Does Subsidy Drive Productivity? A Cross-Country Analysis of Nordic Dairy Farms

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Abstract

One of the foremost objectives of the Common Agricultural Policy (CAP) in the European Union (EU) is to increase agricultural productivity. However, little empirical research has been done to examine the effects of subsidy on farm performance and, in particular, the channels through which subsidy affects productivity. Using a Bayesian hierarchical model in which input elasticities, efficiency change and technical change depend on subsidy and other factors including farm location, we analyze empirically how subsidy affects the performance of farms. We use an unbalanced panel from the EU’s Farm Accountancy Data Network on Danish, Finnish and Swedish dairy farms and partition the data into 8 regions. The data set covers the period 1997 - 2003 and has a total of 6609 observations. The results suggest that subsidy drives productivity through efficiency and input elasticities and the relative importance of these channels differ across regions. In stark contrast to existing studies, we find that subsidy has a positive impact of technical efficiency. The marginal product of subsidy is largest for dairy farms in Denmark, Southern, Central and Northern Sweden.

Key words: Subsidy; Facilitating Input; Technical Efficiency; Technical Change; Input Elasticities; Bayesian Analysis.

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1 Introduction and Motivation

Farm subsidy or support is a direct or indirect income transfer payment to farmers. Farmers experiencing higher productivity growth than their competitors will increase their comparative advantage and market share in domestic and possibly international markets. Thus the less competitive farmers, either domestic suppliers or exporters, will require some sort of support to guarantee their market existence. In such a case subsidy might not increase productivity; it merely helps some inefficient farms to live (stay in business) longer. One political argument in favor of support to farmers is that a country that is unable to domestically produce enough to meet its demand might be vulnerable to trade pressure. Social justification is also provided for this type of transfer payment. The common perception being that farmers are among the hard working poor and therefore, it is socially justified to use tax dollars to supplement farmers’ incomes (although it has been argued that in many cases, farm subsidies benefit rich more than poor farmers). Here our focus is on the economic aspects and more specifically we examine whether subsidy affects farm productivity, and if so through what channels. We use dairy farm data from three Nordic countries to examine the subsidy-productivity nexus.

Farmers within the European Union (EU) enjoy the benefits of the Common Agricultural Policy (CAP), a system of agricultural subsidies and programs that was established in 1957. The CAP absorbs, on average, about half of the EU’s annual budget which makes this policy rank as the EU’s most expensive budgetary commitment. One of the foremost initial objectives of the CAP is “to increase productivity, by promoting technical progress and ensuring the optimum use of the factors of production, in particular labor” (http://www.europarl.europa.eu/factsheets/4,1,1_en.htm). Nevertheless, little empirical work has been done to investigate the usefulness of the CAP in this regard. Against this backdrop, our main question is: has the CAP accomplished its productivity goal? In this paper we examine the productivity effects of subsidy through changes in input productivity, efficiency change and technical change, especially when subsidy is coupled to inputs and production environment.1

The existing literature on the productivity effects of subsidy is quite small. Theoretical analysis includes Hennessy (1998) and Roe et al. (2002). Hennessy (1998) predicts that in a stochastic environment with producers possessing decreasing absolute risk aversion, an increase in coupled or decoupled support policy can increase producers’ optimal input levels and thus increase productivity.2 Roe et al. provide evidence that a coupled subsidy policy is one that is explicitly related to production decisions. That is, coupled subsidy directly affects the optimal amount of input or output. Otherwise, the subsidy policy is “decoupled”, thus the policy does not alter short-run marginal production decisions (see Bezelkina, Oude Lansink and Oskam (2005)).

Hennessy theorizes that either form of support policy induce a wealth effect and an insurance effect which can alter producers’ decisions. Support policies provide producers with a stable income (the insurance effect) and also increases their wealth (the wealth effect).
(2002) find that under the assumption of imperfect capital markets, in the short- to medium-run direct payments have a positive but small effect on output by increasing capital deepening and employment of labor. However, in the long-run direct payments are not linked to output. Some empirical works on the nexus between subsidy and the productivity of farmers include Giannakas et al. (2001), Iraizoz et al. (2005), Karagiannis (2005) and Rezitis et al. (2003). These studies employ a classical stochastic production frontier approach and allow subsidy to enter only the mean function of the technical efficiency distribution. The common finding is that subsidy has a negative impact on technical efficiency and hence productivity. These existing studies, however, do not examine concurrently the impact of subsidy on overall productivity through changes in input productivity, technical efficiency and technical change.

To analyze empirically the impact of subsidy on productivity, we consider a simple but flexible model that enables decomposition of the overall productivity change (i.e., the effect of subsidy on output) into input productivity, technical change and technical efficiency change. We label the former as the technology effect (which is further decomposed into input-specific components) as opposed to technical change (which might be purely neutral, i.e., not related to any specific input). We model the technology effect by allowing the production function coefficients to be functions of subsidy and environmental factors such as location. Following the standard production theory we model technical change through time, which in our model is also affected by subsidy. Finally, we use a non-frontier approach to model technical efficiency, which also depends on subsidy and location and is assumed to be random to account for latent heterogeneity such as managerial quality. Thus in contrast to the existing literature, we do not assume subsidy affects productivity only through one particular channel. We emphasize that subsidy is not necessary for production of output. Furthermore, subsidy alone cannot produce any output. Our rationale for modeling input productivity as functions of subsidy is guided by the theoretical prediction of the effect of subsidy on traditional inputs such as labor and capital. Coupled subsidy distorts relative prices of traditional inputs and consequently affects their marginal rates of transformation. With respect to technical change, subsidized producers are less credit constrained and can invest in research and development and advanced technologies thereby achieving technical progress. Why would subsidy be linked to technical efficiency? If farmers are technically efficient and cost of production is higher than revenue then these farmers cannot survive in the long run without subsidy (or some kind of support). However, if production is inefficient, cost can be higher than revenue (implying loss). Thus the fact that a farmer is operating under loss and therefore cannot survive in the long run does not necessarily mean that the farmer should be supported. If the loss is due to inefficiency, subsidizing a farm indirectly means promoting inefficiency. Alternatively, subsidization of inefficient farmers may help them to stay in business. Furthermore, subsidy may discourage farmers from exerting more effort into their production
activities. Thus, in terms of choosing a modeling framework for the impact of subsidy on productivity, it seems plausible to also allow for the possibility that subsidy affects technical efficiency. Our maintained hypothesis therefore is that subsidy is not a traditional input but a “facilitating” input that affects output indirectly through changing productivity of traditional inputs (technology effect), shifting the technology (technological change), and affecting technical efficiency. We model this productivity effect in such a way that subsidy can be complementary with some of the traditional inputs and substitutable with other traditional inputs. To the best of our knowledge, our work is the first Bayesian analysis on the impact of subsidy on productivity. However, the decomposition of productivity into technical efficiency, technical change and input elasticities is not new to the Bayesian literature. Koop et al (2000) and Koop (2001) study the decomposition of aggregate output growth and sectoral output growth into these three components. In contrast to our non-frontier approach, Koop et al (2000) and Koop (2001) use a stochastic frontier approach in their analysis. We note that our idea of a subsidy as a facilitating input is similar but more general than the concept of “effective-factor correction variable” used by Koop et al (2000).

The unbalanced data cover the period 1997-2003 and consist of 6609 farms from 3 Northern EU countries (Denmark, Sweden and Finland). We divide the countries into 8 production regions. For each region the technology parameters are different. The efficiency parameters are allowed to vary across farms as well. In the standard model subsidy is treated like other traditional inputs (labor, capital, etc.) and therefore it affects productivity like any other inputs. We also consider an extended model in which subsidy is allowed to affect productivity through the three aforementioned channels. Using the Savage-Dickey density ratio test we investigate whether our extended model is more consistent with the data than a model in which subsidy affects productivity directly like any other conventional input.

The rest of the paper is organized as follows. In the next section we present two alternative ways of introducing subsidy into the production function. In the first model subsidy is treated as a traditional input, while in the second model subsidy is treated as facilitating input. Section 3 contains a description of the farm accountancy data for Danish, Finnish and Swedish. We present and discuss the empirical results in Section 4. The last section contains a summary of the main findings and some concluding remarks. We defer all of the mathematical details to the technical appendix.

2 Modeling subsidy in production

Assume that farmers use a $K$-variate traditional input $x$ to produce an aggregate output $y$. The functional relationship between $x$ and $y$ is described by a production function $f : \mathbb{R}^K_+ \rightarrow \mathbb{R}_+$ where $y = f(x)$. Suppose the farmers receive a subsidy $S$. The question is how should we incorporate $S$ into the production function.
In the preceding section we discussed several channels through which subsidy can affect productivity. In this section we introduce several model specifications to explore which model can identify what channel. In doing so, our objective is find a model that can identify all three channels of productivity growth.

Suppose the output-subsidy relation can be captured by the production specification

\[ y = Af(x, S, t; \pi) \]  

(2.1)

where \( t \) represents the exogenous technology shifter, \( \pi \) is the vector of parameters representing the technology and \( A \) is the parameter that represents efficiency.\(^3\) The implication here is that subsidy is considered to be a traditional input and therefore have a direct effect on output.\(^4\) In this case subsidy does not affect output through technical efficiency. However, depending on the functional form, subsidy can affect output through input elasticities and technical change.

If we assume the relation between \( S \) and output is

\[ y = A(S)f(x, t; \pi) \]  

(2.2)

then in this formulation subsidy \( S \) is separable from the other inputs and therefore can be viewed as a special case of (2.1). Since \( S \) is separable from other inputs, the rate of change in output due to any input \( x_k \) (elasticity of output with respect to \( x_k \)) is neutral to subsidy meaning that the elasticities of other inputs is not affected by the level of subsidy. For this specification, subsidy affects output only through the efficiency function \( A(S) \). This is true independent of the functional form for \( A(S) \) and \( f(\cdot) \).\(^5\) This specification is similar to that employed by Giannakas et al. (2001), Iraizoz et al. (2005), Karagiannis (2005) and Rezitis et al. (2003) to model the effect of subsidy on efficiency.

It is possible to consider a model that is more general than the above two simply by allowing subsidy to affect both \( A \) and \( f(\cdot) \), viz.,

\[ y = A(S)f(x, S, t; \pi) \]  

(2.3)

Both (2.1) and (2.2) can be viewed as special cases of (2.3) by imposing appropriate restrictions. This specification, under appropriate functional forms of \( f(\cdot) \), will exhibit all three channels of productivity effect.

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\(^3\)Here we follow Lau and Yotopoulos (1971) and call it technical efficiency. Note that this is the traditional interpretation which is not equivalent to the definition of technical efficiency in the stochastic frontier literature (Kumbhakar and Lovell (2000)).

\(^4\)We note that traditional inputs have direct effects on output. If the functional form of \( f(\cdot) \) permits interactions between inputs, they may also have indirect effects on output.

\(^5\)In estimating aggregate production functions using time series data, this type of formulation is often used with the efficiency parameter being a function of the trend variable (see, Solow (1956) and Beckmann and Sato (1969)). The present formulation is a variant of this in which \( A \) is specified as a function of \( S \).
Another possible formulation for the output-subsidy relation is

\[ y = f(A(S)x, t; \pi) \]  

(2.4)

where \( A(S)x = A_1(S)x_1, \cdots, A_K(S)x_K \) and \( A_k > 0 \) is the productivity factor associated with \( x_k, k = 1, \ldots, K \). For this specification, subsidy affects output through input productivities (not necessarily through input elasticities unless the function form of \( f(\cdot) \) is flexible (such as the translog)). Strict positivity on \( A_k \) implies that subsidy will not necessarily increase productivity of all inputs. If \( A_k > 1 \) then subsidy enhances productivity of input \( k \). Note that it is possible to have positive overall productivity even if subsidy reduces the productivity of some inputs.\(^6\) Again we see that the subsidy effect through technical change depends on the functional form of \( f(\cdot) \).

There are some major limitations of the specifications in (2.1) - (2.4). For a log linear functional form the specifications in (2.1) - (2.4) are algebraically the same. That is, assuming that \( f(\cdot) \) is log linear (Cobb-Douglas) and \( A(\cdot) \) is log linear in \( S \), the relationships in (2.1) - (2.4) become

\[ \ln y = \pi_0 + \sum_k \pi_k \ln x_k + \pi_S \ln S + \pi_t t \]  

(2.5)

In this specification subsidy \( (S) \) is productivity enhancing if the coefficient \( \pi_S \) is positive. Technical change is represented by the \( \pi_t \) coefficient and technical efficiency is captured by the intercept term, \( \pi_0.\(^7\) In particular, subsidy in these specifications (as shown in (2.5)) affects productivity directly just like the traditional inputs. Therefore, using specifications (2.1) - (2.4) with a Cobb-Douglas production function (which is equivalent to using (2.5)) it is not possible to identify our three proposed channels in the output-subsidy nexus. Since the main purpose of this paper is to examine the three different channels through which subsidy impacts productivity, we begin by formalizing the concept of a facilitating input which we will use repeatedly in this paper.

**Definition 2.1.** We say an input \( S \) is a *facilitating input* in the production of output \( y \) if (i) \( S \) is not necessary for the production of \( y \), (ii) \( S \) alone cannot produce \( y \), and (iii) \( S \) affects productivity through at least one channel.\(^8\)

Note that the first two criteria distinguish traditional inputs from facilitating inputs.

\(^6\)See Kumbhakar (2004) for a similar formulation in which \( A_k \) are functions of time trend.

\(^7\)Some of these formulations will be different from others if, for example, a translog form is chosen for \( \ln f(\cdot) \). For example, in (2.2) subsidy is neutral to technical change and inputs in the production technology irrespective of the form of the \( f(\cdot) \) function chosen. Therefore, theoretically no amount of subsidy can change any of these measures.

\(^8\)Subsidy can affect input productivity but not necessarily input elasticity. For example, if \( f(\cdot) \) is log linear in ((2.1) - (2.4)), which is nothing but the specification in (2.5) subsidy will affect input productivity but not input elasticities.
Given the limitations of (2.1) - (2.4), we need to look for some other specification in which subsidy can be treated as a facilitating input even for a log linear function. In view of this, we specify the production function in the following way
\[
y = A(S)f(x, t; \pi(S)).
\] (2.6)

This specification accommodates the requirement that subsidy is a facilitating input and it affects input elasticities, technical efficiency and technical change. We can identify all the three channels of transmission even with log-linear specification. Using a Cobb-Douglas production function the relationship in (2.6) becomes
\[
\ln y = \pi_0(S) + \sum_k \ln x_k \pi_k(S) + \pi_t(S)t,
\] (2.7)

which shows subsidy may affect output through the input coefficients (technology parameters) \(\pi_k(S)\), the efficiency parameter \(\pi_0(S)\), and the technology change (shift) parameter \(\pi_t(S)\). The specification in (2.7) general enough to obtain some of the earlier specifications as special cases. Furthermore, it facilitates the decomposition of the overall effect of subsidy on output. Thus, the output elasticity with respect to \(S\), \(\varepsilon_{y,S} = \partial\ln y/\partial\ln S\), is
\[
\varepsilon_{y,S} = \frac{\partial\pi_0(S)}{\partial\ln S} + \sum_k \ln x_k \frac{\partial\pi_k(S)}{\partial\ln S} + t\frac{\partial\pi_t(S)}{\partial\ln S}
\] (2.8)

and has three components: (i) an efficiency component, (ii) an input (technology) component and (iii) a technology change component in that order.

### 2.1 Bayesian hierarchical models

In this subsection we elaborate on the econometrics used. We consider flexible models that are based on the general formulations outlined in (2.1) and (2.7). We begin by fixing notation. The data set has region, farm and time dimensions which we index respectively as, \(i\), \(j\), and \(t\). The input subscript is \(k\) \((k = 1, \cdots, K)\). Time \((t)\) and subsidy \((S)\) are separated from the input vector \((x)\). To capture regional differences in productivity, we allow for heterogeneous input-specific elasticities, technology efficiency and technical change across regions. With these notations our first model is

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9Note that some of the other specifications can accommodate \(S\) as a facilitating input (with fewer channels) but cannot identify these channels with a simple log-linear functional form. We could circumvent this problem by using flexible functions such as the translog. The main problem with the flexible functional forms is that they tend to violate properties of the production technology. Furthermore, the parameters cannot be directly interpreted.
Model I: Subsidy is a Traditional Input

\[
\ln y_{ijt} = \pi_0(C_{ij}) + \sum_{k=1}^{K} \pi_k(C_{ij}) \ln x_{k,ijt} + \pi_s(C_{ij}) \ln S_{ijt} + \pi_t(C_{ij}) t + u_{ijt} \tag{2.9}
\]

\[
\pi_s(C_{ij}) = \alpha_0 + \alpha_1 C_{1,ij} + \alpha_2 C_{2,ij} + \cdots + \alpha_{M-1} C_{M-1,ij},
\]

\[
\pi_k(C_{ij}) = \alpha_0 + \alpha_1 k C_{1,ij} + \alpha_2 k C_{2,ij} + \cdots + \alpha_{M-1} k C_{M-1,ij},
\]

\[
\pi_t(S_{ijt}, C_{ij}) = \alpha_0 + \alpha_1 t C_{1,ij} + \alpha_2 t C_{2,ij} + \cdots + \alpha_{M-1} t C_{M-1,ij},
\]

\[
\pi_0(C_{ij}) = \beta_0 + \beta_1 C_{1,ij} + \beta_2 C_{2,ij} + \cdots + \beta_{M-1} C_{M-1,ij} + v_{ij},
\]

where \( C_{l} \) \((l = 1, \cdots, M - 1)\) are regional dummies and region \( M \) is used as the reference group. Note that in this formulation the efficiency parameter \( \pi_{0,ij} \) is assumed to be random and time-invariant. We append a random component to capture heterogeneity from latent productivity differential such as managerial quality and latent time-invariant factors. In fact, our sample is quite heterogeneous in terms of weather conditions and land quality so it seems plausible to allow for latent productivity differential. The technology shifter represents the time-varying part of efficiency and is labeled as technology change. Thus, the sum of these two components can be viewed as technical inefficiency which is decomposed into a time-invariant and time-varying component. We do not lump these random productivity component \((v_{ij})\) with the noise terms in the production function \((u_{ij})\), since our interest is also to estimate \( \pi_{0,ij} \) which requires estimation of the random component \( v_{ij} \). In a standard random effects model, interest commonly lies in estimating the parameters \( \alpha \) and \( \pi \) and thus \( v_{ij} \) and \( u_{ij} \) are collectively treated as the composite error term. The specification in (2.9) is similar to the standard production function model that accommodates country-specific intercepts, except for the fact that in (2.9) the intercepts are also random effects.

Our second model is in line with (2.7) and is specified as

**Model II: Subsidy is a Facilitating Input**

\[
\ln y_{ijt} = \pi_0(S_{ij}, C_{ij}) + \sum_{k=1}^{K} \pi_k(S_{ijt}, C_{ij}) \ln x_{k,ijt} + \pi_t(S_{ijt}, C_{ij}) t + u_{ijt} \tag{2.10}
\]

\[
\pi_k(S_{ijt}, C_{ij}) = \alpha_0 + \alpha_1 k C_{1,ijt} + \alpha_2 k C_{2,ijt} + \cdots + \alpha_{M-1} k C_{M-1,ijt} + \alpha_{sk} \ln S_{ij}, \text{ for } k = 1, \cdots, K,
\]

\[
\pi_t(S_{ijt}, C_{ij}) = \alpha_0 + \alpha_1 t C_{1,ijt} + \alpha_2 t C_{2,ijt} + \cdots + \alpha_{M-1} t C_{M-1,ijt} + \alpha_{st} \ln S_{ijt},
\]

\[
\pi_0(S_{ij}, C_{ij}) = \beta_0 + \beta_1 C_{1,ij} + \beta_2 C_{2,ij} + \cdots + \beta_{M-1} C_{M-1,ij} + \beta_s \ln S_{ij} + v_{ij}.
\]

This formulation is more general than the one in (2.9). Here the input coefficients \((\pi_k)\) and technology shifter \((\pi_t)\) are functions of regions as well as subsidy. Furthermore, technical efficiency parameter is also a function of regions and subsidy (its mean over time). Similar to the first model, technical efficiency (which is assumed to be time-invariant) is separated from change in technology.
Some informative measures can be extracted from the model in (2.10). Define output elasticity with respect to input \( x_k \) as \( \varepsilon_{y,k} \equiv \partial \ln y / \partial \ln x_k \) and as before output elasticity with respect to subsidy \( S \) as \( \varepsilon_{y,s} \equiv \partial \ln y / \partial \ln S \). Then

\[
\varepsilon_{y,k} = \alpha_{0k} + \alpha_{1k} C_1 + \alpha_{2k} C_2 + \cdots + \alpha_{M-1,k} C_{M-1} + \alpha_{sk} \ln S,
\]

\[
\varepsilon_{y,s} = \beta_s + \sum_{k=1}^{K} \alpha_{sk} \ln x_k + \alpha_{st} t.
\]

For the reference region \( \varepsilon_{y,k} = \alpha_{0k} + \alpha_{sk} \ln S \) and for region \( 1 \) \( \varepsilon_{y,k} = \alpha_{0k} + \alpha_{1k} + \alpha_{sk} \ln S \). Thus \( \alpha_{1k} \) represents the regional differential between region \( 1 \) \((C_1)\) and the reference region \((C_M)\) in the output elasticity of input \( x_k \). The expression for \( \varepsilon_{y,k} \) shows that subsidy has a second-order effect on productivity of input \( x_k \). In particular, since \( \partial \varepsilon_{y,k} / \partial \ln S = \alpha_{sk} \), if \( \alpha_{sk} > 0 \) this implies that an increase in subsidy increases overall productivity and the productivity of input \( x_k \) also increases. That is, subsidy has a complementary effect on input \( x_k \). Thus the sign of \( \alpha_{sk} \) allows us to understand the substitutability and complementarity between the traditional inputs and the facilitating input, subsidy.\(^{10}\) Similarly, an increase in subsidy enhances overall productivity and also increases the contribution of technical efficiency to productivity if \( \partial \pi_0(S, C) / \partial \ln S = \beta_s \) is positive. Also, an increase in subsidy increases overall productivity and the contribution of technical change to productivity if \( \partial \pi_t(S, C) / \partial \ln S = \alpha_{st} \) is positive. Aggregate measures, such as returns to scale (\( RTS \)), technical change (\( TC \)) and technical efficiency (\( TE \)), can also be easily derived from (2.10). These are:

\[
RTS_{ijt} = \sum_{k \in K} \frac{\partial \ln y}{\partial \ln x_k} = \sum_{k \in K} \left[ \pi_k(S_{ijt}, C_{ijt}) \right] = \sum_{k \in K} \varepsilon_{y,k},
\]

\[
TC_{ijt} = \pi_t(S_{ijt}, C_{ijt}),
\]

\[
TE_{ij} = \pi_{0,ij}.
\]

Thus \( RTS \) represents the output change from proportional changes in all inputs. \( TE \) is reflected in the \( \pi_{0,ij} \) term. A formal measure of \( TE \) would be given by \( \exp(\pi^*_{0,ij}) \leq 1 \) where \( \pi^*_{0,ij} = \pi_{0,ij} - \max_{i,j}(\pi_{0,ij}) \).

\( TC \) shows the percentage (when multiplied by 100) by which output changes over time, holding everything else unchanged. It indicates shift in the production function over time, \textit{ceteris paribus}.

To investigate empirically whether subsidy may be considered as a facilitating or traditional input, and also to explicitly account for unobserved factors that may impinge on technical efficiency, we compare the first and second model specifications in terms of their consistency with the data. To do so we abstract from the classical mode of estimation and adopt the Bayesian formalism. This is done to avoid the

\(^{10}\)One disadvantage of using the Cobb-Douglas production function is that it precludes an analysis on substitutability and complementarity between the traditional inputs due to the absence of cross-product terms involving these inputs.
estimation problems and finite sample inconsistency that are common to the existing classical methods of estimating random effects. Bayesian analysis facilitates easy estimation of the random effects and provides exact finite sample results. In addition, economic regularity conditions can easily be imposed in this Bayesian setup.

For ease of exposition we discuss the Bayesian model in terms of Model I in (2.9). We rewrite the main equation as

\[ \ln y_{ijt} = \pi_{0,ij} + \sum_{k=1}^{K} x_{k,ijt}^s \alpha_k + s_{ijt}^s \alpha_s + t^s \alpha_t + u_{ijt} \]  

(2.14)

where \( x_{k,ijt}^s, s_{ijt}^s \) and \( t^s \) are the level 1 covariates interacted with the regional dummies, each has dimension \( 1 \times M \), \( \alpha_k = (\alpha_{0k}, \alpha_{1k}, \cdots, \alpha_{M-1,k})' \), for \( k = 1, \cdots, K \), \( \alpha_s = (\alpha_{0s}, \alpha_{1s}, \cdots, \alpha_{M-1,s})' \), and \( \alpha_t = (\alpha_{0t}, \alpha_{1t}, \cdots, \alpha_{M-1,t})' \). Here \( \tilde{x}_{ijt} \) is the \( 1 \times (K+2) \) row vector containing the entire collection of level 1 regressors with \( \Gamma = (\alpha_1', \alpha_2', \cdots, \alpha_K', \alpha_s', \alpha_t')' \) being the \( (K+2) \times 1 \) common-coefficient vector.

Let us define, \( \tilde{N}_i \equiv \sum_{r=1}^i N_r + 1 \) for \( i > 1 \), \( \tilde{N}_1 \equiv 1 \), and \( \bar{N}_i \equiv \sum_{r=1}^i N_r \). Here \( N_i \) is the number of distinct farms in region \( i \). For a more compact notation, we stack the observations so that the fastest running index is time \( t (t = 1, \cdots, T_j) \), the second fastest running index is the farm index \( j, j = \tilde{N}_i, \tilde{N}_i + 1, \cdots, \bar{N}_i \), and the slowest running index is the region index \( i (i = 1, \cdots, M) \), and write the model in region \( i \) as

\[ Y_i = (I_{N_i} \otimes \nu_{T_j}) \Pi_{0i} + X_i \Gamma + U_i, \]

\[ \Pi_{0i} = Z_i \beta + V_i \]

where \( \beta = (\beta_0, \beta_1, \cdots, \beta_{M-1})' \) is the vector of level 2 parameters, \( Z_i = [\nu_{N_{i1}}; \nu_{C2}; \cdots; \nu_{C_{M-1,i}}] \) is the \( N_i \times M \) matrix of covariates at level 2 of the model, and

\[ Y_i = \begin{pmatrix} \ln y_{i,\tilde{N}_i} \\ \ln y_{i,(\tilde{N}_i+1)} \\ \vdots \\ \ln y_{i,\bar{N}_i} \end{pmatrix}, \quad X_i = \begin{pmatrix} \tilde{x}_{i,\tilde{N}_i} \\ \tilde{x}_{i,(\tilde{N}_i+1)} \\ \vdots \\ \tilde{x}_{i,\bar{N}_i} \end{pmatrix} \]

are respectively of dimensions \( \sum_j T_j \times 1 \) and \( \sum_j T_j \times M(K+2) \). \( I_{N_i} \) is the identity matrix, \( \nu_{T_j} \) is a vector of ones of dimension \( T_j \), and \( \otimes \) denotes the Kronecker product. With the error assumptions of \( U_i \overset{iid}{\sim} N(0, \sigma_u^2 I_{\sum_j T_j}) \) and \( V_i \overset{iid}{\sim} N(0, \sigma_v^2 I_{N_i}) \), the likelihood and population distribution respectively are

\[ Y_i | \Pi_{0i}, \Gamma, \sigma_u^2 \overset{iid}{\sim} N((I_{N_i} \otimes \nu_{T_j}) \Pi_{0i} + X_i \Gamma, \sigma_u^2 I_{\sum_j T_j}) \]

(2.15)

\[ \Pi_{0i} | \beta, \sigma_v^2 \overset{iid}{\sim} N(Z_i \beta, \sigma_v^2 I_{N_i}) \]

(2.16)
To convert the above model to its Bayesian counterpart, we impose distributional specifications and independence assumption on the hyperpriors $\beta$, $\sigma_u^2$, $\sigma_v^2$, and $\Gamma$ so that the priors are:

$$p(\beta, \sigma_u^2, \sigma_v^2, \Gamma) = p(\beta) \cdot p(\sigma_u^2) \cdot p(\sigma_v^2) \cdot p(\Gamma),$$

where

$$\beta \sim N_M(\beta, \Sigma) \quad (2.17)$$

$$\sigma_u^{-2} \sim G(\nu/2, \delta/2) \quad (2.18)$$

$$\sigma_v^{-2} \sim G(\mu/2, \rho/2) \quad (2.19)$$

$$\Gamma \sim N_{K+2}(\Gamma, \Omega) \quad (2.20)$$

and $G$ denotes the gamma distribution, $N_M$ and $N_{K+2}$ are multivariate Gaussian distributions, and the hyperparameters $\Sigma$, $\nu$, $\delta$, $\mu$, $\rho$, $\Gamma$, $\Omega$ are prespecified constants. Then the model in (2.9) and the priors in (2.17), (2.18), (2.19), (2.20) constitute a complete Bayesian hierarchical model. To obtain parameter estimates of the hierarchical model we utilize the Gibbs sampler. We simulate the models using 21,000 iterations and for each iteration, we generate random draws from the set of posterior conditionals in the order: (a) $[\beta|Y, \Gamma, \Pi_{0i}, \sigma_u^2, \sigma_v^2]$, (b) $[\Gamma|Y, \beta, \Pi_{0i}, \sigma_u^2, \sigma_v^2]$, (c) $[\Pi_{0i}|Y, \beta, \Gamma, \sigma_u^2, \sigma_v^2]$, (d) $[\sigma_u^2|Y, \beta, \Gamma, \Pi_{0i}, \sigma_v^2]$, (e) $[\sigma_v^2|Y, \beta, \Gamma, \Pi_{0i}, \sigma_u^2]$. The values for the hyperparameters and the derivations for these full posterior conditionals are in the appendix. To ensure convergence of the MCMC we carry out different diagnostic checks. In the “burning in phase” we discard the first 1,000 iterates to reduce the dependence of the values of the final estimate on the starting values of the chain. We plot a separate autocorrelation function for each set of the posterior iterates to examine the severity of the autocorrelation of each parameter. In the “thinning phase” we then skip every 100 observations reducing the autocorrelations close to zeros. Using the remaining iterates we approximate the posterior mean, posterior standard deviation, and posterior quantiles ($2.5\%, 50\%, 97.5\%$) for each parameter of interest using Monte Carlo estimates. Finally, we use the Savage-Dickey Density ratio by Verdinelli and Wasserman (1995) to compute the Bayes factors for the various hypotheses related to models I and II. We utilize the Deviance Information Criterion (DIC) by Spiegelhalter et al (2002) to compare the fit of models I and II to the data.

3 Data

We use an unbalanced data set from the European Farm Accounting Data Network (FADN) that covers individual dairy farms in Denmark, Finland and Sweden from 1997 to 2003.\footnote{We thank Timo Sipiläinen for running these models in his computer. This indirect access to the FADN data was necessary to comply with the restriction that the data may not be transferred to any third party researchers. The usual disclaimer applies.} These three countries
are quite different in terms of their natural and structural conditions. Denmark has the most favorable climate and land quality for agricultural production and is the most export oriented and competitive. Finland has the least favorable natural conditions. Sweden is intermediate in that the conditions for agricultural production in southern parts of Sweden are quite comparable with those in Denmark while the natural conditions of northern Sweden are similar to Finland.

There are also differences in the trading benefits afforded to these European Union (EU) economies. Denmark gained accession to the EU in 1973 while Finland and Sweden joined the EU in 1995. Under the Common Agricultural Policy (CAP), since 1995 all three economies have been subjected to the same agricultural policy. In addition, special actions have been implemented to assist farmers in Sweden and Finland to smoothly adjust to their new economic environment with low output prices. These actions include investment aids and a price premium for milk. Given these disparities in production conditions and CAP benefits, we divide the countries into 8 regions. These are: Denmark (denoted by DK) in one region; three regions in Sweden (Southern (SS), Central (CS) and Northern (NS) Sweden); and four regions in Finland (Southern (SF), Central (CF), Western (WF) and Northern Finland (NF). We select Denmark as the reference region.

The total number of observations is 6609. The total number of distinct dairy farms in the sample is 1578 of which 647 are from Denmark, 441 from Finland and 490 from Sweden. We use the following inputs: labor, fertilizer, purchased feed, materials and capital. Labor is measured in hours of work in the farm and all other inputs are measured in real monetary values. Capital includes costs of machinery and buildings. We report subsidies, excluding investment aids and price support on milk, as a separate direct payment variable in the data. Output is the revenue from sales of milk and other outputs at market prices. We convert monetary values of inputs and outputs to euros using the exchange rates of national currencies for Denmark and Sweden. Furthermore, we adjust these monetary values for inflation by using country-specific price indices of inputs and outputs.\footnote{Since farm specific prices are not available and there are not enough variations in prices we cannot use the cost function approach.}

Finnish farms are on average the smallest and Danish farms the largest. In this data set, the average sizes of dairy farms (number of cows) in Denmark, Sweden and Finland are 84, 36, and 21 respectively. In Table 1 we report the descriptive statistics (only mean and standard deviation) of the variables used in this paper. In spite of the size differences of farms across countries, average subsidy payments are similar except for Northern Sweden which has the largest subsidy payment. There seems to be a relation between the value of some inputs and the average size of a dairy farm within a region. Denmark spends the most on capital, materials and purchase feed while Eastern Finland spends the least on capital and materials. Labor hours is largest for Southern Sweden followed by Denmark and lowest for Northern
Sweden. Northern Finland spends the most on fertilizer while Northern Sweden has the lowest fertilizer expenditure. In terms of output, Denmark produces the most which is approximately ten times more than Eastern Finland, the region with the lowest output volume. This is quite reasonable since Denmark is the most export-oriented of the 8 regions. The value of subsidy suggest that Northern Sweden is the most subsidized regions in absolute terms and Eastern Finland is the least subsidized. We note the large standard deviations for the variables which suggest that inputs, output and subsidy vary within any given region.

Since our main focus is the impact of subsidy on productivity, we look at the distributions of subsidy within and across regions. The plot of total subsidy by region is shown in Figure 1, and in Figure 2 we plot subsidy per unit of output (subsidy per each euro of output). Both the figures show variations within and across regions. That is, even after controlling for size differences in terms of output we find that distribution of subsidy differs across regions (although some regions appear more different than others). Figure 2 shows that the distributions of normalized subsidy (subsidy per unit of output) may fall into four groups; at one extreme, Denmark appears to form a group by itself and has the smallest variation in normalized subsidy; at the other extreme, Northern Sweden appears to solely form a group and has the largest variation in normalized subsidy; Central Sweden and Southern Sweden seem to be in one group while Southern, Central, Eastern, and Northern Finland appear to form the intermediate group in terms of their distributions.

4 Empirical Results

We present results for Model I (which treats subsidy as a traditional input in (2.9)) and Model II (which treats subsidy as a facilitating input in (2.10)). Tables 2 and 3 show the posterior means and standard deviations of the level 1 and 2 coefficients associated with Models I and II respectively. In Table 2, and at level 1, the elasticities of most traditional inputs including subsidy, within any given region, are more than one standard deviation away from zero. This implies that the data may be consistent with regional differences in input elasticities including those associated with subsidy. The posterior means for output elasticities of subsidy, $\varepsilon_{y,s}$, are approximately 0.43 for Northern Sweden, 0.15 for Eastern Finland, 0.11 for Southern Finland and 0.05 for Denmark. Thus for a 10% increase in subsidy, output increases by approximately 4.3% in Northern Sweden, 1.5% for Eastern Finland, 1.1% for Southern Finland and 0.5% for Denmark. Regional differences in technical change are also borne out by this model. Moreover, technical change for each region is positive, but negative for Denmark. In particular, each posterior mean for technical change is more than two standard deviation away from zero. The posterior estimates of the level 2 coefficients suggest that on average the level of technical efficiency for Southern Finland, Eastern
Finland, Northern Finland and Central Sweden may be similar to that of Denmark. However, Southern and Northern Sweden are less technically efficient than Denmark while Western Finland appears to be more technically efficient. The Bayes factor for the hypothesis that subsidy has no effect on output, $\alpha_{0s} = \alpha_{1s} = \cdots = \alpha_{7s} = 0$, is $3.025 \times 10^{-41}$. This suggests that there is an empirical link between subsidy, as a traditional input, and productivity.

Table 3 shows the results of our flexible specification that accommodates subsidy as a facilitating input. Two main findings are worth mentioning. First, the impact of subsidy on labor, fertilizer, purchase feed, capital and materials elasticities are more than four standard deviation away from zero. In addition, subsidy affects capital and material elasticities positively and labor, fertilizer and purchase feed negatively. To be more precise, and in line with our discussions in the previous section on the complementarity and substitutability roles of subsidy in Model II, we see that subsidy is strongly substitutable with labor, fertilizer and purchase feed but complementary with capital and materials. Thus an increase in subsidy results in a reduction in the marginal product of labor (decrease in the number of workers employed by the farm) but an increase in the marginal product of capital. This latter effect suggests that subsidy promotes investment in capital or capital deepening. The results are also economically meaningful, a 10% increase in subsidy results in approximately 0.51% reduction in the labor elasticity and 0.46% increase in the capital elasticity. The impact of subsidy on technical change is positive but less than one standard deviation away from zero. Technical change in Denmark appears to be close to zero. This implies that for Denmark, the facilitating role of subsidy may have a larger effect on output through input elasticities and efficiency than through technical change.

Second, the impact of subsidy on efficiency is positive and more than one standard deviation away from zero. We note that this positive impact of subsidy is in stark contrast to the empirical findings of Giannakas et al. (2001), Iraizoz et al. (2005), Karagiannis (2005) and Rezitis et al. (2003) who allow subsidy to affect productivity only through the technical efficiency channel and find a negative relation between subsidy and technical efficiency. The results indicate no difference in the efficiency levels across Eastern, Northern and Southern Finland, Central Sweden and Denmark. In addition, Western Finland is more efficient while Southern Sweden and Northern Sweden are less efficient than Denmark. Specifically, relative to Denmark, farms in Northern Sweden are farther away from the frontier while farms in Western Finland are closer the frontier. Overall, the results show that subsidy not only affects productivity through input elasticities and technical efficiency but also in different directions. These findings provide strong empirical support for our treatment of subsidy as a facilitating input in Model II.

We further analyze the implications of modeling subsidy as a facilitating input by using the Bayes Factor (BF) to test various hypotheses. We first investigate whether the regional differences imposed
on the parameters are consistent with the data. For the hypothesis of no differential in efficiency levels across regions, $\beta_1 = \beta_2 = \cdots = \beta_7 = \beta_s = 0$, we find $BF = 0$. For the hypothesis of no differential in technical change across regions, $\alpha_{1t} = \alpha_{2t} = \cdots = \alpha_{7t} = \alpha_{st} = 0$, we obtain $BF = 8.76 \times 10^{-6}$. Also, for the hypothesis of no differential in input elasticities across regions, we obtain $BF = 5.912 \times 10^{-255}$. In particular, we find that Western Finland and Central Sweden have similar labor elasticity to Denmark, while all other regions have larger labor elasticity. Also, Southern Finland, Eastern Finland, Central Sweden have similar capital elasticity as Denmark while Western Finland, Northern Finland and Central Sweden have larger elasticities and Southern Sweden have a smaller capital elasticity. Thus, our flexible specification appears to fit the data quite well.

We now test the validity of our main hypothesis that subsidy affects productivity through three channels - input elasticities, technical efficiency and technical change. For the hypothesis that subsidy affects productivity only through technical efficiency, $\alpha_{s1} = \alpha_{s2} = \alpha_{s3} = \alpha_{s4} = \alpha_{s5} = \alpha_{st} = 0$, we find that $BF = 2.789 \times 10^{-34}$. This provides strong empirical evidence that the other channels may play a role in linking subsidy to productivity. For the hypothesis that subsidy affects productivity only through technical efficiency and technical change, $\alpha_{s1} = \alpha_{s2} = \alpha_{s3} = \alpha_{s4} = \alpha_{s5} = 0$, we find that $BF = 6.512 \times 10^{-36}$. These two hypotheses suggest that input elasticities are empirically relevant to the subsidy-productivity nexus. For the hypothesis that input elasticities and technical change are the only two channels, $\beta_s = 0$, we find that $BF = 51.26$. Finally, for the input elasticities and technical efficiency are the only two channels, $\alpha_{st} = 0$, we find that $BF = 58.20$. These Bayes factors are favor of input elasticities as important channels through which subsidy drives productivity. Given the posterior mean and standard deviation of the impact of subsidy on technical change, our interpretation of these results is that the data are more consistent with input elasticities and technical efficiency as the channels in the link between subsidy and productivity. The regional differences in input elasticities, technical change and efficiency suggest that subsidy alone may not be sufficient to make Danish and Swedish farms fully adjusted to their new economic environment and therefore, other variables may be helpful in explaining these regional differences.

Models I and II suggest that there is a link between subsidy and productivity in the data. To determine which one of our two specifications is preferred by the data, we compute the Deviance Information Criterion (DIC) for both models. We find that $DIC = 29,016$ for Model I and $DIC = 28,815$ for Model II. Thus model II that accommodates subsidy as a facilitating input is preferred by the data. We therefore limit our discussion below to Model II. We now analyze the posterior means of some of the production structure measures such as RTS, TC, TE.
The Distributions of RTS, TC, TE. Although Model II is not as flexible as the translog, it is flexible enough to render returns to scale and technical change observation-specific. Table 4 reports the productive contributions of the various input elasticities along with RTS, TC and TE. Their corresponding values are mean values by region. For all regions except Northern Sweden, the productivity of materials contribute the most to RTS while labor contribute the least to RTS.\textsuperscript{13} We find evidence of increasing RTS for Denmark, Southern and Northern Sweden, and decreasing but close to constant RTS for Southern Finland, Eastern Finland, Western Finland and Central Sweden. Northern Sweden has the largest value for increasing returns to scale with the purchase feed and materials contributing respectively the most and least to RTS, while Western Finland has the lowest value for decreasing RTS. However, Northern Sweden is the least technically efficient but achieve no technical progress while Western Finland is the most technically efficient and show technical progress. Overall, technical change is mostly positive but small in magnitude. Denmark, however, appears to be experiencing technical regress. We note that despite the comparative advantage and export-orientation of the farms in Denmark, this region does not dominate other regions in terms of TC and TE.

At the regional level, we do not see much difference in the estimated RTS, TC and TE. However, there are within variations in the posterior means of these production measures. This can be seen from the plots of TE, RTS and TC by region respectively in Figures 3, 4 and 5. In addition, the distributions of these measures appear symmetric.

Decomposing the Effect of Subsidy on Productivity. We now return to the results related to subsidy. We report the effect of subsidy on output by region in Table 5. Rather than reporting the elasticity, we report the marginal effect of subsidy, i.e., $\partial Y/\partial S$ which gives the value of marginal increment in output for an increase in subsidy by one Euro. The subsidy effect is decomposed into three components (technical efficiency, technology and technical change). The Danish and Swedish farms have relatively larger marginal effects of subsidy than the Finnish farms. In particular, for every € 100 increase in subsidy the value of output increases by € 106.53 for farms in Denmark, € 71.66 for farms in Southern Sweden and € 15.28 for farms in Southern Finland. At the regional level, the variability in total marginal product of subsidy is quite large. The efficiency effects also differ across regions. We obtain negative technology effects for all Finnish regions, although the posterior means of these effects are less than one standard deviation away from zero for Southern and Western Finland. These results require an explanation. There is a threshold effect that is implied by our specification for model II. As a result,

\textsuperscript{13}In particular, material inputs contribute about 35.4\%, 32.3\%, 35.0\%, 45.6\%, 36.1\%, 42.5\%, 34.2\%, 5.48\% to output production respectively in Denmark, Southern Finland, Eastern Finland, Western Finland, Northern Finland, Southern Sweden, Central Sweden and Northern Sweden; labor contributes about 3.52\%, 7.65\%, 7.41\%, 3.49\%, 5.37\%, 5.51\%, 3.0\%, 15.7\%.
regions or farms that do not have a certain level of subsidy have negative input elasticities for some of traditional inputs. Using a truncated multivariate normal as the prior distribution for these elasticities had unfavorable implications for the other parameters of the model and increased the simulation time considerably given the number of observations in the sample. We therefore use the multivariate normal as the prior distribution.

For some regions, the technology effects are larger than the efficiency effects. In particular, Denmark and Northern Sweden, input elasticities are the main channels through which subsidy affects productivity. For Southern and Central Sweden, technical efficiency is the dominant channel in the subsidy-productivity nexus. To gain further insight on the impact of subsidy across regions, we present the density plots by region of the total marginal product of subsidy and its components in Figures 6, 7, 8 and 9. It can be seen from the figures that there are differences both within and between regions for each component of subsidy effect. Overall, regional ranking in decreasing order of the total marginal effect of subsidy on output is Denmark, Southern Sweden, Central and Northern Sweden, Southern, Western, and Eastern Finland then finally Northern Finland.

5 Conclusion

One of the main purposes of the Common Agricultural Policy in the European Union is to increase agricultural productivity by subsidizing farmers. To date, however, not much work has been done to assess the empirical link between subsidy and productivity in the EU economies. This paper investigates empirically the impact of subsidy on agricultural productivity in Denmark, Sweden and Finland through three channels - input elasticities, technical efficiency and technical change. Our results suggest that subsidy drives productivity through efficiency and input elasticities and the relative importance of these channels differ across regions. In stark contrast to the existing studies, we find subsidy has a positive impact on technical efficiency. We find that subsidy is substitutable with labor, fertilizer and purchase feed but complementary with capital and materials. That is, an increase in subsidy will increase overall production by increasing the contribution of capital and materials to production but decreasing the productivity of labor and the other inputs to production. In addition, the marginal product of subsidy is largest for dairy farms in Denmark, Southern, Central and Northern Sweden.

References


Table 1: Descriptive statistics (per farm)

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Note: These values are the regional averages for 1997-2003.
Figure 1: Logarithm of Subsidy.
Region key. —— (DK); —— (SF); ··· (EF);
—···· (WF); —···· (NF); ····· (SS); ····· (CS); —— (NS).

Figure 2: Normalized Subsidy.
Region key. —— (DK); —— (SF); ··· (EF);
—···· (WF); —···· (NF); ····· (SS); ····· (CS); —— (NS).

20
Table 2: Model I - Subsidy as Traditional Input

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Note: These values are posterior mean and standard deviation in ().
### Table 3: Model II - Subsidy as Facilitating Input

#### Level 1 Coefficients

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#### Level 2 Coefficients

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Note: These values are posterior mean and standard deviation in ().
<table>
<thead>
<tr>
<th>Country</th>
<th>Denmark</th>
<th>Finland</th>
<th>Sweden</th>
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<tbody>
<tr>
<td></td>
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<td>Purchase Feed ($\varepsilon_{y,3}$)</td>
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<td>Region</td>
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<td>EF</td>
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Note: These values are the posterior means and standard deviation in ()

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Note: These values are the regional posterior means and standard deviations in () for each component of the marginal effect of subsidy.
Figure 3: Technical Efficiency by Regions.
Region key. _ _ _ (DK); _ _ _ (SF); · · · (EF); 
_ _ _ _ _ (WF); _ _ _ _ _ (NF); _ _ _ _ _ _ (SS); _ _ _ _ _ _ (CS); _ _ _ _ _ _ (NS).

Figure 4: Returns to Scale by Regions.
Region key. _ _ _ (DK); _ _ _ (SF); · · · (EF); 
_ _ _ _ _ (WF); _ _ _ _ _ (NF); _ _ _ _ _ _ (SS); _ _ _ _ _ _ (CS); _ _ _ _ _ _ (NS).
Figure 5: Technical Change by Regions.
Region key. ___ ___ (DK); ___ (SF); ··· (EF);
--- --- (WF); --- (NF); ··· (SS); ... (CS); ___ (NS).

Figure 6: Total Marginal Product of Subsidy.
Region key. ___ ___ (DK); ___ (SF); ··· (EF);
--- --- (WF); --- (NF); ··· (SS); ... (CS); ___ (NS).

25
Figure 7: Efficiency Component of Marginal Product of Subsidy.

Region key. ——— (DK); ——— (SF); ···
— (EF); ——— (WF); ——— (NF); ··· (SS); . . (CS);
—— (NS).
Figure 8: Technology Component of Marginal Product of Subsidy.
Region key. ——— (DK); ——— (SF); ··· (EF); − − − (WF); − − − (NF); ··· (SS); ··· (CS); ——— (NS).

Figure 9: Technical Change of Marginal Product of Subsidy.
Region key. ——— (DK); ——— (SF); ··· (EF); − − − (WF); − − − (NF); ··· (SS); ··· (CS); ——— (NS).
Technical Appendix

Consider the specification for Model II,

\[ \ln y_{ijt} = \pi_0(S_{ijt}, C_{ij}) + \sum_{k=1}^{K} \pi_k(S_{ijt}, C_{ij})\ln x_{k,ijt} + \pi_t(S_{ijt}, C_{ij})t + u_{ijt} \]  \hspace{1cm} (A.1)

\[ \pi_k(S_{ijt}, C_{ij}) = \alpha_{0k} + \alpha_{1k}C_{1,ijt} + \alpha_{2k}C_{2,ijt} + \cdots + \alpha_{M-1,k}C_{M-1,ijt} + \alpha_{sk}\ln S_{ijt}, \text{ for } k = 1, \ldots, K, \]

\[ \pi_t(S_{ijt}, C_{ij}) = \alpha_{0t} + \alpha_{1t}C_{1,ijt} + \alpha_{2t}C_{2,ijt} + \cdots + \alpha_{M-1,t}C_{M-1,ijt} + \alpha_{st}\ln S_{ijt}, \]

\[ \pi_0(S_{ijt}, C_{ij}) = \beta_0 + \beta_1C_{1,ijt} + \beta_2C_{2,ijt} + \cdots + \beta_{M-1}C_{M-1,ijt} + \beta_s\ln S_{ijt} + v_{ijt}. \]

where \( C_{l_i} \) (\( l = 1, \ldots, M - 1 \)) are region dummies and region \( M \) is used as the reference group. For ease of exposition, we suppress the natural log notation. We rewrite the main equation as

\[ y_{ijt} = \pi_{0,ij} + \sum_{k=1}^{K} x_{k,ijt}^{*} \alpha_k + t^{*} \alpha_t + u_{ijt} \] \hspace{1cm} (A.2)

where \( x_{k,ijt}^{*} \) and \( t^{*} \) are the level 1 covariates interacted with the region dummies and subsidy, each has dimension \( 1 \times (M+1) \), and \( \alpha_k = (\alpha_{0k}, \alpha_{1k}, \ldots, \alpha_{M-1,k}, \alpha_{sk})' \), for \( k = 1, \ldots, K \), \( \alpha_t = (\alpha_{0t}, \alpha_{1t}, \ldots, \alpha_{M-1,t}, \alpha_{st})' \) and \( \tilde{x}_{ijt} = [x_{1,ijt}^{*}, x_{2,ijt}^{*}, \ldots, x_{K,ijt}^{*}, t^{*}] \) is the \( 1 \times (M+1) (K+1) \) row vector containing the entire collection of level 1 regressors with \( \Gamma = (\alpha_1', \alpha_2', \ldots, \alpha_K', \alpha_t')' \).

Let us define, \( \tilde{N}_i \equiv \sum_{r=1}^{i-1} N_r + 1 \) for \( i > 1 \), \( \tilde{N}_1 \equiv 1 \), and \( \overline{N}_i \equiv \sum_{r=1}^{i} N_r \). Here \( N_i \) is the number of distinct farms in region \( i \). We now consider a matrix formulation of this model. First, we stack the observations so that the fastest running index is time \( t \) (\( t = 1, \ldots, T_j \)), the second fastest running index is the farm index \( j \), \( j = \tilde{N}_i, \tilde{N}_i + 1, \ldots, \overline{N}_i \), and the slowest running index is the region index \( i \) (\( i = 1, \ldots, M \)), and write the model in region \( i \) as

\[ Y_i = (I_{N_i} \otimes \iota_{T_j}) \Pi_{0i} + X_i \Gamma + U_i, \]

\[ \Pi_{0i} = Z_i \beta + V_i \]

where \( \beta = (\beta_0, \beta_1, \ldots, \beta_{M-1}, \beta_s)' \) is the \((M+1)\times 1\) common-coefficient vector, \( Z_i = [\iota_{N_i}; C_{1,i}; C_{2,i}; \cdots; C_{M-1,i}; S_i] \) is the \( N_i \times (M+1) \) matrix of covariates at level 2 of the model, and

\[ Y_i = \begin{pmatrix} \ln y_{i,\tilde{N}_i} \\ \ln y_{i,(\tilde{N}_i+1)} \\ \vdots \\ \ln y_{i,\overline{N}_i} \end{pmatrix}, \quad X_i = \begin{pmatrix} \tilde{x}_{i,\tilde{N}_i} \\ \tilde{x}_{i,(\tilde{N}_i+1)} \\ \vdots \\ \tilde{x}_{i,\overline{N}_i} \end{pmatrix} \]
are respectively of dimensions $\sum_j T_j \times 1$ and $\sum_j T_j \times M(K + 2)$. $I_{N_i}$ is the identity matrix, $\nu T_j$ is a vector of ones of dimension $T_j$, and $\otimes$ denotes the Kronecker product. With the error assumptions of $U_i \overset{iid}{\sim} N(0, \sigma_u^2 I_{\sum_j T_j})$ and $V_i \overset{iid}{\sim} N(0, \sigma_v^2 I_{N_i})$, the likelihood and population distribution respectively are

\[
Y_i | \Pi_0, \Gamma, \sigma_v^2 \overset{iid}{\sim} N((I_{N_i} \otimes \nu T_j)\Pi_0 + X_i\Gamma, \sigma_v^2 I_{\sum_j T_j})
\]

(A.3)

\[
\Pi_0 | \beta, \sigma_v^2 \overset{iid}{\sim} N(Z_i\beta, \sigma_v^2 I_{N_i})
\]

(A.4)

We append the following priors

\[
\beta \sim N(M+1)(\beta, \Sigma)
\]

(A.5)

\[
\sigma_u^{-2} \sim G(\nu/2, \delta/2)
\]

(A.6)

\[
\sigma_v^{-2} \sim G(\mu/2, \rho/2)
\]

(A.7)

\[
\Gamma \sim N(M+1)(K+1)(\Gamma, \Omega)
\]

(A.8)

and $G$ denotes the gamma distribution, $N(M+1)$ and $N(M+1)(K+1)$ are multivariate Gaussian distributions, and the hyperparameters $\Sigma, \nu, \delta, \mu, \rho, \Gamma, \Omega$ are prespecified constants. We now have a complete Bayesian hierarchical model. Using (A.3) to (A.8) it is straightforward to show that the full conditional posterior distributions are as follows:

Combining A.3 and A.4 we obtain

\[
[\Pi_0 | Y, \beta, \gamma, \sigma_u^2, \sigma_v^2] \sim N(N_i)(\overline{A}_i, \overline{p}_i, \overline{A}_i)
\]

(A.9)

where

\[
\overline{A}_i = \left(\sigma_v^{-2}I_{N_i} + \sigma_u^{-2}(I_{N_i} \otimes \nu T_j)'(I_{N_i} \otimes \nu T_j)\right)^{-1}, \quad \overline{p}_i = \left(\sigma_v^{-2}Z_i\beta + \sigma_u^{-2}(I_{N_i} \otimes \nu T_j)'(Y_i - X_i\Gamma)\right).
\]

Combining A.4 and A.5 we obtain

\[
[\beta | \Pi_0, \sigma_v^2] \sim N(M+1)(\overline{\beta}, \overline{B}),
\]

(A.10)

where

\[
\overline{B} = \left(\sigma_v^{-2} \sum_{i=1}^M Z_i'Z_i + B^{-1}\right)^{-1}, \quad \overline{\beta} = \overline{B}\left(\sigma_v^{-2} \sum_{i=1}^M Z_i'\Pi_0i + B^{-1}\beta\right)
\]

Similarly, combining A.6 and A.3 we obtain

\[
[\sigma_u^{-2} | Y, \Pi_0, \Pi] \sim G(\overline{\mu}/2, \overline{\rho}/2)
\]

(A.11)

where

\[
\overline{\mu} = \sum_{i=1}^M \sum_j T_j + \mu, \quad \overline{\rho} = \sum_{i=1}^M (Y_i - (I_{N_i} \otimes \nu T_j)\Pi_0i - X_i\Gamma)'(Y_i - (I_{N_i} \otimes \nu T_j)\Pi_0i - X_i\Gamma) + \rho.
\]
Recall that the index \( j \) depends on \( i \). Also, combining A.7 and A.4 we find

\[
[\sigma^{-2}_u \Pi_0, \beta] \sim G(\nu/2, \delta/2)
\]  

(A.12)

with

\[
\nu = N_M + d, \quad \delta = \sum_{i=1}^{M} (\Pi_{0i} - Z_i\beta)'(\Pi_{0i} - Z_i\beta) + \delta.
\]

Finally, we find the full conditional posterior of \( \Gamma \) to be

\[
[\Gamma | Y, \Pi_0, \sigma_u^2] \sim N(M+1)(K+1)(\Gamma, \Omega)
\]  

(A.13)

where

\[
\Gamma = \left( \sigma_u^{-2} \sum_{i=1}^{M} X'_i X_i + \Omega^{-1} \right)^{-1}, \quad \tau = \Pi \left( \sigma_u^{-2} \sum_{i=1}^{M} X'_i (Y_i - (I_{N_i} \otimes I_T) \Pi_{0i}) + \Omega^{-1} \Gamma \right).
\]

For estimation, we assign values to the parameters of the prior distributions. We consider different sets of hyperparameter values but each set is proper and informative. Economic theory provides us with some guidance to restricting some of these values. For example, input elasticities and returns to scale are nonnegative. We assume \( a_{0k} \in \{0.2, 0.3, 0.4, 0.5\} \), \( a_{sk} \in \{0, 0.2, 0.3, 0.4, 0.5\} \), \( a_{0t} \in \{0.02, 0.03, 0.04\} \), \( a_{st} \in \{0, 0.02, 0.03, 0.04\} \), \( b_0 \in \{0.5, 1.0, 1.5\} \), \( b_s \in \{0, 0.2, 0.3, 0.4, 0.5\} \). We define \( \alpha \equiv (\alpha'_1, \alpha'_2, \ldots, \alpha'_K, \alpha'_M)' \), with \( \alpha_k \equiv (a_{0k}, a_{1k}, \ldots, a_{M-1,k}, a_{s,k})' \), for \( k = 1, \ldots, K \), and \( \alpha_s \equiv (a_{0s}, a_{1s}, \ldots, a_{M-1,s}, a_{s,s})' \). Then if we set \( \alpha_k \equiv (a_{0k}, a_{1k}, \ldots, a_{M-1,k}, a_{s,k})' = (0.2, 0, \ldots, 0, 0)' \) for \( k = 1, \ldots, 5 \), our prior is that farms exhibit constant returns to scale, there are no regional differences in input elasticities and subsidy has no impact on the productivity of all inputs. If we choose \( a_{0k} = 0.3 \) for \( k = 1, \ldots, 5 \), then our prior is that farms exhibit increasing returns to scale. For simplicity, we assume a priori that the parameters within \( \beta \) and \( \Gamma \) are uncorrelated. Nevertheless we choose their prior variances to be diffuse so that the information in the data can contribute more to their posterior correlations. We set \( \Sigma = c_s \times 10^4 \ diag(1,1,\cdots,1,1) \) and \( \Omega = c_s \times 0.04 \ diag(1,1,\cdots,1,1) \) where \( c_s = 1, 10 \). Also, we choose \( \sigma_u^{-2} \sim G(c_u 10^{-6}, c_u 10^{-6}) \), and \( \sigma^{-2}_v \sim G(c_v 10^{-6}, c_v 10^{-6}) \) with \( c_u, c_b = 1, 10, 100 \). Here \( c_s \), \( c_u \) and \( c_b \) are generic, pre-specified constants that may take different values across priors. We carry out posterior simulation for this model by sequentially drawing from (A.9), (A.10), (A.11), (A.12), and (A.13). For the empirical results reported, the hyperparameter values are \( a_{0k} = 0.5 \) for all \( k = 1, \ldots, 5 \), \( a_{0t} = a_{st} = 0.02 \), \( b_0 = 1.0 \), \( b_s = 0.5 \), \( c_s = 1 \), \( c_a = c_b = 1 \). We find that in our sensitivity analysis, the information in the data dominates the information in the prior. That is, our the qualitative implications of our findings are invariant to the choice of prior values, even for extreme values. This is expected given the large sample size. For model I, our sets of hyperparameter values are similar to those we use for model II.