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Spatial Spillovers on Input-specific Inefficiency of Dutch Arable Farms

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Abstract

Traditional benchmarking implicitly assumes that decision making units operate in isolation from their peers. For arable production systems in particular, this assumption is unlikely to hold in reality. This paper quantifies spatial spillovers on input-specific inefficiency using data envelopment analysis and a second-stage bootstrap truncated regression model. The bootstrap algorithm is extended to allow for the estimation of the parameter of the spatial weight matrix, which captures the proximity between producers. The empirical application concerns Dutch arable farms for which latitudes and longitudes are available. The average inefficiency across years was 3.87% for productive inputs and 2.98% for damage abatement inputs under variable returns to scale. For productive inputs technical inefficiency, statistically significant spillover effects from neighbours' age and their degree of specialisation depended on the type of the spatial weight matrix used (inverse distance or k-nearest neighbours). Statistically significant spillover effects of subsidy payments were adverse while statistically significant spillover effects from insurance payments were beneficial. For damage abatement inputs technical inefficiency, statistically significant adverse effects were found for neighbours' age and subsidy payments and beneficial effects from neighbours' insurance payments and their degree of specialisation.

Keywords: *Bootstrap truncated regression*; *crop farms*; *data envelopment analysis*; *input-output efficiency*; *Netherlands*; *spatial econometrics*; *spatial lag in X model*.

JEL classifications: *C23, C24, D22, M11.*

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1. Introduction

As noted by Tobler (1970, p. 236), 'Everything is related to everything else, but near things are more related than distant things'. In general, due to the interaction with the surrounding environment, analyses of the agricultural sector can be expected to benefit from the inclusion of spatial effects (Weiss, 1996). Spatial effects comprise spatial heterogeneity and spatial dependence (Anselin, 2010). While spatial heterogeneity concerns differences in the operational environment which consequently lead to different input requirement and output possibility sets, spatial dependence arises from interdependencies of measurements in space.

The availability and price of a plot determines whether a farmer decides to purchase or lease in a particular location. As a consequence, fields are usually scattered around a farm and directly intertwined with plots of other farmers. Focusing on the case of Dutch farming, around 90% of farmers purchase their land within a 6.7 km radius (Cotteleer *et al.*, 2008). In turn, fields are not only exposed to environmental conditions (Chambers *et al.*, 2011), but also to management practices on neighbouring fields. For example, the control of pathogens on nearby fields can be expected to suppress the population's ability to disperse into other territories. In turn, spillover effects can be generated by neighbours' management practices. In addition, spillover effects might be generated through the social network via the transfer of knowledge among farmers (Tveteras and Battese, 2006; Lapple and Kelley, 2015).

The environmental consequences of agricultural inputs such as fertiliser and plant protection agents are of societal concern (Kohler and Triebskorn, 2013). In the agricultural economics literature, pesticides are commonly referred to as damage abatement inputs (Lichtenberg and Zilberman, 1986). Damage abatement inputs reduce potential shortfall rather than further increase output (Oude Lansink and Carpentier, 2008). Parametric (Oude Lansink and Carpentier, 2008) as well as non-parametric (Oude Lansink and Silva, 2004; T. Skevas *et al.*, 2014) approaches have been used to assess whether farmers utilise such inputs efficiently. The need to account for environmental differences was acknowledged by Skevas *et al.* (2012) and Skevas and Serra (2017) under the implicit assumption that farmers operate in isolation from their peers. Pest populations are spatial phenomena by nature (Turchin, 2003). Knipling (1980) introduced the idea of area-wide pest management via collective actions. Similarly, we stress that nearby control of pest populations affects pest pressure in the landscape, which in turn influences the efficiency of a farmer in employing damage abatement inputs. Hence, different farm characteristics can be expected to generate externalities for the surrounding farmers. Through social networks, knowledge and experience might be transferred among farmers (Lapple and Kelley, 2015). This can foster improvements in input or output efficiency through observation and conversations with peers (Tveteras and Battese, 2006).

The need to control for spatial heterogeneity has already been emphasised in the seminal work of Farrell (1957). The rise in geo-reference data has greatly benefited scientific efforts to improve the measurement of productivity and efficiency by accounting for unobserved spatial heterogeneity in recent years (Fusco and Vidoli, 2013; Vidoli and Canello, 2016). The spatial econometric literature is rich in applications on spatial interdependencies (Anselin, 2010) and has started to attract the attention of research working on productivity and efficiency. The first contribution in this regard was developed by Druska and Horrace (2004) by modelling spatially correlated error terms within the stochastic frontier setting. Various studies measured spatial dependence in efficiency or productivity in non-agricultural applications (Glass *et al.*, 2016; Tsionas and Michaelides, 2016; Pede *et al.*, 2018). For the agricultural sector, Areal *et al.* (2012) identified spatial dependence in technical efficiency of dairy farms in the UK, Martínez-Victoria *et al.* (2019) found spatial spillovers in productivity growth for Spanish agri-food companies and Skevas and Grashuis (2019) identified spatial spillover effects on efficiency scores among farm cooperatives in the USA. I. Skevas and Oude Lansink (2020) and I. Skevas (2020) found spatial spillover effects on dynamic inefficiency of Dutch dairy farms.

Our study makes three distinct contributions beyond I. Skevas and Oude Lansink (2020). First, and most importantly, it argues for the measurement of spatial spillovers on output and input-specific scores rather than one composite measure of farm performance. While this has clear benefits for policy design and farm management, previous studies on both nonparametric and parametric approaches have solely relied on measuring spillovers on one composite farm-level efficiency score. Thereby, possibly diverse spatial influences have been compressed into one composite effect that might well provide erroneous insights. Second, we contribute by exploiting the advantages of the spatial lag of X (SLX) model by estimating the spatial weight matrix as opposed to the rule of thumb approach employed in I. Skevas and Oude Lansink (2020). Thirdly, in contrast to I. Skevas and Oude Lansink (2020) we employ both a k-nearest neighbour and an inverse distance approach. Subsequently, we communicate and discuss the different results for the two approaches and stress the need for practitioners to make use of different spatial weight matrices or more clearly motivate their choice for either one. While the importance of accounting for spatial spillovers is stressed in all the aforementioned studies, none of the studies simultaneously measured spillovers on input and output specific inefficiency. Furthermore, the above studies used an arbitrary rule of thumb to define neighbouring farmers and construct the spatial weights matrix.

The objective of this study is to quantify the effects of spatial spillovers on input and output specific technical inefficiency in Dutch arable crop farms. We address two gaps in the literature. First, we measure spatial spillovers on input and output-specific inefficiency. This allows for more refined insights regarding which outputs or inputs are influenced by neighbours' characteristics in contrast to the previous studies which did not include input and output-specific inefficiency scores. Second, rather than making an ad hoc selection of the spatial weight matrix, we estimate the parameter of the spatial weight matrix empirically, using farm-level information on coordinates, and report the results for the two most commonly used types (i.e. inverse distance and k-nearest neighbours). Previous studies have found results to be sensitive to the chosen spatial weight matrix, which defines the structure of the spatial relationship between decision-making units (DMUs) (Areal *et al.*, 2012; Pede *et al.*, 2018). The ad-hoc selection of the spatial weight matrix is frequently criticised in the econometric literature (Gibbons and Overman, 2012; McMillen, 2012; Halleck Vega and Elhorst, 2015). For this purpose, a two-stage data envelopment analysis (DEA) approach is used. First, a non-parametric directional distance function is computed to estimate inefficiency scores for output, productive inputs and damage abatement inputs. Second, a spatial econometric model is defined, which incorporates regressors for spatial lags of farm characteristics alongside other non-lagged explanatory variables and time-period fixed effects. In contrast to non-spatial efficiency analyses, this framework extends the farm-level assessment by relaxing the assumption that DMUs operate in isolation from their peers.

Section 2 outlines our methodology, estimation strategy and our data. Section 3 reports our results. Section 4 discusses the implications and section 5 concludes.

2. Methodology

2.1. Directional distance function

Suppose N farmers produce Q outputs from I productive inputs, B damage abatement inputs and F quasi-fixed factors. The damage abatement inputs are exclusively related to plant health here. Non-negative vectors of outputs, productive inputs, damage abatement inputs and quasi-fixed factors are denoted by $\mathbf{y}\in\mathbb{R}_+^Q$, $\mathbf{x}\in\mathbb{R}_+^I$, $\mathbf{a}\in\mathbb{R}_+^B$ and $\mathbf{k}\in\mathbb{R}_+^F$, respectively. The production technology for a DMU is fully represented by the input requirement set as $T(\boldsymbol{y}:\boldsymbol{k})=\{(\boldsymbol{x},\boldsymbol{a})\in\mathbb{R}_+^I\times\mathbb{R}_+^B|(\boldsymbol{x},\boldsymbol{a})\text{can produce}\boldsymbol{y},\text{given}\boldsymbol{k}\}$. A non-parametric representation of the technology can be depicted as $T(\mathbf{y}:\mathbf{k})=\{(\mathbf{x},\mathbf{a}):\mathbf{Y}'\lambda\geq\mathbf{y}_\mathrm{i},\mathbf{X}'\lambda\leq\mathbf{x}_\mathrm{i},\mathbf{A}'\lambda\leq\mathbf{a}_\mathrm{i},\mathbf{K}'\lambda\leq\mathbf{k}_\mathrm{i},\mathbf{L}'\lambda=1,\lambda\geq0\}$.

Where $\mathbf{Y}$ denotes a $N \times Q$ matrix of observed outputs and $\mathbf{y}_\mathrm{i}$ is a vector of observed outputs for farm *i*. $\mathbf{X}$ is the $N \times I$ matrix of observed productive inputs and $\mathbf{x}_\mathrm{i}$ is the vector of productive inputs used by farm *i*. $\mathbf{A}$ is the $N \times B$ matrix of observed damage abatement inputs and $\mathbf{a}_\mathrm{i}$ is the vector of damage abatement inputs used by farm *i*. $\mathbf{K}$ is the $N \times F$ matrix of observed quasi-fixed factors and $\mathbf{k}_\mathrm{i}$ is the vector of quasi-fixed factors used by farm *i*. λ denotes a $N \times 1$ vector of intensity variables (farm weights) and $\mathbf{L}$ denotes the $N \times 1$ unity vector. Constraining the sum of λ to unity enforces variable returns to scale (Banker *et al.*, 1984).

To estimate the input and output specific inefficiency scores, a directional distance function is computed. Following Chambers *et al.* (1998), $\left(g=-g_x,-g_a,g_y\right)$ denotes the directional vector. The distance function aims to expand output and contract productive as well as damage abatement inputs, simultaneously. The distance of DMUs to the frontier (i.e. the inefficiency score) will generally depend on the chosen directional vector. Choosing the observed quantities $\left(g=g_x=x,g_a=a,g_y=y\right)$ allows for a direct interpretation in percentages. Furthermore, the measure is more in line with the Farrell (1957) measure of efficiency as noted in Färe and Grosskopf (2000). The distance function can formally be depicted as follows:

$$\vec{D}(\mathbf{x},\mathbf{a},\mathbf{y};g)=\sup\left(\left(\beta_x,\beta_a,\beta_y:\left(\mathbf{x}-\beta_x g_x,a-\beta_a g_a,\mathbf{y}+\beta_y g_y\right)\in T(\mathbf{y}:\mathbf{k})\right)\right) \tag{1}$$

Within all years T, the mathematical programme aims to identify the maximum attainable expansion of outputs in direction g_y as well as the maximum feasible contraction of productive inputs and damage abatement inputs in direction g_x and g_a, respectively. To achieve this, the following linear programming problem is solved for all N observations separately for all years. By solving model 2 separately for every year, the reference technology is allowed to vary from year to year. This is necessary to account for year-specific weather conditions and changes in the technology over time.

$$\vec{D}(x,a,y,k;g)=\max_{\beta_x,\beta_a,\beta_y,\lambda^i}\left(\left(\beta_x+\beta_a+\beta_y\right)\right) \tag{2a}$$

s.t.

$$\sum_{i=1}^{N}\lambda_i\mathbf{y}_i\geq\mathbf{y}+\beta_y g_y \tag{2b}$$

$$\sum_{i=1}^{N} \lambda_i \mathbf{x}_{ip} \leq \mathbf{x}_p - \beta_x g_x \tag{2c}$$

$$\sum_{i=1}^{N} \lambda_i \mathbf{a}_{ib} \leq \mathbf{a}_b - \beta_a g_a \tag{2d}$$

$$\sum_{i=1}^{N} \lambda_i \mathbf{k}_{if} \leq \mathbf{k}_f \tag{2e}$$

$$\sum_{i=1}^{N} \lambda_i = 1 \tag{2f}$$

$$\lambda_i \geq 0 \tag{2g}$$

where β is the percentage value of the expansion (contraction) of outputs (inputs). Constraints (2b), (2c), (2d) and (2e) impose free disposability of outputs, productive inputs, damage abatement inputs and quasi-fixed factors, respectively. Constraint (2f) imposes variable returns to scale. Model 2 uses three reference bundles to compute output and input specific inefficiencies. Following the seminal work of Chambers *et al.* (1998), various studies used multiple reference bundles in their model specification (e.g. T. Skevas *et al.*, 2012, 2014; Kapelko *et al.*, 2017; Dakpo and Lansink, 2019).

2.2. Determinants of inefficiency

The association of farm characteristics with the computed inefficiency scores is measured with the widely used bootstrap truncated regression model (Simar and Wilson, 2007). As is customary, farm characteristics are included in the second-stage regression to test for their associations with inefficiency scores. This has been done in the context of both radial distance functions (Kapelko and Oude Lansink, 2015; Rezitis and Kalantzi, 2016), and directional distance functions (Singbo and Lansink, 2010; T. Skevas *et al.*, 2012; Singbo *et al.*, 2014). However, this study also tests for spatial spillovers by also including spatially weighted regressors of the farm characteristics. This specification is commonly referred to as the spatial lag of X (SLX) model (Halleck Vega and Elhorst, 2015). The specification is a reduced form approach for measuring spatial interdependency. In contrast to the spatial lag and the spatial error model, the SLX model allows for the estimation of the parameter of the spatial weight matrix which enables practitioners to circumvent rule of thumb approaches. In addition, in contrast to the spatial lag model, the signs of direct and indirect effects are not restricted to be similar when employing the SLX model (Halleck Vega and Elhorst, 2015). Lastly, if error terms are spatially structured yet this structure is not accounted for, the estimates remain unbiased (Strohm *et al.*, 2014). To avoid overestimation of the spatial spillovers and to account for the fact that the reference technology is different across years, temporal fixed effects are included as dummy variables. The truncated regression model can formally be specified as follows:

$$\beta = \alpha I + \eta T + \delta Z + \theta W Z + \in \tag{3}$$

where β is a vector of the dependent variable (i.e. pooled inefficiency scores for N farmers). Following T. Skevas *et al.*'s (2012) study on Dutch arable crop farms, we use the inefficiency scores under variable returns to scale for the second stage motivated by the fact that the variable returns to scale technology represents a less restrictive formulation of the technology. While the observed distribution of β is censored at zero, true inefficiency remains unobserved. Therefore, the dependent variable in equation (3) must be treated as having a truncated distribution with a point of truncation at zero. I is the vector of ones associated with the constant term parameter α. T depicts the temporal fixed effects with the vector of response parameters η. Z denotes the matrix of J explanatory variables and δ denotes the vector of unknown parameters to be estimated. W is the spatial weight matrix which captures the spatial proximity between farmers. WZ depicts the linear combinations of neighbours' characteristics obtained by inner products of the spatial weight matrix with a variable of interest. θ denotes the vector of parameters of the spatially lagged farm characteristics and $\in$ denotes a vector of independent and identically distributed error terms with zero mean and variance σ^2. Despite panel data at hand, fixed or random effects could not be included in equation 3 due to the use of the Simar and Wilson (2007) bootstrapping algorithm (T. Skevas *et al.*, 2012, 2014; Kapelko and Oude Lansink, 2015; Rezitis and Kalantzi, 2016; I. Skevas and Oude Lansink, 2020).

The spatial weight matrix (W) is constructed based on geographic proximity. W is always symmetric. w_{ij} denotes the elements of W. We employ two common types of spatial weight matrices. In the inverse distance spatial weight matrix (IVD), the value of w_{ij} is the inverse distance between farmers i and j. In the k-nearest neighbour spatial weight matrix (KNN), distances between farmers i and j are computed. Subsequently, a binary matrix is constructed in which, for every farm, the k smallest distances receive a value of 1 while all others a value of 0 (see e.g. Martínez-Victoria *et al.*, 2019). While IVD results in larger weights on characteristics of DMUs in closer proximity, this weight matrix implicitly assumes that spatial influences extend far beyond the nearby vicinity. In contrast, KNN restricts the spillovers to k neighbours, but the spatial influences from these k neighbours are assumed to be of equal importance. Diagonal elements (w_{ij} where $i = j$) are always set to zero. IVD is standardised by dividing every element by the maximum eigenvalue of W, whereas KNN is standardised by dividing W by its row-sums (LeSage and Pace, 2009; Elhorst, 2014b; Halleck Vega and Elhorst, 2015). As mentioned above, using IVD ensures that nearby DMUs exert larger influence compared to distant DMUs. Nonetheless, a distance cut-off (γ) from which onward no spatial influence is assumed to exist is usually arbitrarily determined by the scholar (e.g. T. Skevas and Grashuis, 2019). In contrast to previous work, we estimate the optimal distance cut-off empirically instead of choosing an arbitrary value. For KNN, we estimate the optimal number of neighbours which we also denote with γ for simplicity. The absence of information on the true spatial weight matrix is one of the major hurdles of applied spatial econometrics (Gibbons and Overman, 2012; McMillen, 2012). A data-driven approach for the selection of W is therefore one of the major advantages of the SLX model (Halleck Vega and Elhorst, 2015). The ad-hoc selection of either IVD or KNN is analysed by estimating both to assess the robustness of our results. In traditional spatial econometric applications, ordinary least squares residuals are minimised to estimate the optimal spatial structure for the SLX model (Elhorst, 2014a). In line with this, we maximise the log-likelihood of observing the data within the maximum likelihood estimation of the Simar and Wilson (2007, pp. 41-42) bootstrap algorithm to search for the optimal distance cut-off or the optimal number of neighbours. This selection goes beyond testing a number of predefined spatial structures, as it allows practitioners to optimise the parameter of the spatial weight matrix empirically.

2.3. Estimation

To estimate the parameter of the spatial weight matrix, a non-standardised (inverse) distance weight matrix is generated first. The optimisation algorithm either searches for the optimum distance cut-off between 2.5 and 100 km or for the optimum number of neighbours between 2 and 70. Setting lower and upper bounds ensures feasible values (e.g. $\gamma > 0$ for IVD; $\gamma < N$ for KNN). If the lower or upper limit is found to be binding (i.e. the evaluated quantiles for the bootstrapped distribution of γ fall on one of the limits), the search-range for γ should be widened. The following steps are taken within the optimisation of the spatial weight matrix.

1 For IVD, w_{ij} smaller than $1/\gamma$ are set to zero. In other words, spatial influences from neighbours which are further away than the drawn cut-off value are removed. For KNN, for every farm the γ smallest distances are set to 1 and others to 0. In other words, only the spatial influences from the γ neighbours are retained.
2 The spatial weight matrix is standardised by the maximum eigenvalue for IVD and row-sums for KNN.
3 Spatially lagged variables are generated by computing inner products of the rows of the particular spatial weight matrix and the farm characteristics at hand.
4 Equation (3) is computed and the AIC returned.

As true inefficiency scores are unobserved and the estimates serially correlated, we implement the second stage using Algorithm 1 developed by Simar and Wilson (2007, pp. 41–42). First, inefficiency estimates are computed using model (2). Second, maximum likelihood in a truncated regression setting is used to obtain estimates of the environmental response parameters as well as the variance of the error term for the inefficient DMUs. At this stage, the aforementioned optimisation routine is performed once. Succeeding, the inefficiency scores are replaced by linear predictions using the environmental response parameters for the optimal value of γ Third, for 2,000 iterations errors are sampled out of a truncated normal distribution, the optimisation of γ performed and the environmental variables regressed onto the predicted inefficiencies. Lastly, confidence intervals are constructed for the empirical distributions of the coefficients as well as γ. obtained from the bootstrap.

Following Singbo *et al.* (2014), the bootstrapped coefficients are used to compute marginal effects at the mean of the variables in Z as follows:

$$\frac{\partial E(\beta|Z,\beta>0)}{\partial Z} = \left(\left(1 - \frac{Z'\delta^*}{\sigma^*} \times \frac{\phi\left(Z'\delta^*/\sigma^*\right)}{\Phi\left(Z'\delta^*/\sigma^*\right)} - \left[\frac{\phi\left(Z'\delta^*/\sigma^*\right)}{\Phi\left(Z'\delta^*/\sigma^*\right)}\right]^2\right)\right)\delta^* \quad (4)$$

where β is the estimated inefficiency score, Z is the mean of a particular environmental variable, δ^* is the bootstrapped coefficient for the environmental variable, σ^* is the estimated variance of the error term, $\phi(\cdot)$ is the standard normal distribution and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Table 1
Descriptive statistics

Variable	Dimension	Mean	S.D.
Output	1000 Euro	672.07	608.21
Productive inputs	1000 Euro	110.99	81.37
Damage abatement inputs	1000 Euro	64.01	51.02
Buildings and machinery	1000 Euro	776.78	817.39
Labour	100 hours	48.53	30.01
Area	100 hectare	1.27	0.92
Age of farmer	10 years	5.23	1.00
Subsidies per ha	100 Euro	3.80	1.73
Insurance per ha	100 Euro	1.14	0.54
HHI	[0,1]	0.34	0.13

2.4. Data

The balanced panel data[1] on Dutch arable farms are provided by Wageningen Economic Research and cover the period from 2011 to 2016. The data set comprises farm-level information on revenues, expenses and balance sheet items as well as geographical information in the form of longitude and latitude coordinates. Furthermore, characteristics of the primary operator are also available. As coordinates were rounded at one minute by the data provider, we added random noise by sampling out of a uniform distribution of minus one minute to plus one minute to prevent DMUs with the exact same coordinate.[2] Since this study focuses on farms engaged primarily in the arable crop production, we have selected farms whose revenue from sales of arable crops comprises at least 66% of their total revenues within every year the farm is observed. The final data set constitutes a balanced panel of 75 farms with 450 observations. Table 1 presents the descriptive statistics. While a larger number of DMUs would have been desirable, the parsimony of model 2 justifies the use of annual reference technologies. DEA is frequently used in the context of a small number of DMUs (Dimara *et al.*, 2005). However, the resulting spatial coverage requires care when extrapolating the results.

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[1]The data was balanced to ensure that the spatial weight matrix does not change over time. Using unbalanced data would allow for the estimation of the spatial weight matrix as described above if only one overall γ for all year-specific weight matrices is used. Alternatively, one could estimate year-specific γ_t. However, this would significantly increase the complexity of the optimisation problem and might result in numerical instability.

[2]The storing of location information in the rounded format resulted in DMUs with the same location. This would have resulted in (infeasible) implausible values when computing the (inverse) distances. Omitting duplicate coordinates is highly undesirable as this would remove DMUs within close proximity which are expected to be critical in generating spillovers. While adding random noise between minus and plus one-degree minute means that the spatial weight matrix inherited a random aspect, in practice the consequences were found to be minimal. We computed 10,000 draws and constructed distance matrices to test the Spearman correlation of DMU distances between them. We found a correlation of 99.96%, suggesting that the ordering of importance among DMUs is virtually unaffected by the random noise.

In our data on Dutch arable crop farms, the vast majority of total revenue is generated by potatoes, barley, sugar-beet, wheat, onions and vegetables.[3] Using 2010 as the base year, a Törnqvist index is constructed.[4] The deflated total revenue, excluding subsidies, is used as output (**Y**). Five categories of inputs are used. First, productive inputs (**X**) comprise expenses of seeds and plants, fertilisers, energy, other crop-specific costs and contract work, which were deflated with a Törnqvist index of the input prices. Second, chemical and biological crop protection agents (**A**) are measured by deflating the aggregated expenditures for both using the price index for *crop protection agents*. Third, buildings and machinery are measured in deflated book values using a Törnqvist index. Fourth, total labour is measured in man-hours and consists of family and hired labour. Fifth, total utilised agricultural area is measured in hectares and includes owned, as well as rented land. Capital, labour and area are included in the matrix of quasi-fixed factors (**K**).

For the second stage, information on the farmer's age, the received subsidies and insurance payments are obtained from the data set. Subsidies and insurance payments are included as payments per hectare to avoid measuring farm-size effects (Minviel and Latruffe, 2017). The Herfindahl-Hirschman Index (HHI) is computed as proxy for the farm specialisation (see e.g. Pope and Prescott, 1980; Dimara *et al.*, 2005; Kim *et al.*, 2012). The HHI is computed by summing the squared revenue shares of ware potatoes, energy crops, barley, grass-seed, oats, other arable crops, other cereals, pulse, seed potatoes, rye, sugar-beet, wheat, fodder crops, onions, starch potatoes, flower bulbs, turnips, vegetables, other horticulture, cattle, cut flowers, pigs, poultry and other sources of revenue. Our one-output approach is motivated by the curse of dimensionality and the limited number of DMUs per year at hand. The effects of farm specialisation, or diversification, have previously been analysed not only in single-output models (Dimara *et al.*, 2005; Baležentis and De Witte, 2015), but also in the context of one overall farm-level score (Zhu and Oude Lansink, 2010; Zhu *et al.*, 2012; Singbo *et al.*, 2014; I. Skevas *et al.*, 2018). Despite our one-output approach, economies of scope would become apparent through positive estimates for the coefficient with respect to HHI. This would reflect that lower input-specific technical inefficiencies are associated with lower scores for the HHI (i.e. more diversified farms). Finally, the available latitude and longitude coordinates are used to calculate the distance between farmers. Within the previously described algorithm, the spatially lagged variables for age, subsidies per hectare, insurance payments per hectare and the HHI are computed as inner products of the spatial weights matrix with the farms' characteristics.[5]

Age can be associated with lower inefficiency through the accumulated knowledge from learning-by-doing. On the other hand, it can be associated with higher inefficiency due to decreased motivation or health (Tauer, 1995). The literature is split

[3]Differences in the revenue shares from these crops were found not to be associated with differences in technical inefficiency.

[4]The Törnqvist index was constructed as $\ln\frac{P_t}{P_{t-1}} = \frac{1}{2}\sum_{i=1}^{n}\left(\frac{p_{i,t-1}q_{i,t-1}}{p_{t-1}q_{t-1}} + \frac{p_{i,t}q_{i,t}}{p_t q_t}\right)\ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$, where time is indexed with t, the inputs or quasi-fixed factors are indexed with i, prices are denoted with p, and quantities with q. Total expenses were divided by the Törnqvist price indices to obtain implicit quantities.

[5]Ideally, additional farm characteristics such as education and agricultural training would be included in the second-stage regression. However, such information is not available in our data set.

Table 2
Average annual inefficiency scores in percent for the output (β_y), productive inputs (β_x), and damage abatement inputs (β_a)

	2011	2012	2013	2014	2015	2016	Mean
Variable returns to scale							
β_y	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_x	5.91	3.60	3.06	5.47	2.55	2.61	3.87
β_a	2.51	2.35	2.98	4.00	3.73	2.34	2.98
Scale inefficiency							
β_y	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_x	−0.06	0.13	−0.51	0.78	1.05	2.53	0.65
β_a	1.66	1.19	1.46	0.40	1.37	3.27	1.56

regarding the potential effects of subsidies on farm-level efficiency (Minviel and Latruffe, 2017). Subsidies may improve the ability to invest in new technology which would have beneficial effects on efficiency. Alternatively, subsidies can reduce the incentives to make economically rational decisions and thereby decrease efficiency (Zhu *et al.*, 2012). A higher degree of insurance coverage might result in farmers undertaking more risky investments in new technology (Dercon and Christiaensen, 2011; Farrin and Miranda, 2015), which could reduce inefficiency. However, larger payments might be associated with higher inefficiency of pesticides as farmers' perception of yield risk might influence their degree of insurance coverage (Sherrick *et al.*, 2004), as well as their tendency to overuse damage abatement inputs. The degree of specialisation is expected to be associated with lower inefficiency due to more experience in producing the particular product as well as the ability to better optimise production processes (Sauer and Latacz-Lohmann, 2015). In terms of neighbours' characteristics, the neighbours' age could be associated with lower inefficiency due to knowledge spillovers (Porter, 2003; Tveteras and Battese, 2006). Theory regarding the expected effect of the neighbours' subsidies per hectare are absent from the literature. One exception is Strohm *et al.* (2014), who found adverse effects on farm survival from increased subsidy payments to neighbouring farms. Strohm *et al.* (2014) hypothesised that neighbours' subsidy payments increase land prices in the vicinity, which negatively affects the ability to optimise the scale of production. Risk averse farmers are more likely to have higher insurance coverage (Sulewski and Køoczko-Gajewska, 2014). Spatial effects from higher insurance payments of neighbouring farms might measure spillovers of risk attitudes. On the one hand, this could result in adverse effects on pesticide inefficiency through social pressure to safeguard against pathogen multiplication. On the other hand, risk averse neighbours might increase vigilance toward pests and thereby improve technical inefficiency of damage abatement inputs through collective efforts as well as through a reduced pest pressure in the landscape as a result of improved phytosanitary conditions on their own fields. Finally, the neighbours' degree of specialisation is expected to be associated with reduced inefficiency due to experience spillovers (Tveteras and Battese, 2006).

Table 3
Bootstrapped regression results for productive inputs (β_x)

	Technical		Scale	
	IVD	KNN	IVD	KNN
Intercept	0.203***	0.910***	−0.052	0.423
2012	−0.050***	−0.031***	−0.032	−0.014
2013	−0.055***	−0.035**	014	0.046
2014	−0.004	0.009	−0.027	0.000
2015	−0.065***	−0.035**	0.003	0.048
2016	−0.061***	−0.019	0.054***	0.119*
age	−0.010***	−0.017***	0.008*	0.008
subsidies	−0.156***	−0.129***	0.045	0.054
insurance	−0.088	−0.035	0.155*	0.094
HHI	−0.089***	0.002	−0.117***	−0.092**
W_age	0.025**	−0.129***	−0.007	−0.018
W_subsidies	−0.127	0.177**	0.038	−0.321
W_insurance	−1.066***	−0.487	0.288	−1.891
W_HHI	0.138*	−0.219***	−0.086	−0.239
sigma	0.038***	0.039***	0.037***	0.037***
AIC	−1397	−1382	−1411	−1384
γ	42.3	16	54.3	38
γ90%CI	[15.4, 87.1]	[11, 19]	[14.7, 91.2]	[17, 56]

Note: ***$P < 0.01$; **$P < 0.05$; *$P < 0.10$

3. Results

3.1. Directional distance function

Table 2 presents the annual average inefficiency for output, productive inputs and damage abatement inputs under Variable Returns to Scale (VRS). The mean inefficiency scores under VRS of 0, 3.9 and 3.0 suggest that the potential for producing output is fully exploited whereas farmers can decrease the use of productive inputs and damage abatement inputs by 3.9% and 3.0%, respectively. Farmers operate at an almost optimal size with average scale inefficiencies of 0% for output, 0.6% for productive inputs and 1.5% for damage abatement inputs.

The technical and scale inefficiency scores are not comparable between years, because within-year computations relate to a different reference technology. This is accounted for in the second stage bootstrap truncated regression by including temporal fixed effects. There is some variation in the inefficiencies over the years, which are likely to reflect differences in weather, rather than underlying changes in technologies for these crop farms.

3.2. Determinants of inefficiency

Tables 3 and 4 present the results of the bootstrap truncated regression of productive inputs and damage abatement inputs, respectively. Given the sensitivity of some results to the type of spatial weight matrix used, the tables also provide the AIC for

Table 4
Bootstrapped regression results for damage abatement inputs (β_a)

	Technical		Scale	
	IVD	KNN	IVD	KNN
Intercept	0.089**	0.534	−0.041	0.339
2012	−0.009	0.002	−0.016	−0.007
2013	0.027*	0.043*	−0.007	0.011
2014	0.052***	0.066***	−0.103***	−0.078**
2015	0.047***	0.097***	−0.014	0.006
2016	0.022	0.118***	0.023**	0.043
age	−0.016***	−0.014**	0.009**	0.005
subsidies	−0.232***	−0.218***	0.029	0.028
insurance	0.121	−0.035	0.111*	0.112*
HHI	0.014	−0.007	−0.036	−0.024
W_age	0.028**	0.027	−0.001	−0.068
W_subsidies	0.169	0.255**	−0.082	−0.174
W_insurance	−1.019***	−3.541***	0.150	−0.173
W_HHI	−0.140	−0.817***	0.008	0.148
sigma	0.039***	0.047***	0.038***	0.037
AIC	−1530	−1437	−1786	−1798
γ	57.5	29	54.8	30
γ90%CI	[25.3, 86.7]	[27, 31]	[15.2, 94.2]	[17, 49]

Note: ***P < 0.01; **P < 0.05; *P < 0.10

comparison. The bootstrap truncated regression was not feasible for outputs due to lack of variation in output specific inefficiency.

For the regression of VRS technical inefficiency of productive inputs, 80% and 66% of the parameters are significant (at the 10% level or lower) for the IVD and KNN model, respectively. For the scale inefficiency on the other hand, only 33% and 20% of the parameters are significant for the IVD and KNN models. Table 3 also shows that the results of the productive input-specific technical and scale inefficiency are sensitive to whether an IVD or a KNN spatial weight matrix was used. The results in Table 3 show that the signs of the statistically significant parameters generally (with the exception of *W_age* and *W_HHI*) do not change when using either IVD or KNN. However, some variables are only significant in one of the models (e.g. *HHI*, *W_subsidies* and *W_insurance* for the VRS inefficiency and *age* and *insurance* in the scale inefficiency).

For damage abatement inputs inefficiency, a similar pattern arises with 60% and 66% of the parameters being significant (at the 10% level or lower) for the VRS technical inefficiency regression of the IVD and KNN models, respectively. For scale inefficiency, only 33% and 13% of the parameter were significant for the IVD and KNN models, respectively. The signs of the statistically significant parameters generally do not change when using the IVD or KNN model, but the statistical significance of some variables does depend on choosing IVD or KNN (e.g. *W_age*, *W_subsidies* and *W_HHI* for the VRS inefficiency, and farmers' *age* for scale inefficiency).

For productive inputs, the optimal distance cut-off was estimated to be 42.3 km for technical inefficiency and 54.3 km for scale inefficiency. However, the 90% confidence interval obtained from the bootstrap suggests rather large intervals ranging from 15.4 to 87.1 km and 14.7 to 91.2 km for technical and scale inefficiency, respectively. This could be caused by the sizeable error terms sampled within the bootstrap. In addition, it is important to note that only a subsample of the population is included in the data. Consequently, the estimation of distance decay effects is certainly aggravated. Arguably, the large confidence intervals suggest a minor influence of the distance cut-off on model performance. This seems plausible given the strong weight of close-by DMUs when constructing spatially lagged regressors using the IVD weight matrix. The optimal number of neighbours was estimated to be 16 for technical inefficiency and 38 for scale inefficiency. The 90% confidence interval ranged 11 to 19 for technical inefficiency and 17 to 56 for scale inefficiency. For damage abatement inputs, the optimal distance cut-off was estimated to be 57.5 km for technical inefficiency and 54.8 km for scale inefficiency. The 90% confidence interval ranged from 25.3 to 86.7 km and 15.2 to 94.2 km for technical and scale inefficiency, respectively. The optimal number of neighbours was estimated to be 29 for technical inefficiency and 30 for scale inefficiency. The confidence interval ranged from 27 to 31 neighbours for technical inefficiency and 17 to 49 neighbours for scale inefficiency.

In terms of model performance, the IVD based regressions obtained a lower AIC score compared to the KNN equivalents for all inefficiencies except the scale inefficiency of damage abatement inputs. This suggests that including influences from nearby DMUs, and weighting them more, was able to explain the inefficiency scores better than including influences of the nearby community of *k* farmers. However, we should be careful about extrapolating this result to other data. The IVD and KNN approach could very well perform differently if a more complete spatial coverage was available. The balanced panel data used for this analysis comprises only 75 DMUs which are distributed across the Netherlands. Consequently, measuring influences from *k* nearest neighbours does not necessarily reflect *k* tightly connected farms in space. The IVD matrix takes distance into account more directly and places th majority of the weight on the farmer(s) in close proximity. As near things tend to be more related than distant things (Tobler, 1970), it might well be that IVD was able to explain the data better than KNN given the spatial coverage at hand.

To allow for interpretation of the association, marginal effects are calculated at the mean of the data after equation (4). The marginal effects are depicted in Table 5. While statistically significant, some marginal effects are not economically significant. In particular, the marginal effects from a 10-year increase in age, but also from a rise in subsidy payments of €1,000 per hectare were small with a decrease in productive inputs and damage abatement inputs inefficiency of around 0.2% and 2%, respectively.

For damage abatement inputs inefficiency, insights on the direction of spillover effects were more robust compared to productive inputs inefficiency. The spatial spillover effects from the neighbours' degree of specialisation (as measured with HHI) on productive inputs inefficiency were particularly sensitive to the type of spatial weight matrix used. Our results could suggest that farmers are influenced differently depending on whether one proximate peer is highly specialised or whether the neighbourhood is characterised by a community of specialised peers. Areas with neighbourhoods of highly specialised farmers might be characterised by operational conditions more tailored to arable farming. These beneficial effects do not necessarily emerge when having one specialised peer in proximity.

Table 5
Marginal effects on productive inputs and damage abatement inputs inefficiency

	Technical		Scale	
	IVD	KNN	IVD	KNN
Productive inputs				
age	−0.002***	−0.002***	0.005*	0.005
subsidies	−0.023***	−0.022***	0.022	0.027
insurance	−0.027	−0.012	0.075*	0.040
HHI	−0.020***	0.001	−0.022***	−0.020**
W_age	0.022**	−0.001***	−0.002	−0.002
W_subsidies	−0.029	0.146**	0.016	−0.019
W_insurance	−0.124***	−0.077	0.146	−0.047
W_HHI	0.078*	−0.027***	−0.023	−0.024
Damage abatement inputs				
age	−0.002***	−0.002**	0.006**	0.003
subsidies	−0.024***	−0.028***	0.013	0.012
insurance	0.054	−0.012	0.049*	0.050*
HHI	0.005	−0.002	−0.011	−0.008
W_age	0.026**	0.027	−0.000	−0.001
W_subsidies	0.109	0.231**	−0.022	−0.022
W_insurance	−0.120***	−0.046***	0.065	−0.046
W_HHI	−0.031	−0.019***	0.003	0.109

Note: ***$P < 0.01$; **$P < 0.05$; *$P < 0.10$

The most sizeable spillover effects are for neighbours' received subsidies, in the form of direct payments, and their insurance payments. For KNN, a cumulative increase of €1,000 in subsidy payments per hectare is associated with an increase in productive inputs technical inefficiency by 14.6% and in damage abatement inputs technical inefficiency by 23.1%. For IVD, a cumulative increase of €1,000 in insurance payments per hectare is associated with a decrease in productive inputs inefficiency by 12.4% and in damage abatement inputs technical inefficiency by 12%.

4. Discussion

Our estimated technical inefficiency scores for productive inputs and damage abatement inputs are in line with earlier findings by T. Skevas *et al.* (2012) and T. Skevas *et al.* (2014) who identified technical inefficiency scores (0.03 to 0.10) for productive inputs in the Netherlands during 2003 to 2007, including undesirable inputs and outputs. T. Skevas *et al.* (2014) estimated annual averages of output technical inefficiency to range between 7% and 13% for Dutch arable farmers, compared with our 2011 to 2016 annual average inefficiency of 0% (cf. Dakpo and Lansink, 2019). Furthermore, to ease the estimation of the spatial weight matrix we decided to focus on a balanced panel. This could also explain why we find no inefficiency in output and very low inefficiencies in inputs.

The results from the second stage regression (Table 5) suggest that older farmers are associated with lower technical inefficiency of productive inputs and damage abatement inputs. This could stem from their accumulated knowledge and past experiences (Tauer, 1995). However, a cumulative increase in the neighbours' age is associated with higher input technical inefficiency scores. Tveteras and Battese (2006) suggest that firms which operate next to knowledge-intensive producers are more likely to be technically efficient. Younger farmers might be more up to date with recent developments and in turn could provide signals to neighbouring peers that improve their decision-making. Age is also associated with a higher scale inefficiency suggesting that older farmers operate farms at a sub-optimal scale. This finding might reflect the shorter time horizon for older farmers, resulting in a lower incentive to invest in scale changes (Davis *et al.*, 2013).

Our results suggest that higher subsidies, comprising only direct payments, are associated with lower technical inefficiencies of productive and damage abatement inputs, albeit not economically significant. The literature is divided regarding the effects of subsidies on farm-level efficiency (Zhu and Oude Lansink, 2010; Minviel and Latruffe, 2017). For the Netherlands, previous studies have identified small impacts of subsidies or a significant positive associations between subsidies and technical inefficiency (Reidsma *et al.*, 2009; T. Skevas and Serra, 2016). The conflicting results in our study might be related to differences between our approach of measuring output and input-specific inefficiency scores and the approach used in previous studies. Our findings could suggest that subsidies allow for investments in improved technologies that might operate more efficiently (Zhu and Oude Lansink, 2010). Similarly, Reidsma *et al.* (2009) found direct effects of subsidies per hectare on input intensity per hectare and further argue that increased intensity can lead to a more profitable use of the area.

In terms of spatial spillovers, our results for subsidies were statistically insignificant for IVD. However, for KNN the results suggest a statistically significant positive association with technical inefficiency of productive inputs and damage abatement inputs. The sensitivity of results to the choice of the spatial weight matrix was also stressed in previous studies (Areal *et al.*, 2012; Pede *et al.*, 2018). Our results highlight the importance of employing multiple approaches and to report on the robustness of results. The spatial spillover effect of subsidies does not occur for scale inefficiency. Strohm *et al.* (2014) found adverse effects of neighbours' subsidy payments on farm survival. Higher subsidy payments can improve farmers' ability to purchase land and thereby increase land prices in the vicinity (Strohm *et al.*, 2014). Our results for scale inefficiency reject Strohm *et al.*'s (2014) hypothesis in this case.

Higher insurance payments per hectare are associated with larger scale inefficiency. This might stem from the need of farmers with sub-optimal scales of production to more rigorously safeguard their income. Alternatively, this could suggest that a base-level of insurance is seen as essential by Dutch arable farmers. Our results on the spatial spillover of neighbours' insurance payments suggest statistically significant negative relations with the technical inefficiency of productive inputs and damage abatement inputs. Farmers with a high perception of yield risk might opt for higher insurance coverage (Sherrick *et al.*, 2004). At the same time, these farmers might be more likely to control diseases in their fields more rigorously to avoid a shortfall in yield. This extra effort could improve the bio-security in the vicinity and could thereby benefit their neighbours.

Consistent with the literature, the degree of specialisation (as measured by HHI) is associated with lower technical inefficiency in productive inputs. Specialisation implies expertise in producing the particular good (Zhu *et al.*, 2012; I. Skevas *et al.*, 2018).

The mixed results for IVD and KNN are likely related to the different nature of the spatial weight matrices. While IVD strongly emphasises the degree of proximity, KNN treats the selected number of neighbours as equally important. In turn, our results shed light on the different effects that could arise from an individual versus a community of neighbours. The mixed results for the spatial spillovers could suggest that distance itself is of greater importance when measuring effects of certain farm characteristics. We argued that many of the spillover effects on damage abatement inputs technical inefficiency from different farm characteristics are rooted in the interdependence among fields which arises through pathogen multiplication and dispersal. In contrast, spatial spillovers on technical inefficiency of productive inputs are hypothesised to arise through the social network of farmers. Consequently, it might well be that different effects arise depending on whether proximity is taken into account directly, as in IVD, or whether a nearby community of k neighbours is investigated jointly. Certainly, in line with Areal *et al.* (2012) and Pede *et al.* (2018) our analysis stresses the need to communicate the robustness of results in spatial econometric applications depending on the different formulations of the spatial weight matrix.

While some research has evaluated community effects on individuals' behaviour (Stephenson, 2009; Foster and Brooks-Gunn, 2013), more work is needed on such effects within the context of production economics. Signals for improving operational processes could very well differ depending on whether individual peers or the general neighbourhood characteristics are referenced by the decision-making unit. Certainly, a clearer distinction between individual-centric versus community-based spillovers is necessary to improve the design of policy. As evident from our results on the spillover effect from subsidies, adverse effects might go unnoticed if analyses do not aim at capturing the different channels of influence.

5. Conclusions

Our objective was to empirically quantify the effects of spatial spillovers on output and input-specific technical inefficiency in Dutch arable crop farms. First, a non-parametric directional distance function was computed using DEA to estimate technical and scale inefficiency scores for output, productive inputs and damage abatement inputs (pest control spending). Second, a spatial econometric model was estimated which incorporates regressors for spatial lags of farm characteristics alongside other non-lagged explanatory variables and time-period fixed effects. We use both the inverse distance weight matrix and the binary k-nearest-neighbours weight matrix and also estimate the distance cut-off and the optimal number of neighbours rather than imposing rules of thumb.

The average technical inefficiency across years was found to be 0% for output, 3.9% for productive inputs and 3.0% for damage abatement inputs. Results of spatial spillovers were sensitive to the choice of the spatial weight matrix which suggests a need to apply multiple lenses when estimating the spatial spillovers in spatial econometric applications. The differences in the results of the two approaches may well reflect the different types of spillovers, where the inverse distance approach emphasises spatial proximity and the k-nearest neighbours assigns equal importance to every farmer in the community of k neighbours. For productive inputs technical inefficiency, statistically significant spillover effects from neighbours' age and their degree of specialisation depended on the type of the spatial weight matrix used, statistically significant spillover effects of subsidy payments were adverse and statistically significant spillover effects from insurance payments were beneficial. For damage abatement inputs technical inefficiency, statistically significant adverse effects were found for neighbours' age and subsidy payments and beneficial effects from neighbours' insurance payments and their degree of specialisation. For scale inefficiency, no spatial spillover effects were found.

Accounting for spillover effects in estimating the determinants of technical and scale inefficiency relaxes the assumption that farmers operate in isolation from their peers. Fostering the influx of young farmers is often emphasised by EU policy-makers (e.g. Rovný, 2016). Our results suggest that young farmers could not only lead to more optimal scales of production but benefit the close-by network of peers. The need for farm subsidy payments is often strongly debated in the literature (e.g. Minviel and Latruffe, 2017). We found significant adverse spillover effects from subsidy payments on the technical inefficiency of both productive inputs and damage abatement inputs. Hence, the discussion on the need for subsidies might be broadened to also include spillovers to the nearby community of peers. We found that insurance payments are not statistically associated with the technical inefficiency of the insured. However, sizeable beneficial spillover effects were found for both productive inputs inefficiency and damage abatement inputs technical inefficiency. The spatial insurance coverage could inform insurance design by signalling the risk awareness of a community of farmers. The beneficial spillover effects might suggest that risk premia could be lowered if a community of farmers is insured. The spatial nature of pathogens certainly results in a mutual dependence between farmers, which is best approached through collective actions (Knipling, 1980). The optimal degree of specialisation is subject to discussion in the agricultural economics literature (Kurosaki, 2003; Kim *et al.*, 2012). While results for productive inputs technical inefficiency differed for the two spatial weight matrices, having a community of specialised neighbours seems to benefit own inefficiency for productive inputs and damage abatement inputs.

The key message from our analysis of spatial dependence is that the estimation of the appropriate spatial weights is important, since our results indicate that they are sensitive to the weight structure, emphasising either the number of neighbours or their spatial proximity. In the case of pest control, proximity might be more important, while knowledge and experience spillovers might be more associated with the population size of the neighbourhood.

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