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Paper Title	Specialization vs Diversification: An Application of the Dual Measure of Economies of Scope

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Abstract	***200 words max***
This study estimates an input-oriented stochastic distance function (IDF) to evaluate diversification economies on dairy farms in Southern Germany in a Bayesian framework. 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 often 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 empirically estimate scope economies between different farm outputs for a panel data set of Bavarian dairy farms covering the years 2006 - 2014. The results reveal that economies of scope exist between milk and livestock production and between livestock and crop production for the average farm in this sample. We further show that farms did not move towards are more optimal level of diversification over the time. From a policy perspective, we recommend to not only support diversification beyond agricultural production but also within and to facilitate the adjustment of farm strategies.	

Keywords	Agricultural Management, Bayesian Estimation, Economies of Scope, Farm Diversification, Input Distance Function
JEL Code	Q12

Specialization vs Diversification: An Application of the Dual Measure of Economies of Scope

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 nonagricultural 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 (2012) 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. Even though equation (1) has been widely used in the literature, serious concerns arise when the cost function is evaluated outside the range of data. As this approach compares highly specialized firms to diversified firms, it implicitly assumes the same production technology for firms producing different outputs. An alternative way to test for (dis-)economies of scope is to evaluate

$$Sco_{mn} = \frac{\partial c(y,p)}{\partial y_m y_n} < 0, m \neq \mathrm{n}\,. \qquad (2)$$

In contrast to the measure above, equation (2) does not require to extrapolate 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. Economies of scope exist if $Sco_{mn} < 0$, while diseconomies of scope exist if $Sco_{mn} > 0$.

Commonly, these scope measures are 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, 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 empirical case of this study, only nationwide price indices for various inputs are available but no price data on sub-regions or even farm-level, thus we prefer distance functions to cost functions.

Distance functions offer an alternative framework to represent multi-output technologies, but they do not directly provide a measure of economies of scope. Studies that investigate diversification economies based on input distance functions include CHAVAS and DI FALCO (2012), COELLI and FLEMING (2004), or PAUL and NEHRING (2005). However, their measure of scope economies is purely based on output complementarities and not on cost savings as a result from diversification. It can be shown that output complementarities (i.e. a positive sign for the second derivative of the distance function with respect to two distinct outputs) are not sufficient evidence for scope economies. Thus, HAJARGASHT et al. (2008) propose a method to derive point estimates of a cost function from the parameters of a distance function (dual approach).

To illustrate this method, we will first revise the concept of distance functions and then summarize the dual measure of economies of scope formulated by HAJARGASHT et al. (2008).

An output distance function (ODF) describes the degree to which a firm can expand its output vector given an input vector, while an input distance function (IDF) describes the degree to which a farm can contract its input vector without changing its output vector (O'DONNELL and COELLI, 2005). We make use of the IDF as it is dual to the cost function and therefore allows deriving point estimates of the latter. It further treats outputs as exogenous which is adequate in our sample of dairy farms because the production of milk was limited by a dairy quota during the period of the data. 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

$$L(y) = \{x: (y, x) \, \epsilon \, T\}\,, \tag{3}$$

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

$$D_I(x, y) \ = max \left\{\lambda: \ \frac{x}{\lambda} \epsilon \, L(y)\right\}. \tag{4}$$

In equation (4), 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 shown in Färe and Primont (1995), duality theory allows specifying the cost function as a function of the input distance function:

$$C(p, y) = \min\{p'x: D(x, y) \geq 1\} \tag{5}$$

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

$$C_{yy} = C\{D_y D_y' - D_{yy} + D_{yx}[D_{xx} + D_x * D_x']^{-1} D_{xy}\}, \tag{6}$$

where $\mathrm{D_x}$ is a vector of first derivatives and $\mathrm{D_{xy}}$, $\mathrm{D_{xx}}$, and $\mathrm{D_{yy}}$ are matrices of second-order derivatives. The resulting matrix holds the economies of scope between product *m* and *n* as defined in (2) in the (*m*, *n*)-th element. From (6) it becomes clear that a positive (negative) sign in $\mathrm{D_{yy}}$ is not a sufficient condition for scope (dis-)economies.

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

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

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 true estimation parameters, we use dummy variables that indicate whether output m is zero or greater than zero as described in BATTESE (1997). This allows the intercept to vary across farms with different output compositions.

Estimating the input distance function as defined in equation (8) is involved with some concerns on endogeneity. As a consequence of the normalization of inputs, 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. Additionally, we treat the output variables as exogenous, assuming cost-minimizing behavior of farms in the dairy industry[1]. This argument is valid in the context of this study as milk output was limited by the dairy quota over the whole period of the data.

[1] Earlier in the paper, we 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.

Since the dual measure of economies of scope, as defined in equation (6), is a complex non-linear function of the estimated parameters of the IDF, 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 many draws from the posterior distribution. 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 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

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

where $z = (z_1, \ldots, z_N)'$. To account for unbalanced panel data, N denotes the number of observations while T_i is the number of observations for the i-th farm. The dependent variable is represented by y, and $\tilde{X}$ is the vector of normalized independent variables. Further, ι_T is a T-vector of ones, h is the error precision 1/σ^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. Specifically, 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.

Data Description and Variable Definitions

Farm accounting data were obtained from the Federal Ministry of Food and Agriculture in Germany (BMEL), which annually collects data from a representative rotating sample of German farms. 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 rather homogenous technology for the analysis, the sample has been reduced to farms that made at least 60 per cent of total revenue from dairy production with a share of at least 60 per cent from milk production on average over the 9 years of the panel. Thus, the data set consists of more or less 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.

To estimate the empirical model, we categorize the farm outputs into four groups: milk, livestock products, crops, and other outputs. The output *milk* includes revenue from both milk and milk products. *Other livestock* mainly consists of sales of calves, dairy cows, and other cattle. For a very small number of farms, this category also includes hogs or poultry products. Furthermore, *crop output* captures all field crops for sale and *other output* includes the provision of contract services, electricity production, farm tourism, or forestry and horticultural products. Figure 1 illustrates the average revenue composition in constant € for each year from 2006 to 2014. As a consequence of the sample construction, the dairy enterprise accounts for the major portion of farm revenue. Total revenue increased from 90,632€ in 2006 to 207,474€ in 2014. However, the share of milk revenue remained relatively stable between 74 and 76%. Cattle and other livestock, crop sales, and other output account for 12%, 5%, and 7%, respectively, on average over the 9 years period.

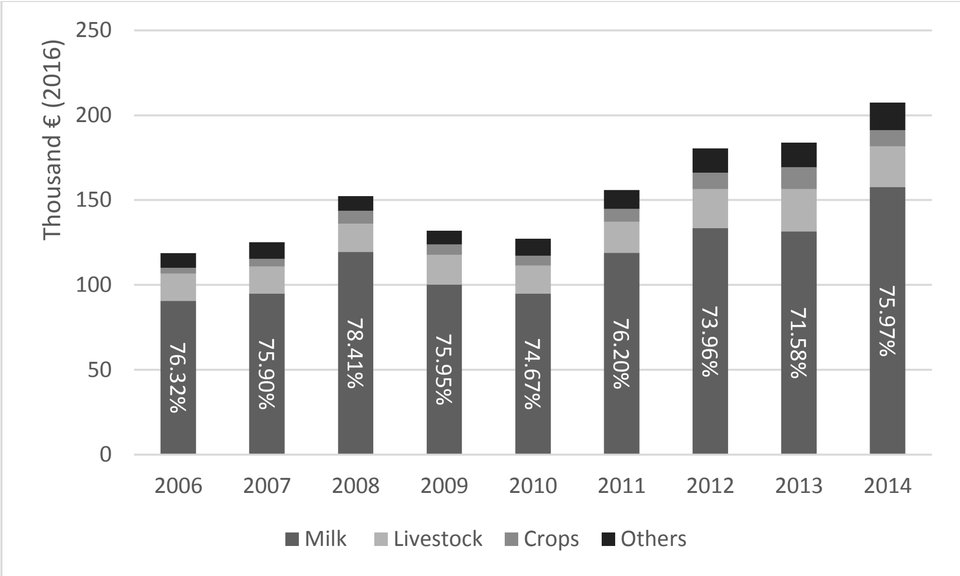

Figure 1. Output composition and share of revenue from milk for the farms in the sample, 2006-2014

For the estimation of the empirical model, 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. With respect to 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 these intermediate inputs are deflated by their respective price indices to obtain implicit quantities. The final input, capital, is measured as the end-of-year value of livestock, buildings, technical facilities and machinery related to agricultural production. 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 (6) 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, n = 11459

Variables	Unit	Mean	St. Dev.	Min	Max
Milk	€*	96075.15	55470.68	617.427	599022.2
Livestock	€	25941.96	17137.5	0	276929.9
Crops	€	6588.49	12674.73	0	156665
Other outputs	€	6046.9	10813.35	0	367107.1
Land	Ha	48.10	27.66	0.14	291.77
Intermediate inputs	€	51346.83	31013.48	1746.83	382280.9
Labor	AWU	1.60	0.48	0.3	4.97
Capital	€	230399	175040.2	4105	2753362

* Revenue deflated by Destatis price index

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 in the base year (t=2006) of the estimation. The land variable is used as numeraire, following the standard agricultural economics approach to model production in inputs (and outputs) per acre (PAUL and NEHRING, 2005). Parameter estimates with regard to the land variable are recovered after the estimation by making use of the homogeneity conditions as outlined in COELLI and PERELMAN (1999). The Bayesian first-order estimates of the IDF and the corresponding first-order ordinary derivatives are presented in Table 2. As a robustness check of 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 coefficients, n = 11459

	mean	St. Dev.	99%-credible interval		Parameter estimate ML	St. Dev. ML
Output milk (y1)	-0.320	0.006	-0.341	-0.317	-0.320	0.006
Output livestock	-0.037	0.003	-0.040	-0.027	-0.037	0.003
Output crops	-0.023	0.002	-0.030	-0.024	-0.023	0.003
Output other	-0.006	0.001	-0.008	-0.004	-0.007	0.001
Land	0.397	0.007	0.383	0.411	0.450	-
Intermediate inputs	0.311	0.006	0.299	0.323	0.278	0.006
Labor	0.261	0.005	0.250	0.271	0.249	0.006
Capital	0.031	0.003	0.025	0.037	0.030	0.003

As seen 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, 38 of 53 parameters are statistically significant at the 10 % significance level (thereof, 34 at the 0.1 % 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 3 that the IDF is decreasing in outputs and increasing in inputs at the sample mean. Checking the distance elasticities for each individual observation reveals that monotonicity in inputs and outputs are satisfied at almost every 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-concavity 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 IDF derivatives and violation of regularity conditions

	$\frac{\partial lnD^I}{\partial ln\, y_1}$	$\frac{\partial lnD^I}{\partial ln\, y_2}$	$\frac{\partial lnD^I}{\partial ln\, y_3}$	$\frac{\partial lnD^I}{\partial ln\, y_4}$	$\frac{\partial lnD^I}{\partial ln\, x_1}$	$\frac{\partial lnD^I}{\partial ln\, x_2}$	$\frac{\partial lnD^I}{\partial ln\, x_3}$	$\frac{\partial lnD^I}{\partial ln\, x_4}$
Mean	-0.3009	-0.0918	-0.2695	-0.0158	0.1439	0.1256	0.1086	0.2870
Min	-1.044	-0.0882	-0.0305	-0.0303	-0.9885	-0.0472	-0.0193	-0.0049
Max	0.1185	0.2325	0.0183	0.0197	0.8711	1.003	0.8655	0.1202
Monotonicity Violations	2	1785	384	2044	10	1	6	18
Violation in %	0.02%	15.58%	0.34%	17.84%	0.09%	0.01%	0.05%	0.16%

Next, Table 3 presents output complementarities and economies of scope evaluated at the sample means.

Table 4. Synergies and economies of scope at the sample mean

Output pairs	Complementarities (D_{yy})	Economies of Scope (C_{yy})
Milk – livestock	0.071 (0.019) ***	-0.072 (0.016)***
Milk – crops	0.131 (0.052) ***	0.042 (0.016)**
Milk – other	-0.006 (0.006)	0.036 (0.080)
Livestock – crops	-0.054 (0.033)*	-0.009 (0.02)***
Livestock – other	-0.003 (0.003)	-0.002 (0.002)
Crops – Other	0.019 (0.009)**	-0.008 (0.019)
Standard deviations in parentheses		

Table 4 confirms that a positive sign in D_{yy} is not a sufficient condition for C_{yy} being negative or vice versa. This is only true for the output pairs of milk-crops, milk-other, livestock-crops, and crops-other. The difference between the two measures is that the input-mix is hold fixed in the input distance function, whereas the relative usage of inputs is variable in the cost function.

The results show that economies of scope exist between milk and livestock production and between livestock outputs and crops in this data set of Bavarian dairy farms. Other output, which is mainly trade and provision of services, does not show statistically significant scope economies with any other output. This is not surprising as these activities are less related to the production of primary agricultural outputs but are still operated as additional income sources.

To analyze economies of scope across farm size, we categorized the farms into 10 quantiles according to income and land as proxy for farm size but could not find any statistically significant differences in the level of scope economies across groups. This contradicts the finding of MELHIM and SHUMWAY (2011) who found that economies of scope decrease with farm size. Second, we regressed scope economies on time to see if farms had captured economies of scope over time. The null hypothesis of the effect of time being zero could not be rejected (p-value: 0.9). Lastly, we tested whether farms with a higher level of scope economies were more likely to diversify in the following years than farms without.

For this purpose, we regressed the level of scope economies in the first year of the panel data on the total chance in a Herfindahl diversification index between the first and the last year. This index is calculated as:

$$HHI = \sum_{i=1}^{N} a_i^2 \,, \qquad a_i = \frac{y_i}{\sum_{j=1}^{N} x_j}, \tag{10}$$

where x_j represents the output categories. Again, the null hypothesis that the level of scope economies had no effect on an adjustment of the degree of diversification could not be rejected (p-value: 0.83). Figure 2 illustrates that the diversification index decreased for most farms in the sample over the period of the study, i.e. farms became more diversified over the years. However, the data indicates that adjustments in the degree of diversification have been made regardless of the level of economies of scope faced by the individual farm.

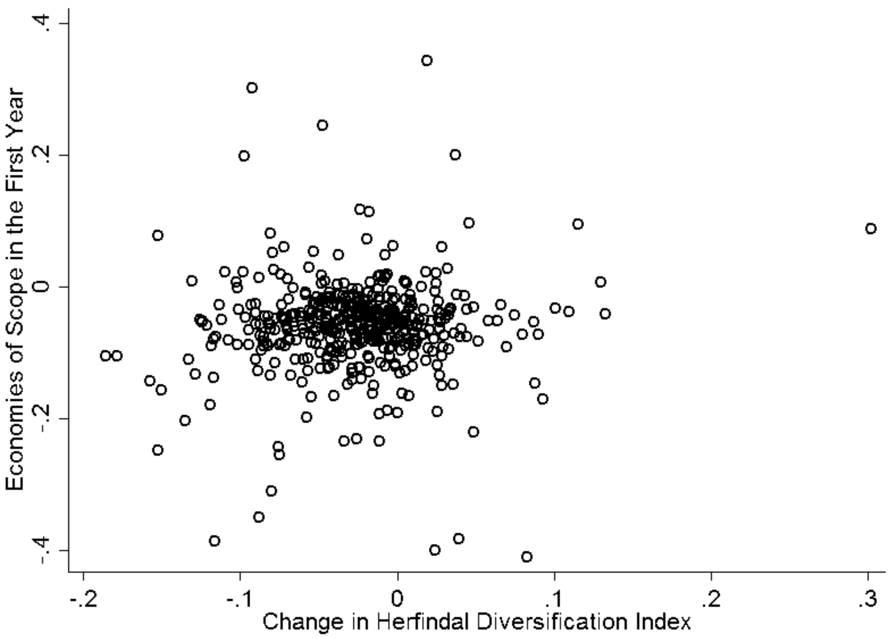

Figure 2. Scatter plot of economies of scope and the change in the HHI

Conclusion

In this study, we analyzed economies of scope for a representative sample of Bavarian dairy farms. The results show that statistically significant economies of scope exist between milk and livestock production and between livestock outputs and crops in this data set of Bavarian dairy farms. This is in line with the fact that a significant portion of Bavarian farms are grazing livestock farms (49.8 %) that combine dairy and livestock production or mixed crop-livestock farms (9.7 %) (BStMELF, 2014). Furthermore, diseconomies of scope exist between milk and crop production at the sample mean. This means that a reduction of crop production would be convenient for these farms. It is an interesting finding that farms have not moved to a more optimal level of diversification over the years. This gives reason to consider policy attempts that increase the flexibility of farm management strategies.

Finally, it must be noted that the results have to be carefully interpreted as the estimated input distance function fails to fulfil the curvature conditions as required by economic theory. Sauer (2006) emphasizes the importance of such. The Bayesian approach applied in this study allows imposing curvature by combining the posterior probability density function with a likelihood function that takes the value zero if the candidate draw does not satisfy the regularity conditions, as shown in O'Donnell and Coelli (2005).

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