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Dynamic Inefficiency and Spatial Spillovers in Dutch Dairy Farming

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Abstract

This article examines the presence of spatial spillovers in farms' dynamic technical inefficiency scores using Data Envelopment Analysis and a second-stage spatial truncated bootstrap regression model. Dynamic inefficiency is measured in terms of variable input contraction and gross investment expansion, while the second-stage model allows an individual's dynamic inefficiency to be influenced by both own and neighbours' characteristics. The empirical application focuses on the panel data of specialized Dutch dairy farms observed over the period 2009-2016 and for which exact geographical coordinates of latitude and longitude are available. The results confirm the existence of spatial spillovers in farmers' dynamic technical inefficiency levels. Although changes in neighbours' subsidies do not significantly influence an individual's inefficiency, an increase in neighbours' age reduces an individual's performance, while an increase in neighbours' levels of intensification improves an individual's dynamic efficiency.

Keywords: *Dynamic inefficiency; spatial spillovers; Dutch dairy farms.*
JEL classifications: *C23, D22, D24, D25.*

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1. Introduction

Despite the numerous theoretical and methodological advances in the area of firm-level benchmarking, the measurement of firms' performance remains a challenging task. This is because producers operate under a complex environment in which temporal as well as spatial links in their decisions may exist. Tackling the intertemporal nature of producers' decisions has been well documented in the related literature. The assumption that firms instantaneously adjust their production factors to their optimal levels has been severely criticized, motivating the move from static to dynamic modelling. In a dynamic setting, firms' optimal policy is to gradually adjust their quasi-fixed factors of production due to the existence of adjustment costs (Penrose 1959; Treadway 1970; Stefanou 1989; Stefanou 2009). Empirically, the constraint that capital is not freely adjusted is imposed through an equation of motion where capital depends on the rate of depreciation of existing capital and investment in new capital. Examples of such dynamic efficiency studies include Silva and Stefanou (2003), Serra et al. (2011), Kapelko et al. (2015), Kapelko and Oude Lansink (2017) and Ang and Oude Lansink (2018).

Although a plethora of studies have accounted for the intertemporal nature of producers' decision-making processes, spatial spillovers, which represent externalities arising from neighbouring producers, have not been addressed so extensively. The scarcity of studies accounting for such effects may be due to modelling complications or the unavailability of spatial data. However, Anselin (2001) warns that, conditional on their existence, ignorance of spatial spillovers may lead to biased inference. Furthermore, the identification of spatial links between producers may be valuable to more effectively disseminate knowledge and/or promote new technologies so as to improve firms' economic and environmental performance.

In the agricultural economics literature, Foster and Rosenzweig (1995) and Weiss (1996) were some of the first to discuss the potential existence of spatial links between farmers in a technology adoption setting. Subsequent empirical studies including Wollni and Andersson (2014) and Läpple et al. (2017) verified the existence of spatial spillovers in farmers' decisions to adopt new technologies. Additionally, in a farm survival analysis setting, Storm et al. (2014) found adverse spatial spillovers from economically larger farms due their greater ability to expand their businesses by biding up land prices and the associated inability of the surrounded farms to reach their optimal

size. This discussion was gradually extended to efficiency analysis with Areal et al. (2012), Pede et al. (2018) and Skevas (2019) arguing that producers may learn from their neighbours or imitate them, thus resulting in spatial spillovers in their inefficiency scores. For instance, an individual farmer may experience efficiency gains by learning how to use his resources more effectively from surrounding farmers. Furthermore, an individual's working motivation may be influenced by that of neighbouring farmers and result in similar investment decisions that will improve performance. Thus, we might expect the existence of spatial spillovers in farmers' inefficiency scores.

Early attempts to account for spatial effects in agricultural efficiency analysis focused on the regional or the municipality level. For instance, Hadley (2006) and Schmidt et al. (2009) included regional-specific dummies and municipality-specific covariates respectively, in an inefficiency regression setting. However, recognising that spatial spillovers may take place at a more disaggregated level led the subsequent (few) studies to focus on lower scale. For example, Areal et al. (2012) used a kilometer grid-square level, while Pede et al. (2018), Skevas and Grashuis (2019), Martínez-Victoria et al. (2019) and Skevas (2019) used exact geographical coordinates (i.e. latitude and longitude) to test for the presence of spatial spillovers in firms' inefficiency/productivity scores, with the results verifying their existence. However, and as long as the identification of spatial spillovers on inefficiency is concerned, previous studies merely examined their presence on static inefficiency, disregarding the temporal links of production decisions that are implied by the sluggish adjustment of quasi-fixed factors of production. Failing to account for intertemporal linkages can lead to misleading efficiency estimates.

We contribute to the literature as follows: unlike previous studies that have only accounted for spatial spillovers on static inefficiency, we examine the presence of spatial spillovers in farms' dynamic inefficiency scores. Dynamic technical inefficiency is measured in terms of variable input contraction and gross investment expansion using DEA. Subsequently, a second-stage spatial truncated bootstrap regression model is used to examine the presence of spatial spillovers on farm dynamic inefficiency. Own as well as neighbours' characteristics are specified as determinants of an individual's dynamic inefficiency and the related marginal effects are calculated. The application focuses on the panel data of specialized Dutch dairy farms, observed over the period 2009-2016, for which geographical coordinates of latitude and longitude are available. Dutch dairy farming is an interesting case study for two reasons. First, the sector is characterized by high capital intensity

and rapid technological progress, which give rise to the existence of high adjustment costs that justify the dynamic framework. Second, according to Groeneveld et al. (2013) Dutch dairy farmers tend to communicate with their neighbours and be aware of their production practices, which makes it interesting to study potential spatial spillovers in their inefficiency levels. The following section presents the method used to measure dynamic technical inefficiency and the specification of the second-stage spatial model. A description of the dataset follows. Results are presented and discussed in the subsequent section, while the final section concludes.

2. Methodology

2.1. Dynamic technical inefficiency measurement

As in Silva and Stefanou (2007), a dynamic directional distance function is used to measure dynamic technical inefficiency. In this context, farms use a vector of fixed inputs $\mathbf{L} \in \mathscr{R}_+^B$, a vector of quasi-fixed inputs $\mathbf{K} \in \mathscr{R}_+^F$ with associated gross investments $\mathbf{I} \in \mathscr{R}_+^Z$, a vector of variable inputs $\mathbf{x} \in \mathscr{R}_+^J$ and produce a vector of outputs $\mathbf{y} \in \mathscr{R}_+^M$. The input requirement set is represented as $V(\mathbf{y} : \mathbf{K}, \mathbf{L})$ = {(x, I) : (x, I) can produce y given K, L}. According to Silva and Stefanou (2007), the input requirement set $V(\mathbf{y} : \mathbf{K}, \mathbf{L})$ is a closed and nonempty set, has a lower bound, is positive monotonic in variable inputs $\mathbf{x}$, negative monotonic in gross investments $\mathbf{I}$, is a strictly convex set, has output levels that increase with the stock of capital and quasi-fixed inputs, and can be disposed of freely. For farm i and time t, the input-oriented dynamic directional distance function $\overrightarrow{D}_{i,t}(\mathbf{y}, \mathbf{K}, \mathbf{L}, \mathbf{x}, \mathbf{I}; \mathbf{g_x}, \mathbf{g_I})$ with variable input and investment directional vectors $\mathbf{g_x}$ and $\mathbf{g_I}$ respectively, is defined as:

$$\begin{aligned}\overrightarrow{D}_{i,t}(\mathbf{y}, \mathbf{K}, \mathbf{L}, \mathbf{x}, \mathbf{I}; \mathbf{g_x}, \mathbf{g_I}) = &\max\{\beta \in \mathscr{R} : (\mathbf{x} - \beta\mathbf{g_x}, \mathbf{I} + \beta\mathbf{g_I}) \in V(\mathbf{y} : \mathbf{K}, \mathbf{L})\} \\ &\mathbf{g_x} \in \mathscr{R}_+^N, \mathbf{g_I} \in \mathscr{R}_+^Z, (\mathbf{g_x}.\mathbf{g_I}) \neq (\mathbf{0}^N, \mathbf{0}^Z)\end{aligned} \tag{1}$$

if $(\mathbf{x} - \beta\mathbf{g_x}, \mathbf{I} + \beta\mathbf{g_I}) \in V(\mathbf{y} : \mathbf{K}, \mathbf{L})$ for some β, $\overrightarrow{D}_{i,t}(\mathbf{y}, \mathbf{K}, \mathbf{L}, \mathbf{x}, \mathbf{I}; \mathbf{g_x}, \mathbf{g_I}) = -\infty$, otherwise. This directional distance function measures the maximal translation of $(\mathbf{x}, \mathbf{I})$ in the direction that is defined by the vector $(\mathbf{g_x}, \mathbf{g_I})$ that keeps the translated input combination in the set $V(\mathbf{y} : \mathbf{K}, \mathbf{L})$. Given that $\beta\mathbf{g_x}$ is subtracted from $\mathbf{x}$ and $\beta\mathbf{g_I}$ is added to $\mathbf{I}$, the aim is to find by how much to

contract the vector of variable inputs ($\mathbf{x}$) and expand the gross investments ($\mathbf{I}$) in the direction $(\mathbf{g_x}, \mathbf{g_I})$ onto the boundary of the technology. Dynamic technical inefficiency is measured by β. The dynamic directional distance function in equation (1) is estimated using DEA. We consider a Variable Returns to Scale (VRS) technology because previous studies, such as Zhu and Oude Lansink (2010), report increasing returns to scale for Dutch dairy farms, which is allowed for in the VRS specification. Omitting the time subscript for the remainder of this paper, for simplicity, the optimization problem is written as follows:

$$
\begin{aligned}
&\overrightarrow{D}_i(\mathbf{y}, \mathbf{K}, \mathbf{L}, \mathbf{x}, \mathbf{I}; \mathbf{g_x}, \mathbf{g_I}) = \max_{\beta, \boldsymbol{\lambda}^i} \beta \\
&\text{s.t.} \\
&\mathbf{y}_m \leq \sum_{i=1}^{N} \boldsymbol{\lambda}^i \mathbf{y}_m^i \quad m = 1, ..., M; \\
&\sum_{i=1}^{N} \boldsymbol{\lambda}^i \mathbf{x}_j^i \leq \mathbf{x}_j - \beta \mathbf{g}_{x,j}, \quad j = 1, ..., J; \\
&\mathbf{I}_f + \beta \mathbf{g}_I - \delta_f \mathbf{K}_f \leq \sum_{i=1}^{N} \boldsymbol{\lambda}^i (\mathbf{I}_f^i - \delta_f \mathbf{K}_f) \quad f = 1, ..., F; \\
&\sum_{i=1}^{N} \boldsymbol{\lambda}^i \mathbf{L}_b^i \leq \mathbf{L}_b \quad b = 1, ..., B; \\
&\sum_{i=1}^{N} \boldsymbol{\lambda}^i = 1 \\
&\boldsymbol{\lambda}^i \geq 0, \quad i = 1, ..., N
\end{aligned}
\tag{2}
$$

where $\boldsymbol{\lambda}$ is an intensity vector of firm weights and δ is the depreciation of capital. The first four constraints impose restrictions on outputs, variable inputs, gross investments and fixed inputs respectively, while the fifth and the sixth constraints allow for VRS technology and nonnegativity of the farm weights respectively. In our application, the directional vectors for variable inputs $\mathbf{g_x}$ and gross investments $\mathbf{g}_I$ are the quantity of variable inputs and 20% of the size of capital respectively, as in Kapelko et al. (2015).

2.2. Spatial truncated bootstrap regression

Once the dynamic technical inefficiency scores are obtained, typical second-stage censored regression models can be used to explain variation in inefficiency scores. However, we go one step further and examine the potential presence of spatial spillovers in the dynamic technical inefficiency

scores. This is achieved by allowing dynamic inefficiency to be a function of both individual and neighbour characteristics as Skevas and Grashuis (2019) do in a static inefficiency framework.[2,3]

Given that DEA analysis yields relative inefficiency scores that are serially correlated, the independence assumption in the second-stage truncated regression is violated making the regression's estimates biased. For this purpose, the Simar and Wilson (2007) single bootstrap approach is used, which has been shown to be a valid method for correcting the small sample bias and the serial correlation of the non-parametric inefficiency estimates both in radial (Kapelko and Oude Lansink (2015), Rezitis and Kalantzi (2016)) and directional distance function settings (Singbo and Oude Lansink (2010); Skevas et al. (2012); Singbo et al. (2014)). This is achieved by replacing the inconsistent estimates of the original truncated regression with bootstrap estimates while allowing for heterogeneity in the distribution of inefficiency and separability of the production set and the independent variables. Subsequently, the bootstrap estimates are used to perform inferences (i.e. construction of confidence intervals). The bootstrap algorithm is applied to each observation separately, which allows to provide empirical representations of the impact of individual and neighbours characteristics on farm dynamic technical inefficiency. Details for implementing each step of the bootstrap algorithm can be found on the description of algorithm 1 in Simar and Wilson (2007). Note also that this study does not specify fixed effects, which is a common choice in studies that adopt the truncated bootstrap regression setting (Aramyan et al. (2006); Skevas et al. (2012); Skevas and Oude Lansink (2014); Kapelko and Oude Lansink (2015); Horta et al. (2016); Rezitis and Kalantzi (2016)). This is because the Simar and Wilson (2007) bootstrap approach is applied at the individual level, whereas specifying fixed effects and eliminating them through the common mean-differencing approach makes the transformed variables consist of a group rather than individual observations.

[2]In the related literature, this model is called the Spatial Lag of X model, abbreviated as SLX (LeSage and Pace 2009; Vega and Elhorst 2015).

[3]Although not using exact location information of latitude and longitude and not applied to agriculture, Fusco et al. (2018) and Fusco et al. (2019) present an alternative single-step DEA approach in which the inefficiency of each unit is measured relatively to other units that belong to the same territory and where the number of neighbours is estimated empirically. However, this study uses the Skevas and Grashuis (2019) approach where inefficiency is first calculated based on a common frontier and spatial spillovers are sought in a second-stage regression. This allows us to quantify spatial spillovers and identify the channels through which they may arise.

The spatial truncated bootstrap model is written as:

$$\hat{\boldsymbol{\beta}}_{TI} = \alpha\boldsymbol{\iota} + \mathbf{Z}\boldsymbol{\eta} + \mathbf{WZ}\boldsymbol{\theta} + \boldsymbol{\xi}_{TI} \geq 0 \tag{3}$$

where $\hat{\boldsymbol{\beta}}_{TI}$ is the $N \times 1$ vector of the individuals' dynamic technical inefficiency scores obtained from equation (2), $\boldsymbol{\iota}$ is an $N \times 1$ vector of ones associated with the constant term parameter α, $\mathbf{Z}$ is an $N \times L$ matrix of farm-specific characteristics, $\boldsymbol{\eta}$ is the associated $L \times 1$ vector of parameters to be estimated and $\boldsymbol{\xi}_{TI}$ is the $N \times 1$ vector of noise terms. Focusing on the spatial component of equation (3), the term $\mathbf{WZ}$ represents neighbours' characteristics. This is achieved by placing elements on the $N \times N$ spatial weights matrix $\mathbf{W}$ such that the product $\mathbf{WZ}$ yields an $N \times L$ matrix that contains linear combinations of the values of neighbours' independent variables. Finally, the $L \times 1$ parameter vector $\boldsymbol{\theta}$ quantifies the strength of spatial spillovers. Note that the constant term is not included in $\mathbf{Z}$ because it would be perfectly collinear with the corresponding $\mathbf{WZ}$ variable. The same holds for the time dummies that are included in the application that follows. Inference in the spatial truncated bootstrap model presented in equation (3) is based on the so-called direct and spillover effects. The direct effects are the coefficient estimates with respect to the farm-specific characteristics $(\boldsymbol{\eta})$, while the spillover effects are those associated with the neighbours' characteristics $(\boldsymbol{\theta})$. To be able to make quantitative statements with respect to these effects, the corresponding marginal effects are calculated using the formula presented in Cameron and Trivedi (2010) who derive the marginal effects of a variable that is left-truncated at 0[4]. The derivative of $\hat{\boldsymbol{\beta}}_{TI}$ with respect to a variable contained in $\mathbf{Z}$ yields the corresponding direct marginal effect, which reveals the percentage change in a farmer's dynamic inefficiency due to a unit increase in his own respective characteristic. The derivative of $\hat{\boldsymbol{\beta}}_{TI}$ with respect to a variable contained in $\mathbf{WZ}$ yields the corresponding spillover marginal effect, which captures the percentage change in a farmer's dynamic inefficiency due to a (cumulative) one unit increase in his neighbours' respective characteristic.

[4]Consider the case where a (left-truncated at 0) variable y is a function of K explanatory variables contained in a vector $\mathbf{x}$ with associated parameter vector $\boldsymbol{\beta}$ and an error component $\boldsymbol{\epsilon}$ with standard deviation σ. The derivative of y with respect to the k^{th} explanatory variable in $\mathbf{x}$ is calculated as: $\frac{\partial y}{\partial x_k} = \beta_k \times \left[1 - \frac{\mathbf{x}'\boldsymbol{\beta}}{\sigma} \times \frac{\phi(\mathbf{x}'\boldsymbol{\beta}/\sigma)}{\Phi(\mathbf{x}'\boldsymbol{\beta}/\sigma)} - \left(\frac{\phi(\mathbf{x}'\boldsymbol{\beta}/\sigma)}{\Phi(\mathbf{x}'\boldsymbol{\beta}/\sigma)}\right)^2\right]$, where $\phi(\cdot)$ is the standard normal distribution and $\Phi(\cdot)$ represents the standard normal cumulative distribution function.

3. Dataset

Description of the data

Our data come from the Farm Accountancy Data Network (FADN) which are collected by Wageningen Economic Research of the Netherlands. The dataset contains information on specialized Dutch dairy farms and covers the period between 2009 and 2016. FADN defines specialized dairy farms as those whose revenues from sales of milk, milk products and turnover and growth of cattle comprise at least 2/3 of their total revenues. The dataset is a balanced panel of 1,584 observations from 198 farms.[5]

One output, two fixed inputs, one quasi-fixed input with its associated gross investments and two variable inputs are considered. The output comprises farm total output which includes milk, milk products, turnover and growth of cattle, crop products and other. The two fixed inputs are farms' total labour measured in hours and farms' total utilized agricultural area measured in hectares, as in Serra et al. (2011). Labour is considered to be a fixed input because it almost entirely comes from family labour. Buildings and machinery (capital) constitute the quasi-fixed input, while gross investments in this component are also considered. Finally, the two variable inputs are costs of intermediate inputs excluding feed and feed expenses. The former is an aggregate of veterinary expenses, crop-specific costs, energy expenses, contract work and other variable costs. Note that animals are not used as a separate quasi-fixed input so that the employed model is empirically tractable. The same approach was followed by Hüttel et al. (2017) and Ang and Oude Lansink (2018). The output and inputs measured in monetary values are defined as implicit quantity indices by calculating the ratio of value to its associated price index obtained from EUROSTAT, with base year being that of 2010.

Apart from output, input and investment indices, we also use financial, social and management indicators. These are included in the $\mathbf{Z}$ matrix of the second-stage spatial truncated bootstrap regression model presented in equation (3) to test for their (direct and spillover) impact on dynamic

[5]Employing balanced panel data is a very typical procedure followed in the spatial econometrics literature because the properties of spatial estimators become problematic for unbalanced panel datasets. This is because several restrictive assumptions and sensitive estimation techniques are needed, including statements regarding why the data are missing and imputation methods for recovering them (Elhorst 2014b).

technical inefficiency. Subsidies constitute the financial indicator and represent the total payments that farms receive under the Common Agricultural Policy (CAP) framework, while the Dutch Consumer Price Index obtained from EUROSTAT is used to measure them in the base year of 2010 in €10,000. Though there are ample studies examining the relationship between subsidies and inefficiency, the direction of the effect is debatable. On the one hand, there exist studies including - Zhu and Oude Lansink (2010), Zhu et al. (2012), Minviel and Sipiläinen (2018) and Skevas et al. (2018a) - who report a positive effect on inefficiency as a result of the income effect nature of subsidies that lowers farmers' motivation to work efficiently. On the other hand, studies such as Blancard et al. (2006), Kumbhakar and Bokusheva (2009), and Rizov et al. (2013) report a negative effect of subsidies on inefficiency when the former acts as a source of credit that allows farms to innovate and operate closer to the frontier. The social indicator is age and is measured in years.[6] The effect of age on inefficiency is also an empirical question. While Luh and Stefanou (1993) argue that as farmers grow older they become less inefficient because they acquire higher experience and learning ability, Hadley (2006) and Abdulai and Tietje (2007) stress that older farmers may lose their working motivation and refrain from productive investments, thus becoming more inefficient. Finally, the management indicator is farmers' stock density measured as the ratio of livestock units to total land. This variable represents farms' degree of intensification. Utilizing the same indicator, Alvarez and del Corral (2010) report a negative relationship between stock density and inefficiency, attributing it to the easier management of more intensive farms and the associated lower probability of their operators to misuse their resources. Alternatively, stock density can be negatively associated with inefficiency given that intensive farms are more keen on adopting new technologies (Läpple et al. 2017), which can decrease their inefficiency. Furthermore, time dummies are included to make the dynamic inefficiency scores comparable across different years. The year 2009 is used as a base category. Table 1 offers summary statistics

[6]Although age can be specified either as a continuous variable or as a dummy variable that can capture differences across age groups (i.e. young, middle-aged and old), the former approach is used in the present study. This is because most farmers in the sample are old (as the mean value of age on Table 1 manifests), which would make the remaining categories consisting of very few observations. Furthermore, given that the main objective of the paper is to identify spatial spillovers among farms, specifying age as a dummy variable would simply capture differences in inefficiencies between different age groups across space and not the impact of increasing neighbours' age on an individual's performance, which could manifest knowledge or motivation spillovers.

of all our variables.

Table 1

Summary statistics of the utilized variables

Variable	Unit	Mean	Std.
y	Total output (index)	340,131.40	238,714.00
L_1	Total labour (hours)	4,683.26	2,705.19
L_2	Total land (hectares)	70.01	42.65
K	Buildings & machinery (index)	484,526.70	395,674.50
I	Gross investment in buildings & machinery (index)	114,603.30	160,228.00
x_1	Intermediate inputs (index)	77,592.18	58,051.79
x_2	Feed (index)	79,558.85	63,441.16
p	EUROSTAT output price (index)	1.09	0.10
c	EUROSTAT buildings & machinery price (index)	1.03	0.04
w_1	EUROSTAT intermediate inputs' price (index)	1.09	0.07
w_2	EUROSTAT feed price (index)	1.15	0.14
Subsidies	CAP payments (index in €10,000)	6.52	5.55
CPI	Dutch Consumer Price Index (index)	0.97	0.34
Age	Years	52.54	10.19
Density	Livestock units/total land (ratio)	3.77	10.69

Finally, the effect of the farmer's neighbours' indicators on his own inefficiency is our main focus here. Some prior expectations follow. Concerning subsidies, if they are viewed as a source of finance that allows farmers to adopt new technologies and decrease their inefficiency levels, one would expect that changes in the farmer's neighbours' subsidies would not influence the farmer's own inefficiency as they do not entail changes in the farmer's financial capacity. Positive spillover effects on efficiency could however arise if neighbouring farmers communicate the advantages of the uptake of new technologies with an adjoining farmer, which can increase his probability of uptake and therefore his efficiency. However, if subsidies are perceived as an additional source of income that lower farmers' motivation to work efficiently, this may also result in an efficiency

decrease for an adjoining farmer, through a reduced motivation spillover effect from neighbouring farmers. With respect to age, positive or negative spillover effects may arise. On the one hand, older neighbours may share their experience and their accumulated knowledge on production-related issues with a neighbouring farmer, resulting in a farmer's own efficiency gains. On the other hand, a farmer's efficiency may decrease if his working motivation is (negatively) impacted by his neighbours' reduced motivation, which may occur especially if they are close to retirement. Finally, given that producers who employ intensive production practices tend to commit less production mistakes and be more keen and familiar with using new technologies, an individual farmer that is surrounded by more intensive farmers may experience efficiency gains due to learning spillover effects from his neighbours.

3.1. Construction of the spatial weights matrix

The construction of the spatial weights matrix requires an assumption regarding the network through which spatial influences arise. While Foster and Rosenzweig (1995) assume that spatial spillovers are more likely to exist between farms located in close geographical proximity, Conley and Udry (2010) argue that spatial spillovers do not necessarily exist between neighbouring farms but rather flow from more 'successful' farms to the rest. Nevertheless, the latter argument is more likely to hold in the context of developing countries in which large heterogeneity of farms' performances, sizes and technology choices exists. However, in a developed country such as the Netherlands, dairy farms tend to be more technologically advanced and more homogeneous in terms of performance. We assume that spatial spillovers in Dutch dairy farms are more likely to arise at the neighbourhood level and construct the spatial weights matrix based on farms' geographical distance.

The available dataset contains information on farms' latitude and longitude. These variables allow for calculating the distance between farms and, therefore, the construction of the spatial weights matrix $\mathbf{W}$ in equation (3). Following Roe et al. (2002), we recognise that an individual farmer may be more strongly influenced by close neighbours than more distant ones and use an inverse distance matrix that places more weight on the former. The inverse distance matrix has elements $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} is the Euclidean distance between individual i and j. The conventional practice of setting a distance cut-off point d^* is followed, implying that all spatial weights w_{ij} out-

side this distance are zero. The cut-off point d^* is set equal to the minimum distance within which all farms in the sample have at least one neighbour, as in Marasteanu and Jaenicke (2016). This distance is 18km. Note that the diagonal elements of $\mathbf{W}$ (w_{ii}) are exempted from the above procedure and equal zero so that an individual is not defined as neighbour to himself. Finally, we follow Vega and Elhorst (2015) and standardize the spatial weights matrix $\mathbf{W}$ by scaling its elements by its maximum eigenvalue instead of the row sums. This is done because according to Kelejian and Prucha (2010), row normalizing a spatial weights matrix that is based on inverse distances makes its distance decay interpretation invalid. This is because the impact of observation i on j is not the same as that of the observation j on i, and the information about the mutual proportions between the elements in the different rows of $\mathbf{W}$ disappears.

4. Results and Discussion

Linear programming is used to solve the DEA problem in equation (2). Table 2 reports the mean and standard deviation of the dynamic inefficiency scores per year. Average dynamic technical inefficiency across all individuals and years is 22%. That is, farms can on average and under ceteris paribus conditions reduce their variable inputs by 22% and increase their gross investments by 4.4% of the value of the capital stock (i.e. 0.2×0.22). The reported average inefficiency score is higher than Serra et al. (2011) but similar to Steeneveld et al. (2012), who measured the dynamic and static inefficiency of Dutch dairy farms, respectively. However, the inefficiency scores of the aforementioned studies can't be directly compared with those reported in this study. This is because Serra et al. (2011) use an older dataset and the technique of SFA, while Steeneveld et al. (2012) estimate inefficiency in a static setting using also an older dataset. In contrast, this study estimates dynamic inefficiency using DEA and a more recent dataset that covers the period after the economic crisis of 2008/2009, which is also characterized by several technological advances, perhaps especially automatic milking machines.

Table 2

Mean and standard deviation of dynamic inefficiency per year

Year	Mean dynamic inefficiency	Std.
2009	0.24	0.17
2010	0.22	0.18
2011	0.23	0.17
2012	0.23	0.19
2013	0.17	0.15
2014	0.21	0.17
2015	0.22	0.18
2016	0.26	0.20
Average	0.22	0.18

In fact, studies that employ more recent datasets tend to report higher inefficiency scores for dairy farms. For instance, Namiotko and Baležentis (2017) measure the inefficiency of Lithuanian dairy farms under the presence of investment spikes and estimate average inefficiency at 23%.[7] Furthermore, Skevas et al. (2018b) use a reduced form dynamic inefficiency model and report an average dynamic inefficiency score of 35% for German dairy farms.

Turning to the results of the spatial truncated bootstrap regression model, Table 3 reports the corresponding parameter estimates along with the estimates from a non-spatial truncated bootstrap model. The reported results are based on a distance cut-off point of 18km, which is the minimum distance at which all farms in the sample have at least one neighbour. Another practice used in the literature is to choose a higher cut-off point such that all farms have several neighbours (Roe et al. 2002). However, this article relies on a standard rather than an arbitrary threshold.[8]

[7]This estimate concerns farms with similar size to the ones used in this article.

[8]Robustness checks are performed using 20km and 22km distance cut-off points. Parameter estimates are virtually the same. Furthermore, the Akaike's Information Criterion (AIC) is slightly lower in the model that uses the 18km cut-off point, implying that it fits the data better than the rest. The results from the robustness checks are reported in Table A1 in the on-line Appendix. The robustness checks concern the spatial truncated bootstrap regression model because this is the model that is favoured by our data.

Table 3

Estimates of the non-spatial and the spatial truncated bootstrap model

	Non-spatial			**Spatial**		
Variable	Mean	Std.	5% Interval	Mean	Std.	5% Interval
Constant	0.22	0.03	**[0.17, 0.27]**	0.25	0.03	**[0.19, 0.30]**
Dummy_2010	-0.01	0.02	[-0.04, 0.02]	-0.01	0.02	[-0.04, 0.02]
Dummy_2011	-0.02	0.02	[-0.05, 0.02]	-0.02	0.02	[-0.05, 0.02]
Dummy_2012	0.01	0.02	[-0.02, 0.04]	0.01	0.02	[-0.03, 0.04]
Dummy_2013	-0.09	0.02	**[-0.12, -0.05]**	-0.09	0.02	**[-0.12, -0.06]**
Dummy_2014	-0.02	0.02	[-0.05, 0.01]	-0.02	0.02	[-0.05, 0.01]
Dummy_2015	-0.01	0.02	[-0.04, 0.02]	-0.01	0.02	[-0.05, 0.02]
Dummy_2016	0.03	0.02	**[0.00, 0.06]**	0.03	0.02	**[0.00, 0.06]**
Subsidies	-0.02	0.01	**[-0.04, -0.01]**	-0.02	0.01	**[-0.04, -0.01]**
Age	0.01	0.00	**[0.01, 0.02]**	0.02	0.01	**[0.01, 0.02]**
Density	-0.03	0.01	**[-0.06, -0.02]**	-0.03	0.01	**[-0.05, -0.01]**
WSubsidies	-	-	-	0.00	0.03	[-0.05, 0.05]
Wage	-	-	-	0.01	0.01	**[0.00, 0.02]**
Wdensity	-	-	-	-0.03	0.01	**[-0.04, -0.03]**
σ	0.17	0.00	**[0.16,0.18]**	0.17	0.01	**[0.16, 0.18]**
AIC		-1,292.03			-1,322.90	
BIC		-1,230.67			-1,246.19	

Note: Statistically significant confidence intervals are presented in bold.

The estimates with respect to the year dummies do not differ across models. However, the estimates with respect to the constant term and the age variable differ across models as they are deflated in the non-spatial model. This implies a severe deflation of the calculated marginal effect of age on inefficiency. Finally, the data present substantial evidence in favour of the spatial model since the quantities of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are lower when compared to the non-spatial model. Given this last result, all subsequent inferences

are based on the estimates of the spatial truncated bootstrap regression model.

Focusing on the estimates with respect to the year dummies, the dynamic inefficiency scores exhibit significant differences in the years 2013 and 2016. Specifically, dynamic technical inefficiency is significantly lower in 2013 and significantly higher in 2016 when compared to 2009 (i.e. base year). Moving to the direct effects, which correspond to the estimates with respect to the individual farm characteristics, statistically significant effects are observed. Subsidies and density are associated with lower inefficiency levels, while age is linked to higher inefficiency. Concerning the spillover effects represented by the parameter estimates associated with neighbours' characteristics, statistically significant positive and negative spillovers are observed for age and density respectively.

As mentioned in the methodology section, the marginal effects of the determinants on inefficiency are calculated and are presented in Table 4.

Table 4

Marginal effects of the dynamic inefficiency determinants

Variable	Mean	Std.	5% Interval
Dummy_2010	-0.01	0.02	[-0.03, 0.02]
Dummy_2011	-0.01	0.02	[-0.04, 0.01]
Dummy_2012	0.00	0.02	[-0.02, 0.03]
Dummy_2013	-0.07	0.02	**[-0.09, -0.04]**
Dummy_2014	-0.02	0.02	[-0.04, 0.01]
Dummy_2015	-0.01	0.02	[-0.04, 0.01]
Dummy_2016	0.03	0.02	**[0.00, 0.05]**
Subsidies	-0.02	0.01	**[-0.03, -0.01]**
Age	0.01	0.00	**[0.01, 0.02]**
Density	-0.02	0.01	**[-0.04, -0.01]**
WSubsidies	0.00	0.02	[-0.04, 0.04]
WAge	0.01	0.00	**[0.00, 0.01]**
WDensity	-0.03	0.00	**[-0.03, -0.02]**

Note: Statistically significant confidence intervals are presented in bold.

Compared to 2009, dynamic technical inefficiency is 7% lower in 2013. However, in 2016 the dynamic inefficiency is 3% higher than that observed in 2009. For the remaining years, no significant differences occur. Explanations on why the average inefficiency of farms decreased in 2013 and increased in 2016, when compared to 2009, can either be based on changes in the prices of variable inputs or on differences in the variation of inefficiency among farms during these years. Regarding price changes, according to EUROSTAT feed price increased from €13.40 per 100kg in 2009 to €22.40 in 2013, while the price of Diesel increased from €61.15 per 100 litres in 2009 to €110.50 in 2013. Therefore, a possible explanation is that the aforementioned increases in the prices of variable inputs in 2013 motivated farmers to use them in more parsimonious ways that decreased their inefficient use. However, in 2016 the price of feed went down to €16.41 per 100kg and the price of Diesel decreased to €86.5 per 100 litres. Therefore, an explanation for the higher inefficiency in 2016 is that the decreases in the prices of variable inputs motivated farmers to increase their use, which can be associated with more production mistakes (i.e. overuse of variable inputs) that led to higher inefficiency. Additionally, the year 2016 follows the recent 2015 abolition of milk quota, which motivated farmers to increase milk production thus increasing their probability of committing production mistakes and experiencing lower inefficiencies. Regarding differences in the variation of inefficiency, given that the year dummies pick up differences in farms' production technologies across years, the lower inefficiency in 2013 may simply be due to less variation in inefficiency between farms when compared to 2009, while the higher inefficiency in 2016 can simply be due to higher variation in farms inefficiency as opposed to 2009.

Regarding the direct and spillover marginal effects of subsidies on inefficiency, only the former is statistically significant. In particular, a one unit (i.e. €10,000) increase in subsidies leads to a 2% decrease in inefficiency. The related literature reports two different effects of subsidies on inefficiency, where on the one hand, more subsidies may relieve farmers' credit constraints and make them less technically inefficient, while on the other hand, increasing subsidies may lower farmers' motivation to perform technically at a high level, thus increasing their technical inefficiency. Our results indicate that the former effect dominates, as in Kumbhakar and Bokusheva (2009). As mentioned above, neighbours' subsidies do not significantly affect an individual's inefficiency. This suggests that an increase in the subsidies received by neighbours does not change an individual's budget and motivation and consequently his ability or inclination to invest. When it

comes to age, significant direct and spillover marginal effects are observed. A one-year increase in the farmer's age leads to a 1% increase in inefficiency. This suggests that as farmers move towards the end of their life cycle, their lack of motivation to perform at a high technical level prevails over their experience advantage, thus experiencing inefficiency increases (Hadley 2006; Abdulai and Tietje 2007). A (cumulative) one-year increase in neighbours' age increases an individual's inefficiency by 1%, highlighting the existence of a reduced motivation domino effect between farmers when becoming older. This probably occurs because neighbouring farmers gradually lose their interest in searching for new technologies and investing in them, with this behavior being transmitted to an adjoining individual resulting in his own efficiency losses. With respect to stock density, statistically significant direct and spillover marginal effects also occur. A one unit (i.e. livestock unit per total land) increase in stock density decreases dynamic inefficiency by 2%, which can be due to the easier management of more intensive farms and the associated lower probability of their operators to misuse their resources (Alvarez and del Corral 2010) or due to the tendency of more intensive farmers to adopt new technologies that can increase their efficiency (Läpple et al. 2017). Interestingly, the spillover marginal effect of density on dynamic inefficiency has a higher magnitude than the corresponding direct marginal effect. Specifically, a (cumulative) one unit increase in neighbours' density decreases an individual's inefficiency by 3%, providing evidence of a strong learning spillover effect among farmers. That is, an individual farmer surrounded by more intensive peers may take advantage of their more efficient and up-to-date production techniques and learn how to use his own resources more accurately, thus experiencing efficiency increases.

All in all, the above results verify the hypothesis that communication between neighbouring farmers can either have adverse or beneficial effects in the form of efficiency losses and gains, respectively. The former is verified by the positive relationship between neighbours' increasing age and an individual's inefficiency, which can arise due to the reduced motivation of older farmers that spillovers to neighbours. The latter is evident from the negative link among neighbours increased density and an individual's inefficiency, which can be due to the flow of knowledge among neighbours regarding the accurate use of resources as this is hypothesized by Areal et al. (2012), Pede et al. (2018) and Skevas (2019).

5. Conclusions

We measure farms' dynamic technical inefficiency using DEA and specify a second-stage spatial regression model to test for the existence of spatial spillovers in the estimated inefficiency scores. We depart from previous studies in the literature by examining the presence of spatial spillovers on farms' dynamic inefficiency. The temporal dynamics stem from the fact that quasi-fixed factors of production such as capital are not instantaneously adjusted, due to the existence of high adjustment costs (Stefanou 2009). Dynamic inefficiency is measured in terms of contraction of variable inputs and expansion of gross investments. Subsequently, we recognise that interactions with neighbours may influence an individual's dynamic inefficiency and specify a second-stage spatial truncated bootstrap regression model in which inefficiency depends on individual as well as neighbours' characteristics. The hypothesized spillovers are based on learning and motivation domino effects that may arise through the interactions among neighbouring producers (Areal et al. 2012). Accounting for the potential existence of spatial spillovers in inefficiency scores is important both from a theoretical and from a methodological point of view. Theoretically, detecting spillovers across neighbouring farmers can help effectively disseminate knowledge and promote adoption of innovative technologies to increase farm efficiency. Technically, second-stage DEA models that ignore spatial spillovers may result in biased inference (Anselin 2001).

Our data concern specialized Dutch dairy farms observed from 2009 to 2016. This very recent dataset, apart from the traditional output, input and investment information, also contains exact geographical coordinates for farms based on their latitude and longitude. This information allows the calculation of the distance between farms and therefore the identification of neighbouring producers. Average dynamic technical inefficiency is 22%, highlighting the potential of Dutch dairy farms to improve their variable input use and investments allocation. Farmers' dynamic inefficiency levels are significantly influenced by individual characteristics. Subsidies decrease farms' dynamic inefficiency levels as they may relax their credit constraints, enabling them to invest in new technologies and move closer to the frontier. Increasing age leads to higher dynamic inefficiency. This may occur because as farmers grow older and approach the end of their life cycle, they become less motivated to work efficiently. Finally, stock density decreases dynamic inefficiency, which can be either due to the lower probability of more intensive farms to misuse their resources

or due to their higher probability to adopt new technologies and the related efficiency gains. Furthermore, significant spatial spillovers in farms' dynamic inefficiency scores are found. Although neighbours' subsidies do not influence an individual's inefficiency as they do not lead to changes in his funds that can be used for investment purposes, significant spatial spillovers are observed for age and, particularly, density. On the one hand, farmers surrounded by older neighbours tend to be more inefficient. This is potentially because the reduced motivation of neighbours as they grow older is transmitted to an individual farmer through imitation/communication, resulting in his reduced performance. On the other hand, producers that farm close to more intensive peers decrease their inefficiency. This suggests that farmers learn how to use their resources more effectively from neighbours that employ more efficient and state-of-the art production practices, which is ultimately translated as own efficiency gains.

Our results can be of particular interest to policy-makers. Knowing that learning spillover effects between farmers exist highlights the importance of local farmers' associations and/or farm visits in spreading knowledge and information. For instance, dissemination of information on using new equipment (i.e. milking robots) and new management programmes may benefit not only those targeted but also those around them. Additionally, since our findings reveal that the trend of older farmers becoming less efficient can also influence their neighbours, younger people could be encouraged. Given that young farmers may be more aware of state-of-the art technologies and more keen to invest in them, a motivation domino effect may result in efficiency gains for neighbours. Strategies for attracting young people to farming can include setting aside a small portion of direct payments for them, as is one of the key proposals for the future of the CAP after 2020. Additionally, intergenerational transfer of tangible and non-tangible assets such as access to land, information, education and financial services can also be an incentive. In the Netherlands, the main problem does not concern the intergenerational transfer of information and, in general, the intangible assets but rather the transfer of land due to its very high price. Therefore, farm succession can be eased by enhancing the access of new (institutional) investors to the financial market, who are willing to invest in land and who can enable farms to lease the land and buy it back over time.

Moving to the limitations of this research, the lack of data hinders the possibility of conducting a broader empirical analysis. Specifically, this study utilizes only three socioeconomic character-

istics to test for their impact on dynamic inefficiency, which also entails that three spatially lagged explanatory variables are specified in the truncated regression model. Additional characteristics were either not available or contained severe gaps, particularly for the most recent years, preventing the investigation of the impact of additional variables on dynamic inefficiency. Furthermore, the lack of price information prevented examination of spatial spillovers on other components of farms' performance such as allocative and economic inefficiency.

Finally, future research can explore both methodological and application areas. One direction is related to the specification of the distance cut-off point of the spatial weights matrix. Although we use the conventional minimum distance cut-off threshold and the robustness checks reveal no significant changes in the results when alternative arbitrary thresholds are concerned, a more data-driven approach would be to estimate the distance cut-off point of the spatial weights matrix. An estimation procedure is presented in Elhorst (2014a), where the distance cut-off point is estimated based on an algorithm that minimizes the ordinary least squared residuals. Hence, future research can extend this optimization routine to a truncated regression setting to estimate the distance cut-off point and the related spatial spillovers on inefficiency. Additionally, future research could focus on applying a similar empirical study to other countries such as France and Germany. This could form an interesting case study because farms in such countries are not so densely located compared to those in the Netherlands, which makes it interesting to test whether spatial spillovers still exist. Also, spatial spillovers in other stages of the supply chain could be examined, such as amongst processing firms.

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On-Line Appendix

Table A1

Estimates of the spatial truncated bootstrap model for the three different cut-offs

	18km		20km		22km	
Variable	Mean	Std.	Mean	Std.	Mean	Std.
Constant	0.25	0.03	0.25	0.03	0.26	0.03
Dummy_2010	-0.01	0.02	-0.01	0.02	-0.01	0.02
Dummy_2011	-0.02	0.02	-0.01	0.02	-0.02	0.02
Dummy_2012	0.01	0.02	0.01	0.02	0.01	0.02
Dummy_2013	-0.09	0.02	-0.09	0.02	-0.09	0.02
Dummy_2014	-0.02	0.02	-0.02	0.02	-0.02	0.02
Dummy_2015	-0.01	0.02	-0.01	0.02	-0.01	0.02
Dummy_2016	0.03	0.02	0.03	0.02	0.03	0.02
Subsidies	-0.02	0.01	-0.03	0.01	-0.03	0.01
Age	0.02	0.01	0.02	0.01	0.02	0.01
Density	-0.03	0.01	-0.03	0.01	-0.03	0.01
WSubsidies	0.00	0.03	0.01	0.03	0.01	0.03
WAge	0.01	0.01	0.01	0.01	0.00	0.01
WDensity	-0.03	0.01	-0.03	0.01	-0.03	0.01
σ	0.17	0.01	0.17	0.00	0.17	0.00
AIC	-1322.90		-1320.89		-1315.42	