Empirical Policy Analysis with Parameter Uncertainty: The Case of Austrian Agricultural Policy *)

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Abstract

Parameter values of empirical economic models are commonly fraught with significant uncertainty. Recently, some studies have tried to overcome this problem by assuming a probability distribution rather than an exact value for each parameter. By randomly picking a value for each parameter from its probability distributions, using these values to estimate (simulate) the impacts, and repeating this procedure a great number of times, a probability distribution of the (policy) impacts can be derived. Moreover, the data created by this procedure can be utilized to estimate surface response functions and carry out extensive sensitivity analysis. The paper in hand reviews these developments and conducts such a statistical impact analysis. In particular, it is analyzed if the market interventions into the Austrian bread grain market were designed to efficiently meet the main stated objectives: to support farm income, and to be self-sufficient.

Keywords: agricultural policy, statistical policy analysis, sensitivity analysis, efficient combination of policy instruments,

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1. Introduction

Empirical economic modeling is frequently utilized to analyze the impacts of proposed (actually observed, or hypothetical) policies in regard to various “policy measures”, e.g. output, employment, trade balance, benefit-cost ratios, efficiency. No matter if an econometric modeling approach (i.e. relationships are estimated using econometric techniques) or a synthetic modeling approach (i.e. functional relationships are assumed in accordance with economic theory and made computational by plugging in values of model parameters estimated somewhere else or simply assumed), is chosen, the estimated policy measures crucially depend on model parameter values.

Since parameter values are commonly fraught with a significant uncertainty, a likewise dubiety about the measured impacts can be assumed. So far, most studies do not account for this parameter uncertainty at all or only in an insufficient way, e.g. by assuming a few alternative values for all (or a few) parameters. Only recently, some applied studies have employed computer intensive simulation techniques to overcome this problem (Tremblay and Tremblay, 1995; Davis and Espinoza, 1998; Sinabell, Salhofer and Hofreither, 1999; Alston, Chalfant and Piggott, 2000; Zhao, Griffiths, Griffith and Mullen, 2000; Jeong, Garcia and Bullock, 2001).[1] These studies do not assume an exact value for each model parameter, but rather a probability distribution. By randomly picking a value for each parameter from its probability distributions, using these values to estimate (simulate) the impacts, and repeating this procedure a great number of times, a probability distribution for each policy measure can be derived. Moreover, following Zhao, Griffiths, Griffith and Mullen (2000) the data created by this procedure can be utilized to estimate response functions and simulate (calculate) elasticities of how sensitive each parameter is with respect to the policy measures (Salhofer and Schmid, 2000; Salhofer, 2000)

The objectives of this study are i) to discuss recent trends in statistical policy analysis, and ii) present an example of such an analysis. In particular, it is analyzed if the market interventions into the Austrian bread grain market before the EU accession were designed to efficiently meet the main stated objectives: to support farm income, and to be self-sufficient. To do so, the actually observed policy is compared to a hypothetical optimal policy using the same instruments, but at optimal levels.

The next section reviews recent trends in statistical policy analysis. Section 3 discusses the underlying economic model. In Section 4 the simulation model is used to test for the efficiency of the bread grain policy. Section 5 provides a sensitivity analysis of the results. Section 6 gives a summary and discussion.

2. Trends in statistical policy analysis

Economic policy analysis can be formalized as follows: let $\mathbf{y} = (y_1, \ldots, y_n)$ be a vector of policy measures (e.g. y_1 is output, y_2 is the unemployment rate, y_3 is social cost etc.), let $\mathbf{x} = (x_1, \ldots, x_m)$ be a vector of policy instruments (e.g. x_1 is floor price, x_2 is quota, etc.), let $\mathbf{b} = (b_1, \ldots b_z)$ be a vector of parameters (e.g. b_1 is the elasticity of substitution between farm-owned inputs and purchased inputs, b_2 the farm labor supply elasticity, etc.), and Let $\mathbf{f}(\cdot) = (f_1(\cdot), \ldots, f_y(\cdot))$ be a vector of functional relations describing the economic system as well as some calculation methods to derive policy measures (Bullock, Salhofer and Kola, 1999; Salhofer 2000). Then, policy measures $\mathbf{y}$ are in a functional relationship with policy instruments and parameters:

$$(1) \qquad \mathbf{y} = \mathbf{f}(\mathbf{x}, \mathbf{b}).$$

Assuming some specific functional form of the relations describing the economic system, a given set of policy measures, and a specific policy (change) to be simulated, the derived values of the policy measure depend solely on the assumed parameter values. However, since there usually is some uncertainty about parameter values it is more reliable to assume a distribution for each parameter value rather than specific values, implying a distribution for each policy measure. Let, $\mathbf{f}(\mathbf{b}) = (\phi_1(b_1), \ldots, \phi_z(b_z))$ be a vector of distributions of parameters and let $\mathbf{q}(\mathbf{y}) = (\theta_1(y_1), \ldots, \theta(y_n))$ be a vector of distributions of policy measures. Then

(2) $\theta(y) = f(x, \phi(b)),$

To derive a distribution of a specific policy measure $\theta(y_i)$, more than one methods are available. Here, we distinguish between three different categories in regard to what kind of information about the distributions of parameter values is needed: i) methods based on actual data (bootstrapping); ii) methods based on an econometric estimation result (Monte Carlo simulations); and iii) methods based on parameter values taken from the literature (Baysian approach).

A sampling method based on actual data is bootstrapping (Efron, 1979; Freedman and Peters, 1984). To derive a distribution for each parameter one needs a data set *A* to econometrically estimate them. However, instead of running one regression and deriving one set of parameters **b**, one would create a large number *T* of new data sets $A^1, A^2, \ldots, A^T$ from the original data set by resampling either from the empirical error distribution (e.g. Kling and Sexton, 1990; Graham-Tomasi et al, 1990) or from the data set directly (e.g. Jeong et al. 1999, 2001) and use these *T* data sets to estimate *T* parameter sets. Substituting these *T* parameter sets into Equation (2) one can derive *T* values for each policy measure and form a distribution $\mathbf{q}(\mathbf{y})$.

To derive a distribution of parameter values based on already existing econometric estimation results there are two different ways: i) classical linearization; and ii) the Monte Carlo simulation approach. For both methods the information needed are estimates of the parameters and of the associated variance-covariance matrix. The classical linearization method uses first-order Taylor series expansions to derive the variance of a policy measure by knowledge of the variances and covariances of the parameters (Hausmann, 1981; Kealy and Bishop, 1986; Bockstael and Strand, 1987). Obviously this method becomes less and less tractable with an increasing number of parameters. Beside, the appropriateness of such a procedure depends, of course, on the nature of the non-linearity between the policy measure and the parameters and has been criticised for that reason (Graham-Tomasi et al., 1990; Kling, 1991; Krinsky and Robb, 1991).

Krinsky and Robb (1986, 1990, 1991) and Adamowicz, Graham-Tomasi, and Fletcher (1989) (Further references are Adamowicz, Fletcher and Graham-Tomasi (1989) and Alston et al. (1998, 2000)) discussed how one can estimate a distribution of policy measures by knowledge of their means, variances and covariances and the assumption that they are distributed normally. First, a great number T of parameter sets ($\mathbf{b}^1, \ldots, \mathbf{b}^T$) is drawn randomly from the multivariate normal distribution of the parameters. Second, by substituting the T parameter sets into Equation (12) one can derive $\mathbf{q}(\mathbf{y})$.

If the parameter values are actually distributed normally the bootstrapping procedure and this Monte Carlo simulation procedure should yield the same results. Clearly, the advantage of the Monte Carlo procedure is that it is computationally cheaper, while bootstrapping is theoretically more accurate.

However, for many policy analysis models it is neither within the scope of the study to derive the needed set of parameters independently, starting from raw data, nor are estimation results (including a variance-covariance matrix) for exactly such a parameter set available from some other study. Rather, parameter values have to be taken from different sources with only means (and sometimes standard deviations) available.

Very recently, Davis and Espinoza (1998), Griffiths and Zhao (1999), Davis and Espinoza (1999), Salhofer and Schmid (2000), and Zhao et al. (2000) discussed how to derive a distribution of a policy measure in such a situation. Firstly, they derive a subjective distribution, as typically used in Baysian inference, for each parameters from all prior information available such as published econometric estimates, expert surveys, theoretical restrictions as well as modeller's subjective judgement. Secondly, a large number *T* of random draws is taken from each parameter distribution. Thirdly, distributions of policy measures are derived by running *T* simulations with the *T* different parameter sets.

Usually with only a few point estimates available from the literature review one will assume either a normal distribution around the mean of the assumed range or a uniform distribution.[2] In many cases, one can expect that both distributions will result in similar means, while the variance will be larger in the case of a uniform distribution (e.g. Sinabell, Salhofer and Hofreither 1999, Salhofer and Schmid, 2000).

Obviously, The Krinsky-Robb procedure is a special case of the Monte Carlo simulation approach when variance-covariance Matrix of all parameters is available.

3. The model

The Austrian agribusiness of bread grain is modeled by a log-linear, three-stage, vertically-structured model (Figure 1). The first stage includes four markets of input factors used for bread grain production: land, labor, durable investment goods (e.g. machinery and buildings), and operating inputs (e.g. fertilizer, seeds). Since 95% of farmland is owned by farmers and 86% of labor in the agricultural sector is self-employed, land and labor are assumed to be factors offered solely by farmers in perfectly competitive markets. On the contrary, investment goods, and operating inputs are supplied by upstream industries, which are assumed to have some market power to set the prices above marginal cost. Export and import of input factors are not considered. Hence, it is assumed that domestic consumption of input factors equals domestic production. This is certainly correct for land and agricultural labor and is also appropriate for important industrially produced input factors (e.g. tractors, fertilizer) before joining the EU.

At the second stage, input factors of the first stage are used to produce bread grain assuming a CES production technology. The first and the second stage are linked by the assumption that bread grain producers maximize their profits. The produced quantity of bread grain is used for food production, animal feed, and exports.

The third stage aggregates firms which process and distribute bread grain, such as wholesale buyers, mills, exporters, and foodstuffs' producers. Bread grain along with other input factors of labor, and capital are combined to produce food (bread grain products like flour, bread, noodles) assuming a CES technology. Again market power is assumed in the food sector

Import and export of processed bread grain do not play an important role in Austria. According to Astl (1991), the ratio of imports to total consumption of bread and baker's ware is less than 7%. According to Raab (1994), exports of flour and flour products increased but were still only 20,000 t or 4% of domestically processed bread grain in 1993. Given these facts, we assume that domestic demand of bread grain products equals domestic supply.

Welfare levels for different social groups are calculated using standard Marshallian welfare measures, Hueth and Schmitz (1982).

4. Empirical Analysis

The way government intervened in the bread grain sector is described in Figure 2 with D_{fo} being the domestic demand for bread grain for food production and D being the total domestic demand for bread grain including demand for feeding purposes. Initial domestic supply is represented by S and supply including a fertilizer tax by S_t. World market price is assumed to be perfectly elastic at P_w. Farmers obtain a high floor price (P_D) for a specific contracted quantity (or quota) Q_Q. Since farmers have to pay a co-responsibility levy (CL_{PD}) the net producer price is P_D - CL_{PD}. Quantities, which exceed the quota can be delivered at a reduced price P_E. Again, farmers' net floor price is P_E - CL_{PE}, with CL_{PE} being the co-responsibility levy for bread grain beyond the quota. Food processors have to buy bread grain at the high price P_D, while the price of bread grain for feeding purposes is P_E. Therefore, domestic demand for bread grain in food production is Q_D, domestic demand for feeding purposes is Q_E – Q_D, total domestic demand is Q_E, and exports are $Q_X = Q_S – Q_E$.

To run the model and to calculate the welfare of social groups 32 parameter values are necessary. While 13 values of these 32 parameters are endogenously derived in the calibration process, 19 specific parameter values have to be assumed: supply elasticities of land (e_A), labor (e_B), investment goods (e_G), and operating inputs (e_H) at the farm level; factor shares of land (a_A), labor (a_B), and investment goods (a_G) at the farm level; supply elasticities of labor (e_J), and capital (e_K) at the food industry level; supply elasticities of labor (e_J), and capital (e_K) at the food industry level; factor share of labor (a_J) at the food industry level; elasticity of substitution between input factors at the farm level (s_S); elasticity of substitution between input factors at the food industry level (s_F); demand elasticity of bread grain for feeding purposes (h_E); demand elasticity of processed bread grain (h_F); Lerner indices of agricultural investment goods sector (L_G), agricultural operating inputs (L_H), and bread grain processing industry (L_F); agricultural share of expenditures for bread grain products (l), and marginal cost of public funds (MCF)

In contrast to most empirical studies of this kind we do not assume one (or a few) specific value(s) for each parameter, but rather assume each parameter to be in a plausible range. The upper (a) and lower (b) bounds of these ranges are based on extensive literature and data analysis (described in detail in Salhofer, Schmid, Schneider and Streicher, 2001) and are presented in Table 1. Two alternative distributions are assumed between the upper and lower bounds: i) a uniform distribution $U(a, b)$; and ii) a symmetric normal distribution $N(m,$ $s,)$ with $m = (a+b)/2$ and $s = (m-a)/1.96$, which is truncated at a and b.

On the base of these parameter ranges, 10,000 independent draws are taken for every single parameter and each alternative distribution. Hence, we derive 10,000 parameter sets including 19 elements for each alternative distribution, separately. These parameter sets are used to derive 10.000 welfare measures for each defined group and each alternative parameter distribution.

Thus, official objectives of farm policy as stated in national agricultural legislation are manifold there also appears to be a high degree of unanimity about the goals of agricultural policy among developed countries. Following Winters (1987, 1990) in analyzing the objectives of agricultural support in OECD countries one may identify four categories of farm policy goals: i) support and stabilization of farm income; ii) self-sufficiency with agricultural (food) products; iii) regional, community and family farm aspects; iv) the environment. There is not much doubt among agricultural policy analysts that farm income support has been the most important goal over the last decades (Josling, 1974; Gardner, 1992).

In general, Austrian agricultural legislation is not different from other developed countries. The overall goals of agricultural policy are stated in paragraph 1 of the "Landwirtschaftsgesetz" (Agricultural Status) (see Gatterbauer et al. 1993, Ortner, 1997) and perfectly fit in the four categories mentioned above.

The particular objectives of bread grain market interventions are stated in the "Marktordnungsgesetz" and can be summarized as (Astl,1989, p. 88; Mannert, 1991, p. 74): i) safeguarding domestic production, ii) stabilizing flour and bread prices; and iii) securing a sufficient supply and quality of bread grain, bread grain products and animal feedstuffs.

Given this, we may simplify government's decision problem as trying to maximize social welfare given a socially demanded level of farmer's welfare and self-sufficiency.[3]

Furthermore it is assumed that the socially demanded transfer level is reflected in the actually observed transfer level, that self-sufficiency is given when domestic supply is greater or equal domestic demand, and that the policy instruments available to government are the actually used instruments.

The official goal of introducing a tax on fertilizer was soil protection and hence environmentally motivated. For simplicity, it is assumed that this environmental goal is separable from other goals and optimally met by the current level of fertilizer tax. Hence, government can freely choose the levels of five policy instruments (P_E, CL_{PE}, P_{QD}, CL_{PQD}, Q_Q) to maximize welfare under given constraints.

Utilizing the described simulation model, assumed distributions of parameter values, and welfare measures, the nonlinear optimization problem (18) is solved numerically for 2 times 10,000 alternative parameter sets utilizing GAMS software (Brooke et al. 1988). As a result two alternative distributions of the optimal welfare levels as well as the optimal policy instrument levels and combinations are derived.

Utilizing the same model, parameter sets, and welfare measures, but taking the world market price of bread grain one can simulate a hypothetical nonintervention scenarios. Thus, the social cost of the optimal policy are measured as $SC^* = W^* - W^W$ where W^* and W^W are the welfare level in the optimal situation and in the world market price situation, respectively. Similarly, assuming plugging in the actually observed prices into the simulation model one could calculate the social cost of the actual observed policy $SC^A = W^A - W^W$ where W^A is the actual welfare level. Finally, the relative social cost (RSC) give the share by which the social cost could have been reduced, if the government would have used an optimal combination and levels of policy instruments RSC = $(SC^A - SC^*)/SC^A$. This gives a measure of how close the actual policy is to the optimal policy.

This is illustrated in Figure 3 with the welfare of farmers U_{BF} and non-farmers, as an aggregate of all other groups $(U_{UI} + U_{DI} + U_{CS} + U_{BS} + U_{TA})$, on the axes. Point *E* describes the welfare distribution between these two groups without government intervention. If lump-sum transfers as well as lump-sum taxes would be possible, government could redistribute welfare from non-farmers to farmers along a 45° line through point E. However, here with the assumption of no lump-sum policy instruments the best government can do is described by a concave utility possibility curve. If U_{BF}^{A} is the socially demanded welfare level of farmers and point *A* is the actually observed welfare distribution, distance *AB* are the social cost of the actual policy (Bullock and Salhofer, 1998). The policy derived by the optimization problem (18) would be point *O*. The social cost of this optimal policy are *OB* and $(SC^{A} - SC^{*})/SC^{A} = AO/BO$.

The empirical results for the assumption of normally distributed parameters are summarized in Table 2. At the mean the social cost of the actually policy are measured to be € 159 million (about 42% of the value of bread grain production) with a standard deviation of € 23 million. In 95% (9,500 cases) of our 10,000 simulations the social cost are in a range of € 116 million to € 206 million. The 75% probability interval is between € 131 million € 188 million. In the case of the optimal policy the social cost are significantly smaller with a mean of € 91 million, a standard deviation of € 24 million, a 95% probability interval between € 45 million and € 139 million, and a 75% interval between € 62 million and € 121 million. Therefore, by using the same instruments at different levels government could have reduced the social cost on average by € 68 million, about 44% of the actual social cost, and with a 95% (75%) probability between 32% (35%) and 63% (53%).

Assuming a uniform distribution of the parameter values between the upper and lower boundary does not change the mean and median significantly (Table 3), but certainly causes higher standard deviations and hence wider probability intervals.

5. Sensitivity Analysis

To analyze the sensitivity of the RSC with respect to the model parameters, surface response functions are utilized (Zhao, Griffiths, Griffith, Mullen, 2000). The nonlinear relationships between RSC and model parameters are described by its second order approximation, i.e. a quadratic polynomial, comprising a constant, the 19 parameters par_i, (α_A, α_B, α_G, α_J, λ, ε_A, ε_B, ε_G, ε_H, ε_K, ε_J, η_F, η_E, σ_S, σ_F, L_F, L_G, L_H, MCF) and the permutations par_i par_j of the products of all 19 parameters.

(3) $$RSC = c_0 + \sum_{i=1}^{19} c_i par_i + \sum_{i=1}^{19} \sum_{j=1}^{i} d_{ij} par_i par_j + e,$$

with c_0, c_i, and d_{ij} being regression coefficients, and e an error term.

Equation (3) is estimated using the 10,000 parameter sets drawn from the uniform distributions and the implied RSC-values. However, to exclude extreme parameter combinations the lowest and highest 2.5% of RSC-values are omitted, leaving 9,500 observations.

OLS-estimation of the response function exhibits an extremely good fit ($R^2 = 0.993$) as well as medium to high levels of significance for a majority of coefficients. About 57% of the coefficients are significant at the 99% level, 3% at the 95% level, and 12% at the 90% level (Table 4 and Table 5).

The elasticity of the Relative Social Costs with respect to the 19 parameters was calculated performing the following Monte Carlo experiment: First, the 9,500 parameter sets and the estimated response function were used to calculate 9,500 RSC “base”-values. Second, the parameter sets were slightly changed by increasing all 9,500 values of the first parameter, e.g. α_A, by 1% and calculating 9,500 RSC "new"-values. Third, subtracting the 9,500 new RSC values from the 9,500 base-values and dividing the difference by the base values lead to 9,500 elasticity values, i.e. the percentage change of the RSC with respect to a 1% change in the first parameter. The left block of Table 6 reveals that at the mean (median) of all 9,500 calculated elasticity values a 1% change in the parameter α_A decreases the RSC by 0.007% (0.005%) with a standard deviation of 1.8%, a maximum value of 0.055% and a minimum value of –0.092%. The same procedures lead to elasticities for all other parameters. The fact that the minimum elasticities are negative and the maximum elasticities are positive for all parameters reveals how the effect of a change in one parameter depends on the levels of all other parameters. Only four elasticities are significant different from zero at the 90% level or higher: the agricultural share of expenditures for bread grain products (λ), the Lerner index of the downstream industry (L_F), the elasticity of substitution at the food industry level (σ_F), and the marginal cost of public funds (MCF).

Alternatively to the mean value in the left block of Table 6, the first column represents the percentage change in RSC, when one parameter is changed by 1% and all other parameters are kept unchanged at their mean values. The results in the first columns of the left and the right block do not differ significantly from each other. The second and third columns of the right block, RSC_{min} and RSC_{max}, do not denote percentage changes, but the values of Relative Social Cost, when one parameter is set respectively at the lower and upper bound of its associated range, and all other parameters are set at their mean values. The last column, $\Delta(RSC)$, simply indicates the difference in the absolute Relative Social Costs ($\Delta(RSC) = RSC_{max} - RSC_{min}$). This can be interpreted as the „imprecision" in RSC due to the fact that in the model, the parameters used are range estimates rather than point estimates. The higher the absolute value of this last column, the greater the gain in the precision of the estimated RSC associated with a narrower parameter range. The parameters λ, σ_F and L_F exhibit the widest ranges. Hence, additional information on their actual values would be most beneficiary to the simulation model.

6. Discussion

The results derived in this study are based on computer intensive simulation and sensitivity-analysis techniques. Therefore, ranges of parameter values, rather than a few specific values are assumed. This has several advantages: First, instead of producing one (or a few) specific but highly uncertain number(s) about the effect of a policy, we are able to give a plausible range as well as a mean. Second, the results of the sensitivity analysis clearly reveal how a change in one parameter influences the results as well as what parameters are especially sensitive to the results. Hence, this gives a hint in which direction additional research effort (time) is invested efficiently.

As a rule, governments defend their policy as efficient in common political statements. Utilizing a three-stage vertically structured model including upstream and downstream industries it was shown over a wide range of possible model parameter values that the Austrian bread grain policy was quite inefficient in meeting its two main objectives, namely supporting farm income and self-sufficiency. In fact, the social cost could on average have been reduced by more than 40% by using the same policy instruments, but at efficient levels.

Footnotes

[1] Throughout the text references are mainly given to studies in agricultural economics. Similar developments might be perceived in other applied economic fields.

[2] Zhao et al. (2000) also discuss a hierarchical distribution.

[3] Note, that equally one could describe government's decision problem as minimizing social cost, given a certain amount of wealth transfers to farmers and self-sufficiency.

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Table 1: Summary of parameter ranges

Parameter	Range	Parameter	Range
e_A	0.1 – 0.4	a_A	0.06 – 0.1
e_B	0.2 – 1.0	a_B	0.29 – 0.39
e_G	1.0 – 5.0	a_G	0.11 – 0.19
e_H	1.0 – 5.0	a_J	0.27 – 0.37
e_J	0.2 – 1.4	l	0.07 – 0.10
e_K	1.0 – 5.0	L_G	0 – 0.2
s_S	0.1 – 0.9	L_H	0 – 0.2
s_F	0.5 – 1.5	L_F	0 – 0.2
h_E	-0.1 – -0.6	MCF	0.1 – 0.4
h_F	-0.5 – -1.5		

Table 2: Social cost of actual and optimal policy given a normal distribution of parameter values

				95% Probability interval		75% Probability interval	
	Mean	Median	Std. Dev.	from	to	from	to
Social cost of actual policy	159.3	158.6	23.2	116.3	206.2	131.4	188.4
Social cost of optimal policy	91.2	91.1	24.0	45.0	138.7	61.7	120.9
Percentage improvement	0.44	0.42	0.08	0.32	0.63	0.35	0.53

Table 3: Social cost of actual and optimal policy given a uniform distribution of parameter values

				95% Probability interval		75% Probability interval	
	Mean	Median	Std. Dev.	from	to	from	to
Social cost of actual policy	158.9	157.2	30.4	104.3	221.5	122.2	197.5
Social cost of optimal policy	90.2	89.3	31.6	31.4	152.8	51.5	129.7
Percentage improvement	0.45	0.43	0.11	0.30	0.72	0.33	0.59

Table 4: Values of the coefficients of the surface response function

Const.	Par$_{i\backslash j}$	1	α_A	α_B	α_G	α_J	λ	ε_A	ε_B	ε_G	ε_H	ε_K	ε_J	η_F	η_E	σ_S	σ_F	L_F	L_G	L_H	MCF
	α_A	0.305	-0.445	-0.030	-0.155	0.053	-0.105	0.080	-0.114	0.048	0.011	-0.002	0.045	0.003	0.119	-0.051	-1.334	-0.010	-0.294	-0.205	-0.738
	α_B	-0.388		-0.392	0.233	0.068	0.026	-0.050	0.023	-0.100	0.020	0.002	-0.003	0.035	0.005	0.045	0.049	-0.332	0.096	-0.033	-0.061
	α_G	-0.162			-0.041	0.077	0.002	0.004	0.027	0.046	-0.007	-0.010	0.020	-0.001	0.030	-0.026	-0.008	0.034	0.888	0.005	-0.115
	α_J	0.036				-0.002	0.015	0.072	-0.181	0.009	-0.020	-0.002	0.127	-0.026	0.003	0.001	0.001	-0.016	-0.017	-0.262	0.192
	λ	-48.461					-3.706	2.371	0.837	10.275	8.301	0.186	-2.188	-2.788	0.171	0.062	0.165	0.054	0.825	0.139	111.352
	ε_A	-0.020						0.038	-0.036	0.030	0.015	0.011	-0.019	0.009	-0.009	-0.001	0.000	0.000	0.000	-0.013	-0.013
	ε_B	-0.105							0.097	-0.031	-0.016	0.053	0.044	-0.014	0.026	-0.016	0.001	0.000	-0.003	-0.001	-0.017
	ε_G	-0.021								-0.001	0.001	-0.001	0.006	0.002	0.000	-0.001	-0.002	0.000	0.000	0.000	0.001
	ε_H	-0.073									-0.003	-0.010	-0.001	0.015	0.006	-0.002	-0.003	-0.004	0.000	0.000	0.003
7.058	ε_K	-0.042										-0.002	0.000	-0.003	0.029	-0.003	0.000	-0.001	-0.015	0.001	0.001
	ε_J	-0.109											-0.009	0.000	0.001	0.079	-0.002	0.000	-0.001	-0.034	0.005
	η_F	1.994												0.117	-0.041	-0.006	-1.429	-0.110	-0.003	0.052	0.141
	η_E	0.493													-0.046	0.024	0.003	-0.182	-0.093	0.013	-0.028
	σ_S	-0.052														0.054	0.047	0.003	0.004	0.010	-0.010
	σ_F	-1.886															-0.296	0.091	0.044	0.391	0.196
	L_F	-4.096																-0.303	0.138	0.065	0.754
	L_G	-0.278																	0.003	0.031	0.030
	L_H	-0.579																		-0.023	0.047
	MCF	1.162																			0.043

Table 5: Significance of the coefficients of the surface response function

Const.	$Par_{i\backslash j}$	1	α_A	α_B	α_G	α_J	λ	ε_A	ε_B	ε_G	ε_H	ε_K	ε_J	η_F	η_E	σ_S	σ_F	L_F	L_G	L_H	MCF
	α_A	+	+++		+		+++	+++	+++	+			+++		+++		+				+
	α_B	+++		+++	+++	+		+++	++	+++	+		+	+++	++	+++	+		+		
	α_G	+			+	+			+++	+++			+++		+++	+++			+		
	α_J							+	+++		++		+++	+++	+			+			++
	λ	+++					+++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++		+++
	ε_A							+++	+++	++		+++	+++	+++	+					+++	+
	ε_B	+++							+++	+++	+++	+++	+++	+++	+++	+++	+		+++	+++	+++
	ε_G	+++								+		+	+++	+++		+++	+++			+++	+++
	ε_H	+++									+++	+++		+++	+++	+++	+++	+++		+++	+++
+++	ε_K	+++										+++		+++	+++	+++	+	+++	+++	+++	+++
	ε_J	+++											+++			+++	+++		++	+++	+++
	η_F	+++												+++	+++		+++	+++	+	+++	+++
	η_E	+++													+++	+++		+++	+++	+++	+++
	σ_S	+++														+++	+++			+++	+++
	σ_F	+++															+++	+++	+++	+++	+++
	L_F	+++																+++	+++	+++	+++
	L_G	+++																		+	+
	L_H	+++																		+	++
	MCF	+++																			+++

+++ represents a 99% significance level, ++ represents a 95% significance level, + represents a 90% significance level,

Table 6: Sensitivity Analysis

Par.	Monte Carlo-results (n=9500)					Evaluation at parameter means			
	Mean	**Median**	**S.E.**	**Min**	**Max**	**Avg.**	**RSC_{min}**	**RSC_{max}**	**D (RSC)**
α_A	-0.007	-0.005	0.018	-0.092	0.055	-0.006	0.418	0.417	-0.001
α_B	-0.035	-0.033	0.055	-0.245	0.168	-0.036	0.420	0.415	-0.004
α_G	-0.001	-0.002	0.018	-0.064	0.087	-0.002	0.418	0.417	0.000
α_J	0.015	0.015	0.021	-0.059	0.105	0.015	0.417	0.419	0.002
λ	-1.106***	-1.187	0.277	-1.588	0.118	-1.232	0.494	0.364	-0.130
ε_A	0.000	0.000	0.005	-0.028	0.027	0.000	0.418	0.417	0.000
ε_B	-0.016	-0.012	0.032	-0.153	0.094	-0.015	0.419	0.411	-0.008
ε_G	-0.019	-0.023	0.015	-0.049	0.059	-0.029	0.431	0.415	-0.016
ε_H	-0.054	-0.064	0.034	-0.129	0.136	-0.078	0.453	0.409	-0.044
ε_K	-0.016	-0.018	0.024	-0.080	0.102	-0.023	0.428	0.415	-0.013
ε_J	-0.011	-0.011	0.014	-0.061	0.055	-0.015	0.424	0.415	-0.009
η_F	-0.109	-0.098	0.078	-0.366	0.225	-0.132	0.388	0.466	0.079
η_E	-0.176	-0.158	0.108	-0.539	0.076	-0.177	0.374	0.448	0.074
σ_S	0.005	0.005	0.012	-0.069	0.073	0.007	0.414	0.419	0.005
σ_F	-0.538***	-0.543	0.138	-1.028	0.123	-0.644	0.603	0.332	-0.271
L_F	-1.023**	-1.058	0.417	-2.116	0.604	-1.124	0.478	0.372	-0.106
L_G	-0.007	-0.012	0.032	-0.088	0.125	-0.013	0.419	0.417	-0.001
L_H	-0.019	-0.029	0.074	-0.225	0.317	-0.031	0.420	0.417	-0.003
MCF	0.107**	0.101	0.054	-0.068	0.287	0.118	0.389	0.448	0.059

*, **, *** indicate a significance level of 90%, 95%, and 99%, respectively.

Figure 1: Model of bread grain sector

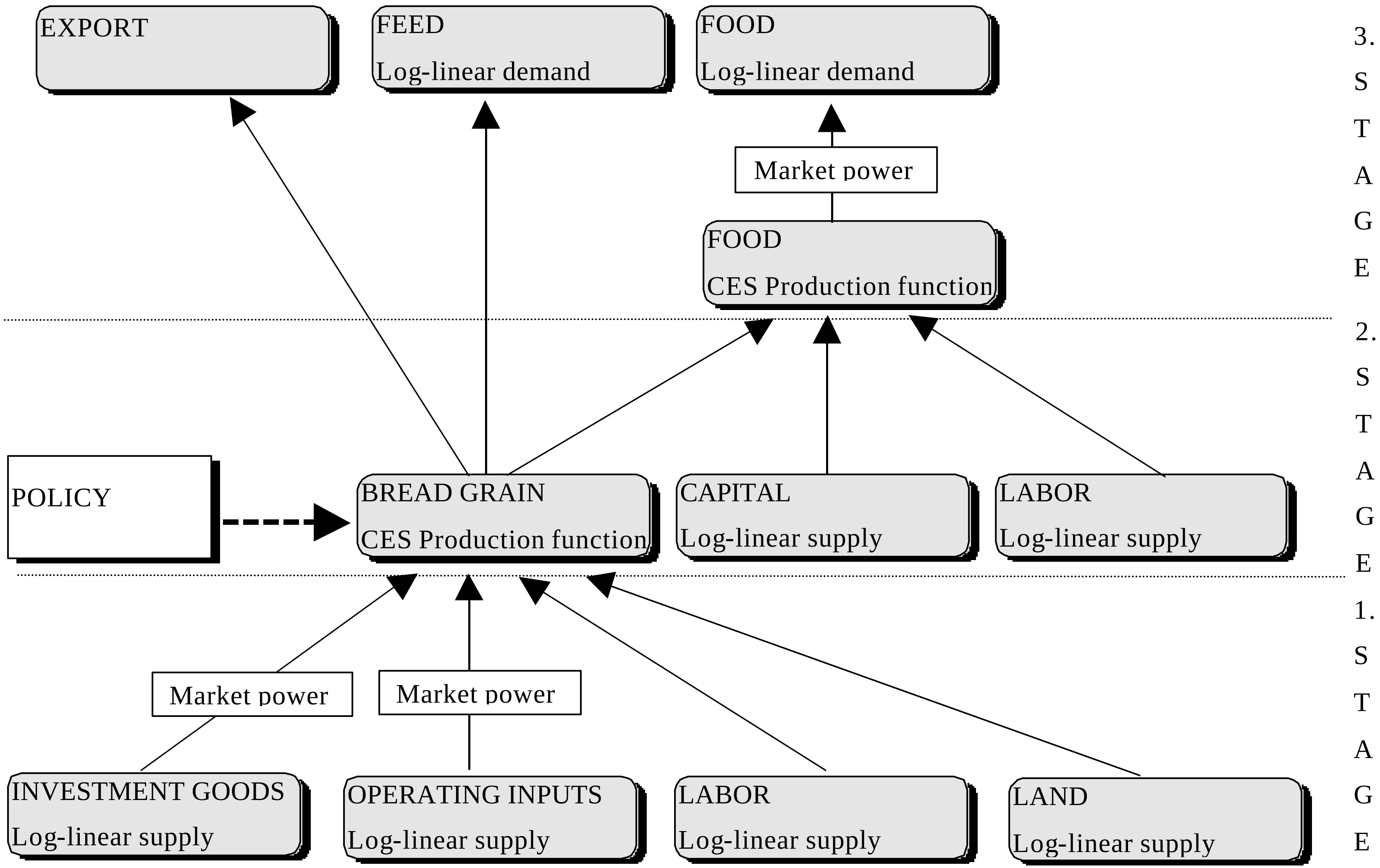

Figure 2: Bread grain market and policy

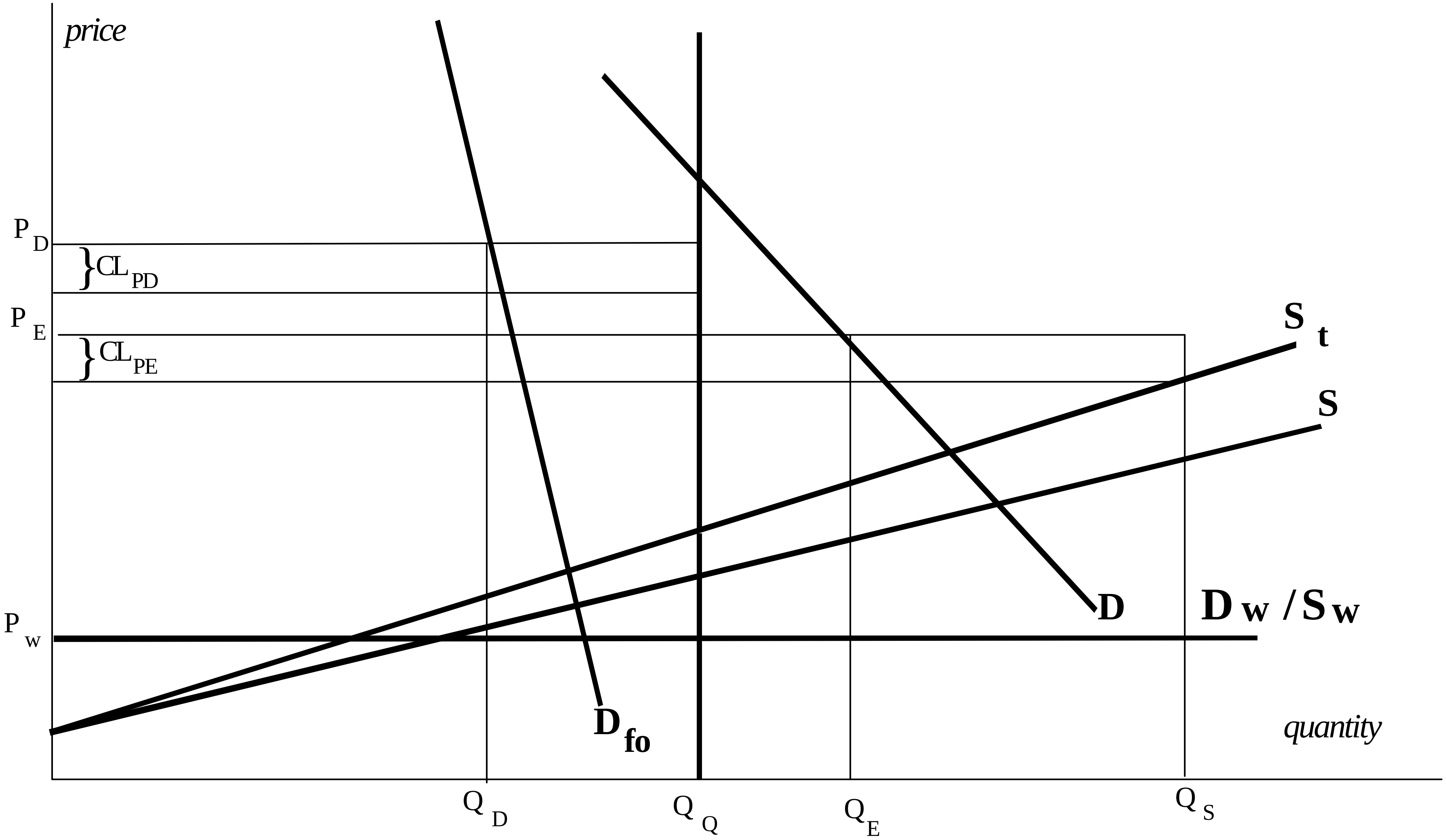

Figure 3: Social cost of actual and optimal policy