Calibration of an Agricultural Sector Model for the Region Khorezm (Uzbekistan) based on Survey Data

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Abstract

The paper describes the approach used for the calibration of a price-endogenous programming model, developed for the agricultural sector of the region Khorezm in Uzbekistan. Extensive datasets from farm surveys were used to parameterize the model, which nevertheless tended to over-specialization and failed in general to replicate the observed levels of primal model variables. Calibration of the model with "Positive Mathematical Programming" approaches was not satisfying as the additional cost terms introduced to replicate the observed situation were in many cases not plausible and deviated substantially from any available information on cost structure of the agricultural production activities in the study region. After revising the survey data it became obvious that the variances of technical parameters of the model, namely the input coefficients, were significantly larger than any other used set of information. Consequently, instead of introducing additional cost terms, we decided to estimate the technology parameters, such that the observed situation was replicated and the Kuhn-Tucker conditions for an optimum in this point were fulfilled. The estimation was based on a cross entropy approach. The needed support points and prior distributions of the technology coefficients and dual values were drawn from survey data and additional sources of information, such as expert interviews. The result is a calibrated agricultural sector model with a technology representation that was derived by systematical exploitation of relevant data sources for the study region.

Keywords: supply model calibration, positive mathematical programming, technology coefficient estimation

1 Background

The Khorezm region is located in the northwest of Uzbekistan, in the lower reaches of the Amu Darya River. Agriculture remains the most important sector of Khorezm's economy: in 2003, it accounted for 67% of the regional GDP and employed 40% of regional labor.

In the agricultural sector of Uzbekistan several reforms have been taken as part of a transition to a market-based economy. However, since agriculture is the main source of the country's export, state involvement in this sector remains substantial via a state procurement system.

It was argued by many authors that the implicit taxation of the agricultural sector, via the state procurement system, deprived the agricultural producers of profits (Guadagni et al 2005). Therefore, further reforms in the agricultural sector are geared toward an increase in producer incentives by abolishing the state procurement system. However, while such policy may have a positive impact on agricultural output, it is unclear how it will affect regional production. The problem, therefore, requires a tool for systematic policy analysis. An agricultural sector model is one such tool which can deal with the quantitative problems, while taking into account the specific settings of regional agriculture. Application of such model may provide a better understanding on how a sector functions and information valuable for evaluating policy effects.

2 Main Model Characteristics

The model developed for the agricultural sector of Khorezm (KhoRASM) is a static price-endogenous partial equilibrium model as presented in Hazel and Norton (1986). KhoRASM is applied to answer the question how production patterns will react to changes in policy conditions, such as abolishment of state procurement tasks.

The model consists of eight cropping and three animal producing activities specified for three producer aggregates in five production districts. The reference year is 2003.

For the sake of computational simplicity, the commodity prices and balances are defined in a single regional commodity market. KhoRASM does not incorporate cross-price and income effects, exporting and importing activities.

The model's objective function maximizes regional producer and consumer surplus:

$$\max_{\mathbf{q}} Z = \mathrm{u}(\mathbf{q}) - \mathrm{c}(\mathbf{q}) \tag{1}$$

Where u and c denote the consumer and producer surplus associated with the production and consumption of commodities **q**. The consumer surplus in its most general form can be expressed according to Hazell and Norton (1986):

$$\mathrm{u}(\mathbf{q}) = \sum_{k=1}^{K} \int_{0}^{q_k} \varphi_{\mathrm{k}}(q_k \mid q_{k+i} = 0, all\ i = 1\ to\ K-k)\ dq_k \tag{2}$$

Author 2 specified $\mathrm{u}(\mathbf{q})$ via Normalized Quadratic-Quadratic Expenditure System (NQQES). However, this paper focuses on the calibration of the supply side of KhoRASM and we restrict ourselves to more simplistic version of a system of linear demand curves, which results in a quadratic objective function:

$$\mathrm{u}(\mathbf{q}) = (\boldsymbol{\alpha} - \tfrac{1}{2}\mathbf{q}'\boldsymbol{\beta})\mathbf{q} \tag{3}$$

The producer surplus $\mathrm{c}(\mathbf{q})$ is expressed as the product of variable inputs purchased from outside the agricultural sector times the respective input-price **g**:

$$\mathrm{c}(\mathbf{q}) = \mathbf{v}(\mathbf{q})'\mathbf{g} \tag{4}$$

Levels of agricultural activities, the corresponding demand for variable and fixed inputs (like water, land, but also production targets), and the resulting commodity outputs are linked as depicted in Table 1. KhoRASM distinguishes between inputs produced and traded within the agricultural sector (namely fodder crops) and inputs purchased from outside the agricultural sector (fertilizer and diesel). This distinction was necessary to account for the fact that prices for fodder inputs were not available in the same manner as for other inputs, market prices of which were observable. Table 2 provides an overview on different model components and their dimensions.

Table 1 Structure of KhoRASM

		Activity level l in district d in farm type f	Marketing of output k from activity n	Purchase of fodder crops	Purchase of variable input v of nth activity	RHS	Dual values
	Dimension	n=l×d×f	k	vf	vp	1	1
	1	**X'**	**q'**	**f'**	**v'**		
Balance of market commodity k	k	$-Y^m$	**I**			≤0	π
Fodder supply	fs	$-Y^f$		**I**		≤0	ϕ^1
Fodder demand	fd	B^f		**-I**		≤0	ϕ^2
Input balance	v	B^p			**-I**	≤0	ψ
Resource balance	r	**A**				≤b	λ
Objective function	1		u(**q**)		**g'**	Maximize!	

Table 2 Model Parameters and Variables

Model parameters	Description	Dimension
A	Demand for fixed factor or resource (including production targets) per level unit of activity n	**r×n**
b	Vector of resource constraints (including production targets)	**r×1**
B^f, B^p	Demand for variable input produced within the agricultural sector (fd) and variable input purchased from outside the agricultural sector (v) per level unit of activity n	**fd×n,v×n**
Y^m, Y^f	Yields of market commodity k and fodder commodity fs from activity n	**k×n,fs×n**
g	Price for variable input v	**vp×1**
Model variables		
x	Level of activity l in district d and farm type f	**n×1**
q	Output of marketed commodity k	**k×1**
f	Purchase of inputs produced in agriculture (fodder)	**vf×1**
v	Purchase of other inputs	**vp×1**
Dual values		
π	Shadow price of market balance constraint (commodity price)	**k×1**
ϕ^1, ϕ^2, ϕ	Shadow price of fodder constraint	**fs×1,fd×1**
ψ	Shadow price of input constraint (input price)	**v×1**
λ	Shadow price of resource constraints	**r×1**

The model´s Lagrangian takes the following form:

$$L = u(\mathbf{q}) - \mathbf{g'v} + \boldsymbol{\pi}'\left(\mathbf{Y^m x} - \mathbf{q}\right) + \boldsymbol{\varphi}^{1\prime}\left(\mathbf{Y^f x} - \mathbf{f}\right) + \boldsymbol{\varphi}^{2\prime}\left(\mathbf{f} - \mathbf{B^f x}\right) + \boldsymbol{\psi}'\left(\mathbf{v} - \mathbf{B^p x}\right) + \boldsymbol{\lambda}'\left(\mathbf{b} - \mathbf{Ax}\right) \quad (5)$$

This model was parameterized based on survey data and official statistics. The different data sources are discussed in the next section.

3 Parameterization with Survey Data

The sources used for parameterization of the model are presented in Table 3. For KhoRASM we used data of several categories compiled from values for 2003: regional prices, production patterns, input-output coefficients, and resource endowments.

Table 3 Sources for Model Parameters

Parameters	**Description**	**Main source**	**How derived**	**Alternative source**	**How derived**
A	**Demand for fixed factor or resource l per level unit of activity n**	Own survey	Average	Norm values, expert interviews	Average or most plausible value
B	**Demand for variable input v per level unit of activity n**	Own survey	Average	Norm values, expert interviews	Average or most plausible value
Y	**Yields of commodity k from activity n**	Own survey	Average	Official statistics, norm values, expert interviews	Average or most plausible value
G	**Price for variable input v**	Own survey	Average	Official statistics, norm values, expert interviews	Average or most plausible value

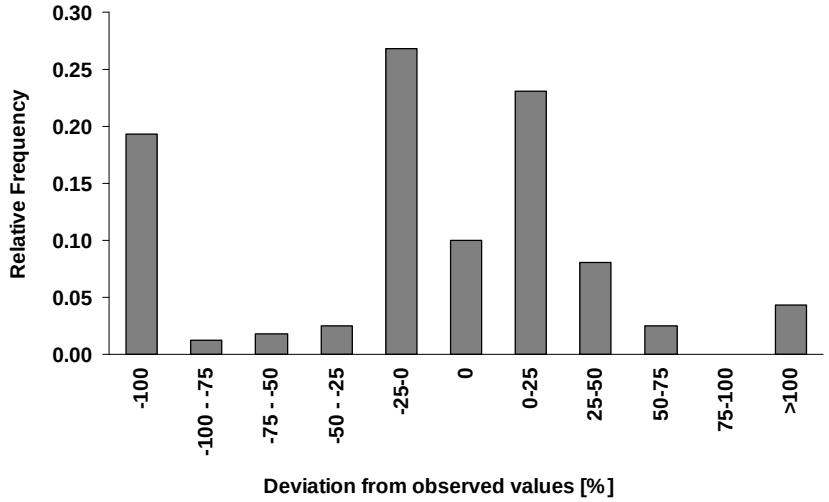
The model consists of three agricultural producer aggregates. While there is an official record on state-owned agricultural enterprises, the data on households and farms is poor. Therefore, such information was obtained via conducting farm and household surveys.

The aggregated data were obtained from official agencies. Annual reports of Regional Department of Statistics provided the main source of data on cropping area and animal stock, input and resource endowments and policy constraints in 2003. Due to complications in

covering the crop-water use in the surveys, the norm values of crop-water requirements were obtained from Regional Department of Agriculture. To supplement the information about production technologies collected via the surveys, experts on crop and livestock production were interviewed.

The base-run solution of KhoRASM using the expected values for all parameters did not reproduce the observed situation for 2003. Figure 1 demonstrates the deviations between the production activities levels in the model's base-run solution and their actual observed values.

Figure 1 Deviation of Production Activities from Observed Values



Source: Base run of the uncalibrated KhoRASM

4 Calibration of the supply module

The calibration of the supply module of KhoRASM should modify the parameters such that its base run exactly replicates the observed activity levels without limiting the model's flexibility: This can be achieved via a calibration procedure which incorporates the information on the observed activity levels for the base year to derive certain model parameters and keeps the number of the model constraints unchanged (Howitt 2002). An elegant approach to exactly calibrate the programming model solution to observed quantities without restraining its flexibility is the 'Positive Mathematical Programming' (PMP) (Heckelei 2002).

4.1 Standard PMP Calibration

The PMP calibration process is based on two main assumptions: First, that the observed situation is in fact the optimal solution for the modeled system in the base year. Second, that there are hidden costs associated with each production activity unobservable directly by a modeler, but relevant to the producers. Based on these assumptions, a PMP calibration introduces the concept of decreasing marginal returns. This is done by incorporating nonlinear cost terms into the model's objective function (Heckelei 2002).

The standard PMP approach consists of two consecutive stages. In the first stage, additional constraints are imposed which bound the model activities to their observed levels. The dual values of the binding observation constraints are considered as the difference between price and marginal cost for preferable activities and are interpreted as values that capture the model's false specification, data errors, aggregation bias, risk behavior and price expectations (Paris and Howitt 1998).

In the second stage, nonlinear cost terms are introduced using the dual values of the calibration constraints. The introduction of such nonlinear cost terms will force the optimal solution to exactly replicate the observed situation without additional unrealistic and empirically unjustified constraints (Howitt 2005).

Doing this, the PMP calibration solves overspecialization problem, maintains the model's flexibility, and produces the exact fitness of the activities in the base-run solution to their observed values requiring less data than standard approaches of calibrating linear programming models.

In KhoRASM, the additional cost terms were in some cases so large that they could not be supported by any information provided either in the surveys or by experts. Consequently, we re-examined the available information and methods.

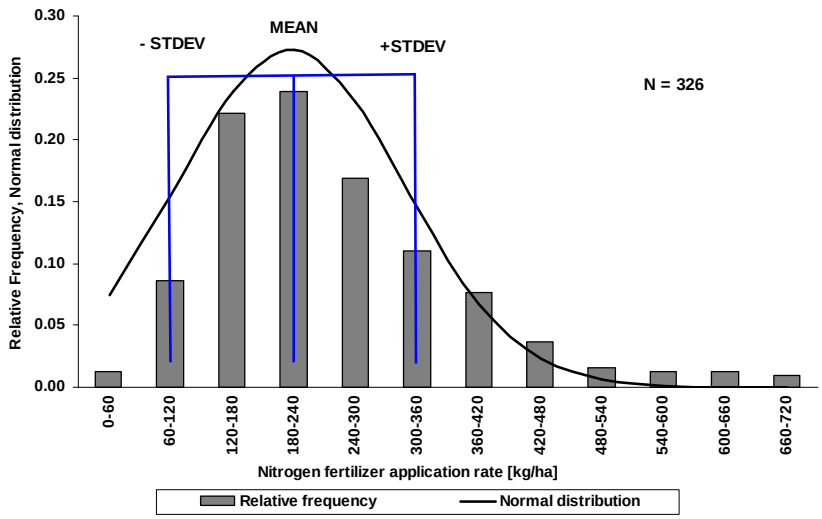
4.2 Model Calibration Approach Alternative to PMP

Normally, a sector model is validated by comparing its base-run activity levels with their observed values, which are available from the statistical offices. Lacking additional sources for the regional production data, it is assumed that these values are accurate.

In contrast, the technology coefficients of the sector model are derived from micro-level studies such as farm and household surveys. Modelers often use average values of the technology coefficients obtained from surveys. The use of the first argument of the samples disregards information on standard deviation and skewness, which are also relevant for calibrating the sector model.

Additionally, micro-level data relies on subjective responses. In surveys, respondents, i.e. farmers, may give unreliable answers regarding input use as they may simply not measure or recall such information over multiple seasons. As a result, the coefficients obtained from surveys may have a stretched distribution which is presented in Figure 2: here the micro-level dataset has a high standard deviation and a wide range of observed application rates.

Figure 2 Nitrogen Fertilizer Application for Wheat by Households



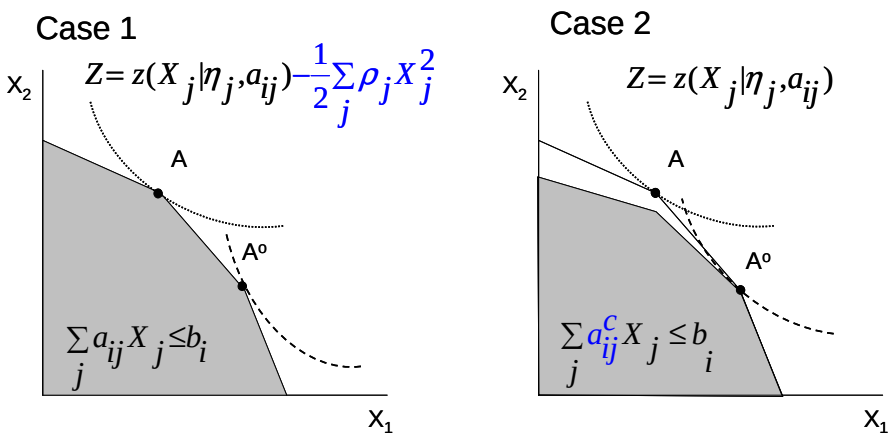
Source: Household survey in Khorezm, 2004

Note: MEAN–Sample mean; STDEV–Standard deviation of the sample; N–Number of respondents

Therefore, we treat the micro-level data as least reliable which may cause deviations in the model's base-run solution. The main assumption of this calibration approach is that the observed values of production activities, input and output prices, input endowments, and quantitative policy constraints are correctly specified, while the micro-level data obtained from the farm and household surveys, such as fertilizer, labor and diesel use rates, and irrigation requirements, are of the least reliability.

The differences between PMP and the proposed approach are visually presented in Figure 3: a model maximizes a non-linear objective function (Z) via production activities (X_j) over activity gross-margins (η_j) and technology coefficients (a_{ij}). The model in its base run solves at point A, while the actual observation in the reference year is in point A^o.

Figure 3 Comparison of PMP and Proposed Calibration Approach



Source: Own compilation

Case 1 shows the model calibration via PMP where the model is calibrated without altering the shape of the feasible solution space, but affecting the specification of the objective function by incorporating the increasing production cost term (ρ_j).

Case 2 demonstrates the proposed approach which calibrates via modifications in the technology coefficients. Since the information on technology coefficients (a_{ij}) is included explicitly both in the feasible solution space and the objective function, their modification will alter both feasible solution shape and objective function location. However, contrary to PMP, the original specification of the objective function is maintained.

The proposed approach has several similarities with a PMP when solving the overspecialization problem and calibrating exactly. First, it maintains the model's structure and does not restrict its flexibility to the exogenous changes. Secondly, this approach uses the information on the observed activity levels assuming equilibrium in the reference year.

However, the proposed approach has an advantage over the standard PMP. While the proposed approach calibrates exactly without changing the specification of objective function, the standard PMP approach changes it via incorporating the nonlinear cost terms values of which may be complicated to explain. Nevertheless, the proposed approach has shortcomings similar to those of the standard PMP calibration. First of all, since the original model and calibration process are static, as they use information on production activity levels for one reference year, the model can be applied only under the base year conditions and inconsistent for observations in other periods. Second, technology coefficients are modified within a range derived from the information available where they may assume any value. Therefore, the calibration outcome is sensitive to the choice of support points. Finally, the calibration approach is *ad hoc*, as it has been tested only for the specific case of a quadratic objective function. In case of a linear objective function the proposed approach would create a degenerate base solution.

4.2.1 Stage 1: Exploitation of Survey Data

Originally, only the first arguments of survey data and official statistics are used to parameterize the model causing substantial deviations of the base-run solution from the observed situation. To calibrate now the model to the observed values of activities, we use a Cross-Entropy (CE) procedure which requires the definition of support points S for each model parameter in question, and the specification of prior weights which reflects the distribution of the sample data.

Within the CE framework, the final values of the parameters in question (E) can be expressed as function of prior information on the possible outcomes and associated weights:

$$E = \sum_s S_s w_s \ , \ \sum_s w_s = 1 \qquad (6)$$

where:

E: Final model parameter value (the unknown elements of Table 1)

S: Support points for E

w: Weights for support points.

Since the outcome of the CE estimation depends on the chosen values for S, we have to specify them in such a way that the sample information is reflected in the most efficient manner. Here, we use only 2 support points because this choice allows for a simple and efficient utilization of the sample information to determine prior weights and support points:

$$E = S_1 w_1 + S_2 \left(1 - w_1\right) \qquad (7)$$

Visual examination of the sample data (e.g. the frequencies of nitrogen fertilizer usage for wheat by households, Figure 4) indicated that the sample distribution has a positive skew and resembles a log-normal rather than a normal distribution (see the fitted log-normal distribution in Figure 4). In this case, the sample mode would be the more appropriate choice for the model parameterization. Furthermore, we assume that the final value of the parameter in question lies within a 95% confidence interval of the sample distribution. Under the assumption that the sample data are log-normal distributed, the following desired properties of the final model parameters can be derived:

Highest probability (mode): $m[E] = \exp\left(\mu - \sigma^2\right)$

Lower bound of 95% confidence interval: $S_1 = \exp\left(\mu - 2\sigma\right)$

Upper bound of 95% confidence interval: $S_2 = \exp\left(\mu + 2\sigma\right)$

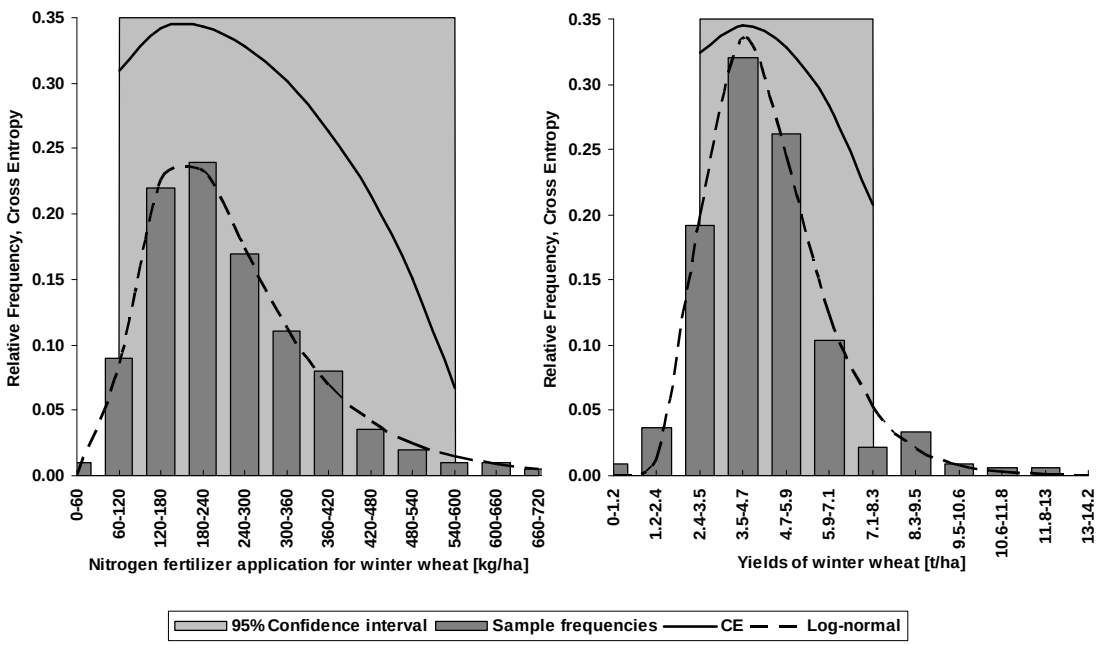
where μ and σ are mean and standard deviation of the natural logarithms of the sample data.

Equation (7) can now be re-phrased into:

$$m[E] = S_1\overline{w}_1 + S_2\left(1-\overline{w}_1\right) \Leftrightarrow \overline{w}_1 = \frac{m[E]-S_2}{S_1-S_2} \tag{8}$$

The resulting shape of the CE function is depicted in Figure 4 (note that the CE function was linearly transformed for illustrative purposes). The parameterized CE function is defined over the 95% confidence interval and has its optimum at the same point as the sample frequencies.

Figure 4 Sample Frequency, CE Function, and Fitted Log-Normal Distribution of Fertilizer Use and Yields



Source: Household survey in Khorezm, 2004

Note: The CE functions depicted here was linearly transformed for illustrative purposes (CE=0.345-0.2*CE)

Although sample data for the majority of model parameters in question were available, many crucial parameters could not be evaluated via the surveys. A typical example is the application of irrigation water. Interviewed farmers could at most indicate the number of irrigation events during the last vegetation period, but they usually did not record the volume as would be needed for the model parameterization. For these situations, we used norm values recommended by research institutes and the support points were defined as their ± 50% deviations.

Furthermore, the presented calibration requires a set of dual values from the original model constraints; e.g. of resource and policy constraints and commodity market balances. The expected values of the shadow prices for some production inputs such as land, diesel, fertilizer, and labor were inferred by the authors from the farm and household surveys, such as unofficial land rents, black-market prices for diesel and fertilizers, and total value of agricultural wages which includes also the value of payments in kind.

4.2.2 Stage 2: Modification of Technology Coefficients

In the second stage, the observed activity values and the derived support points are used to modify the technology parameters of KhoRASM. When the observed activity levels represent an optimum of the model as in equation (5), the Kuhn-Tucker conditions have to hold.

These conditions require that the shadow prices of the commodity balances ($\boldsymbol{\pi}$) are equal to the observed prices of corresponding commodities ($\mathbf{P^o}$). The same applies to inputs purchased outside of agriculture ($\boldsymbol{\psi}, \mathbf{g^o}$). Therefore, according to the first assumption, where the equilibrium was achieved under the observed values of production activities, the marginal commodity value and marginal opportunity cost constraints of the dual model are set to the following equalities:

$$\boldsymbol{\pi}^{\mathbf{o}} = \mathbf{P}^{\mathbf{o}}, \boldsymbol{\psi}^{\mathbf{o}} = \mathbf{g}^{\mathbf{o}} \tag{9}$$

$$\mathbf{Y}^{\mathbf{m}\prime}\boldsymbol{\pi}^{\mathbf{o}} + \mathbf{Y}^{\mathbf{f}\prime}\boldsymbol{\varphi}^{\mathbf{1}} = \mathbf{B}^{\mathbf{f}\prime}\boldsymbol{\varphi}^{\mathbf{2}} + \mathbf{B}^{\mathbf{p}\prime}\boldsymbol{\psi}^{\mathbf{o}} + \mathbf{A}'\boldsymbol{\lambda} \tag{10}$$

The next set of equations within the Kuhn-Tucker conditions are complementary slackness equalities which stipulate that binding resources at the optimum solution will have shadow price values greater than zero:

$$\left(\mathbf{b}\text{-}\mathbf{A}\mathbf{x}^{\mathbf{o}}\right) \circ \boldsymbol{\lambda} = \mathbf{0} \tag{11}$$

$$\left(\mathbf{Y}^{\mathbf{m}}\mathbf{x}^{\mathbf{o}}\text{-}\mathbf{q}^{\mathbf{o}}\right) \circ \boldsymbol{\pi}^{\mathbf{o}} = \mathbf{0} \tag{12}$$

$$\left(\mathbf{Y}^{\mathbf{f}}\mathbf{x}^{\mathbf{o}} - \mathbf{B}^{\mathbf{f}}\mathbf{x}^{\mathbf{o}}\right) \circ \boldsymbol{\varphi} = \mathbf{0} \tag{13}$$

$$\left(\mathbf{v^o} - \mathbf{B^p x^o}\right) \circ \boldsymbol{\psi}^{\mathbf{o}} = \mathbf{0} \tag{14}$$

Where "$\circ$" denotes the Hadamard (element-wise) product of two matrices.

To solve the ill-posed problem of calibrating KhoRASM, the CE estimation allows taking into account additional information about the range of parameter modification, i.e. support space specified by a priori information. For the purpose of model readability, we summarize all technology coefficients and dual values to be estimated in one matrix $\mathbf{E}$ which is basically the first and last column of Table 1:

$$\mathbf{E} = \begin{bmatrix} \mathbf{Y^m} & \\ \mathbf{Y^f} & \\ \mathbf{B^f} & \boldsymbol{\varphi} \\ \mathbf{B^p} & \boldsymbol{\psi} \\ \mathbf{A} & \end{bmatrix} \tag{15}$$

In principle, it is possible to include also commodity prices and input prices in the second column of $\mathbf{E}$, depending on the assumed reliability of the observed prices. $\mathbf{E}$ is expressed as product of support points S and weights w:

$$\mathrm{vec}(\mathbf{E}) = \mathbf{Sw} = \begin{bmatrix} \mathbf{s_1'} & 0 & \cdots & 0 \\ 0 & \mathbf{s_1'} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{s_M'} \end{bmatrix} \begin{bmatrix} \mathbf{w_1} \\ \mathbf{w_2} \\ \vdots \\ \mathbf{w_M} \end{bmatrix} \tag{16}$$

Where vec is the operator that transforms the matrix $\mathbf{E}$ with dimensions [i,j] into a column vector with dimensions [ij,1], with ij=M. The sub-vectors of $\mathbf{S}$ are the support points for each model parameter as it was derived from the sample data in section 4.2.1:

$$\mathbf{s_m'} = \left[s_{m1}, s_{m2}\right]$$

The CE objective function for the described estimation problem is now implemented as:

$$\min \mathbf{CE} = \mathbf{w}\ln\left(\mathbf{w}/\bar{\mathbf{w}}\right) \tag{17}$$

The CE problem is constrained by the following requirements, presented by Golan et al. (1996), and Kuhn-Tucker conditions related to the assumption on the optimum solution in the observed situation:

1) Normalization-additivity requirements:

$$\boldsymbol{\iota}'\mathbf{w}_{\mathbf{m}} = 1$$

where $\boldsymbol{\iota}$ is a M×1 summation vector that ensures that the weights add up to one.

2) For ensuring the fulfillment of the optimal solution at the observed activity values, equalities of the Kuhn-Tucker conditions must hold (equation 10);

3) Additionally, the complementary slackness equalities imposed by the Kuhn-Tucker conditions must hold for every constraint and shadow prices (equations 11 to 14);

4) The original model's constraints are imposed to ensure that parameters are calibrated under the model's original structure:

$$\mathbf{b}^{\mathbf{o}} - \mathbf{A}\mathbf{x}^{\mathbf{o}} \geq 0$$

5) Non-negativity constraints:

$$\mathbf{E} \geq 0$$

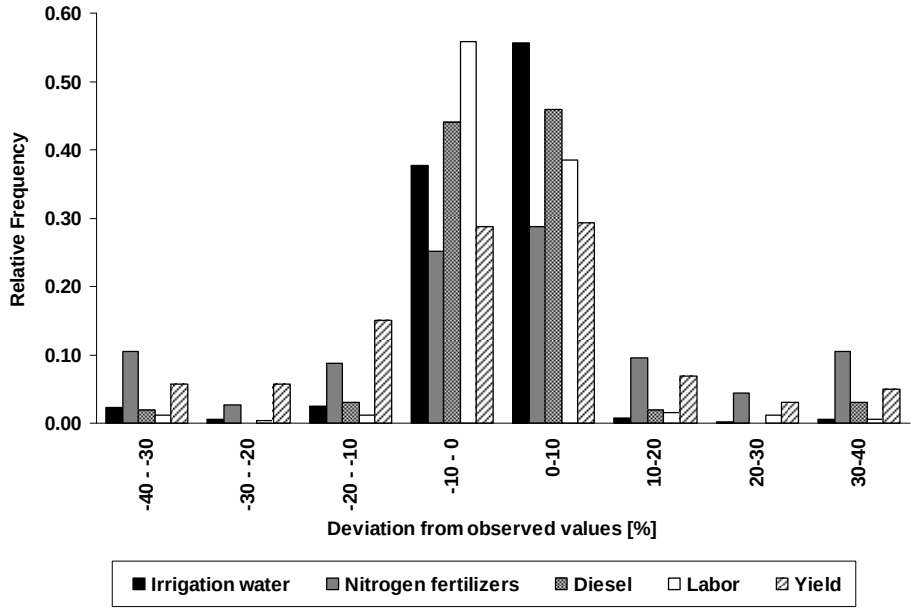
5 Calibration Results

The CE calibration of KhoRASM was programmed in GAMS and solved as non-linear problem via CONOPT3 solver. After calibration, KhoRASM is solved with the modified technology coefficients and commodity yields, producing an optimal solution that exactly replicates the reference year situation.

To validate the calibration results, the percentage deviation of adjusted values of technology coefficients was calculated such as absolute difference between the adjusted and observed values divided by the observed value. The largest share of deviation in modified yield coefficients from their observed values is between ±10% (Figure 4).

While the support space for modification of fertilizer, diesel and labor coefficients was a range defined by their standard deviations based on the information obtained from the surveys, the largest deviation from their observed values was mostly in the range of ±10%. The same pattern is observed for the modified values of crop-water use parameters (Figure 5).

Figure 5 Deviation of Technology Coefficients from Observed Values



Source: Model calibration results

To motivate the calibration results, the modified technology coefficients should be compared with their original values. If their new values are inconsistent with empirical observations, the model can be recalibrated imposing different support space until it produces plausible results.

6 Conclusion

The calibration of KhoRASM is based on two assumptions. First, the actual observed information on production activities, obtained from the official statistical bulletin, are assumed as equilibrium in the agricultural sector of Khorezm in the reference year. According to the second assumption, the information on the micro-level data on technology coefficients used in the aggregated sector model is the least reliable for the modeler.

Consequently, to reproduce the actual observed activity levels without altering the original model's structure, the model is calibrated via modifications in technology and commodity yield values using the CE estimation subject to the Kuhn-Tucker conditions. The main advantage of this calibration approach is that similar to PMP, it avoids overspecialization,

retains the model's flexibility, and calibrates exactly. Moreover, this calibration approach allows the modeler to incorporate more properties of information on technologies obtained via surveys.

In general, as a starting point, the selected calibration approach allows the modeler to use minimum number of data for policy analysis of changes in agricultural and food systems. However, the simple specification of the calibration model can generate unreasonable responses to the policy simulations (Heckelei 2002). Therefore, in next studies additional information on the system behavior should be incorporated into the calibration process.

At the optimum solution of the CE model, where probabilities of modified parameters are maximized satisfying the Kuhn-Tucker conditions, the technology and commodity yield parameters are modified at new levels such as they steer the original model's optimal solution to reproduce the observed activity values. Nevertheless, although the unique solution for the ill-posed problem of the technology coefficient modification has been found, the problem of arbitrary simulation behavior of the calibrated model remains unsolved, since the ME estimation is heavily dominated by support points (Heckelei and Britz 2000).

The main limitation of the proposed approach is that it is *ad hoc*, meaning that it works only for this specific case, i.e. price-endogenous quadratic programming model. Since the applicability of this approach for other models has not been tested yet, the author does not claim that this approach can be used as general method for calibrating the programming models. This can be a subject of further studies to check the applicability of this calibration approach for other models.

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