Comparing accuracy and costs of revealed and stated preferences: the case of consumer acceptance of yellow maize in East Africa

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Abstract

For quite a while, stated preferences have been a major tool to measure consumer preferences for new products and services. Revealed preference methods, in particular experimental economics, have gained popularity recently because they have been shown to be more incentive compatible, and therefore more accurate. However, this advantage comes at the expense of higher survey costs. In the developing countries with limited funding for research, it is important to determine whether the extra cost can be justified by the extra gain in accuracy. A survey of 100 farmers was carried out in Western Kenya to determine consumer preference for yellow maize using the contingent valuation, choice experiments and experimental auction methods. Experimental auctions produced the most realistic results for mean willingness to pay. They are also the most accurate at all budget levels, but also the most expensive. Considering their accuracy and realistic results, we conclude that they should be the recommended method in measuring consumer preference in developing countries, since the extra cost is more than recovered by the gain in accuracy.

Keywords: Kenya, maize, consumer, experimental auctions, stated preference, WTP

JEL: D6, Q12

1. Introduction

1.1. Background information

Accurate estimates of consumers' willingness to pay (WTP) are important in the developing countries, since they provide basic information needed for pricing decisions and adoption forecasts (Lusk and Hudson, 2004). Since the success of technological innovations depends on whether consumers will accept them (Springer et al., 2002), developers of technologies are interested in knowing the acceptance of their products by consumers beforehand. It is therefore important to study potential demand for new products before they are developed, in order to avoid costly investments in products that might not have a market.

In developed countries, with relatively high budget allocations for research, different methods to study consumer preferences are tested, applied and compared. In developing countries, however, research funds are limited, and donors request that they be used where maximum outputs can be obtained. It therefore very important to use the best available methods, in particular those that provide the best results for the limited resources.

1.2. Measuring consumer preferences

Earlier consumer surveys mostly used the Contingent Valuation (CV) method to estimate consumers' WTP for new products or services. In this method, the researcher creates a hypothetical market in a non-market or new good, invites a group of subjects to operate in that market, and records the results. The values generated through the use of the hypothetical market are treated as estimates of the value of the non-market good or service, contingent upon the existence of the particular hypothetical market (Mitchell and Carson, 1989).

Choice experiments (CE) have also been widely used. These are based on Lancasterian consumer theory which proposes that consumers make choices, not on the simple marginal rate of substitution between goods, but based on preferences for different attributes of these goods. CE predicts consumers' choice by determining the relative importance of various attributes in consumers' choice process (Hanemann and Kanninen, 1998).

Both of these methods are relatively common and cheap. The data can be analyzed using discrete choice models to obtain average WTP for a product as well as for its particular attributes, and to determine which factors influence WTP. However, stated preference methods have been criticized for being unrealistic and not offering proper incentives for consumers to reveal their true preferences. People have been found overstating their WTP in hypothetical settings, as compared to more realistic conditions with real money and budget constraints (Lusk et al., 2004). There is a growing concern that the hypothetical nature of CV might not produce good estimates for WTP, since they are not incentive compatible (Umberger and Feuz, 2004). A mechanism is incentive compatible if it provides an incentive for consumers to reveal their true preferences. Therefore, experimental economics recently have gained more prominence.

In experimental auctions, real transactions take place and participants bid with real money on real products. Auction outcomes can therefore be considered closer to true WTP. Unfortunately, auctions are also more difficult to organize, and require more time and resources. In a typical incentive compatible experimental auction, subjects make a bid to obtain a novel good. The highest bidder wins the auction and pays a price that is determined exogenously from the individuals' bid (Lusk et al., 2004). Experimental auctions have the advantage of creating an active market environment with feedback where subjects exchange real goods and real money. In such an environment, individuals have an incentive to truthfully reveal their preferences.

Revealed preference methods generally produce better estimates of WTP, but are also more expensive. In the developing countries, with tight research budgets, there is a concern if the increased cost is justified by the increased accuracy. Therefore, this study compares the costs and accuracy for stated and revealed preference methods, as used in measuring consumer preference for yellow maize in East Africa. Maize scientists are breeding new varieties with higher pro-vitamin A levels, a process called biofortification (Bouis, 1999), The major source of pro-vitamin A in maize is beta carotene, which gives maize a yellow colour. These new varieties would be particularly useful in East and Southern Africa, were maize is the major food staple and levels of vitamin A deficiency are very high. Unfortunately, most of the maize grown in this region is white (FAO and CIMMYT, 1997), and maize consumers here have a rather strong preference for white (Rubey et al., 1997).

2. Methodology

2.1. Measuring consumer preferences

Contingent Valuation (CV): the double bound logistic model

The most common CV method uses a two-stage process, usually referred to as the double-bound method. In the first stage the respondent *n* is asked if she would be willing to pay a certain bid *B* for a good. . If she accepts, she will be offered a second, higher bid B_n^u; but if she rejects the initial bid, she is offered a second, lower, bid, B_n^d. There are four possible outcomes, with "yes-yes", "yes-no", "no-yes" and "no-no" responses. The probabilities $P^\bullet$ of each outcome can be written as:

$$P^{yy}(B_n, B_n^u) = \Pr(WTP_n > B_n^u) = 1 - G(B_n^u; \theta) \quad (1)$$

$$P^{yn}(B_n, B_n^u) = \Pr(B_n < WTP_n < B_n^u) = G(B_n^u; \theta) - G(B_n; \theta) \quad (2)$$

$$P^{ny}(B_n, B_n^d) = \Pr(B_n^d < WTP_n < B_n) = G(B_n; \theta) - G(B_n^d; \theta) \text{ and} \quad (3)$$

$$P^{nn}(B_n, B_n^d) = \Pr(WTP_n < B_n^d) = G(B_n^d; \theta) \quad (4)$$

where WTP_n is the maximum willingness to pay, $G(\bullet; \theta)$ is a cdf of the WTP and θ are the parameters to be estimated (Hanemann et al., 1991). In this study the cdf is assumed to be logistically distributed and hence

$$G(B_n^\bullet) = [1 + e^v]^{-1} \text{ where } v = \alpha - \rho B_n^\bullet . \quad (5)$$

The parameters of the index function α and ρ are then estimated by maximizing the log-likelihood function

$$\ln L^D(\theta) = \sum_{n=1}^{N} \{ d_n^{yy} \ln P^{yy}(B_{n,} B_n^u) + d_n^{nn} \ln P^{nn}(B_{n,} B_n^d) + d_n^{yn} \ln P^{yn}(B_{n,} B_n^u)$$

$$+ d_n^{ny} \ln \pi^{ny}(B_{n,} B_n^d) \} \quad (6)$$

where $d_n^{\bullet}$ are binary-valued indicator variables that are 1 if the respective responses were chosen. The estimated mean willingness to pay is then derived by calculating $\frac{\alpha}{\rho}$ (Hanemann et al., 1991).

Choice experiments (CE): the McFadden Conditional Logit model

In a choice experiment a respondent *n* is asked to choose one out of *J* alternatives that differ in their attributes x_{nj}. With each alternative *j* there is a utility *U* associated which can be different for different respondents. The utility that decision maker *n* obtains from alternative *j* is U_{nj}. The researcher cannot observe U_{nj}, but he can assume that *n* will only choose *i* if and only if

$$U_{ni} > U_{nj} \forall j \neq i \,. \quad (7)$$

Using this assumption, it is possible to construct the representative utility *V* (Train, 2003)

$$V_{nj} = V(x_{nj}) \forall j \,. \quad (8)$$

which is the explained part of utility *U*:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad (9)$$

where ε_{nj} captures the variables that influence utility but cannot be included in V_{nj} as they are not observed. If the representative utility is linear in the observed attributes of the alternatives it can be noted as

$$V_{nj} = x_{nj}{'} \beta \,. \quad (10)$$

The probability that the consumers selects an alternative is than calculated as:

$$\begin{aligned} P_{ni} &= \Pr(U_{ni} > U_{nj} \forall j \neq i) \\ &= \Pr(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \forall j \neq i) \\ &= \Pr(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj} \forall j \neq i) \end{aligned} \tag{11}$$

Following McFadden's conditional logit model a type I extreme value distribution of the error terms is assumed. All unobserved factors are assumed to be uncorrelated over alternatives and the variance is implicitly normalized. For each ε_{nj} the probability to be chosen is then the cdf of the type I extreme value distribution evaluated at

$$\varepsilon_{ni} + V_{ni} - V_{nj} \tag{12}$$

and is written as

$$F(\varepsilon_{nj}) = \exp(-\exp(-(\varepsilon_{ni} + V_{ni} - V_{nj}))) \tag{13}$$

The cumulative distribution over all alternatives $j \neq i$ is, due to the assumed independence of the ε's, the product of the individual cdf's. But since ε_{in}'s are not known, the sum must be derived by integrating over all values of ε_{in} weighted by its density as given above (13).

$$P_{ni} = \int \left\{ \prod_{j \neq i} \exp(-\exp(-(\varepsilon_{ni} + V_{ni} - V_{nj}))) \right\} \exp(-\varepsilon_{ni}) \exp(-\exp(-\varepsilon_{ni}) d\varepsilon_{ni} \tag{14}$$

Algebraic manipulation results in a succinct, closed form expression for linear parameters (Train, 2003):

$$P_{in} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \text{ and } P_{in} = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \tag{15}$$

The probability that a respondent *n* chooses the alternative he actually chose, can then be expressed as

$$\prod_i (P_{ni})^{y_{in}} \tag{16}$$

where $y_{ni} = 1$ for the chosen alternative and zero otherwise. Given that each decision maker's choice is independent of the others, the probability that each respondent chooses the alternative actually chosen is

$$L(\beta) = \prod_{n=1}^{N} \prod_{i} (P_{ni})^{y_{ni}} \tag{17}$$

and the log-likelihood is then

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i} (y_{ni} \ln P_{ni}) \tag{18}$$

where β is the vector of parameters to be estimated. As variance-covariance matrix the information matrix may be used. To derive the mean willingness to pay for an attribute the negative of the parameter for the attribute must be dived by the parameter for the price. The variance for the willingness to pay can be estimated by bootstrapping from the distributions of the two parameters and then calculating the variance of the fraction of the bootstrapped parameters.

Experimental auctions (EA)

In a typical incentive compatible experimental auction, subjects bid to obtain a good. The highest bidder wins the auction and pays a price that is determined exogenously from the individuals bid (Lusk et al., 2004). In the Becker-DeGroote-Meshack (BDM) auction employed in this study, an individual bids against a random price and purchases the good if her bid is greater than a randomly drawn price. The bids collected from an experimental auction state the willingness to pay of a respondent for a particular product. The mean and the variance are then derived by the bids from all participants.

2.2. The Error model

A natural and intuitive measure of estimation error is the mean squared error (MSE), the expected value of the difference between the estimate and the estimated parameter, squared so that positive and negative errors do not cancel each other out. The MSE can also be seen as a loss function, and is commonly used as such (Cochran, 1977)

$$MSE(T) = E(T-\theta)^2 = V(T) + [\,\theta - E(T)\,]^2 \qquad (19)$$

The MSE can thus be regarded as the combination of the variance $V(T)$ and the bias $B = \theta - E(T)$, which makes it a useful criterion to compare biased estimators (Cochran, 1977).

In this study, a simpler error model is used (De Groote and Traore, 2004) based on the relative total error (RTE), calculated as the square root of the MSE divided by the mean of the population. This is a unit-free measure, analogous to the coefficient of variation (CV):

$$RTE(\bar{y}) = \frac{1}{\bar{\bar{X}}}\sqrt{V(\bar{y}) + B^2} = \sqrt{\frac{\sigma_y^2}{n\bar{\bar{X}}^2} + \frac{B^2}{\bar{\bar{X}}^2}} = \sqrt{\frac{SR_y^2}{n} + BR^2} \leq \sqrt{\frac{SR_x^2}{n} + BR^2} \qquad (20)$$

(De Groote and Traore, 2004)

In this study, a two-stage stratified sampling design was used. The precision of the sample mean of such a design, or standard error of the sample mean, is given by:

$$\sigma_{\bar{\bar{x}}} = \sqrt{(1-\frac{n}{N})\frac{\sigma_e^2}{n} + (1-\frac{nm}{NM})\frac{\sigma_i^2}{nm}} \qquad (21)$$

where n is the number of first-stage units (villages in this case) and m the number of second-stage units (farmers or consumers) per village, σ_e^2 is the variance between villages and σ_i^2 is the variance within villages.

The cost of a two-stage sample survey can be calculated by estimating the coefficients of a cost function. For two-stage sampling, the standard formula is composed of a fixed cost C_0, a variable cost C_1 per primary unit (village) and a variable cost C_2 per secondary unit (household). The budget constraint becomes:

$$C_0 + nC_1 + nmC_2 \leq Bud \qquad (22)$$

There are now two choice variables: the number of villages *n* and the number of households per village *m*. The size of the sample is then given by *nm*. By calculating the accuracy of the sample mean by the RMSE on the one hand, and the cost of the survey with the cost function, the balance can be made and the best solution found. Mathematically, this can be done by an optimization:

$$\underset{n,m}{Min}\left(\sqrt{(1-\frac{n}{N})\frac{\sigma_e^2}{n}+(1-\frac{nm}{NM})\frac{\sigma_i^2}{nm}}\right) \; s.t. \quad (C_0+nC_1+nmC_2 \leq Bud) \tag{23}$$

This can easily be done with optimization software such as the Solver Add-in that comes with the Excel spreadsheet software.

2.3. Sample selection

Two districts, Siaya and Vihiga in Western Kenya were purposely selected for the survey. The criteria was a region where the population was familiar with yellow maize (Kimenju et al., 2005). A stratified two-stage design, with the two districts forming the strata was used. From each district, five sublocations (villages) where randomly selected proportionate to size, with the number of households in each sublocation, obtained from the 1999 population census, as an indicator of size. From each sublocation, 10 households were randomly selected, resulting in a sample size of 100 households. From each household, either the head of the household or the spouse was selected, based on availability of being at home, and responsibility for food purchases in the household.

3. Results

3.1. Estimating willingness to pay

In the contingent valuation method, people were first told the current price of white maize in the market (40 Ksh/2kg or about US$0.25 per kg), and then asked if they would accept to buy yellow maize at that same price. Those who accepted this bid were then asked if they would buy yellow maize at a second, higher, bid. The same was done for the other maize types. Those who rejected the first bid were offered a second, lower, bid. Mean WTP can be estimated from the parameters of a logistic, double-bound model using the standard logistic procedure. For yellow maize, for example, the constant (α) is estimated at 4.9, and the coefficient of the bid (ρ) at 0.096 (Table 1). From here, the mean WTP (α / ρ) is calculated at 51 Ksh/2kg. Similar calculations indicate a mean WTP for yellow biofortified maize at 64.5 and white biofortified at 65.2 Ksh/2 kg.

In the choice experiments, respondents were asked repeatedly to choose between three products, a randomized combination of color (yellow or white), nutritional quality (fortified or not) and price. Coefficients for the attributes are obtained by estimating the standard conditional logit model, and mean WTP for the attribute (the premium or discount) is calculated by dividing the attribute coefficient by the price coefficient.

For the experimental auctions, respondents received cash and were invited to bid for three products, which were physically presented: yellow maize meal, white maize meal, and white fortified maize meal, one at a time. According to the rules of the BDM auction, the transaction was concluded if the bids fell above a the randomly drawn price, and the respondent bought the maize meal at the bid she set. The average bid can then be interpreted as the average WTP for the different products.

The results show that the average WTP is 39.9 Ksh/2kg for yellow maize and 39.6 for white maize, which is very close to the market price (Table 3). As expected, Siaya has a slight premium for yellow, since the district grows more yellow maize than Vihiga which has a small discount. Mean WTP for the white fortified meal is 51.8 Ksh/2kg, and a bit higher in Vihiga.

The mean WTP and the standard errors from each method are compared in Table 4. It is clear that both the CV method and the choice experiments method provide unrealistic results as the derived WTP for fortified maize is much higher than the price of fortified maize meal that is now on the market. Estimates from EA turn out to be the most realistic, since they are very close to market prices at the time of the survey.

3.2. Comparison of cost and accuracy

As expected, the experimental auction is the most expensive method (Table 5). It has a higher fixed cost (C_0) than CE and CV, because it required a more extensive preparation phase. The preparations for the CV took the least time because the authors had some previous experience with it. The fixed cost per village (C_1), mostly consisting of the travel cost to the village, is the same for all methods, The cost per household (C_2), on the other hand, is much higher for the EA than for to the other methods. Not only does EA need more enumerator time, but the process also uses real money and products, thus increasing the costs..

To compare cost and accuracy, we consider two methods, CV and EA. CV generally has higher bias compared to EA (Table 6). To obtain the comparison of cost and precision, an optimization procedure is used at different budget levels. For each budget figure from US$ 2500 to 30000, we obtain a corresponding measure for precision, the RMSE (Figure 1). The results show that for all budget levels, a higher precision can be obtained using EA to estimate the WTP for both maize products. Because CV has such a high bias, and only the variable part of the RMSE decreases with increased sample size, the accuracy obtained with CV hardly improves with increasing budgets. . With EA, on the other hand, accuracy clearly improves with increasing budgets, although it starts to levels off at a budget of about US$5000 . Increasing the budget level beyond US$ 10000 is not indicated, since it hardly improves accuracy.

Using this optimization procedure, the optimal number of villages and households per village can be calculated for a certain budget. It follows that, for a budget of US$ 7500 using EA and employing two-stage sampling, we can sample 11 villages and 34 farmers within each village at a good accuracy, with a RMSE of 2.18 %.

4. Conclusions

Using RMSE as indicator of accuracy, this study shows that the use of revealed preferences is far superior to that of stated preference in measuring the preferences of the rural African maize consumer. Experimental auctions produced the most realistic estimates of WTP for yellow and for fortified maize. Contingent valuation and choice experiments provided very high estimates of WTP, much higher than the prices observed in the market.

Experimental auction is also the most expensive method. It has a high fixed cost due to the cost of preparation that entails wide literature review. It also has the highest cost per farmer, because of the money involved, the materials needed and higher enumerator time. However, compared with CV, it has the highest accuracy at all budget levels. Although, at a given budget, the sample size that can be obtained with EA is substantially smaller than with CV, the quality is much higher, resulting in higher accuracy.

The experience gained in this research showed that contingent valuation methods are easy and fast. Choice experiments are more difficult, people often have a hard time making a choice and are afraid they are going to make mistakes (examination fear). Experimental auctions take a lot of preparation time and require more financial resources and training of the enumerators. However, after some experience, enumerators had no problem executing the procedure and could easily obtain the bids from the respondents. The procedure was also perceived as very enjoyable by the respondents.

Given the ease of use, the more realistic results, and the high precision obtained, we conclude that experimental auctions are the indicated method. Even if the initial cost and the cost per interviewee are higher, this is more than recovered by the higher precision. For this particular study, experimental auctions produce, always superior results for a given budget.

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Tables

Table 1. Consumers' WTP for maize estimated using CV

Type of maize meal	analysis	Estimate	Siaya (N=50)	Vihiga (N=50)	Total (N=100)
Yellow unfortified	regression	Constant (α)	4.8165	5.0038	4.9070
			(0.8169)	(0.8087)	(0.5746)
		Bid (ρ)	0.09453	0.0975	0.0960
			(0.0162)	(0.0161)	(0.0114)
		Loglikelihood fn.	60.8885	59.6032	120.5066
	calculation of WTP	Mean WTP (α / ρ)	50.95	51.32	51.14
			(3.1880)	(2.6790)	(2.047)
Yellow biofortified	regression	Constant	7.9798	5.6275	6.7596
			(1.8887)	(1.1373)	(0.9792)
		Bid	0.1308	0.0800	0.1048
			(0.0332)	(0.0201)	(0.0173)
		Loglikelihood fn.	41.1910	37.0392	79.5816
	calculation of WTP	Mean WTP (α / ρ)	60.99	70.31	64.50
			(2.9180)	(6.6750)	(3.4330)
White biofortified	regression	Constant	9.3401	6.8824	8.0862
			(3.0679)	(1.4521)	(1.3315)
		Bid	0.1502	0.0982	0.1239
			(0.0538)	(0.0253)	(0.0233)
		Loglikelihood fn.	34.2639	31.6944	66.9509
	calculation of WTP	Mean WTP (α / ρ)	62.18	70.10	65.25
			(4.2090)	(7.3580)	(2.6080)

Table 2. Estimation of WTP from choice experiments

	Estimate	Siaya (N=50)		Vihiga (N=50)		Total (N=100)	
Regression	Price (x_p)	-0.04	***	-0.02	***	-0.03	***
		(0.0064)		(0.00587)		(0.0043)	
	Yellow (x_y)	0.33	**	-0.09		0.10	
		(0.1167)		(0.1098)		(0.0794)	
	fortification (x_f)	2.71	***	2.14	***	2.39	***
		(0.1821)		(0.1583)		(0.1186)	
	Log likelihood	-343.477		-400.181		-750.412	
	Pseudo R2	0.3632		0.2656		0.3079	
Calculation	WTP yellow (x_p/ x_y)	8.76		-4.18		3.50	
		(4.7451)		(7.9855)		(3.7016)	
	WTP fortification (x_p/ x_f)	72.36		94.48		81.64	
		(13.6478)		(304.3652)		(13.8340)	

Table 3. Mean WTP derived from the experimental auctions.

Maize meal type	Siaya	Vihiga	Total
Yellow maize meal	40.60	39.14	39.87
	(13.27)	(11.7)	(12.47)
White maize meal	38.72	40.54	39.63
	(10.72)	(11.04)	(10.86)
White fortified maize meal	50.40	53.20	51.80
	(12.64)	(14.28)	(13.49)

Table 4. Comparison of mean WTP and standard deviations for the three methods

Product	CV		CE		Auction		
	WTP	S.E	WTP	S.E	WTP	S.D	S.E
Plain yellow	51.14	-2.05	43.22	3.94	39.87	-12.47	-1.25
Plain white			36.78	4.04	39.63	-10.86	-1.09
Fortified yellow	64.50	-3.43					
Fortified white	65.25	-2.61	123.39	14.45	51.80	-13.49	-1.35

Table 5. Cost incurred for the three methods in US$

	CV	CE	EA
Fixed cost (c0)	992.73	1441.80	1931.69
Cost per village (c1)	303.24	303.24	303.24
Cost per farmer (c2)	0.74	0.94	4.68
Total cost	1296.71	1745.98	2239.62

Table 6. Comparison of variance from CV and EA

	CV		EA	
	Plain yellow	Fortified white	Plain yellow	Fortified white
Variance between villages	6.5829	6.2741	2.2206	3.0735
Variance within villages	4.5146	0.1815	12.8839	13.8081
Bias in KShs	-10.847	-21.887	0.130	-11.800

Figures

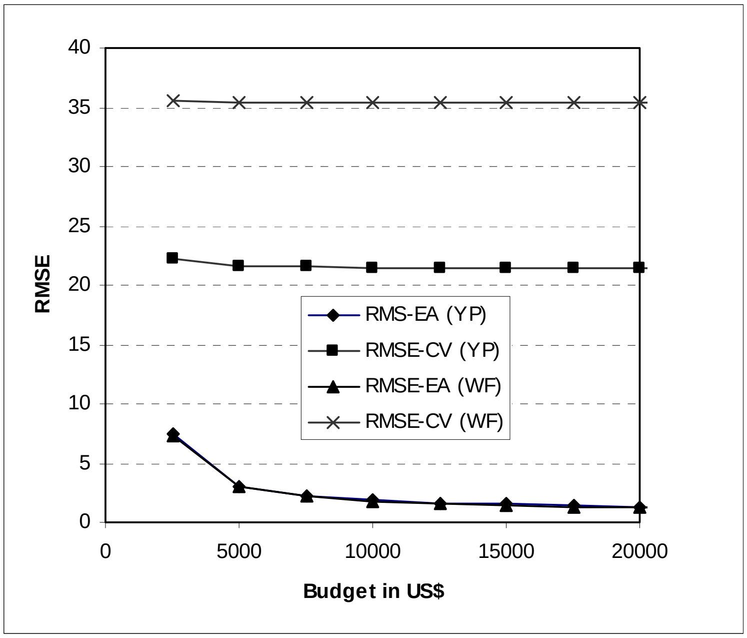

Figure 1. A comparison of cost and precision for CV and EA