The Economic Benefits of Farm Diversification:
An Empirical Analysis of Economies of Scope Using the Dual Approach

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Abstract

Structural change in agriculture often comes along with a trend towards intensification and specialization as it allows farms to capture economies of scale and thus reduce costs. However, society rather favors diversified and less intensive farms. In this article, we aim to analyze the extent farms can economically benefit from diversification. To this end, we estimate an input-oriented stochastic distance function (IDF) to evaluate diversification economies on dairy farms in Southern Germany in a Bayesian framework. Specifically, we empirically estimate scope economies between different farm outputs for a panel data set of Bavarian dairy farms covering the years 2006 - 2014. To be consistent with economic theory, we impose the regularity conditions of monotonicity and curvature on the IDF. The results show that smaller farms are more likely to benefit from diversification between milk and livestock production while larger farms are more likely to benefit from diversification between milk and crop production. This finding has clear management implications as it advises farm managers on how to optimize their farms' production structure in terms of output combination and depending on farm size.

Keywords

Bayesian Estimation, Economies of Scope, Farm Diversification, Input Distance Function

Introduction

The optimal production structure of firms in terms of size and degree of specialization has been questioned for decades. Especially in agriculture, a significant structural change has been observed in recent years. While the number of farms in the EU-18 decreased by 25 per cent from 14.5 Mio in 2005 to 10.8 Mio in 2013, the average farm size increased by 31 per cent from 21.4 to 28.1 hectares (Eurostat, 2016). This trend towards larger but fewer farms is often critically seen by society and politics. In order to slow down the structural change and to support rural development, the European Union promotes farm activities that go beyond agricultural production such as farm tourism or direct marketing. However, the concept of diversification is not limited to activities that take place outside agricultural production. Since our primary interest is in structural change in agriculture, which is defined by the number of farms and the average farm size expressed in utilized agricultural area, we put our focus on farm diversification within agricultural production, for example the joint production of livestock products and cash crops. The article aims to investigate whether promoting diversification within agricultural production can be an effective measure to slow down the structural change. For this purpose, we empirically estimate economies of scope in a sample of dairy farms in Bavaria, a federal state in Southern Germany, and group the outputs into milk, other livestock products, crops sales, and other outputs such as electricity production or contract services. If considerable economies of scope exist between two or more outputs, costs could be reduced by jointly producing these outputs and thus farm diversification would increase competitiveness.

A large body of previous literature has estimated economies of scope based on cost functions: In the agricultural sector, FERNANDEZ-CORNEJO et al. (1992) find cost complementarities between various pairs of milk, cattle, crop, and hog production in Germany. WU and PRATO (2006) show that cost complementarities exist between crop and livestock production in Missouri, US, even though challenged by a reduction of allocative efficiency. MELHIM and SHUMWAY (2011) show that the degree of scale and scope economies decreases with farm size in their respective sample of farms, implying that larger farms have less incentives to diversify production than smaller farms. Studies estimating economies of scope based on a cost function in non-agricultural sectors include CANTOS and MAUDOS (2001), FARSI et al. (2007), and TRIEBS et al. (2016). However, estimating a cost function is problematic if input price data are not accessible or lack variation across firms. Thus, several studies interested in diversification economies used distance functions as an alternative approach to model multi-output technologies. For example, COELLI and FLEMING (2004) evaluate diversification economies between coffee, subsistence food and cash food production in Papua New Guinea using an input distance function, PAUL and NEHRING (2005) assess the impact of scale and scope economies on farm performance in the United States, RAHMAN (2009) finds evidence of diversification economies between various crop combinations in Bangladesh, and CHAVAS and DI FALCO (2012a) find complementarities among different field crops in Ethiopian farms. However, these studies measure scope economies purely based on output complementarities and thus do not consider the possibility of a change in input composition. In contrast, we apply the dual measure of economies of scope proposed by HAJARGASHT et al. (2008) that has also been applied by FLEMING and LIEN (2009) in the farm context, who calculated economies of scope in Norwegian agriculture. Since they restricted the analysis to the sample mean of their data, we contribute to the literature by estimating scale and scope economies at the farm level. This allows analyzing which farms are operated at optimal levels of diversification and whether farms have moved to more optimal levels of diversification over time. In a further step, it will also facilitate the identification of factors that prevent farms from operating at the optimal level of output combination. Additionally, as opposed to previous literature in this field, we impose regularity conditions (monotonicity and curvature) to comply with economic theory and discuss how this affects the results.

Conceptual Framework

Introduced by BAUMOL (1977), BAUMOL et al. (1982) and WILLIG (1979), economies of scope exist when less costs occur for a multi-output firm than for multiple firms producing the same amount of output separately, i.e.,

$$C\left(\sum_i y^i\,; p\right) < \sum_i C\left(y^i; p\right), \tag{1}$$

where C denotes costs, y^i the i-th output, and p is a vector of input prices. Commonly in the literature, the relation in (1) is empirically evaluated based on the estimated parameters of a cost function (e.g. FERNANDEZ-CORNEJO et al. (1992), MELHIM and SHUMWAY (2011), WU and PRATO (2006)). However, by setting different output values to zero, the cost function is evaluated outside the data range in this approach, and it is implicitly assumed that firms with different specializations and different levels of diversification share one common technology. Moreover, estimating a cost function is problematic if input price data are not accessible (e.g. the price of capital) or lack variation across firms. In the empirical case of this study, nationwide price indices are available for many inputs but no price data on sub-regions or even farm-level. For these reasons, we prefer a dual approach in this study proposed by HAJARGASHT et al. (2008) that allows evaluating economies of scope based on the parameters of a distance function (IDF). The IDF describes the degree to which a firm can contract its input vector without changing its output vector (O'DONNELL and COELLI, 2005). As it is dual to the cost function, it allows to deriving point estimates of the latter. Another advantage of distance functions over cost functions is that they do not impose any behavioral assumptions such as cost-minimization.

(see what recent AJAE publications write about distance functions here)

To define the IDF, let y be a firm's output and x its input. Then, the input set of the production technology is defined as

$$L(y) = \{x: (y, x)\,\epsilon\, T\}, \tag{2}$$

where $x \epsilon R_+^N$ and $y \epsilon R_+^N$ are vectors of input and output quantities, respectively. The input distance function is then formally represented by

$$D_I(x,y) = max \left\{\lambda: \frac{x}{\lambda} \epsilon L(y)\right\}. \tag{3}$$

In equation (3), λ is a scalar between 1 and infinity. Firms with $\lambda = 1$ are called technically efficient, because they operate on the boundary of the input requirement set. If $\lambda > 1$, it is possible to produce the same amount of output with less input and therefore these firms are said to be technically inefficient. O'DONNELL and COELLI (2005) emphasize that the duality of input (or output) distance functions and cost (or revenue) functions rely on theoretical properties of the input (or output) distance functions: to be consistent with economic theory, the IDF must be non-decreasing, concave, and homogenous in inputs, and non-increasing and quasi-concave in outputs. As our empirical results strongly depend on duality, we put a particular focus on these regularity conditions. Specifically, we estimate and present both an unrestricted and a restricted distance function where monotonicity and concavity are imposed[1].

As shown in Färe and Primont (1995), duality theory allows specifying the cost function as a function of the input distance function:

$$C(p,y) = \min\{p'x: D(x,y) \geq 1\} \tag{4}$$

HAJARGASHT et al. (2008) use this relationship to derive an expression for the second order derivatives of the cost function, which are needed to evaluate economies of scope, in terms of the derivatives of an input distance function. Making use of Shephard's (1954) lemma ($x = C_p(p,y)$) and the envelope theorem, they show that the matrix of scope economies is given by

$$C_{yy} = C\{D_y D_y' - D_{yy} + D_{yx}[D_{xx} + D_x * D_x']^{-1} D_{xy}\}, \tag{5}$$

where D_x is a vector of first derivatives and D_{xy}, D_{xx}, and D_{yy} are matrices of second-order derivatives. It can be easily shown, that a sufficient condition for the presence of economies of scope is given by

$$Sco_{mn} = \frac{\partial c(y,p)}{\partial y_m y_n} < 0, m \neq \text{n}. \tag{6}$$

[1] At the time of submission of this draft, we did not have the results for the restricted model. However, we are confident to achieve this during the next few weeks.

Thus, equation (5) can be used to evaluate the presence of (dis-) economies of scope. The resulting matrix holds the economies of scope between product *m* and *n* as defined in (6) in the (*m*, *n*)-th element. Note that this measure does not require extrapolating the data to regions where there are no data points. Instead, it measures the change in marginal costs of producing the m-th output as a response to a change in the production of the n-th output.

It also becomes clear from equation (5) that a positive (negative) sign in $\mathrm{D_{yy}}$ is not a sufficient condition for scope (dis-)economies. It purely reflects output complementarities, which neglects the possibility of changing the input mix. This is the reason why CHAVAS and DI FALCO (2012a), COELLI and FLEMING (2004), or PAUL and NEHRING (2005) refer to diversification economies rather the economies of scope in their analysis of diversification benefits using $\mathrm{D_{yy}}$.

Empirical Model

The IDF is specified in a transcendental logarithmic (translog) form for M outputs and K inputs:

$$\begin{aligned} ln\, D_{it}^{I}(x,y,t) = {} & \alpha_i + \sum_m \beta_m \ln y_{mit} + \sum_k \beta_k \ln x_{kit} + \frac{1}{2}\sum_m \sum_n \beta_{mn}\, y_{mit} y_{nit} \\ & + \frac{1}{2}\sum_k \sum_l \beta_{mn} x_{kit} x_{lit} + \sum_m \sum_k \beta_{mk}\, y_{mit} x_{kit} \\ & + \beta_t\, t_i + \sum_m \beta_{mt}\, y_m t + \sum_k \beta_{kt} x_m t \\ = {} & TL(y,x,t) \end{aligned} \tag{7}$$

Since the distance is not observable, equation (7) must first be transformed to make it empirically estimable. Following LOVELL et al. (1994), D_i is normalized by one of the inputs to impose linear homogeneity with respect to inputs as required by economic theory. Homogeneity implies that $D_i(x, \omega y) = \omega D_i(x,y)$ for any $\omega > 0$. Using the M-th input as normalizing factor and setting $\omega = 1/x_m$ yields $D_i(x/x_M, y) = D_i(x,y)/x_m$. After rearranging and including error terms, equation (7) can be written in the estimable form of

$$-\ln x_{kit} = TL(\tilde{x}_{kit}, y_{mit}, t_{it}) - u_{it} + v_{it}\,, \tag{8}$$

where v_{it} is an independently and identically distributed error term with mean zero and variance σ_v^2 and $u_{it} = \ln D_I(x,y,t)$ is a one-sided error term that is also independently and identically distributed but truncated at the mean to reflect inefficiency. To allow firm-specific technical efficiency to be varying over time, we adopt the approach proposed by BATTESE and COELLI

(1992) to model $u_{it} = \left(u_i \exp\left(-\eta(t-T)\right)\right)$, where η is a parameter to be estimated. Some of the outputs considered in this study take zero values for a considerable number of observations, which cannot be accommodated in a translog functional form as the logarithm of zero is not defined. Excluding these observations from the analysis would lead to a significant loss of information, and replacing zero values with arbitrarily small numbers to a serious bias in the estimation of parameters. Therefore, to obtain the true estimation parameters, we use dummy variables that indicate whether output m is zero or greater than zero as described in BATTESE (1997).

Several concerns about endogeneity have been raised in the context of the estimation of input distance functions. The assumption of exogenous outputs can be justified by the premise of cost minimizing behavior by firms, because the production of milk was limited by a dairy quota during the period of the data[2]. However, there is concern that the distance functions still suffers from endogeneity because of the input ratios used as explanatory variables. Due to the normalization of inputs in the estimation process, the left-hand-side variable appears in the denominator of some right-hand-side variables. This simultaneity of the input allocation leads to correlation with the error term. As we do not have any valid instrumental variables at hand, we do not attempt to correct such potential bias.

A Bayesian approach was selected to empirically estimate equation (8) for two reasons. First, the dual measure of economies of scope as defined in equation (5) is a complex non-linear function of the estimated parameters of the IDF. Thus, it is not straightforward to compute standard deviations of the resulting scope measures in a frequentist statistic approach. In contrast, estimating the IDF in a Bayesian framework allows us to calculate credibility intervals for the resulting scope economies based on the results from numerous successive draws from the posterior distribution. Second, the Bayesian approach offers a convenient and intuitively appealing method to impose regularity conditions on (8) (O'DONNELL and COELLI, 2005) without destroying the flexibility of the translog functional form.

To this end, we adopt a stochastic frontier model with farm-specific individual effects as described in KOOP (2010). Following this approach, we use independent Normal-Gamma priors for the individual effects and coefficients of the IDF and a hierarchical prior for the inefficiencies. The best fitting model was achieved with an exponential distribution for inefficiency. For a more rigorous explanation of the priors used, please refer to KOOP (2010, p. 170). The likelihood function depends on assumptions about the error terms. The usual

[2] It is often stated that an advantage of IDF over cost functions is that no behavioral assumptions have to be made. This is true for the general concept of distance functions and does not refer to econometric issues.

assumptions are that ε_i is normally distributed around 0_T with the covariance matrix $h^{-1}I_T$, ε_i and ε_j are independent for $i \neq$ j, and all variables are independent of the error terms. In the stochastic frontier model, it is further assumed that z_i and ε_j are independent of each other. Together with the IDF specification in equation (8), these assumptions imply the likelihood function

$$p(y|\beta, h, v) = \prod_{i=1}^{N} \frac{h^{\frac{T_i}{2}}}{(2\pi)^{\frac{T_i}{2}}} \left\{\exp\left[-\frac{h}{2}(y_i - X_i\beta + v_i\iota_T)'\left(y_i - \tilde{X}_i\beta + v_i\iota_T\right)\right]\right\}, \tag{9}$$

where N denotes the number of observations and T_i is the number of observations for the i-th farm to account for the unbalanced panel data set. The dependent variable is represented by y and X is the vector of independent variables. Further, ι_T is a T-vector of ones, h is the error precision $1/\sigma^2$, and β is the vector of unknown parameters to be estimated. Statistical inference about the marginal posterior distributions of β is made by successively drawing sample observations from the posterior $p(\beta|y)$ using MCMC methods. In the unrestricted model, we make use of the basic Gibbs sampler, a sampling algorithm that draws from the joint posterior density by sampling from a series of conditional posteriors (see GELFAND and SMITH (1990) for a detailed explanation). A burn-in period of 5000 replications followed by 45000 sampling replications proved to be enough for the model to converge and provide consistent estimates of the parameters. In the restricted version of the model, we employed a Metropolis-Hastings algorithm that assigns zero weights to all likelihood values for proposed vectors of parameters where the monotonicity or curvature conditions are violated. This procedure was adopted in the WinBUGS software as outlined in GRIFFIN and STEEL (2007). We first attempted to impose the regularity conditions on each observation in the data set but this procedure was computationally too hard to solve[3]. In addition, if the conditions are imposed at every data point, the restrictions would become close global and therefore suffers from a loss in flexibility. As RYAN and WALES (2000) argue, imposing constraints on an appropriate reference point can lead to satisfaction of the regularity conditions at most data points in the sample. While GRIFFITHS et al. (2000) imposed the regularity conditions on 23 representative price points in a cost function

[3] With 11,459 observations in the dataset, imposing regularity conditions on each individual data point would require more than 100,000 constraints. With that many constraints, the probability that none of them is violated approaches zero.

framework, we chose to imposed the restrictions on the sample mean only to keep it computationally simple. By dividing all variables by their sample mean prior to estimation (i.e., the logarithm of these means become equal to zero), the translog IDF is non-decreasing in inputs and non-increasing in outputs at the sample mean if $\beta_{x_n} \geq 0$ and $\beta_{y_n} \leq 0$. Concavity in inputs and quasi-concavity in outputs is satisfied if the (bordered) Hessian matrix of inputs (outputs) is negative semidefinite. For translog functional forms, as it is shown by DIEWERT and WALES (1987) for the case of cost functions, the Hessian matrix of inputs is negative definite if and only if $A - SS' - S^k$ is negative semidefinite. A is the matrix of the second-order derivatives of $\ln D$ with respect to $\ln x_{mn}$, S are the elasticities, and S^k is a $k\ x\ k$ diagonal matrix of elasticities. Therefore, to impose the restrictions at the sample mean, we only accept draws where the following matrix has non-positiv eigenvalues:

$$M_{inp} = \begin{bmatrix} \beta_{x1x1} + \beta_{x1}\beta_{x1} - \beta_{x1} & \cdots & \beta_{x1xn} + \beta_{x1}\beta_{xn} \\ \vdots & \ddots & \vdots \\ \beta_{xnx1} + \beta_{xn}\beta_{x1} & \cdots & \beta_{xnxn} + \beta_{xn}\beta_{xn} - \beta_{xn} \end{bmatrix} \quad (10)$$

Analogously, to ensure quasi-concavity in outputs at the sample mean, we impose non-positive eigenvalues on the bordered matrix

$$M_{outp} \begin{bmatrix} 0 & \beta_{y_1} & \cdots & \beta_{y_n} \\ \beta_{y_1} & \beta_{y_1y_1} + \beta_{y_1}\beta_{y_1} - \beta_{y_1} & \cdots & \beta_{y1yn} + \beta_{y1}\beta_{yn} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{y_n} & \beta_{y_ny_1} + \beta_{y_n}\beta_{y_1} & \cdots & \beta_{y_ny_n} + \beta_{y_n}\beta_{y_n} - \beta_{y_n} \end{bmatrix} \quad (11)$$

Data Description

Farm accounting data were obtained from the Bavarian State Ministry for Food, Agriculture, and Forestry, which annually collects data from a representative rotating sample of farmers as part of the German contribution to the EU Farm Accountancy Data Network. In addition to balance sheets and income statements, the data set contains information on animal stock, land use, farm equipment, inventories, labor, crop yields, received prices, and further details on the farm and the farm manager. From this data set, we created an unbalanced panel that covers nine years from 2006 to 2014. To secure a homogenous technology for the analysis, the sample has been reduced to farms that made at least 66 per cent of total revenue from the dairy enterprise with a share of at least 66 per cent from milk production on average over the 9 years of data. Thus, the data set consists of specialized dairy farms but still contains a wide range of farming activities in order to evaluate diversification economies. The final sample consists of 1554 farms and 11,459 total observations.

Since our focus is on diversification economies between multiple farm outputs, we illustrate the revenue shares from the resulting sample in figure 1. As a consequence of the sample construction, the dairy enterprise accounts for the major portion of farm revenue. On average, milk sales account for 72 % of the obtained revenue, and livestock sales intrinsically linked to milk production (mainly the sale of calves and old dairy cows) contribute 8 %. Revenue from downstream fattening of cattle contribute 11 % to the total revenue, and crop sales and other output account for only 3 or 4 % of revenue, respectively.

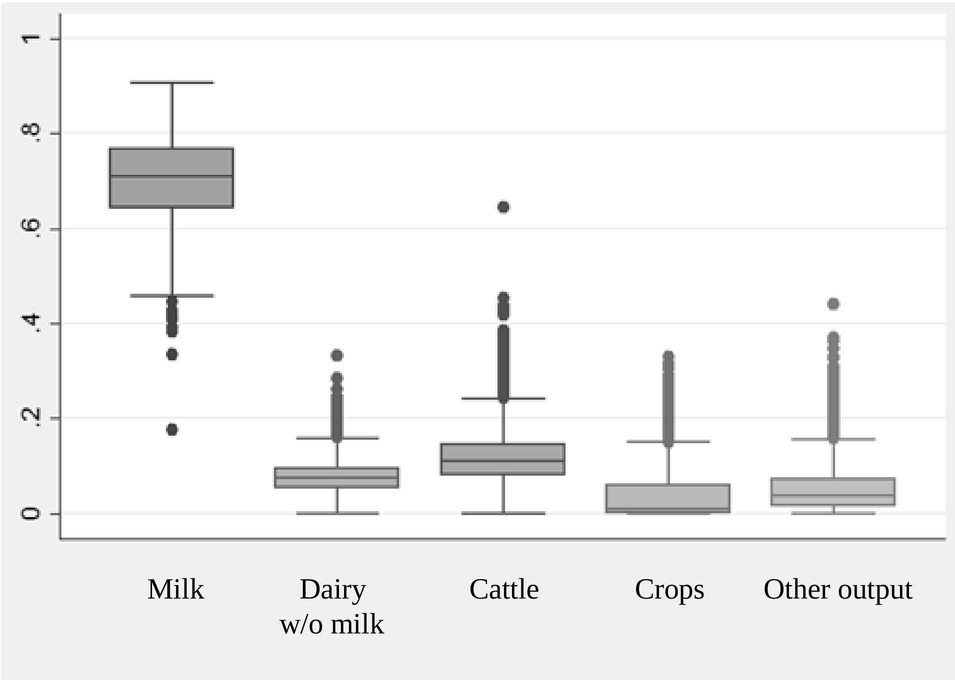

Figure 1. Share of various activities of farms in the sample

To estimate the empirical model, we reduce the outputs to four groups by combining dairy without milk and cattle. All outputs are measured in revenues deflated by their respective nationwide price indices from the Destatis database. This way, we obtain implicit quantities that also reflect quality differences. As discussed in REINHARD et al. (1999), dividing the revenue by price indices that do not vary across farms cancels out price differences that result from a variation in quality. Regarding the inputs, land is measured in hectares and labor in annual working units. Intermediate inputs include both animal-specific inputs (feed and veterinary inputs) and crop-specific inputs (seed, fertilizer, pesticides, and other crop material) and also other intermediate inputs such as electricity, fuel, or heating material.

Like the output measures, the individual components of the intermediate inputs are deflated by their respective price indices to obtain implicit quantities. Lastly, capital is proxied by depreciation costs. We categorize the farm inputs into fewer groups than most empirical studies. The reason is purely mathematical, as more variables lead to larger matrices in equation (5) which complicates and considerably slows down the Markov chain process. The summary statistics of the variables used in the empirical model are presented in table 1.

Table 1. Summary Statistics of Variables

Variables	Unit	Mean	St. Dev.	Min	Max
Milk	1000 c€	94.21	55.49	0.62	599.02
Livestock	1000 c€	25.97	17.14	0.30	276.93
Crops	1000 c€	6.60	12.68	0.00	156.67
Other outputs	1000 c€	6.05	10.82	0.00	367.11
Capital	1000 c€	230.71	175.19	4.05	2753.34
Land	ha	48.15	27.67	0.14	291.77
Interm. Inputs	1000 c€	51.42	31.02	3.72	382.28
Labor Labor	awu	1.59	0.48	0.30	4.97

n = 11,459
c€ = constant €, ha = hectares, awe = annual working units

Results and Discussion

All variables have been divided by their sample mean prior to estimation so that first-order coefficients can be interpreted as elasticities at the sample mean. The capital variable is used as numeraire, and parameter estimates that contain the numeraire are recovered after the estimation by making use of the homogeneity conditions as outlined in COELLI and PERELMAN (1999), for example. The Bayesian first-order estimates of the unrestricted IDF and the corresponding first-order ordinary derivatives are presented in table 2. As a robustness check to the Bayesian estimation method, we also present the corresponding parameter estimates of a maximum likelihood (ML) estimation.

Table 2. Bayesian MCMC and ML Estimates of the IDF First-Order Terms

	mean	St. Dev.	95%-credible interval		Parameter estimate ML	St. Err. ML
Output milk	-0.3064	0.0065	-0.3190	-0.2928	-0.3029	0.0062
Output livestock	-0.0303	0.0034	-0.0367	-0.0237	-0.0304	0.0033
Output crops	-0.0189	0.0014	-0.0219	-0.0161	-0.0190	0.0014
Output other	-0.0071	0.0010	-0.0090	-0.0053	-0.0071	0.0010
Capital	0.0272	0.0030	0.0210	0.0330	0.0275	0.0028
Land	0.4799	0.0074	0.4644	0.4937	0.4750	0.0071
Interm. Inputs	0.2706	0.0064	0.2570	0.2828	0.2711	0.0065
Labor	0.2223	0.0053	0.2120	0.2332	0.2264	0.0052

As shown in table 2, parameter estimates obtained from Bayesian and ML estimation proved to be almost identical. Thus, we are confident that the Bayesian framework is adequately adopted. In total, 42 of 54 parameters are statistically significant at the 10 % significance level and the hypothesis that a Cobb-Douglas functional form is a better fit is clearly rejected.

With regard to regularity conditions of the IDF, it becomes clear from table 2 that the IDF is decreasing in outputs and increasing in inputs at the sample mean. Checking the distance elasticities $\frac{\partial \ln D^I}{\partial \ln x}$ and $\frac{\partial \ln D^I}{\partial \ln y}$ for each individual observation reveals that monotonicity in inputs and outputs are satisfied at most data point in the sample (see table 3). For the distance function to be concave in inputs, the Hessian matrix of inputs must be negative-semidefinite. We find that this not only the case at the sample mean but also for the vast majority of observations except for the land variable. KUMBHAKAR et al. (2008) also find some concavity violations for land, arguing that this might arise from the fact that land is a less variable input. In contrast, quasi-convexity in outputs is fulfilled neither at the sample mean nor in many observations. This observation underlines the importance of imposing curvature conditions as emphasized by SAUER (2006).

Table 3. Farm-level Elasticities and Regularity Violations, Unrestricted Model

	Mean	Std. Dev.	Min	Max	Violations
Monotonicity					
E_{y1}	-0.3104	.0598	-.9816	0.0299	1
E_{y2}	-0.0297	.0211	-.1897	0.1633	871
E_{y3}	-0.0182	.0069	-.0432	0.0207	333
E_{y4}	-0.0055	.0050	-.0269	0.0155	1608
E_{x1}	0.0294	.0167	-.0316	0.1036	393
E_{x2}	0.4556	.1042	-.8681	0.8231	11
E_{x3}	0.2689	.0669	-.0376	1.0519	1
E_{x4}	0.2461	.0745	-.0241	0.7508	2
Curvature					
Quasi-concavity in outputs					11113
Concavity in inputs					7124

n = 11,459

The full parameter estimates of both the restricted and unrestricted model are presented in table A1 in the appendix. Due to the trade-off between statistical fit and theoretical consistency (see, e.g., TERRELL, 1996), we present and compare the results of both models in the following. The measures for the sufficient condition for (dis-)economies of scope, Sco_{mn}, are presented in table A2. At the sample mean, we observe economies of scope between milk and other outputs, and crop and other outputs, and diseconomies of scope between milk and livestock production, milk and crops, livestock and crops, and livestock and other outputs in the unrestricted model. In the restricted model, we observe economies of scope between milk and crops, milk and other outputs, and crops and other outputs, and diseconomies of scope between milk and livestock, livestock and crops, and livestock and other outputs. However, none of these measures are statistically significant at the 10 % significance level, and thus it is not surprising that these results are not robust compared to the restricted model. As we analyze specialized dairy farms, we are mainly interested in scope economies between milk and livestock production and milk and crop production. The share of observations with scope economies between milk and livestock and milk and crops is roughly the same between the two models. One interesting question is the impact of farm size on potential benefits from diversification. To address this point, observations associated with economies of scope and diseconomies of scope are plotted against the number of dairy cows at the farm (as proxy of farm size) and the level of specialization in figures A1 and A2 in the appendix. Figure A1 indicates that farms that benefit from diversification between milk and livestock production are more dominant among smaller farms in terms of herd size, while larger farms are more likely to benefit from specialization (i.e. show diseconomies of scope). On the other hand, larger farms are more likely to benefit from diversification between milk and crop production than smaller farms (Fig. A2). These findings are backed up by numbers: The average herd size among farms with economies of scope between milk and livestock production is 37.89 cows and the number of cows among farms with diseconomies of scope is 57.21 on average. Further, farms that experience economies of scope between milk and crop production milk 58.65 cows on average while farms that experience economies of scope between milk and crop production keep 42.69 cows on average. Simple t-tests confirm that the differences are statistically significant at the 1 % significance level.

Conclusion

In this study, we analyzed economies of scope for a representative sample of Bavarian dairy farms. As curvature conditions of the estimated input distance function where considerably violated, we estimated an alternative model where regularity conditions were imposed at the sample mean. Economies of scope differed between the models, but turned out to be non-significant in neither of them if evaluated at the sample mean. However, the share of farms that experience economies of scope between milk and livestock and milk and crop production, respectively, was in a similar range. Further analysis showed that smaller farms are more likely to benefit from diversification between milk and livestock production, whereas larger farms tend to benefit from diversification between milk and crop production. One possible explanation is that farms with larger herd sizes adopt new technologies that are less labor-intensive, and thus more labor is available for engaging in crop production. Smaller farms, on the other hand, tend to be operated with older technologies that require a larger amount of labor. Still, these farms can benefit from diversification between milk and livestock production, as these two production systems share more common inputs than milk and crop production. A second explanation may be that smaller farms accumulate in less-favored areas that do not allow crop production because of the soil quality. Thus, these farms experience diseconomies of scope between milk and crop production.

Finally, it has to be noted that not only economies of scope but also risk considerations determine production decisions. In this study, we only looked at the technological relationship between multiple outputs. If a farm manager’s strategy is to reduce price risk and production risk by output diversification, it can be beneficial to diversify even if experiencing diseconomies of scope between two or more outputs. CHAVAS and DI FALCO (2012b), for example, provide an empirical analysis on the relative contribution of risk and scope economies towards production decisions.

Appendix

Table A1. Bayesian Estimates for Unrestricted and Restricted IDF

	Unrestricted Model				Restricted Model			
Parameter	Posterior mean	St. Dev.	95% CrI		Posterior mean	St. Dev.	95% CrI	
b_ycro0	0.033	0.003	0.027	0.038	-0.291	0.013	-0.315	-0.257
b_yoth0	0.025	0.004	0.018	0.032	-0.11	0.027	-0.161	-0.066
b_y1	-0.306	0.006	-0.319	-0.293	-0.22	0.003	-0.228	-0.217
b_y2	-0.030	0.003	-0.037	-0.024	-0.079	0.005	-0.086	-0.073
b_y3	-0.019	0.001	-0.022	-0.016	-0.132	0.003	-0.134	-0.127
b_y4	-0.007	0.001	-0.009	-0.005	-0.198	0.001	-0.201	-0.195
b_y1y1	-0.031	0.006	-0.043	-0.019	-0.382	0.006	-0.391	-0.37
b_y1y2	0.029	0.004	0.020	0.037	-0.084	0.006	-0.094	-0.076
b_y1y3	0.004	0.002	0.001	0.008	0.014	0.001	0.011	0.016
b_y1y4	0.002	0.001	-0.001	0.004	0.022	0.002	0.019	0.026
b_y2y2	-0.005	0.004	-0.014	0.004	-0.148	0.004	-0.156	-0.144
b_y2y3	-0.001	0.001	-0.003	0.002	0.019	0.003	0.014	0.024
b_y2y4	0.000	0.001	-0.002	0.002	0.032	0.007	0.024	0.043
b_y3y3	-0.005	0.001	-0.007	-0.004	-0.286	0.000	-0.287	-0.286
b_y3y4	0.000	0.000	-0.001	0.000	0.08	0.003	0.077	0.083
b_y4y4	-0.003	0.001	-0.004	-0.002	-0.23	0.004	-0.235	-0.226
b_y1x2	0.149	0.007	0.135	0.163	-0.081	0.029	-0.132	-0.021
b_y1x3	-0.083	0.008	-0.100	-0.067	0.31	0.025	0.262	0.354
b_y1x4	-0.053	0.007	-0.065	-0.040	-0.37	0.026	-0.419	-0.316
b_y2x2	-0.040	0.006	-0.051	-0.029	-0.01	0.032	-0.061	0.056
b_y2x3	0.002	0.006	-0.010	0.014	0.064	0.033	-0.007	0.129
b_y2x4	0.040	0.006	0.028	0.051	-0.091	0.024	-0.137	-0.048
b_y3x2	0.001	0.002	-0.003	0.005	0.057	0.012	0.030	0.079
b_y3x3	-0.002	0.002	-0.006	0.003	0.16	0.014	0.136	0.189
b_y3x4	0.000	0.002	-0.004	0.004	-0.216	0.010	-0.240	-0.196
b_y4x2	0.004	0.002	0.001	0.007	-0.052	0.010	-0.073	-0.035
b_y4x3	0.002	0.002	-0.002	0.005	-0.058	0.009	-0.073	-0.04
b_y4x4	-0.006	0.002	-0.009	-0.002	0.000	0.009	-0.014	0.017
b_x2	0.480	0.007	0.464	0.494	0.121	0.025	0.073	0.164
b_x3	0.271	0.006	0.257	0.283	0.242	0.023	0.203	0.293
b_x4	0.222	0.005	0.212	0.233	0.486	0.024	0.443	0.52
b_x2x2	0.243	0.007	0.229	0.256	0.042	0.026	-0.009	0.091
b_x2x3	-0.160	0.011	-0.182	-0.139	0.074	0.030	-0.012	0.136
b_x2x4	-0.080	0.011	-0.101	-0.059	-0.167	0.021	-0.199	-0.122
b_x3x3	0.177	0.014	0.148	0.205	-0.186	0.041	-0.287	-0.122
b_x3x4	-0.054	0.011	-0.074	-0.033	0.255	0.017	0.224	0.282
b_x4x4	0.148	0.014	0.121	0.174	-0.188	0.023	-0.248	-0.139
b_t	0.000	0.007	-0.019	0.009	0.032	0.006	0.024	0.042

b_t2	-0.055	0.008	-0.068	-0.042	-0.054	0.004	-0.061	-0.045
b_y1t	-0.005	0.001	-0.007	-0.003	-0.003	0.005	-0.012	0.008
b_y2t	0.003	0.001	0.002	0.004	0	0.005	-0.009	0.009
b_y3t	0.000	0.000	0.000	0.000	0.014	0.002	0.010	0.017
b_y4t	0.000	0.000	-0.001	0.000	-0.002	0.002	-0.005	0.001
b_x2t	0.002	0.001	0.000	0.004	0.002	0.005	-0.008	0.013
b_x3t	0.003	0.001	0.001	0.005	0.006	0.006	-0.004	0.019
b_x4t	-0.001	0.001	-0.002	0.001	0.006	0.005	-0.004	0.016
b_year2	-0.237	0.024	-0.269	-0.193	-0.272	0.022	-0.317	-0.238
b_year3	-0.245	0.037	-0.293	-0.173	-0.389	0.027	-0.438	-0.339
b_year4	-0.397	0.045	-0.454	-0.307	-0.558	0.032	-0.613	-0.494
b_year5	-0.468	0.047	-0.531	-0.373	-0.684	0.036	-0.750	-0.622
b_year6	-0.396	0.041	-0.455	-0.310	-0.689	0.04	-0.762	-0.615
b_year7	-0.282	0.034	-0.339	-0.218	-0.653	0.036	-0.721	-0.599
b_year8	-0.221	0.040	-0.280	-0.132	-0.582	0.033	-0.644	-0.534
b_year9	0.075	0.063	-0.001	0.229	-0.355	0.037	-0.420	-0.281
b_x1	0.027	0.003	0.021	0.033	0.151	0.019	0.109	0.184
b_y1x1	-0.012	0.004	-0.021	-0.004	0.141	0.02	0.096	0.177
b_y2x1	-0.002	0.004	-0.009	0.006	0.038	0.024	-0.009	0.089
b_y3x1	0.001	0.001	-0.002	0.003	0	0.008	-0.017	0.016
b_y4x1	0.000	0.001	-0.002	0.002	0.11	0.008	0.095	0.127
b_x1x2	-0.003	0.006	-0.014	0.008	0.051	0.024	-0.000	0.095
b_x1x3	0.037	0.007	0.023	0.051	-0.143	0.038	-0.200	-0.042
b_x1x4	-0.014	0.006	-0.025	-0.003	0.1	0.025	0.046	0.151
b_x1x1	-0.020	0.006	-0.031	-0.009	-0.008	0.034	-0.089	0.042

n = 11459

Table A2. Economies of Scope Evaluated at the Sample Mean and at the Farm-level

	Unrestricted Model (30,000 runs)				Restricted Model (1000 runs)			
Output pairs	ESco at the Sample Mean	Mean ESco	SD ESco	Nr ESco <0	ESco at the Sample Mean	Mean ESco	SD ESco	Nr ESco <0
Milk – livestock	0.00017894 (0.0097451)	0.0006884	.0661447	5577/ 11459	0.00017655 (0.00382181)	0.0010836	.1024192	5247/ 11459
Milk – crops	0.00091118 (0.13248226)	-0.0003908	.0081225	1565/ 6306	-0.00126714 (0.0387272)	-0.0096966	.131423	2818/ 6306
Milk – other	-0.00027763 (0.04803606)	-0.0051363	.46173	7069/ 10796	-0.00011729 (0.02645438)	-0.0061379	.3640588	5256/ 10796
Livestock – crops	0.00008972 (0.00404193)	0.0001972	.0094924	1365/ 6306	0.00604426 (0.10615622)	-0.0238717	.2353762	4496/ 6306
Livestock – other	0.00005074 (0.00805)	0.0078577	.695059	1257/ 10796	0.00148931 (0.07877947)	-0.0252945	1.264514	8032/ 10796
Crops – Other	-0.00007482 (0.0337424)	0.0078577	.0751745	849/ 5946	-0.01278207 (0.00519116)	-0.5358597	14.55609	4002/ 5946

Standard deviations in parentheses

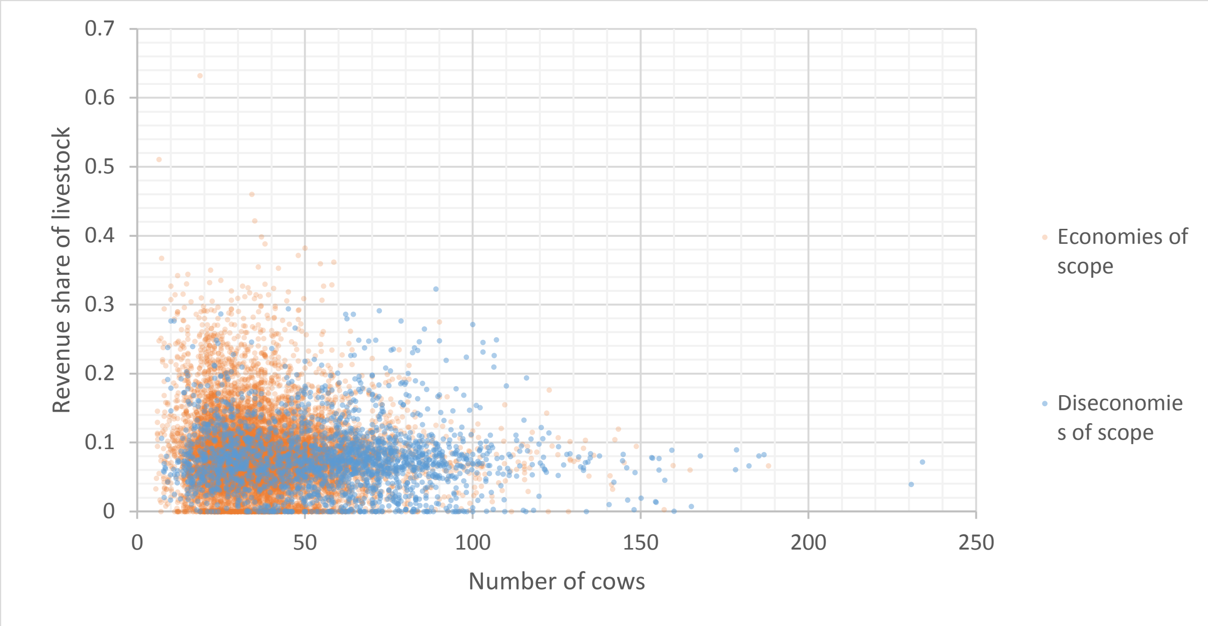

Figure A1. Farm size and (dis-)economies of scope between milk and livestock production

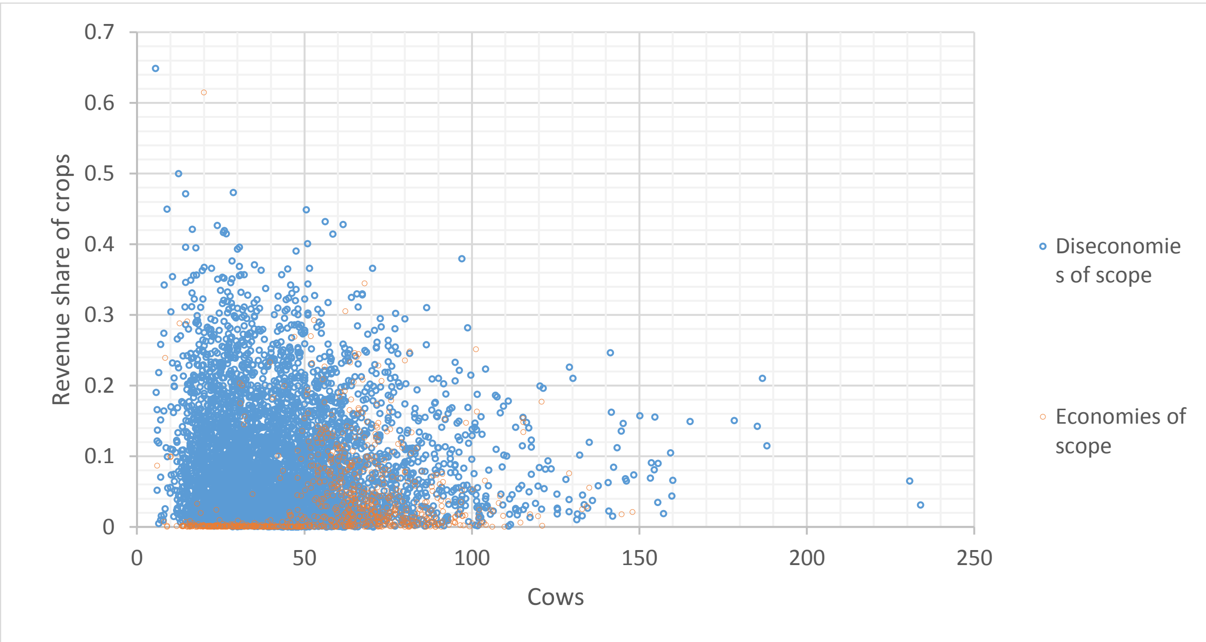

Figure A2. Farm size and (dis-)economies of scope between milk and crop production

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