Testing for the Efficiency of a Policy Intended to Meet Objectives: General Model and Application

Klaus Salhofer, Erwin Schmid, and Gerhard Streicher

This study presents a general model demonstrating how to measure the (in)efficiency of a policy intended to meet objectives. If it is assumed that the government has available only those policy instruments it actually utilizes, our method is a test as to whether the government combines these instruments efficiently. In addition, one could also include other policy instruments, which are not actually used, but are available to the government. Our general model is applied to bread grain policy in Austria. The primary result is that this policy was quite inefficient in meeting the two main objectives of farm income support and self-sufficiency. The stochastic nature of our efficiency measures is acknowledged by taking into account the inherent uncertainty of model parameters. A response surface function is used to identify those parameters which contribute most to model output uncertainty.

Key words: agricultural policy, policy efficiency, statistical policy analysis

Introduction

Economists regularly judge the efficiency of a policy according to the deadweight losses (DWL) it generates. More specifically, they compare the welfare outcome of a particular policy with the non-intervention situation. Since the early work of Griliches (1958), measuring net welfare changes of government intervention has been utilized by agricultural economists. [See Winters (1987a) for a review of more recent studies measuring the DWL of agricultural policy interventions.] However, this practice also has an equally long history of criticism from many renowned agricultural economists (e.g., Nerlove, 1958; Josling, 1969, 1974; Rausser, 1982; Gardner, 1983; Just, 1984), because measuring DWL does not consider that (agricultural) policy is intended to achieve specific objectives as defined in farm bills or national agricultural acts.[1] As Josling wrote, "A 'cost' calculation is of no interest unless it can be tied to the magnitude of desired effect for which the cost is endured" (p. 242). Consequently, agricultural economists have developed measures that in some way take into account at least what is considered to be the most important objective of agricultural policy in developed countries—farm income support. For

---

[1] See Winters (1987b, 1990) for a review of agricultural policy objectives in developed countries. Other objectives agricultural policy is required to meet might include bilateral and international agreements, such as the World Trade Organization (WTO).

example, Nerlove (1958) suggested a measure of "relative social cost" (= DWL per $ of income transfer to farmers), and Gardner (1983) suggested a measure of "average transfer efficiency" (income transfer to farmers per $ costs to non-farmers). While these frequently used measures [see Bullock, Salhofer, and Kola (1999) for a review] give insights into the ratio between costs and benefits of a policy, they neither answer the question of how close the policy is to the optimum, i.e., how (in)efficient it is, nor do they consider that agricultural policies often try to meet several objectives at the same time.

The present study seeks to close this gap. To judge a policy intended to meet specific objectives, we argue that this policy should be compared with an optimal policy which achieves the same objectives, but at minimum DWL. A general model is presented for measuring the (in)efficiency of a policy aiming to achieve specific objectives, independent from the number of objectives and instruments considered, and for illustration purposes is applied to the Austrian bread grain policy between 1991 and 1993.

Another interesting feature of this study is its approach in dealing with model parameter uncertainty in policy analysis. Instead of assuming only one or a few different values for each model parameter, we assume an entire plausible distribution. These plausible parameter distributions are used to derive probability distributions of policy measures, reflecting researchers' uncertainty about parameter values. Though this approach is not completely novel (e.g., Davis and Espinoza, 1998; Zhao et al., 2000; Alston, Chalfant, and Piggott, 2000; Jeong, Garcia, and Bullock, 2003), to our knowledge only Horan, Claassen, and Howe (2001) have applied this technique to a complex non-linear optimization problem comparable to our work. Moreover, building on Zhao et al. (2000), we use a response surface methodology to identify those parameters which add most to the uncertainty in the model output, and also discuss how commonly used sensitivity elasticities can be misleading in finding these parameters.

The remainder of the paper proceeds as follows. First, we discuss theoretically how to measure the efficiency of a policy intended to meet specific objectives. Next, we examine how to deal with the uncertainty of model parameters. These methods are then applied to the Austrian bread grain policy before EU accession (1991–1993). Results are summarized, and the paper ends with a general discussion and concluding remarks.

How to Measure the Efficiency of a Policy Intended to Meet Objectives

(Agricultural) policy is usually intended to meet certain objectives. For example, assume a hypothetical situation where the only objective of agricultural policy is to be self-sufficient with regard to agricultural products, but this is not the case in a non-intervention situation. Figure 1 provides a very simple illustration of this situation, where S represents domestic supply, D is domestic demand, and P_w indicates the world market price, infinitely elastic for a small country. In a non-intervention situation, domestic demand (Q_d) exceeds domestic supply (Q_s) for this country, and self-sufficiency is not attained.[2]

To achieve self-sufficiency, government must create an incentive for agricultural producers, like a production subsidy $s = P_s - P_w$. Producers gain $a + b + c + d + e + f + g$,

---

[2] We are aware that self-sufficiency, like every other objective of agricultural policy, permits alternative interpretations. Here, we use the simplest possible definition: domestic supply equals domestic demand.
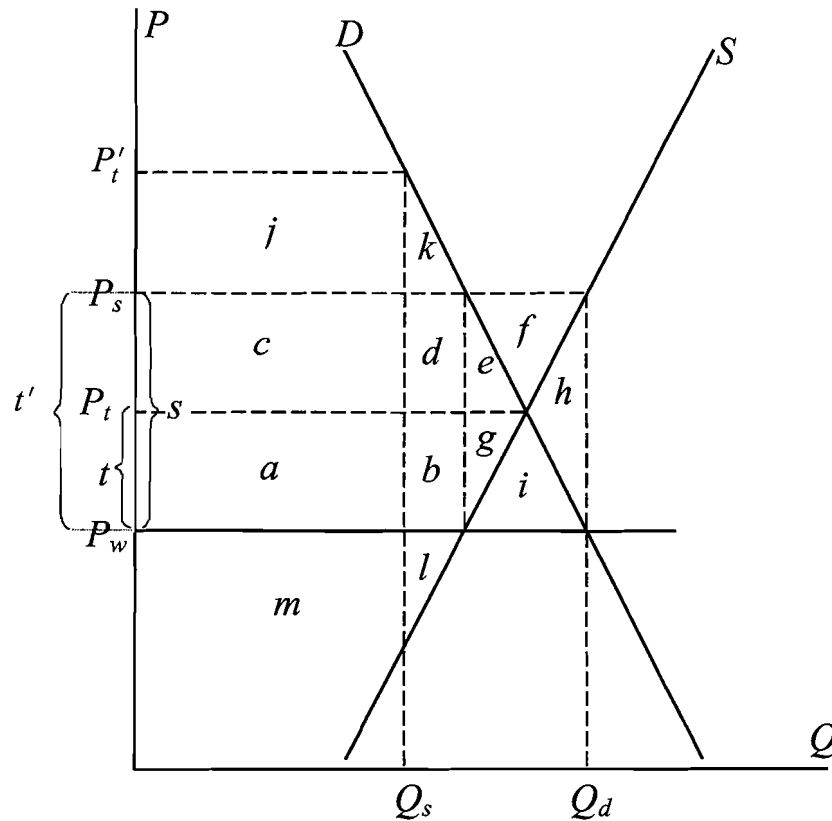
Figure 1. Floor price versus production subsidy with self-sufficiency and income transfer objectives

while taxpayers lose $a + b + c + d + e + f + g + h + i$, implying DWL of $h + i$. The existence of DWL does not necessarily imply the utilized policy is inefficient, in the sense that it achieves the policy objectives at minimum social costs. To judge the efficiency of a production subsidy, one has to answer if and by how much government could have done better by implementing alternative policies. Therefore, the DWL created by the production subsidy must be contrasted with the DWL created by all other policies available to government, which at the same time meet the self-sufficiency objective.

Using our simple model in figure 1, let us assume that government can only choose between the implemented production subsidy and an alternative tariff policy. The tariff required to become self-sufficient is t, indicating a domestic price of P_t. This would imply producer gains of $a + b + g$, consumer costs of $a + b + g + i$, and DWL of i. Hence, given that self-sufficiency is the only policy objective, and government has only these two alternative policies from which to choose (and abstracting from administrative costs, transaction costs, and costs of raising public funds), the tariff policy would be deemed efficient, since it causes the lowest possible DWL. Furthermore, because there is a policy available that results in lower DWL to reach the same objective, the production subsidy policy might be deemed inefficient. Moreover, we might divide the DWL generated by

the production subsidy policy $(i + h)$ into two parts: area h represents avoidable dead-weight losses (ADWL), and area i represents unavoidable deadweight losses (UDWL), given the objective of self-sufficiency and the availability of these two policies.

Now, assume that in addition to self-sufficiency, a certain level of farm income (welfare) transfer is a second objective of agricultural policy. Further assume that the intended income transfer is equal to area $a + b + c + d + e + f + g$ in figure 1. To achieve such an amount with a production subsidy (and at the same time derive at least self-sufficiency), government must implement a production subsidy of s, again causing DWL of $i + h$. Since $j = b + d + e + f + g + l$, a farm income transfer equal to that of a production subsidy policy s is derived by introducing a tariff of t', yielding a domestic price of P_t' and DWL of $b + d + e + g + i + k + l$. Hence, in meeting both objectives of a farm income transfer of $a + b + c + d + e + f + g$ and self-sufficiency, the production subsidy policy is more efficient: $b + d + e + g + k + l > h$, since $e + g = h$. Looking at the tariff policy, area $b + d + k + l$ represents ADWL, and area $e + g + i$ represents UDWL, given the two assumed objectives and two assumed instruments.

Clearly, the situation becomes more complicated and difficult to depict graphically as the number of instruments and objectives increases. In a multi-instrument world govern-ment can not only use more than one instrument at a time, but also can combine these instruments at different levels. However, to test if a policy is efficient in meeting stated objectives, one has to ask if some of the DWL caused in fulfilling policy objectives might have been avoidable.

The optimal policy (the one without any ADWL) is the one which fulfills all objectives at minimum DWL. Technically, let $\mathbf{x} = (x_1, x_2, ..., x_m; x_{m+1}, ..., x_n)$ be a vector of n policy instruments, where m instruments are actually used by government in the current policy (or used in the policy to be analyzed), and $n - m$ instruments are available and known, but are not used at present.[3] The existing policy might be a mix of a target price x_1, a loan rate x_2, and a set-aside requirement x_m, while, for example, a fertilizer tax x_{m+1} is not in place.

Each instrument can be set at various levels. A specific government policy is described by a vector of the values of all available policy instruments; e.g., policy A is described by $\mathbf{x}^A = (x_1^A, ..., x_n^A)$ and policy B is described by $\mathbf{x}^B = (x_1^B, ..., x_n^B)$, where the policies not used are corner solutions (e.g., the fertilizer tax $x_n = 0$). Let the non-intervention policy be denoted by $\mathbf{x}^0 = (x_1^0, ..., x_n^0)$. Furthermore, let $\mathbf{b} = (b_1, ..., b_o)$ be a vector of o parameter values describing the utilized economic model (Bullock, 1994). Here, b_1 might be an elas-ticity of wheat demand of -0.3, b_2 might be an elasticity of substitution between labor and capital of 0.9, b_3 might be a factor share of labor for wheat production of 0.3, and so forth. Welfare of individual (or social group at an aggregated level) i is a function of policy and market conditions: $u_i = u_i(\mathbf{x}, \mathbf{b})$. The DWL are the sum of welfare changes initiated by a policy A as compared to a non-intervention situation 0: $DWL^A = -[\Delta u_1 + ... + \Delta u_p] = -[(u_1(\mathbf{x}^A, \mathbf{b}) - u_i(\mathbf{x}^0, \mathbf{b})) + ... + (u_p(\mathbf{x}^A, \mathbf{b}) - u_p(\mathbf{x}^0, \mathbf{b}))] = DWL(\mathbf{x}^0, \mathbf{x}^A, \mathbf{b})$, where p is the number of individuals (or social groups).

---

[3] As one reviewer correctly pointed out, not all available (existing) policies might be known to government and/or the researcher. Since the full set of $\mathbf{x}$ is never known, our vector of optimal instruments $\mathbf{x}^*$ is most likely not the solution to the problem in a global sense. It will always depend on what instruments we assume to be available and known to the government.

In addition, assume that agricultural policy has r policy objectives: $z_1, ..., z_r$. Let z_i^+ be a specific value by which a policy objective can be made operational; e.g., z_1^+ might be a self-sufficiency ratio of 100%, z_2^+ a farm income of \$50,000 per year, z_3^+ a threshold value of 45 milligrams nitrate per liter of groundwater, and z_4^+ a limit of 20 million tons of subsidized wheat exports. Then, $\mathbf{z}^+ = (z_1^+, ..., z_r^+)$ is a vector that describes the specific set of objectives of agricultural policy.

The optimal (efficient) policy is the one which minimizes DWL given that policy objectives are fulfilled:[4]

$$(1) \qquad \min_{\mathbf{x}} DWL(\mathbf{x}, \mathbf{x}^0, \mathbf{b}),$$

$$\text{s.t.: } z_i(\mathbf{x}, \mathbf{b}) \gtrless z_i^+, \quad i = 1, ..., r.$$

The optimal policy vector which solves optimization problem (1) is $\mathbf{x}^*$, and the lowest possible deadweight losses (given policy objectives are $\mathbf{z}^+$) are $DWL(\mathbf{x}^*, \mathbf{x}^0, \mathbf{b})$. Depending on which policy instruments are included in the vector of choice variables $\mathbf{x}$ in the optimization problem (1), the term "optimal policy" must be interpreted in different ways. If $\mathbf{x} = (x_1, x_2, ..., x_m)$, $\mathbf{x}^*$ gives the optimal mix of actually used policy instruments. If $\mathbf{x} = (x_1, x_2, ..., x_m; x_{m+1}, ..., x_n)$, $\mathbf{x}^*$ gives the optimal mix not only of policy instruments actually used, but also of a set of policy instruments which are not used but are available (considered known). Instead of minimizing DWL, one could also maximize the sum of welfare over all p individuals or social groups: $W = u_1(\mathbf{x}, \mathbf{b}) + ... + u_p(\mathbf{x}, \mathbf{b}) = W(\mathbf{x}, \mathbf{b})$.[5]

Avoidable DWL of a specific (observed, past, proposed) policy described by $\mathbf{x}^A$ (ADWL) is given by

$$(2) \qquad ADWL = DWL(\mathbf{x}^A, \mathbf{b}) - DWL(\mathbf{x}^*, \mathbf{b}),$$

while unavoidable DWL of policy $\mathbf{x}^A$ (UDWL) is

$$(3) \qquad UDWL = DWL(\mathbf{x}^*, \mathbf{b}).$$

ADWL gives an absolute measure of how much better government could have done. Since ADWL does not necessarily provide a good intuition of the efficiency of a policy, here we use the percentage ADWL (%ADWL):

$$(4) \qquad \%ADWL = ADWL/DWL(\mathbf{x}^A, \mathbf{b}) \times 100,$$

---

[4] For a unique solution to exist, $DWL(\mathbf{x}, \mathbf{x}^0, \mathbf{b})$ must be twice continuously differentiable and a strictly convex function.

[5] Finding the optimal policy is to some extent related to the theory of optimal economic policy as established by Tinbergen (1952) and Theil (1954). Their approach translated in our notations can be described as follows. Let $\mathbf{z}$ be a vector of target variables (comparable to our policy objectives), $\mathbf{x}$ a vector of policy instrument variables, and $\mathbf{b}$ a vector of other exogenous variables, comparable to our parameters. Hence, the level of target variables depends on policy instruments and exogenous factors: $\mathbf{z} = f(\mathbf{x}, \mathbf{b})$. The objective function V is not the sum of individuals' (groups') welfare, but rather a (weighted) function of target variables. The policy problem then is to maximize the objective function subject to the restrictions:

$$\max_{\mathbf{x}} V(\mathbf{z}), \quad \text{s.t. } \mathbf{z} = f(\mathbf{x}, \mathbf{b}).$$

The objective function can include all targets, or only part of all targets, while for the others fixed values are chosen: $z_i^+ = f_i(\mathbf{x}, \mathbf{b})$ for some i (Johansen, 1965; Hallett, 1989). In the extreme case where all target values are fixed, the maximization problem is replaced by a set of equations to be solved: solve $\mathbf{z}^+ = f(\mathbf{x}, \mathbf{b})$ for $\mathbf{x}$. Obviously, the existence of a solution requires the famous order condition; i.e., the number of instrument variables should be at least as large as the number of target variables (Don, 2004).

where %ADWL is the percentage of actually observed DWL that is avoidable, given policy objectives z^+ are fulfilled. If $\mathbf{x} = (x_1, x_2, ..., x_m)$, %ADWL can be interpreted as the percentage of DWL which could be avoided by government by using the same instruments, but at different (optimal) levels. If $\mathbf{x} = (x_1, x_2, ..., x_m; x_{m+1}, ..., x_n)$, %ADWL gives the percentage of DWL which could be avoided by government also considering other instruments and combining all instruments in an optimal way. Obviously, if the only policy objective is to redistribute welfare, and the set of available policy instruments would include lump-sum transfers and lump-sum taxes, ADWL = DWL, and our framework would be redundant. However, agricultural policy usually has a number of objectives (Winters, 1987b), and at least lump-sum taxes are regarded as only a theoretical option (Alston and Hurd, 1990; Moschini and Sckokai, 1994; Chambers, 1995).

Dealing with Parameter Uncertainty

Policy measures as described above (DWL, ADWL, UDWL, %ADWL) are functions of parameter values and policy instrument levels. Let Φ be such a policy measure. Then, $\Phi = f(\mathbf{x}, \mathbf{b})$. Assuming some specific functional forms of the relations describing the economic system (e.g., log-linear demand and supply functions), then Φ of a specific policy (e.g., $\mathbf{x}^A$) depends solely on the assumed parameter values. However, since there usually is some uncertainty about parameter values, it is more realistic to assume a probability density function for the parameters $\varphi(\mathbf{b})$. This implies a probability distribution of the policy measure Φ:

$$(5) \qquad\qquad \theta^A(\Phi) = f(\mathbf{x}^A, \varphi(\mathbf{b})).$$

To derive $\theta(\Phi)$, at least three methods have been utilized:[6]

- If a data set Y is available and sufficient to econometrically estimate all parameters of $\mathbf{b}$, one could use bootstrapping procedures (Efron, 1979; Freedman and Peters, 1984). Instead of running one regression and deriving one set of parameters $\mathbf{b}$, one would create a large number T of new data sets $(Y^1, Y^2, ..., Y^T)$ from the original data set by resampling either from the empirical error distribution or from the data set directly, and then use these T data sets to estimate T values for each parameter. As a result, T parameter sets can be derived $(\mathbf{b}^1, \mathbf{b}^2, ..., \mathbf{b}^T)$ which describe the probability density function $\varphi(\mathbf{b})$. Substituting these T parameter sets into equation (5), T estimates are derived of the policy measure $(\Phi^1, ..., \Phi^T)$ which describe the probability distribution $\theta(\Phi)$.

- Alternatively, one could use only the original data set Y, run only one regression, and use the estimated parameter values, the variance-covariance matrix, and the assumption that parameters are distributed normally, to Monte Carlo simulate the probability distribution of policy measure $\theta(\Phi)$ (Krinsky and Robb, 1986). If the estimated parameter values are actually distributed normally, the bootstrapping procedure and the Monte Carlo simulations yield the same results. Clearly, the

---

[6] A very early reference to the problem of parameter uncertainty in optimal policy analysis is Theil (1964).

advantage of the Monte Carlo simulation is that it is computationally cheaper, while bootstrapping is theoretically more accurate (as it does not critically depend on the assumption of normally distributed parameter values being reasonable).

■ For many policy analysis models, however, neither is it within the scope of the study to derive the needed set of parameters, starting from raw data, nor are estimation results (including a variance-covariance matrix) for exactly such a parameter set available. In this case one can use a procedure discussed in Davis and Espinoza (1998); Griffiths and Zhao (2000); Davis and Espinoza (2000); and Zhao et al. (2000). As typically used in Bayesian inference, a subjective probability distribution for the parameter set $\varphi(\mathbf{b})$ is formed utilizing all information available—e.g., published econometric estimates, own calculations, and theoretically required restrictions. (Typically, the only information available consists of a few point estimates of each parameter from the literature. In this case, one could determine a plausible parameter range and assume a specific distribution within this range. Theoretically, covariances between parameters can be considered, but often are not available.) From this subjective probability distribution, a large number T of parameter sets $(\mathbf{b}^1, ..., \mathbf{b}^T)$ is drawn randomly and used to derive a probability distribution of policy measure $\theta(\Phi)$. Obviously, the Monte Carlo procedure is a special case of this Bayesian approach when a variance-covariance matrix of all parameters is available.

Empirical Example

The Model

The Austrian bread grain policy just prior to European Union (EU) accession (1991–1993) serves as an empirical example. As represented graphically in figure 2, and analytically in the appendix, the Austrian bread grain sector is modeled by a log-linear, three-stage, vertically structured model including upstream industries (inputs necessary to produce bread grain) and the downstream industry (food processing and distribution).

The first stage includes four markets of input factors used for bread grain production: land, labor, durable investment goods (machinery and buildings), and operating inputs (fertilizer, seeds, pesticides, etc.). Since farmers own 95% of the farmland, and 86% of the laborers in the agricultural sector in Austria are self-employed, land and labor are assumed to be factors offered solely by farmers. Because there are many farmers supplying land and labor and there are no substantial barriers to entry, a competitive market structure is chosen for the land and labor markets.

Investment goods and operating inputs are supplied by upstream industries. These inputs as defined in the model are conglomerates of separate industries in at least two vertical stages (production and trade). Investment goods are comprised of agricultural machinery and agricultural buildings, and operating inputs include fertilizer, pesticides, seeds, energy, and insurance. For this reason, the market structure of these aggregations of industries is difficult to define.

While strong competition might be observed in the building industry, one clearly can see some concentration in the machinery industry. For example, according to BMLF (1997), the two Austrian tractor brands (Steyrer and Lindner) held 54% of the market
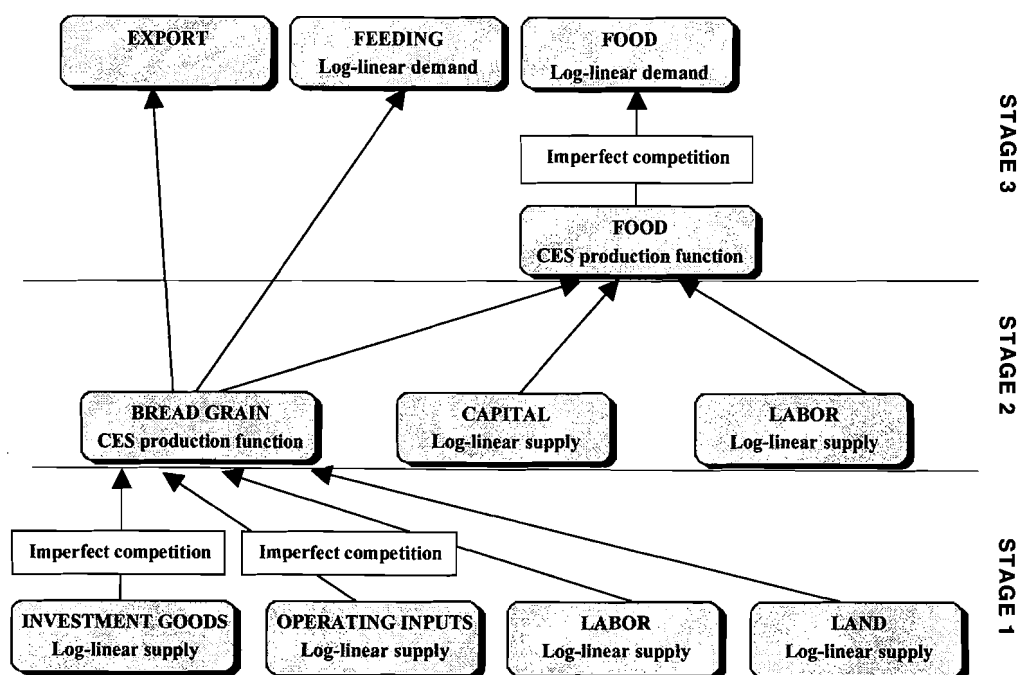
Figure 2. Three-stage vertical structured model of Austrian bread grain market

share in 1996. Similar observations can be made with respect to some operating inputs. Three firms (RWA, Saatbau Linz, and Pioneer) had a share of 62% in the seed market in 1995 (BMLF, 1996). For commercial fertilizer, two Austrian firms (Agro Linz and Donau Chemie AG) had at least 66% of the market. Moreover, there was a strong concentration in trade of agricultural machinery and operating inputs. One firm (RWA) traded about 75% of the pesticides, 70% of the fertilizer, and 40% of the agricultural machinery. Given this information, it is assumed upstream industries are able to exert some market power and set the prices above marginal cost.

For simplicity, export and import of input factors are not considered. While this seems reasonable for land and agricultural labor, some further remarks are necessary with regard to industrially produced input factors. Defining the share of investment goods and operating inputs produced domestically is not an easy task. First, both input categories are conglomerates of separate industries. Second, Austria has simultaneously been an importer and exporter for most inputs. Nevertheless, some relevant comments can be noted. Over the 1991–1993 study period, the value of imports of wheat and rye seeds was below 1% of farmers' expenditures for these inputs; however, there certainly have been some license fees paid to foreign seed firms. Austria was a net exporter of fertilizer with a self-sufficiency ratio (defined as the value produced divided by domestic consumption) of 1.3. The value of imports of commercial fertilizer and manufactured raw materials was about 30% of domestic expenditures for this input. Because we cannot classify how much of the imported raw materials have been manufactured and exported again, this 30% is only an upper bound of the market share of imports. The self-sufficiency ratio of agricultural machinery was 0.92. Again, since Austria was an exporter and importer at the same time, the market share of domestically produced

machinery is hard to define, but according to our calculations was at least 60%. Clearly, for some input factors, imports are negligible, e.g., agricultural buildings or hail insurance. Given these observations and considering the cost share of each input factor (e.g., fertilizer, seeds, machinery) within the two defined categories of operating inputs and durable investment goods, the most extreme (lowest) estimate of how much of the market value is produced domestically is about 75% for both categories.

At the second stage of the model, input factors of the first stage are used to produce bread grain. The first and second stages are linked by the assumption that bread grain producers maximize their profits. Based on the observations of many suppliers, no substantial barriers to entry, and farmers being price takers, we use the standard assumption of a perfectly competitive agricultural market; hence, factor prices must equal the value of marginal products.

The produced quantity of bread grain is used for food production, animal feed, and exports. The model's third stage represents firms which process and distribute bread grain, such as wholesale buyers, millers, exporters, and foodstuff producers and retailers. Bread grain, in combination with other input factors of labor and capital (which is a residual of all other inputs), is used to produce and distribute bread grain products.

Not much information is available if the downstream industry is able to exert some market power to set the prices above marginal cost. To a great extent, the Austrian food manufacturing sector is made up of small enterprises. In 1993, about 93,000 employees worked in approximately 7,000 enterprises of food and luxury food industries, which implies an average of about 14 employees per enterprise (Mazanek, 1995, 1996). However, approximately 70% of these enterprises had fewer than 20 employees, and accounted for only 8% of the output. While the concentration ratio in food manufacturing is unclear, there is some evidence of market concentration in food retailing. Aiginger, Wieser, and Wüger (1999) report a four-firm concentration ratio (CR-4) of the food-retailing sector in Austria of 58% in 1993. Accordingly, we assume some market power in the food sector.

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

The Policy

Thus, objectives of farm policy as stated in national agricultural legislations are numerous. There also appears to be a high degree of unanimity about the objectives of agricultural policy among developed countries. Following Winters (1987b, 1990), in analyzing the objectives of agricultural support in Organization for Economic Cooperation and Development (OECD) countries, six categories are identified: (*a*) efficient use of production factors; (*b*) support and stabilization of farm income; (*c*) self-sufficiency with agricultural (food) products; (*d*) regional, community, and family farm aspects; (*e*) environmental protection; and (*f*) the assurance of reasonable prices for consumers. There is not much doubt among agricultural policy analysts that farm income support has been the most important objective over the last few decades (Josling, 1974; Gardner,
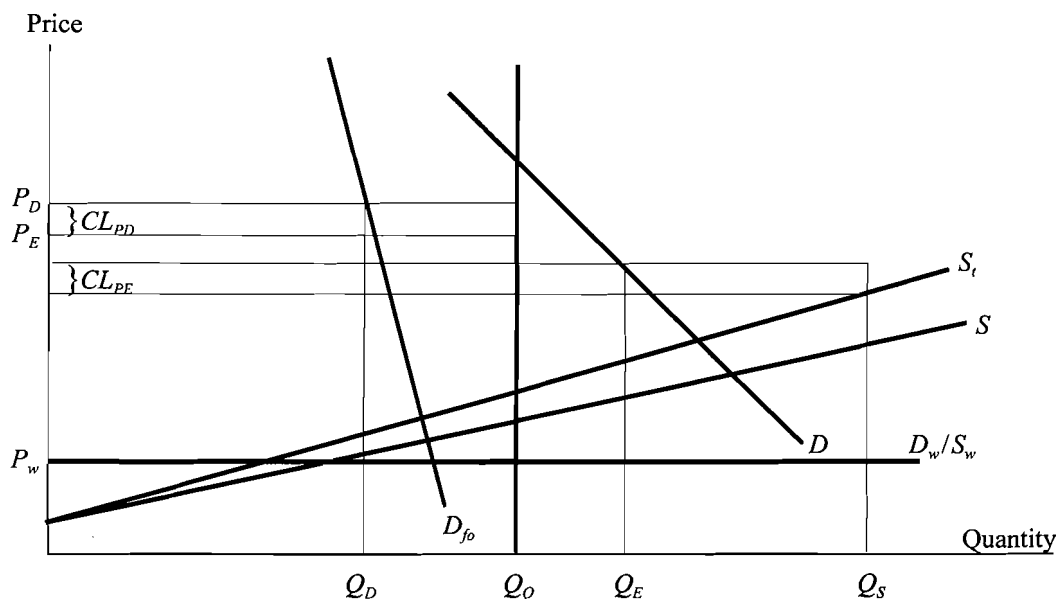
Price

Figure 3. Bread grain market and policy

1992). In general, Austrian agricultural legislation is not different from other developed countries, and paragraph 1 (clause 1-5) of the *Landwirtschaftsgesetz* (*Agricultural Status*) includes all six of the objectives identified above (see Gatterbauer, Holzer, and Welan, 1993; Ortner, 1997).

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

Utilized policy instruments to meet stated policy objectives can be illustrated by means of figure 3, with D_{f_o} 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 are required 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 floor price P_E. Again, farmers' net price is $P_E - CL_{PE}$, with CL_{PE} being the co-responsibility levy for bread grain beyond the quota. Food processors must 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 $Q_X = Q_S - Q_E$.

Empirical Implementation

As discussed above, the main objective of agricultural policy in Austria, as in most developed countries, was to support farm income. Besides income redistribution, securing a

sufficient supply and quality of bread grain products and animal feedstuffs was the most important objective of Austria's bread grain policy in particular (Mannert, 1991). Hence, in this empirical example we concentrate on these two objectives. Regarding the farm income objective, it is assumed that the socially desired level of farm income is the actually observed one. For the self-sufficiency level, we assume domestic supply must be equal to or greater than domestic demand.[7] Therefore, the set of policy objectives in our empirical example is $\mathbf{z}^+ = (z_1^+ \geq$ the actually observed farm income, $z_2^+ \geq$ domestic demand equals domestic supply).

Moreover, for simplicity, it is assumed that the actually applied policy instruments are the ones available to government. Hence, we do not consider the possibility of the government using other instruments, such as a set-aside rate or area payments. Therefore, the set of available policy instruments is $\mathbf{x} = (P_D, P_E, CL_{PD}, CL_{PE}, Q_Q) =$ (high floor price, reduced floor price, co-responsibility levy on the high floor price, co-responsibility levy on the reduced floor price, quota). Also for simplicity, the analysis does not consider that the actual policy included a fertilizer tax. The official objective of introducing a tax on fertilizer was soil protection, and hence environmentally motivated. Although it would be theoretically possible to also consider this objective of a specific environmental quality in the analysis, it would introduce complication to a level beyond the scope of this empirical example.[8] Technically, one could argue that abstracting from the environmental objective is possible if it is separable from all other objectives and optimally met by the current level of fertilizer tax.

To run the model, 19 specific parameter values must be assumed (see the appendix). 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 19 parameter values and their upper (u) and lower (l) limits are based on an extensive literature review and data analysis, described in detail in Salhofer et al. (2001) and Salhofer (2001), and are presented in table 1.[9] Here we assume a symmetric normal distribution $N(\mu, \sigma)$, with $\mu = (u + l)/2$ and $\sigma = (\mu - u)/1.96$, which is truncated at u and l.[10] From the assumed parameter ranges, a probability density function of the parameter set $\varphi_N(\mathbf{b})$ can be derived by taking 10,000 independent draws.[11]

---

[7] While it could be argued that if government intends to secure self-sufficiency in every year, implementing a policy which intends to reach a self-sufficiency level of 100% might not be enough because of unfavorable weather in a specific year. However, our empirical model is based on data averaged over three years.

[8] To be able to judge the environmental effects of the bread grain policy, one would have to combine the market model used here with a model that simulates biophysical processes, e.g., the Environmental Policy Integrated Climate (EPIC) model.

[9] In particular, to identify studies providing estimates of relevant parameters for Europe in general and Austria in particular, we reviewed the two major European agricultural economics journals [*European Review of Agricultural Economics* (1973–1999) and *Journal of Agricultural Economics* (1970–1999)]. In addition, we systematically used the literature databases AG-ECON, AGRIS, and CAB to find other relevant literature. All in all, more than 70 studies were identified and used to derive the values of the model parameters.

[10] The truncated normal distribution and the uniform distribution are typically employed in comparable studies (Davis and Espinoza, 1998; Sinabell, Salhofer, and Hofreither, 1999; Zhao, 1999; Zhao et al., 2000; Horan, Claassen, and Howe, 2001; Salhofer and Schmid, 2004). Zhao et al. (2000) also use a hierarchical distribution. Zhao (1999) uses a mixture of a truncated normal distribution and an exponential distribution. In our work we also tried a uniform distribution. As expected, the results with regard to the central tendency (mean, median, mode) are not very different from the symmetric normal distribution. However, since the results have a higher variance, we found more cases where the optimization problem was difficult to solve.

[11] According to Abler, Rodriguez, and Shortle (1999), if y is a welfare measure to be estimated by the Monte Carlo procedure, then with a 95% probability, the margin of error is no greater than $e = 1.96/\sqrt{K\sigma^2}$, where K is the number of the simulations and σ^2 is the variance of the welfare measure. For the case of the %ADWL measure, e gives the margin of error in percentage points. For all other measures, e must be divided by the mean of the measure and multiplied by 100 to derive the margin of error in percentage points. With 10,000 simulations, the estimated margin of error is smaller than 0.7 percentage points for all measures.

Table 1. Upper and Lower Limits of Model Parameters

Model Parameters	Symbol	Upper Limit (u)	Lower Limit (l)
Supply Elasticities of Agricultural Input Factors:			
Land	ε_A	0.10	0.40
Labor	ε_B	0.20	1.00
Durable Investments	ε_G	1.00	5.00
Operating Inputs	ε_H	1.00	5.00
Supply Elasticities of Food Industry Input Factors:			
Labor	ε_J	0.20	1.40
Capital	ε_K	1.00	5.00
Cost Shares of Agricultural Input Factors:			
Land	α_A	0.06	0.10
Labor	α_B	0.29	0.39
Durable Investments	α_G	0.11	0.19
Cost Shares of Food Industry Input Factors: Labor	α_J	0.27	0.37
Substitution Elasticity of Bread Grain Production	σ_S	0.10	0.90
Substitution Elasticity of Food Production	σ_F	0.50	1.50
Demand Elasticity of Bread Grain for Feeding	η_E	−0.50	−1.50
Demand Elasticity of Bread Grain at the Consumer Level	η_F	−0.10	−0.60
Lerner Indices:			
Operating Inputs Industry	L_H	0.00	0.20
Agricultural Investment Goods Industry	L_G	0.00	0.20
Food Industry	L_F	0.00	0.20
Agricultural Share of Expenditures for Bread Grain Products	λ	0.07	0.09
Cost of Public Funds	MCF	0.10	0.40

DWL of the actual policy is derived by simulating the welfare effects of the actual policy $\mathbf{x}^A$ and of the non-intervention policy $\mathbf{x}^0$, and calculating the difference. Repeating this procedure for 10,000 alternative parameter sets, we derive a probability distribution of the actual DWL.

Unavoidable deadweight losses (UDWL) are derived by solving the following non-linear optimization problem numerically utilizing GAMS software (Brooke, Kendrick, and Meeraus, 1988):

(6) $$\min_{P_D,P_E,CL_{PD},CL_{PE},Q_Q \geq 0} DWL(\mathbf{x}, \mathbf{x}^0, \mathbf{b}),$$

$$\text{s.t.: } W_F(\mathbf{x}, \mathbf{b}) \geq W_F^A; \ Q_X(\mathbf{x}, \mathbf{b}) \geq 0,$$

where W_F is the welfare level of farmers, W_F^A is the welfare level of farmers in the actual situation, and Q_X denotes net exports. Again, repeating this procedure for 10,000

Table 2. Summary of Empirical Results: DWL of Actual Policy, UDWL, ADWL, and %ADWL

Policy Measures	Mean	Median	Mode	Coefficient of Variation	Min.	Max.	95% Probability Interval from / to	75% Probability Interval from / to
DWL of Actual Policy	158.7	157.9	152.5	14.5	81.7	246.1	115.9–205.4	132.1–186.1
Unavoidable DWL	67.8	67.1	66.1	9.1	50.6	94.9	57.6–81.7	61.1–74.7
Avoidable DWL	90.9	90.7	87.7	26.3	6.7	178.7	44.9–138.2	63.0–118.8
%ADWL	56.3	57.7	61.8	14.0	8.2	72.9	37.2–67.9	47.4–64.4

alternative parameter sets, we derive a probability distribution of UDWL.[12] ADWL of the actual policy is measured by the difference between the DWL and UDWL. %ADWL is calculated by dividing ADWL by DWL and multiplying by 100.

Empirical Results

The empirical results are summarized in table 2. As discussed by Davis and Espinoza (1998), if we observe that the results are not normally distributed, it becomes debatable which is the appropriate measure of central tendency. Based on a Jaque-Bera test, normal distribution is rejected for all four reported measures (DWL, UDWL, ADWL, %ADWL) at the 99% significance level. We therefore report the mean, the median, and the mode in table 2. At the mean, the DWL of the actually observed policy is measured to be 159 million Euros (€) (about 42% of the value of bread grain production), while the median is € 158 million and the mode is € 153 million. Therefore, all three measures of central tendency give relatively similar results. The coefficient of variation (CV) is 14.5%. However, a minimum value of € 82 million and a maximum value of € 246 million show how different the results are, depending on the chosen parameter values. This is also reflected in the 95% and 75% confidence intervals, which range between € 116 million and € 205 million, and € 132 million and € 186 million, respectively. In the case of the optimal policy, the unavoidable DWL values are significantly smaller with a mean, median, and mode of € 68, € 67, and € 66 million, respectively. The CV for the optimal policy, at 9%, is smaller than the CV for the actual policy. Given this, the probability distribution of %ADWL has a high mean, median, and mode of 56%, 58%,

---

[12] Since (6) is a complex nonlinear optimization problem, deriving solutions crucially depends on provided starting values. In a first trial with the same starting values for all 10,000 problems, several hundred problems could not be solved. To endogenize the starting values, we use the information of solved problems. In particular, we derive a response surface by estimating a simple OLS regression of the following form:

$$S_i = a_0 + \sum_{i=1}^{19} a_i b_i + e,$$

where S_i denotes the values of those variables for which starting values are needed (mainly quantities, prices, and welfare measures), and b_i represents the exogenously given parameters. The estimates of the parameters $\hat{a}_0$ and $\hat{a}_i$ are afterwards used to derive specific starting values for every single optimization problem by plugging the parameters b_i into the nonstochastic version of the above equation.
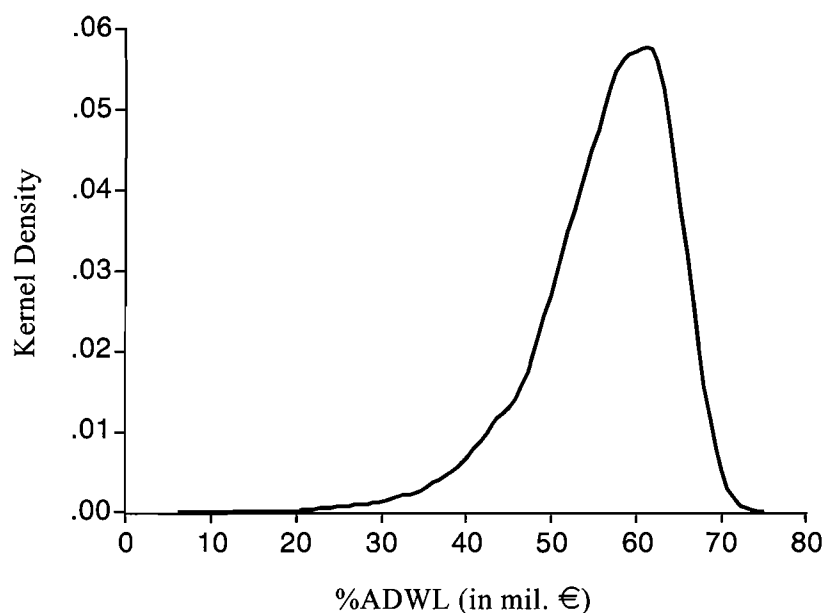
Figure 4. Kernel density function of %ADWL

and 62%, reflecting the inefficiency of the actual policy. The confidence intervals show that this is true over a wide range of assumed parameter values.[13] The distribution derived for %ADWL is also illustrated as a Gaussian kernel density function in figure 4.

With the optimal policy, self-sufficiency is exactly achieved and there are no expensive exports. This result is derived by decreasing the lower price P_E on average by 32%. The quota (Q_Q) is decreased on average by 52% and is much closer to the domestic demand for food production than in the observed situation. To achieve the income transfer objective, the producer price P_D is increased on average by 13%. In all except 15 cases, the co-responsibility levy (CL_{PE}) is zero. The co-responsibility levy CL_{PD} is used in only 12% of the cases and is on average 22% of the actual situation. This result is in accordance with findings reported by de Gorter and Meilke (1989, pp. 597–598), who argue that a co-responsibility levy is a second-best policy, while the first-best policy would be to reduce the prices (P_D, P_E) directly.

It is important to remember that in this empirical example we have assumed the set of available instruments is the set of instruments actually used. Therefore, the ineffici-encies reported are caused by combining the actually used instruments in a suboptimal way, i.e., utilizing them at wrong levels. However, the analysis could be extended by assuming government might also utilize other instruments such as deficiency payments or set-asides.

---

[13] Assuming a uniform distribution of the parameter values between the upper and lower boundaries does not change the means, medians, and modes significantly, but, as expected, causes higher coefficients of variation and wider probability intervals.

Sensitivity Analysis

Given the substantial variation in estimated policy measures, it is helpful to identify those parameters which most influence the results, and on which additional effort should focus. Here, we concentrate on the impact of parameter values on %ADWL.

One way to obtain information about the importance of an exogenous parameter with respect to some variable of interest (%ADWL) is to calculate a sensitivity elasticity (Zhao et al., 2000; Horan, Claassen, and Howe, 2001):

$$(7) \qquad E_{\%ADWL,b_i} = \frac{\partial\%ADWL/\partial b_i}{b_i/\%ADWL}, \quad i = 1, ..., 19,$$

where $E_{\%ADWL,b_i}$ measures the percentage change in %ADWL if parameter b_i changes by 1%. Given the complex nature of the relation between b_i and %ADWL, $E_{\%ADWL,b_i}$ cannot be calculated directly. However, it can be derived numerically.[14] One possibility is to estimate a response surface. Here we follow Zhao et al. (2000) and describe the non-linear relationships between the %ADWL and model parameters by a second-order approximation—i.e., a quadratic polynomial, comprising a constant, the 19 parameters b_i (α_A, α_B, α_G, α_J, λ, ε_A, ε_B, ε_G, ε_H, ε_J, ε_K, η_E, η_F, σ_S, σ_F, L_F, L_G, L_H, MCF), and the permutations $b_i b_j$ of the products of all 19 parameters:[15]

$$(8) \qquad \%ADWL = c_0 + \sum_{i=1}^{19} c_i b_i + \sum_{\substack{i,j=1 \\ i \le j}}^{19} d_{ij} b_i b_j + e,$$

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

Equation (8) is estimated using the 10,000 parameter sets drawn from the parameter distribution and the results for %ADWL as derived in the simulations. An OLS estimation of equation (8) exhibits an extremely good fit ($R^2 = 0.994$). Based on a White test, the null hypothesis of no heteroskedasticity is rejected; consequently, the White procedure to derive a heteroskedasticity-consistent covariance matrix is used (White, 1980). About 45% of the coefficients are significant at the 99% level, 53% at the 95% level, and 59% at the 90% level.

Given the regression results, the sensitivity elasticity of %ADWL to parameter b_i at any parameter point **b** can be derived by partial differentiation of the response surface (Zhao et al., 2000):

$$(9) \qquad E_{\%ADWL,b_i} = \frac{\partial\%ADWL}{\partial b_i} \frac{b_i}{\%ADWL} = \left(c_i + 2d_{ii} b_i + \sum_{\substack{j=1 \\ j \ne i}}^{19} d_{ij} b_j \right) \frac{b_i}{\%ADWL}.$$

---

[14] The most direct way would probably be to use the 10,000 values of %ADWL derived above as "base" values and calculate 10,000 "new" %ADWL values with one parameter b_i changed by 1%. Subtracting the 10,000 base values from the 10,000 new values and dividing the differences by the base values leads to 10,000 elasticity values. However, to derive the 10,000 new %ADWL values, 10,000 additional nonlinear optimization problems must be solved. While this procedure is theoretically possible, it is practically cumbersome and computationally expensive. Additionally, this would have to be performed for all 19 parameters, leading to a total of 190,000 optimization problems.

[15] Zhao (1999); Horan, Claassen, and Howe (2001); and Salhofer (2001) use first-order approximations of the data-generating process.

Table 3. Influence of Parameters on Model Outcome

Parameter	Mean	Standard Deviation	95% Probability Interval		Mean Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE)
			from	to		
λ	2.277***	0.751	1.357	4.028	3.33	6.4%
L_F	2.064***	0.702	1.154	3.707	2.65	5.0%
σ_F	0.839***	0.189	0.645	0.837	6.84	13.1%
η_F	0.126*	0.073	0.181	0.086	1.95	3.8%
ε_H	0.107***	0.035	0.057	0.190	1.11	2.1%
L_H	0.106	0.076	0.124	0.054	0.15	0.3%
η_E	0.091	0.074	-0.010	0.273	1.89	3.6%
MCF	-0.090	0.064	-0.252	-0.012	1.50	2.9%
ε_G	0.042***	0.014	0.022	0.074	0.42	0.8%
L_G	-0.038*	0.020	-0.072	0.007	0.07	0.1%
ε_K	0.030*	0.016	0.007	0.065	0.31	0.6%
ε_J	0.017*	0.010	0.002	0.040	0.23	0.4%
α_B	0.014	0.030	-0.046	0.071	0.13	0.2%
σ_S	-0.009	0.007	-0.006	-0.010	0.16	0.3%
ε_B	0.005	0.019	-0.026	0.049	0.30	0.6%
α_A	0.003	0.009	-0.016	0.019	0.06	0.1%
α_G	0.002	0.011	-0.017	0.025	0.06	0.1%
α_J	-0.002	0.013	-0.026	0.023	0.06	0.1%
ε_A	-0.002	0.004	-0.004	-0.005	0.05	0.1%

Note: Single, double, and triple asterisks (*) denote statistical significance levels of 90%, 95%, and 99%, respectively.

Plugging the 10,000 parameter sets drawn from the parameter distribution and their resulting %ADWL values into equation (9), a distribution of elasticity values is derived. The mean of these 10,000 elasticity values represents the average sensitivity elasticity across the range of parameter b_i. The results are presented in table 3. A 1% change in the parameter λ (the agricultural share of expenditures for bread grain products) increases the %ADWL by 2.277% with a standard deviation of 0.751%, and the 95% probability interval between -1.357% and 4.028%. Five parameters are significantly different from zero at the 1% significance level, and four more at the 10% level. The three parameters with the highest sensitivity elasticity on average are the agricultural share of expenditures for bread grain products (λ), the Lerner index at the food processing level (L_F), and the elasticity of substitution in food processing (σ_F). These findings suggest that much of the uncertainty in the model outcome is explained by the uncertainty in the parameters representing the food sector. This should not come as a surprise, since a high share of the value of the final product is added in the downstream sector. In addition, these results also show that in evaluating agricultural policy it is important to include the effects on the downstream sector.

It is important to clarify when observing (for example) that λ has a higher sensitivity elasticity than (for example) L_H, this does not necessarily imply λ adds more to the uncertainty associated with %ADWL than does L_H. This is because there is a much

larger uncertainty about the real value of L_H ($0.0 \leq L_H \leq 0.2$) than about the real value of λ ($0.07 \leq \lambda \leq 0.9$). No value in the subjective probability distribution of λ has more than a 12.5% difference from the mean/mode, while in the case of L_H this difference is 100%. It is the combination of the direct influence on the outcome (as measured by the sensitivity elasticity) and the uncertainty about the parameter range which determines the uncertainty a parameter adds to %ADWL. In other words, a highly influential but quite precisely known parameter might contribute less to the uncertainty of the model outcome than a moderately influential parameter with a wide range of possible values.

To identify those parameters which add the most uncertainty to %ADWL, we follow Zhao (1999) and calculate the mean absolute error (MAE) and the mean absolute percentage error (MAPE) associated with each of our 19 parameters. Specifically, if all parameters $b_i \in \mathbf{b}$ are known with certainty except for parameter b_i, the MAE associated with using some value $b_i = b_i^*$ is calculated as:

$$(10) \qquad MAE\left(\%ADWL;\, b_i \mid b_i^*\right) = \int_{b_i} \left| f\left(\mathbf{b} \mid b_i = b_i^*\right) - f(\mathbf{b}) \right| \varphi(b_i)\, db_i ,$$

where $f(\mathbf{b})$ is the response surface. However, the parameter values in $\mathbf{b}$ are not known with certainty. Therefore, using their joint distribution, equation (10) can be augmented as follows:

$$(11) \qquad MAE(\%ADWL;\, b_i) = \int_{\mathbf{b}} \int_{b_i} \left| f\left(\mathbf{b} \mid b_i = b_i^*\right) - f(\mathbf{b}) \right| \varphi(\mathbf{b})\varphi(b_i)\, d\mathbf{b}\, db_i .$$

Equation (11) allows for uncertainty in both the value of parameter b_i and the values of all other parameters $b_{j \neq i}$.

Numerically, the MAE associated with parameter b_i can be approximated in the following way. Each of the 10,000 parameter sets $\mathbf{b}$ is consecutively treated as the "true" set, which, plugged into the surface response function, yields a "true" value for $\%ADWL = f(\mathbf{b})$ in equation (10). The mean absolute error for some parameter b_i in equation (10) is approximated by using our 10,000 values for b_i to calculate $f(\mathbf{b} \mid b_i = b_i^*)$, keeping parameters $b_{j \neq i}$ equal to the "true" parameter values. This process yields 10,000 absolute errors $\mid f(\mathbf{b}) - f(\mathbf{b} \mid b_i = b_i^*) \mid$. Since the distribution of parameter b_i has already been utilized in the sampling of b_i, the unweighted average of these 10,000 absolute errors yields the MAE in equation (10). To allow for the fact that all parameters are stochastic, this procedure is replicated for each of our 10,000 parameter sets, and the MAE in equation (11) is the unweighted average of $10,000 \times 10,000 = 10^8$ evaluations of the surface response function. The MAPE is derived analogously as a simple average of 10^8 absolute percentage errors.

The results are reported in table 3. The most important lesson is a corroboration of our initial assumption that the sensitivity elasticity can indeed be a misleading indicator for the identification of those parameters which contribute most to the uncertainty of the model outcome. With an elasticity of 2.28, the agricultural share of expenditures for bread grain products (λ) is the parameter with the highest sensitivity elasticity. However, with respect to model uncertainty (as measured by both MAE and MAPE), the most influential parameter is the elasticity of substitution at the food industry level (σ_F), whose MAPE of 13.1% is more than double λ's MAPE of 6.4%. The reason for this result is that λ's parameter range (from 0.07 to 0.09) is substantially smaller than the range of σ_F (from 0.50 to 1.50).

Discussion and Concluding Remarks

Agricultural policy usually seeks to meet multiple objectives. Consequently, many agricultural economists (e.g., Nerlove, 1958; Josling, 1969, 1974; Rausser, 1982; Gardner, 1983; Just, 1984) have argued that to effectively judge an agricultural policy, measuring implied deadweight losses (DWL) is not sufficient. Rather, the costs must be weighted against the benefits. To date, however, very little work exists which actually applies this insight and judges the performance of a policy by taking into account these objectives. [An exception is the literature on "transfer efficiency," which basically evaluates the efficiency of agricultural policy with regard to the objective of income transfer, usually neglecting all other objectives. For a review of this literature, see Bullock and Salhofer (2003).] The study at hand provides a general framework demonstrating how to judge a policy intended to meet multiple objectives.

The empirical example to which our general framework is applied is still simple in that we assume only two policy objectives: farm income and self-sufficiency. Moreover, these two objectives are comparably easy to evaluate and implement. It is certainly more difficult to model and implement objectives associated with environmental quality or regional development. Nevertheless, the study provides the general structure for doing so, and is still more sophisticated than many of its predecessors.

The results of our empirical example for the bread grain policy in Austria between 1991 and 1993 reveal that the applied policy was very inefficient with respect to the two main objectives of income transfer and self-sufficiency. More than 56% of the observed DWL could have been avoided by a more efficient combination of the actually used policy instruments.

Unlike earlier studies, we do not assign one (or a few) values to each model parameter, but instead assume our model parameters to be in plausible ranges, and derive probability distributions of our policy efficiency measures. This procedure is applied here to a relatively complex nonlinear optimization problem. Findings confirm the importance of such procedures to obtain a more complete picture of the entire range of possible results. However, as discussed by Davis and Espinoza (1998), although this procedure does improve the analysis with regard to the parameter uncertainty, it does not account for the fact that the model structure might be incorrect for explaining the markets being analyzed. A first approach for how to address this problem is presented by Davis (2001). If the model structure is incorrect, then all the analysis is suspect.

Finally, following Zhao et al. (2000) and Zhao (1999), we use a response surface to reveal what parameters most influence the results and on which parameters additional research effort (time) should be invested. Concerning the latter, we discuss how commonly derived sensitivity elasticities (Zhao et al., 2000; Horan, Claassen, and Howe, 2001) might be misleading, and how the mean absolute error or the mean percentage error (as suggested by Zhao, 1999) might give a more complete picture.

References

Abler, D. G., A. G. Rodriguez, and J. S. Shortle. "Parameter Uncertainty in CGE Modeling of the Environmental Impacts of Economic Policies." *Environ. and Resour. Econ.* 14(1999):75–94.

Aiginger, K., R. Wieser, and M. Wüger. "Marktmacht im Lebensmitteleinzelhandel." *WIFO-Monatsberichte* 12(1999):797–809.

Alston, J. M., J. A. Chalfant, and N. E. Piggott. "The Incidence of the Costs and Benefits of Generic Advertising." *Amer. J. Agr. Econ.* 82(2000):665–671.

Alston, J. M., and B. H. Hurd. "Some Neglected Social Costs of Government Spending in Farm Programs." *Amer. J. Agr. Econ.* 72(1990):149–156.

Astl, A. "Getreidemarkt in den 90er Jahren." In *Wintertagung 1989,* ed., Österreichische Gesellschaft für Land- und Forstwirtschaftspolitik, pp. 84–97. Vienna, Austria, 1989.

———. "Markt für Getreide und Mahlprodukte." In *Agrarvermarktung in Österreich: Von der Marktordnung zum Marketing,* eds., G. Breuer, F. Gattermayer, J. Hohenecker, W. Schneeberger, A. Steidl, G. Wöber, and H. Wytrzens, pp. 240–252. Vienna, Austria: Service Fachverlag, 1991.

BMLF (Bundesministerium für Land- und Forstwirtschaft). *Grüner Bericht 1995.* Vienna, Austria, 1996.

———. *Grüner Bericht 1996.* Vienna, Austria, 1997.

Brooke, A., D. Kendrick, and A. Meeraus. *GAMS: A User's Guide,* Release 2.2. South San Francisco: The Scientific Press, 1988.

Bullock, D. S. "In Search of Rational Government: What Political Preference Function Studies Measure and Assume." *Amer. J. Agr. Econ.* 76(1994):347–361.

Bullock, D. S., and K. Salhofer. "Judging Agricultural Policies: A Survey." *Agr. Econ.* 28(2003):225–243.

Bullock, D. S., K. Salhofer, and J. Kola. "The Normative Analysis of (Agricultural) Policy: A General Framework and a Review." *J. Agr. Econ.* 50(1999):512–535.

Chambers, R. G. "The Incidence of Agricultural Policies." *J. Public Econ.* 57(1995):317–335.

Davis, G. C. "Confirmation and Falsification of Equilibrium Displacement Models." Selected paper presented at annual meetings of the American Association of Agricultural Economists, Chicago, IL, 5–8 August 2001.

Davis, G. C., and M. C. Espinoza. "A Unified Approach to Sensitivity Analysis in Equilibrium Displacement Models." *Amer. J. Agr. Econ.* 80(1998):868–879.

———. "A Unified Approach to Sensitivity Analysis in Equilibrium Displacement Models: Reply." *Amer. J. Agr. Econ.* 82(2000):241–243.

de Gorter, H., and K. D. Meilke. "Efficiency of Alternative Policies for the EC's Common Agricultural Policy." *Amer. J. Agr. Econ.* 71(1989):592–603.

Don, F. J. H. "How Econometric Models Help Policy Makers: Theory and Practice." *De Economist* 152(2004):177–195.

Efron, B. "Bootstrap Method: Another Look at the Jackknife." *Annals of Statistics* 7(1979):1–26.

Freedman, D., and S. Peters. "Bootstrapping a Regression Equation: Some Empirical Results." *J. Amer. Statis. Assoc.* 79(1984):97–106.

Gardner, B. L. "Efficient Redistribution Through Commodity Markets." *Amer. J. Agr. Econ.* 65(1983): 225–234.

———. "Changing Economic Perspectives on the Farm Problem." *J. Econ. Literature* 30(1992):62–101.

Gatterbauer, H., G. Holzer, and M. Welan. "Agrarpolitik und Agrarrecht in Österreich—ein Überblick." Discus. Paper No. 21-R-93, Dept. of Econ., Politics, and Law, University of Agricultural Sciences, Vienna, Austria, 1993.

Griffiths, W. E., and X. Zhao. "A Unified Approach to Sensitivity Analysis in Equilibrium Displacement Models: Comment." *Amer. J. Agr. Econ.* 82(2000):236–240.

Griliches, Z. "Research Costs and Social Returns: Hybrid Corn and Related Innovations." *J. Polit. Econ.* 66(1958):419–431.

Hallett, A. H. "Econometrics and the Theory of Economic Policy: The Tinbergen-Theil Contributions 40 Years On." *Oxford Economic Papers* 41(1989):189–214.

Horan, R. D., R. Claassen, and L. Howe. "The Welfare Sensitivity of Agri-Environmental Instruments." *J. Agr. and Resour. Econ.* 26(2001):368–386.

Jeong, K.-S., P. Garcia, and D. S. Bullock. "A Statistical Method of Welfare Analysis Applied to Japanese Beef Policy Liberalization." *J. Policy Modelling* 25(2003):237–256.

Johansen, L. *Public Economics.* Amsterdam: North-Holland, 1965.

Josling, T. "A Formal Approach to Agricultural Policy." *J. Agr. Econ.* 20(1969):175–195.

———. "Agricultural Policies in Developed Countries: A Review." *J. Agr. Econ.* 25(1974):229–264.

Just, R. E. "Automatic Adjustment Rules for Agricultural Policy Controls." AEI Occasional Papers, American Enterprise Institute for Public Policy Research, Washington, DC, 1984.

Krinsky, I., and A. Robb. "On Approximating the Statistical Properties of Elasticities." *Rev. Econ. and Statis.* 68(1986):715–719.

Mannert, J. *Agrarpolitik in Österreich.* Vienna, Austria: Wirtschaftsbetriebe der Universität für Bodenkultur, 1991.

Mazanek, R. "Gewerbestatistik—Jahreserhebung 1993." *Statistische Nachrichten* 50(1995):543–549.

———. "Industriestatistik—Jahreserhebung 1993." *Statistische Nachrichten* 51(1996):725–731.

Moschini, G., and P. Sckokai. "Efficiency of Decoupled Farm Programs Under Distortionary Taxation." *Amer. J. Agr. Econ.* 76(1994):362–370.

Nerlove, M. *The Dynamics of Supply.* Baltimore, MD: Johns Hopkins University Press, 1958.

Ortner, K. M. "Österreichische Agrarpolitik bis zum EU-Beitritt." In *Österreichs Landwirtschaft im EU-Agrarsystem,* ed., Österreichischer Agrarverlag. Klosterneuburg, Austria, 1997.

Raab, F. "Getreide und Mahlprodukte. " In *Agrarvermarktung in Österreich,* 2nd edition, eds., F. Gattermayer, J. Hohenecker, W. Schiebel, W. Schneeberger, A. Steidl, G. Wöber, H. K. Wytrzens, and G. Breuer, pp. 325–342. Vienna, Austria: Service Fachverlag, 1994.

Rausser, G. C. "Political Economic Markets: PERTs and PESTs in Food and Agriculture." *Amer. J. Agr. Econ.* 64(1982):822–833.

Salhofer, K. "Elasticities of Substitution and Factor Supply Elasticities in European Agriculture: A Review of Past Studies." In *Market Effects of Crop Support Measures,* pp. 89–119. Organization for Economic Cooperation and Development (OECD), Paris, 2001.

Salhofer, K., and E. Schmid. "Distributive Leakages of Agricultural Support: Some Empirical Evidence." *Agr. Econ.* 30(2004):51–62.

Salhofer, K., E. Schmid, F. Schneider, and G. Streicher. *Was the Austrian Agricultural Policy Least Cost Efficient?* Res. Rep. No. 2001.02, ed., Ludwig Boltzmann. Institut zur Analyse Wirtschaftspolitischer Aktivitäten, Vienna, Austria, 2001.

Sinabell, F., K. Salhofer, and M. Hofreither. "Aggregated Output Effects of Countryside Stewardship Policies." In *Countryside Stewardship Policies: Farmers, Policies, and Markets,* eds., G. Van Huylenbroeck and M. Whittby, pp. 135–155. Amsterdam: Elsevier, 1999.

Theil, H. "Econometric Models and Welfare Maximisation." *Weltwirtschaftliches Archiv* 41(1954):60–83.

———. *Optimal Decision Rules for Government and Industry.* Amsterdam: North-Holland, 1964.

Tinbergen, J. *On the Theory of Economic Policy.* Amsterdam: North-Holland, 1952.

White, H. "A Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity." *Econometrica* 48(1980):817–838.

Winters, A. L. "The Economic Consequences of Agricultural Support: A Survey." *OECD Economic Studies* 9(1987a):7–54.

———. "The Political Economy of the Agricultural Policy of Industrial Countries." *Euro. Rev. Agr. Econ.* 25(1987b):285–304.

———. "The So-Called 'Non-Economic' Objectives of Agricultural Support." *OECD Economic Studies* 13(1990):237–266.

Zhao, X. "The Economic Impacts of New Technologies and Promotions on the Australian Beef Industry." Unpub. Ph.D. diss., Graduate School of Agricultural and Resource Economics, University of New England, Armidale, 1999.

Zhao, X., W. E. Griffiths, G. R. Griffith, and J. D. Mullen. "Probability Distributions for Economic Surplus Changes: The Case of Technical Change in the Australian Wool Industry." *Austral. J. Agr. and Resour. Econ.* 44(2000):83–106.

Appendix:
The Austrian Bread Grain Sector Model

The supply of inputs used for bread grain production is specified as:

(A1.a)
$$Q_i = X_i P_i^{\varepsilon_i}, \quad (i = A, B),$$

and

(A1.b)
$$Q_i = X_i \left((1 - L_i) P_i \right)^{\varepsilon_i}, \quad (i = G, H),$$

where Q_i denotes the quantity supplied, X_i the shift parameter, P_i the price, ε_i the supply elasticity, and L_i the Lerner index of input factor i. Inputs are land (A), labor (B), investment goods (G), and operating inputs (H).

The bread grain production function is written as:

(A2)
$$Q_S = Z_{QS} \left(\sum_i \alpha_i Q_i^\rho \right)^{1/\rho}, \quad (i = A, B, G, H),$$

with $\rho = \dfrac{\sigma_S - 1}{\sigma_S}$ and $\displaystyle\sum_{i=A,B,G,H} \alpha_i = 1,$

where Q_S denotes the produced quantity of bread grain, Z_{QS} the production function efficiency parameter, α_i the distribution parameter of factor i, ρ the substitution parameter, and σ_S the elasticity of substitution between input factors at the farm level.

The profit-maximization condition (= conditional input demand) is given by:

(A3.a)
$$P_i = Z_{QS}^\rho \alpha_i \left(\frac{Q_S}{Q_i} \right)^{1-\rho} (P_E - CL_{PE}), \quad (i = A, B, G),$$

and

(A3.b)
$$P_H + T_F = Z_{QS}^\rho \alpha_H \left(\frac{Q_S}{Q_H} \right)^{1-\rho} (P_E - CL_{PE}),$$

where P_E is the gross price, CL_{PE} is the co-responsibility levy for bread grain that exceeds the quota Q_Q (see figure 1), and T_F is the fertilizer tax per unit.

The market-clearing condition for bread grain is represented by:

(A4)
$$Q_S = Q_D + Q_E + Q_X.$$

The produced quantity of bread grain is used for food (bread grain products) production (Q_D), animal feed (Q_E), and exports (Q_X).

The supply of labor (J) and capital (K) for food production are specified as:

(A5)
$$Q_i = X_i P_i^{\varepsilon_i}, \quad (i = J, K).$$

The food production function is given by:

(A6)
$$Q_{SF} = Z_{QSF} \left(\sum_i \alpha_i Q_i^\gamma \right)^{1/\gamma}, \quad (i = J, K, D),$$

with $\gamma = \dfrac{\sigma_F - 1}{\sigma_F}$ and $\displaystyle\sum_{i=J,K,D} \alpha_i = 1,$

where Q_{SF} represents the produced quantity of food, Z_{QSF} the production function efficiency parameter, α_i the distribution parameter of factor i, γ the substitution parameter, and σ_F the elasticity of substitution between input factors at the food industry level.

Next, derived input demand given some market power in food production is of the form:

$$(A7) \qquad P_i = (1 - L_F) Z_{QSF}^{\gamma} \alpha_i \left(\frac{Q_{SF}}{Q_i} \right)^{1-\gamma} P_F, \quad (i = J, K, D),$$

where P_F denotes the price of food, P_D the gross price of bread grain under the quota, and L_F the Lerner index of the downstream sector.

Food demand is written as:

$$(A8) \qquad Q_{DF} = X_{QDF} P_F^{\eta_F},$$

where Q_{DF} represents the demanded quantity of food, X_{QDF} a shift parameter, and η_F the elasticity of demand.

The market-clearing condition for food is given by:

$$(A9) \qquad Q_{DF} = Q_{SF}.$$

The bread grain demand for feeding purposes is written as:

$$(A10) \qquad Q_E = X_{QDE} P_E^{\eta_E},$$

where X_{QDE} and η_E are the shift parameter and the elasticity of animal feedstuff demand, respectively.

Finally, the initial agricultural share of expenditures for bread grain products (λ),

$$(A11) \qquad \lambda = \frac{P_D Q_D}{P_F Q_{DF}},$$

is necessary to derive the price for bread grain products P_F in the calibration process.

The model consists of 19 variables (Q_A, Q_B, Q_G, Q_H, Q_J, Q_K, P_A, P_B, P_G, P_H, P_J, P_K, Q_S, Q_D, Q_E, Q_X, Q_{SF}, Q_{DF}, P_F), six policy instruments (P_D, P_E, CL_{PD}, CL_{PE}, Q_Q, T_F) [of which two (CL_{PD} and Q_Q) are not in the model above, but play a role in the welfare calculations], and 32 parameters (ε_A, ε_B, ε_G, ε_H, ε_J, ε_K, α_A, α_B, α_G, α_H, α_J, α_K, α_D, σ_S, σ_F, η_E, η_F, L_G, L_H, L_F, X_A, X_B, X_G, X_H, X_J, X_K, Z_{QS}, Z_{QSF}, X_{QDF}, X_{QDE}, λ, MCF) [of which the marginal cost of public funds (MCF) is not in the model above, but plays a role in the welfare calculations]. To calibrate the model, we have information on 12 variables (Q_A, Q_B, Q_G, Q_H, Q_J, Q_K, Q_S, Q_D, Q_E, Q_X, Q_{SF}, Q_{DF}) and the policy instruments. In addition, we assume values for 19 parameters (ε_A, ε_B, ε_G, ε_H, ε_J, ε_K, α_A, α_B, α_G, α_J, σ_S, σ_F, η_E, η_F, L_G, L_H, L_F, λ, MCF). All other variables and parameters are derived in the calibration.