. J., Trabucco, A., Bossio, D. A., & Verchot, L. V. (2008). Climate change mitigation: a spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. *Agriculture, ecosystems & environment*, *126*(1), 67-80.