Spatial dependence and dynamic productivity growth in Wisconsin dairy farming

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Abstract

This article examines the role of neighboring farmers' characteristics in the analysis of dynamic productivity growth and its components, namely dynamic technical inefficiency change, dynamic technical change, and dynamic scale inefficiency change. The empirical application focuses on spatially explicit farm-level data for the Wisconsin dairy sector covering the period 2009 to 2017. Employing a production framework that accounts for the dynamics of capital adjustment, dynamic productivity growth and its components are calculated as a fist step and subsequently, non-spatial and spatial panel data models are estimated and compared to examine the presence of spatial interdependencies in dynamic productivity growth and its decompositions. Results show that neighboring farmers' characteristics and, more specifically, their financial and production characteristics, influence farm dynamic productivity growth and its components. Judgments are then made, based on theory and institutional context, about the potential channels through which these effects operate. Results also show that in addition to neighboring farmers' characteristics, own-farm characteristics and climatic conditions play an important role in explaining farm dynamic productivity growth and its components.

Keywords: data envelopment analysis, dynamic Luenberger productivity growth, spatial spillovers, spatial panel data models, dairy farms

1 Introduction

Productivity growth, is an important indicator of a firm's economic performance and competitiveness (Emvalomatis, 2012). In the context of agricultural production, productivity growth can be viewed as an indicator of a farm's ability to persist in an environment where regulatory (e.g banning of specific inputs), market (e.g. increased cost of production), and environmental pressures (e.g. extreme weather events) may reduce its economic performance and even lead to farm exit.

Measuring productivity growth and understanding the factors that drive it, can guide future policy interventions and extension programs that seek to enhance farm performance (Lien et al., 2017). To this end, a large number of studies have been conducted to measure and decompose farm-level productivity growth rates, mostly in a static setting (e.g. Brümmer et al., 2002; Lambarraa et al., 2007, and many others). Some studies have gone a step further and examined the factors that affect changes in productivity growth, such as farm policies, climatic conditions, risk, and farm characteristics (e.g. Lien et al., 2017; Mary, 2013; Rizov et al., 2013; Skevas and Lansink, 2014, and many others). However, the role of neighboring farmers' characteristics on dynamic productivity growth and its components remains largely unexplored and, therefore, is the focus of this study.

Farm productivity (and its components) differs between farms due to their different characteristics. For instance, large farms often exhibit higher productivity growth than small farms. This is because large farms adopt innovations earlier than small farms (Weiss, 1999) and, given their larger collateral, have better access to credit (Roberts and Key, 2008), leading to improved ability to invest in capital assets and land improvements. We argue that, apart from own farm characteristics, neighboring farmers' characteristics and decisions also affect a farmer's productivity growth and its components. Social networks and knowledge and technology transfers may be among the channels through which these spillover effects operate [1]. For example, farmers may exchange information with their

[1]A growing body of literature provides evidence that neighborhood networks and social learning play an important role in farmers' production decisions and resource use (Chatzimichael et al., 2014; Conley

neighbors' about the effectiveness of specific farm management practices or technologies, and adjust their practices accordingly. This, in turn, may lead to similarities in performance across neighboring farms. Another channel through which neighboring farmers' characteristics may affect a farmer's performance is competitive interaction on the land or labor market [2]. For instance, often farmers compete for a fixed supply of farm land (Storm et al., 2014; Weiss, 1999). In such cases, larger farms in terms of economic size may be more able to expand their businesses and achieve a more efficient scale of operation. This, in turn, may prevent neighboring farms from achieving the size that would allow them to benefit from economies of scale, leading to decreased productivity growth. On the other hand large farms in terms of economic size can have a positive influence on neighboring farmers' productivity growth. This is because economically successful farms may be more likely to adopt new technologies and since often neighboring farmers follow the practices of their successful neighbors (Chatzimichael et al., 2014), they may adopt similar technologies and become more competitive. Therefore, since neighboring farmers' characteristics can affect a farmer's performance, the value of investigating the importance of such effects on farmers' dynamic productivity growth and its components is obvious.

Currently, only a few studies have examined the role of spatial interdependencies on farmers' performance (Areal et al., 2012; Pede et al., 2018). All these studies have only focused on assessing the effect of spatial interactions on farmers' technical efficiency (under a static production environment) and found that interdependence between neighboring farms is an important determinant of their performance. Against this background, the goal of our article is to examine whether neighboring farmers' characteristics influence a farmer's dynamic productivity growth and its components. By doing so, we are the first to provide empirical evidence on the importance, magnitude, and likely channels through

and Udry, 2010; Foster and Rosenzweig, 1995; Wollni and Andersson, 2014). For example, Conley and Udry (2010) found that farmers in Ghana adjusted their inputs to align with those of their successful neighboring peers. Such adjustments can lead to spatially-structured farm productivity growth.

[2] Storm et al, in study that examined the effect of neighboring farmers' characteristics on farm survival, used the idea of competitive interaction among farmers on the land market to explain their finding that farms with larger neighbors in terms of direct payments have a lower survival probability.

which spatial spillover effects influence nearby farms' dynamic productivity growth and its decompositions. Such empirical evidence may facilitate the design of farm policies aimed at enhancing farm performance. For example, if spatial spillover effects arise as a result of information sharing and imitation of the production decisions of nearby farms, then policy makers can take advantage of these information spillover effects and propagate more efficiently innovative productivity-enhancing technologies and management practices.

The rest of the paper proceeds as follows. The modeling approach is laid out in the next section. Section 3 presents the data used in this article. Section 4 reports and discusses the results, and Section 5 concludes.

2 Research Methodology

The research methodology used in this study consists of two steps. First, using Data Envelopment Analysis (DEA) models that account for the dynamics of capital adjustment, a farm-specific dynamic Luenberger productivity growth indicator is computed and decomposed into dynamic technical inefficiency change, dynamic technical change, and dynamic scale inefficiency change. Non-spatial and spatial panel data models using the dynamic Luenberger indicator and its components as dependent variables are then estimated and compared to examine the role of spatial spillover effects (and some control variables) in farms' dynamic productivity growth and its decompositions.

2.1 Dynamic Luenberger indicator of productivity growth

We use a dynamic directional distance function to define the Luenberger indicator of productivity growth. The dynamic production framework employed in this analysis is based on the theory of gradual adjustment of quasi-fixed production factors in the presence of adjustment costs (Eisner and Strotz, 1963; Epstein, 1981). Let $\mathbf{y}_t \in \mathbb{R}_+^M$ represent a vector of outputs, $\mathbf{x}_t \in \mathbb{R}_+^P$ denote a vector of variable inputs, $\mathbf{k}_t \in \mathbb{R}_+^Q$ represent a vector of quasi-fixed inputs, $\mathbf{I}_t \in \mathbb{R}_+^C$ be a vector of gross investments, $\mathbf{H}_t \in \mathbb{R}_+^F$ be a vector of fixed inputs for which no investments are allowed, and t be a time trend.

The production input requirement set is represented as $V(\mathbf{y}_t : \mathbf{K}_t, \mathbf{H}_t) = \{(\mathbf{x}_t, \mathbf{I}_t) :$ can produce $\mathbf{y}_t$, given $\mathbf{K}_t$, $\mathbf{H}_t\}$. $V(\mathbf{y}_t : \mathbf{K}_t, \mathbf{H}_t)$ is assumed to have the properties defined by Silva, Lansink, et al. (2013) [3]. $V(\mathbf{y}_t : \mathbf{K}_t, \mathbf{H}_t)$ can be represented by the following input-oriented dynamic directional distance function (DDF):

$$\begin{gathered}\overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I) = \\ max\{\beta \in \mathbb{R} : (\mathbf{x}_t - \beta\mathbf{g}_x, \mathbf{I}_t + \beta\mathbf{g}_I) \in T\} \\ \mathbf{g}_x \in \mathbb{R}_+^P, \mathbf{g}_I \in \mathbb{R}_+^C, (\mathbf{g}_x, \mathbf{g}_I) \neq (0^P, 0^C)\end{gathered} \tag{1}$$

if $(\mathbf{x}_t - \beta\mathbf{g}_x, \mathbf{I}_t + \beta\mathbf{g}_I) \in V(\mathbf{y}_t : \mathbf{K}_t, \mathbf{H}_t)$ for some β, and $\overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I) = -\infty$. $\mathbf{g}_x$ and $\mathbf{g}_I$ are the vectors of directions in which variable inputs and investments can be translated. The dynamic DDF in (1) seeks the maximum translation of the variable input and gross investment vectors in the direction defined by the respective directional vector, which keeps the translated input combination in the interior of the production input requirement set. Since $\beta\mathbf{g}_I$ is added to $\mathbf{I}_t$ and $\beta\mathbf{g}_x$ is subtracted from $\mathbf{x}_t$, the dynamic DDF seeks to simultaneously expand gross investments and contract variable inputs. The dynamic inefficiency of decision making units (DMUs) is measured by β. As demonstrated by Silva, Lansink, et al. (2013), $\overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I)0$ is a full characterization of the input requirement set (i.e. $V(\mathbf{y}_t : \mathbf{K}_t, \mathbf{H}_t)$) and is an alternative primal representation of the adjustment cost production technology.

The dynamic DDF is approximated empirically using Data Envelopment Analysis (DEA). The DEA model that computes the dynamic DDF for time t under variable returns to scale (VRS) is as follows:

[3]These properties are the following: the input requirement set is closed and non-empty, negative monotonic in $\mathbf{I}_t$, positive monotonic in $\mathbf{x}_t$, is a strictly convex set, the levels of y_t increase with the stock of capital, and $\mathbf{K}_t$ are strongly (or freely) disposable.

$$
\overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I) = \max_{\beta,\gamma} \left\{ \begin{array}{c} \beta \geq 0 : \mathbf{y}_{t,m} \leq \sum_{j=1}^{J} \gamma^j \mathbf{y}_{t,m}^j, \quad m = 1, ..., M; \\ \sum_{j=1}^{J} \gamma^j \mathbf{x}_{t,p}^j \leq \mathbf{x}_{t,p}^j - \beta \mathbf{g}_{x_p}, \quad p = 1, ..., P; \\ \mathbf{I}_{t,c} + \beta \mathbf{g}_{I_c} - \delta_{t,c}^j \mathbf{K}_{t,c} \leq \sum_{j=1}^{J} (\mathbf{I}_{t,c} - \delta_{t,c}^j \mathbf{K}_{t,c}), \\ c = 1, ..., C; \\ \sum_{j=1}^{J} \gamma^j \mathbf{H}_{t,f}^j \leq \mathbf{H}_{t,f}^j, \quad f = 1, ..., F; \\ \sum_{j=1}^{J} \gamma^j = 1, \quad \boldsymbol{\gamma}_j \geq 0, \quad j = 1, ..., J \end{array} \right\} \tag{2}
$$

where $\boldsymbol{\gamma}$ is an intensity vector of DMU weights, δ is the DMU-specific depreciation of capital, and the $\sum_{j=1}^{J} \gamma^j = 1$ constraint allows for a variable returns to scale technology. The dynamic characterization of equation (2) is shown by the third constraint, which ensures that the technology set accounts for adjustment costs of quasi-fixed inputs.

Following Kapelko et al. (2015) and Skevas and Lansink (2014) the dynamic Luenberger productivity growth indicator (L) can be defined as follows:

$$
L = \frac{1}{2} \left\{ \begin{array}{c} \left[\overrightarrow{D}_{t+1}^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I)\right. \\ \left. -\overrightarrow{D}_{t+1}^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I)\right] \\ +\left[\overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I)\right. \\ \left. -\overrightarrow{D}_t^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I)\right] \end{array} \right\} \tag{3}
$$

L is computed by taking the arithmetic average of dynamic productivity change measured by the technology at time $t + 1$ (i.e. the first two terms in equation (3) and the dynamic productivity change measured by the t period technology (i.e. the last two terms in equation (3)). A positive (negative) value of L indicates productivity growth (decline). Following Kapelko et al. (2015) L can be further decomposed into the contributions of dynamic technical change (ΔT), dynamic technical inefficiency change (ΔPEI), and dynamic scale inefficiency change (ΔSEI):

$$L = \Delta T + \Delta PEI + \Delta SEI \tag{4}$$

The calculation of ΔT involves taking the arithmetic average of the difference between the t and $t+1$ period technologies, evaluated using input-output quantities at time t (first two terms in equation (5)) and $t+1$ (last two terms in equation (5)):

$$\Delta T = \frac{1}{2}\left\{\begin{array}{c} \left[\overrightarrow{D}^i_{t+1}(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I)\right. \\ \left. -\overrightarrow{D}^i_t(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I)\right] \\ +\left[\overrightarrow{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I)\right. \\ \left. -\overrightarrow{D}^i_t(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I)\right] \end{array}\right\} \tag{5}$$

By measuring the average distance between two technologies in time t and $t+1$, ΔT represents the shift of dynamic production technology defined by the simultaneous expansion of gross investments and contraction of variable inputs between two consecutive time periods.

ΔPEI is calculated as the difference between the value of the dynamic DDF under VRS at time t and $t+1$:

$$\begin{aligned} \Delta PEI =& \overrightarrow{D}^i_t(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I|VRS) \\ &- \overrightarrow{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I|VRS) \end{aligned} \tag{6}$$

By capturing the difference between the dynamic DDFs in VRS evaluated using the input-output quantities in time t and $t+1$, ΔPEI provides a measure of the change in the position of a DMU relative to the dynamic production technology (i.e. how close is a DMU to the t period technology as compared to the $t+1$ period technology).

Finally, ΔSEI is defined as follows:

$$
\begin{aligned}
\Delta SEI =& \overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I|CRS) \\
& - \overrightarrow{D}_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{I}_t, \mathbf{K}_t, \mathbf{H}_t; \mathbf{g}_x, \mathbf{g}_I|VRS) \\
& - \big[\overrightarrow{D}_{t+1}^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I|CRS) \\
& - \overrightarrow{D}_{t+1}^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}, \mathbf{K}_{t+1}, \mathbf{H}_{t+1}; \mathbf{g}_x, \mathbf{g}_I|VRS)\big]
\end{aligned}
\tag{7}
$$

ΔSEI measures the difference between the position of a DMU with regard to CRS and VRS technologies between two time periods. A negative (positive) value of a component of the dynamic Luenberger productivity growth suggests a negative (positive) contribution of this component to dynamic productivity growth. For instance, a negative value of ΔPEI implies a negative contribution of dynamic inefficiency change to dynamic productivity growth; that is, dynamic inefficiency increased between period t and $t+1$.

2.2 Accounting for spatial spillover effects in farmers' dynamic productivity growth and its components

Since the main focus of this study is to explore whether neighboring farmers' characteristics affect farmers' dynamic productivity growth and its decompositions, the spatially lagged explanatory variable model (SLX) is used. The form of this model is as follows:

$$
\boldsymbol{S}_t = \xi_0 + \boldsymbol{\xi} \boldsymbol{z}_t + \boldsymbol{\theta} \boldsymbol{W} \boldsymbol{z}_t + \boldsymbol{\alpha} + \boldsymbol{\epsilon} \tag{8}
$$

where $\mathbf{S}_t$ is a $N \times 1$ vector of farm-specific dynamic productivity growth scores (or their decompositions) in year t, $\boldsymbol{\alpha}$ is a vector of farm-specific constants, $\boldsymbol{z}_t$ is a year-specific $N \times V$ matrix of farm characteristics, $\boldsymbol{W}$ is an $N \times N$ spatial weights matrix (defined below) that summarizes the spatial relationship between farms, $\boldsymbol{\xi}$ and $\boldsymbol{\theta}$ are $V \times 1$ vectors of unknown parameters to be estimated, and $\boldsymbol{\epsilon} \sim N(0, \sigma^2 I)$ is an $N \times 1$ vector of disturbance terms. Therefore, the model in (8) assumes that farm dynamic productivity growth and its components can be explained by own and neighboring farm characteristics. These relationships are captured by the parameter vectors $\boldsymbol{\xi}$ and $\boldsymbol{\theta}$, which are known in the spatial econometrics literature as the direct and indirect or spillover effect, respectively.

The direct effect captures the change in a farm's dynamic productivity growth (or its components) attributable to changes in the explanatory variables of that farm itself. The indirect or spillover effect captures how a farm's dynamic productivity growth (or its components) changes when particular explanatory variables in the neighboring farms change. When $\boldsymbol{\theta} = 0$, equation (8) reduces to a non-spatial panel data model.

The SLX model has been recently advocated as a more credible alternative to the more commonly used spatial autoregressive model when the neighbors' characteristics, not the outcomes, are assumed to be relevant for the outcome of interest. This is the case in our study where farmers are unlikely to have an exact knowledge of their neighboring peers' productivity levels (or its components) but are more likely to observe some of their decisions or characteristics (e.g. use and performance of new farm technologies) through, for example, direct communication with them, and adjust their production practices. In other words, the productivity of farms is shaped by their own characteristics and decisions, and information about these decisions or characteristics may spillover to neighboring farms and affect their productivity growth.

Following Kapelko et al. (2015), equation (8) is estimated using a bootstrapped panel regression with heteroskedasticity and autocorrelation robust standard errors. We use a bootstrap approach to tackle the well-known problem of serial correlation among DEA scores (Simar and Wilson, 2007) [4]. We used the Hausman test to determine whether fixed or random effects specifications were most appropriate for each of our regressions. The model in (8) is estimated for dynamic productivity growth and each of its components.

3 Empirical application

3.1 Data

Our empirical application focuses on a sample of specialized dairy farms in Wisconsin, participating in the Agricultural Financial Advisor (AgFA) program at the University

[4] More detailed information about the bootstrap approach used in this study can be found in Kapelko et al. (2015)

of Wisconsin-Madison Center for Dairy Profitability. The used data set is a balanced[5] panel that contains data for 79 Wisconsin dairy farms for the period 2009-2017, a total of 711 observations. This data set includes data on inputs, outputs, and socioeconomic characteristics of dairy farms. We consider two outputs (i.e. milk (y_1) and other output (y_2) (i.e. meet and crop output)), two variable inputs (i.e. feed (x_1) and other inputs (x_2)), two quasi-fixed inputs with their corresponding investments (i.e. machinery (K_1), and buildings (K_2), and two fixed inputs (i.e. total labor (H_1) and agricultural land (H_2)). Following Ang and Oude Lansink (2017), we do not include livestock units (i.e. cows) as a separate quasi-fixed input in the specification of the production technology to keep the model empirically tractable.

Output, variable inputs, capital and investments are measured in monetary units (i.e. at constant 2010 prices), while agricultural land and total labor are measured in acres and hours, respectively. Following common practice, we transform all monetary outputs and inputs into implicit quantity indices by computing the ratio of value to its corresponding price index (Ang and Oude Lansink, 2017; Serra et al., 2011). Price indices of outputs and inputs were obtained from the National Agricultural Statistics Service and, when necessary, aggregated to Törngvist price indexes. Gross investments in quasi-fixed inputs (I) in year t are computed as the beginning value of quasi-fixed inputs in year $t+1$ minus the beginning value of quasi-fixed inputs in year t plus the beginning value of depreciation in year $t+1$. Table 1 provides descriptive statistics for the outputs and inputs used in the DEA models.

Our selection of factors ($\boldsymbol{z}$) that may influence farm productivity growth (and its components) is based on data availability and past research that examines the determinants of farm productivity growth (Skevas and Lansink, 2014). These factors are as follows: farm subsidies, non-farm income, family savings, liquidity, debt-to-asset ratio, land tenure, pasture, somatic cell count (SCC), margin protection program (MPP), precipitation, and

[5]In line with most of the spatial econometrics literature, we use a balanced panel data set in our analysis. The reason behind this choice is that, although estimators for spatial panel data models can be modified for unbalanced panel due to missing observations, their asymptotic properties may become problematic if the rationale why data are missing is unknown (Elhorst, 2014).

temperature. Farm subsidies, non-farm income, family savings and liquidity are measured in monetary units. Liquidity is measured as the beginning of the year cash balance (Skevas et al., 2018). Debt-to-asset ratio is computed as the value of debt divided by total farm assets. Land tenure is measured as the ratio of land owned to total farmland operated. Pasture is a dummy variable that takes the value of 1 if a farmer used pasture for cattle grazing, and 0 otherwise. Somatic Cell Count, which is a main indicator of milk quality, is evaluated at the herd average and measured in 10,000 cells per ml. MPP is a dummy variable that takes the value of 1 in the period 2014-2017 (i.e. the period when the dairy MPP is active), and zero otherwise. Precipitation and temperature data were obtained from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) maps (http://www.prism.oregonstate.edu/). We used farm coordinates to generate monthly mean temperature (measured in degrees Fahrenheit (F)) and precipitation (measured in inches) for each farm, year, and season. Following Qi et al. (2015), we defined the seasons in Wisconsin as follows: winter = December, January, February, and March; and spring = April and May, summer = June through September; and autumn = October and November. The AgFA and climate data sets were merged based on farm and year identifiers. A descriptive statistics of the socioeconomic and environmental factors used in the second stage regressions is presented in Table 2.

3.2 Specification of the spatial weights matrix

We use an inverse spatial weights matrix ($\mathbf{W}$) to capture the structure of spatial relations between farms. The elements of this matrix (i.e. w_{ij}) equal $1/d_{ij}$, where d_{ij} is the Euclidean distance between farmer i and j, if two farmers operate within a certain distance d^*, and 0 otherwise. d^* was set to the minimum distance that all farms in our sample have at least one neighbor, which is 50 km in our sample [6]. Moreover, we set all diagonal elements of W (i.e. w_{ii}) to zero, since no farmer can be viewed as its own neighbor. Finally, we follow common practice and scale all elements of W by its maximum eigenvalue

[6] This is a standard approach followed in the spatial econometric literature (see for e.g. Läpple et al., 2017).

(Halleck Vega and Elhorst, 2015).

4 Results and discussion

Table 3 provides a summary of the mean dynamic Luenberger productivity growth and its components for the period 2009/2010-2016/2017. The average dynamic Luenberger productivity growth for 2000/2001-2016/2017 is negative (-1%). All the components of the dynamic Luenberger indicator make, on average, a negative contribution to dynamic productivity growth. More specifically, dynamic technical change is modestly negative implying that the sample farms have, on average, experienced technical regress during the study period (i.e. they have not been able to improve the technology of using inputs). The average dynamic technical inefficiency change is also modestly negative (-0.4%), which means that farms, on average, use the existing production technology potential less efficiently over time. Dynamic scale inefficiency change also makes a negative but small contribution to dynamic productivity growth (-0.3%). The negative dynamic scale inefficiency change suggests that due to the increase in dynamic scale inefficiency between two consecutive periods, farms produce the same output with 0.3% of the value of the directional vector more variable inputs, and 0.3% of the value of the directional vector less investments.

The results of the bootstrap regressions for the dynamic productivity growth and its components are presented in Tables 4-7. These tables present the results of estimating both a non-spatial and a spatial model for dynamic productivity growth and each of its components. By distinguishing between the non-spatial and spatial models, we can assess whether or not spatial spillovers affect farmers' dynamic productivity growth and its components. Since Hausman tests indicated that random effects are more appropriate than fixed effects for all models, we relied on results of the random effects regressions and show only these results. First we present the non-spatial regression results, and compare them with the results from the spatial models. Notice that the coefficients and significance of the non-spatially lagged regressors differ only slightly between the non-spatial and spatial models. Therefore, their interpretation is the same for both these models.

The coefficients of the non-spatially lagged variables are presented in the left panel of Tables 4-7. Farm subsidies have a negative effect on dynamic productivity growth, technical inefficiency change, and scale inefficiency change. An explanation for this finding may be that farmers have substituted farm income with subsidy income and became less motivated to produce efficiently or expand their operations (Skevas et al., 2012). This result is in line with the findings of previous studies (Skevas and Lansink, 2014; Zhu and Lansink, 2010). The impact of farm subsidies on dynamic technical change is positive, likely because higher farm subsidies provide more income and enable farmers to keep the farm technology up to date. An increase in non-farm income increases dynamic productivity growth, and technical and scale inefficiency change. Higher family savings also contribute to higher dynamic productivity growth, and technical inefficiency change. Family savings and earnings from non-farm income can be used by farmers in the procurement of efficiency enhancing inputs or technologies and in expanding their operations. The effect of non-farm income on dynamic technical change is negative. This result may be attributed to the competition between on- and off-farm activities in terms of resources, labor, etc. (Ahituv and Kimhi, 2002; Holden et al., 2004). In this case, higher non-farm income may reduce farmers' incentive to produce agricultural goods and invest in new technologies. Higher liquidity decreases dynamic productivity growth, and technical and scale inefficiency change. Farms with high liquidity might earn enough income for household expenditure and financing farming activity, and thus are not willing to take on challenges associated with farm efficiency improvements or expansion. The results for liquidity further suggest that higher liquidity is associated with higher dynamic technical change. Higher liquidity implies greater financial flexibility and allows farmers to invest in farm assets and new technologies. The results for debt-to-asset ratio show that dynamic productivity growth, and dynamic inefficiency and technical change decrease with increases in debt-to-asset ratio. One explanation for this finding is that increased debt decreases farmers' ability to access credit and invest in efficiency enhancing technologies. Land tenure was found to impact positively on dynamic productivity growth and dynamic technical inefficiency change. Farmers owning most of the land they farm may be more motivated to adopt efficiency enhancing practices or more able to use land as collateral to obtain funds from lenders and invest them in enhancing their operations. On the other hand, land tenure was found to have a negative impact on dynamic technical change. An explanation for this finding may be that farmers with more owned land have recently invested in land acquisitions and, as a result, have less financial resources left for investments in new farm technologies, buildings and equipment (Skevas et al., 2018). The variable pasture has a positive impact on dynamic productivity growth and all its components except for dynamic scale inefficiency change. Pasture access for dairy cows is associated with welfare, health and production benefits (Auldist et al., 2000; Charlton and Rutter, 2017). These benefits can translate into higher farm profitability and ability to invest in farm assets and new technologies. Farmers with higher herd average SCC have lower dynamic technical change. High SCC is associated with lower milk yield and additional farm costs (Hogeveen et al., 2011) leading to reduced farm profitability and, as a result, lower availability of financial resources for investing in farm assets and innovations.

Regarding the climatic variables, precipitation and temperature impact significantly dynamic productivity growth and its components. More specifically, higher precipitation (mainly during winter and summer) impacts positively dynamic productivity growth and its components. Higher precipitation levels can enhance plant growth and yields and result in greater availability and lower cost of feed. Regarding the temperature variables, higher summer and autumn temperatures (mostly) decrease productivity growth and its components. Qi et al. (2015), in their study of climatic effects and productivity in Wisconsin dairy farms, also found a negative effect of increased summer and autumn temperatures on dairy farms' productivity. High summer and autumn temperatures may contribute to heat stress in cows resulting, among others, in reduced feed intake, decreased milk production, and additional costs to maintain cow performance in hot conditions (e.g. cooling systems) (West, 2003). On the other hand, increased spring temperatures contribute positively to dynamic productivity growth and most of its components. Higher spring temperatures may promote crop growth and increase feed availability, leading farmers to use feed resources more efficiently and reduce production costs. Qi et al. (2015) also reported an increase in dairy farmers' productive as a result of higher spring temperatures. Finally, the dummy for MPP suggests a negative impact of the introduction of MPP on dynamic technical inefficiency change, and dynamic technical change. On the other hand, MPP has a positive effect on farmers dynamic scale inefficiency change.

The results of the spatially lagged variables of the SLX models for productivity growth and its components are presented in the right lower panels of Tables 4-7 [7]. Farmers that have neighbors with higher farm subsidies (ceteris paribus) experience decreases in dynamic productivity growth (-0.4%), dynamic technical inefficiency change (-1%), and dynamic technical change (-1.3%). Farms receiving high government payments could bid up prices of land causing nearby farms to shrink (Key and Roberts, 2006), with negative consequences on their ability to access external financing (e.g. due to reduced collateral value) and make the necessary investments to keep up with technological advances and raise productivity. Another explanation why higher subsidies for neighbors decrease a farm's productivity growth (and its components) is that higher subsidies may make farmers substitute farm income with subsidy income and demotivate them to produce more or improve their operations (Skevas and Lansink, 2014). This negative attitude may spillover on to their neighbors (e.g. through communication) and decrease their motivation to use inputs more efficiently and invest in new technologies.

Farmers operating close to other farmers with high non-farm income exhibit technical progress (+0.2%). Farmers that have higher levels of non-farm income may be more able to invest in new farm technologies. If these farmers exchange information with their neighbors about the effectiveness of the newly adopted technologies, then they may induce their neighbors to adopt these technologies. The spatially lagged liquidity vari-

[7] In all the SLX models, we included all of the variables except the MPP and climatic variables as spatially lagged variables. The reason behind this is that climatic factors do not differ significantly across neighboring farms, and all farms face the same policies.

able has a negative and significant effect on dynamic productivity growth, and all its components except for dynamic scale inefficiency change. As mentioned above, farmers with high liquidity may earn enough income for financing farming activity and household expenditures, and thus are less motivated to adopt new technologies and improve their farm management practices. Neighboring farmers may imitate this negative behavior and experience performance losses. Farmers surrounded by neighbors with increased family savings have higher dynamic productivity growth, inefficiency change, and technical change. Farms with higher family savings may be more able to invest in new farm technologies. Nearby farmers may learn from these investments by observing success or failure, and therefore, make more optimal input and investment decisions that result in higher productivity growth. Farmers with more indebted neighbors have a higher dynamic productivity growth, inefficiency change, and technical change. Debt accumulation may be related to higher investments in new farm technology. Knowledge on the use and benefits of these new technologies may spillover to nearby farms (e.g. through communication) and lead to more optimal investment decisions that enhance farm productivity. The spatially lagged land tenure variable has a negative effect on dynamic inefficiency (-0.3%) and technical change (-0.3%). Higher land tenure may give farmers more access to credit, using land as collateral (Skevas et al., 2018), and allow them to expand their operations. If farmers compete with their neighbors for a limited amount of land, the expansion of a farmers' operation may limit the growth prospects and investments of its neighbors, leading to lower farm performance. Farmers with neighbors that use pasture land for cattle grazing exhibit lower dynamic productivity growth (-0.2%), efficiency change (-0.1%), and technical change (-0.1%). This could be due to competition for a limited amount of available land. A closer look of the data shows that farmers using pasture land for cattle grazing own, on average, more land than farmers that do not pasture cows (710 acres vs 580 acres). This, in turn, may limit the ability of the latter to expand their operations and benefit from economies of scale, leading to lower efficiencies and higher overall production costs. Finally, the dynamic productivity growth and all its components (except dynamic technical change) are lower for farmers operating close to other farmers that have cows with high SCC. High SCC may be related to lack of knowledge and technical skills to control mastitis. Farmers lacking such knowledge may share wrong information about prevention and control of mastitis with their neighbors, leading to milk yield losses and additional expenditures to reduce the level of mastitis (Hogeveen et al., 2011). This, in turn, will result in lower farm profitability and ability to invest in farm assets and new technologies.

5 Conclusions

This article examines the effect of neighboring farmers' characteristics on dynamic productivity growth and its decompositions. The empirical application focuses on dairy farms in Wisconsin over the period 2009-2017 and shows that neighboring farmers' characteristics play an important role in explaining farm performance. More specifically we found that neighboring farmers' financial and production characteristics influence farm dynamic productivity growth and its components. Higher liquidity and subsidies for neighbors decrease a farm's dynamic productivity growth and its components, while higher debt and savings have the opposite effect. Regarding farmers' production characteristics, farmers with neighbors that own more of the land they farm, own cows with elevated SCC, and use pasture land for cattle grazing experience declines in dynamic productivity growth and its components. One channel through which these effects may arise is through competition between neighboring farms for a limited amount of production resources (e.g. land, labor). For example, farmers that receive more subsidies may be more able to invest in new technologies and expand their operations. When farms compete with their neighbors for a limited amount of available farm land, then such expansions may limit the growth prospects of neighboring farms and result in decreased productivity. A second channel through which neighboring farmers' characteristics may affect farm performance is through information sharing and influence between neighboring farmers. For instance, if farmers that own cows with elevated SCC levels lack the knowledge to control mastitis and give wrong information about mastitis prevention and control to their neighbors, then they may all experience productivity regress. In addition to neighboring farmers' characteristics, own-farm characteristics, such as debt-to-asset ratio and climatic conditions, were found to play an important role in explaining variability in productivity growth and its components.

The findings from this study have implications for the development of programs aimed at improving farm performance. Specifically, the fact that interdependence between neighboring farms affects their performance, implies that policies aiming at improving farm performance should not assume independent farmer behavior but account for spatial interactions among neighboring farms. For example, extension programs aiming at promoting productivity enhancing technologies or management practices may target neighborhood networks (rather than individuals) and take advantage of existing interactions between neighbors to more efficiently reach their goals.

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Tables

Table 1: Descriptive statistics for the variables used in the DEA analysis

Variable	Unit	Mean	Standard deviation
Milk	Index, Constant 2010 $	1,397,255	1,778,692
Other output	Index, Constant 2010 $	51,121	73,941
Feed	Index, Constant 2010 $	386,469	550,028
Variable inputs, except feed	Index, Constant 2010 $	649,628	764,945
Buildings	Index, Constant 2010 $	415,620	583,401
Machinery and equipment	Index, Constant 2010 $	194,681	780,084
Gross investment in buildings	Index, Constant 2010 $	87,711	243,673
Gross investment in machinery and equipment	Index, Constant 2010 $	73,432	108,704
Labor	Hours	14,115	17,506
Land	Acres	589	505

Table 2: Descriptive statistics of data used in the regressions

Variable	Units	Mean	Standard deviation
Farm subsidies	\$10,000	1.380	2.267
Non-farm income	\$10,000	1.500	4.207
Family savings	\$10,000	8.731	10.040
Liquidity	\$10,000	0.491	11.569
Debt-to-asset ratio	ratio	0.341	0.229
Land tenure	ratio	0.585	0.273
Pasture	(0/1)	0.030	0.171
Somatic cell count	10,000 cells	9.981	10.740
Autumn precipitation	inches	2.571	0.584
Spring precipitation	inches	3.684	0.837
Summer precipitation	inches	3.826	0.927
Winter precipitation	inches	1.677	0.47
Autumn temperature	degrees F	43.296	2.879
Spring temperature	degrees F	49.789	2.462
Summer temperature	degrees F	66.491	1.391
Winter temperature	degrees F	23.811	4.154
MPP	(0/1)	0.375	0.485

Table 3: Evolution of dynamic Luenberger productivity growth and its components

Period	Dynamic Luenberger productivity change	Dynamic technical change	Dynamic technical inefficiency change	Dynamic scale inefficiency change
2009/2010	-0.041	-0.004	-0.021	-0.016
2010/2011	-0.040	-0.004	-0.022	-0.013
2011/2012	0.005	-0.009	0.000	0.014
2012/2013	0.035	0.014	0.026	-0.006
2013/2014	-0.009	-0.009	-0.007	0.007
2014/2015	-0.021	-0.008	-0.014	0.001
2015/2016	-0.020	-0.005	-0.012	-0.002
2016/2017	0.021	0.011	0.016	-0.006
Average, 2009/2010 -2016/2017	-0.010	-0.002	-0.004	-0.003

Table 4: Results of the non-spatial random effects (RE) and SLX models to explain dynamic productivity growth

	Non-spatial RE			SLX		
		90% CI			90% CI	
	Coef.	Lower bound	Upper bound	Coef.	Lower bound	Upper bound
Farm subsidies	-0.003	-0.004	-0.002	-0.002	-0.003	-0.001
Non-farm income	0.001	0.001	0.001	0.001	0.001	0.001
Family savings	4.0E-04	1.9E-04	0.001	0.001	3.4E-04	0.001
Liquidity	-0.001	-0.001	-3.7E-04	-0.001	-0.001	-4.5E-04
Debt/asset ratio	-0.026	-0.035	-0.018	-0.029	-0.039	-0.02
Land tenure	0.011	0.004	0.019	0.009	-4.5E-05	0.017
Pasture	0.016	0.005	0.028	0.013	3.9E-04	0.024
Somatic Cell Count	-1.8E-04	-3.7E-04	2.4E-05	-3.3E-05	-2.5E-04	1.9E-04
Precipitation_autumn	-0.001	-0.005	0.004	-2.2E-04	-0.006	0.005
Precipitation_spring	0.002	-0.001	0.005	0.001	-0.002	0.004
Precipitation_summer	-0.004	-0.007	-4.5E-04	-0.004	-0.007	2.4E-05
Precipitation_winter	0.049	0.04	0.057	0.05	0.041	0.058
Temperature_autumn	-0.006	-0.007	-0.005	-0.006	-0.007	-0.004
Temperature_spring	0.004	0.003	0.006	0.005	0.003	0.007
Temperature_summer	-0.004	-0.007	-0.001	-0.007	-0.011	-0.004
Temperature_winter	-3.7E-04	-0.001	4.5E-04	3.9E-04	-0.001	0.001
Margin Protection Program	0.007	-7.4E-05	0.013	0.007	-0.002	0.016
W_Farm subsidies	-	-	-	-0.004	-0.009	-3.7E-04
W_Non-farm income	-	-	-	0.002	-0.002	0.007
W_Liquidity	-	-	-	-0.001	-0.002	-3.9E-04
W_Family savings	-	-	-	0.003	0.001	0.004
W_Debt/asset ratio	-	-	-	0.008	0.004	0.013
W_Land tenure	-	-	-	-0.002	-0.006	0.001
W_Pasture	-	-	-	-0.002	-0.003	-0.001
W_Somatic Cell Count	-	-	-	-0.002	-0.003	-0.001

Table 5: Results of the non-spatial random effects (RE) and SLX models to explain dynamic inefficiency change

	Non-spatial RE			SLX		
		90% CI			90% CI	
	Coef.	Lower bound	Upper bound	Coef.	Lower bound	Upper bound
Farm subsidies	-0.001	-0.001	-4.2E-04	-0.001	-0.001	-2.5E-04
Non-farm income	4.0E-04	2.1E-04	1.0E-03	4.0E-04	2.0E-04	0.001
Family savings	1.8E-04	9.0E-05	2.7E-04	2.6E-04	1.7E-04	3.5E-04
Liquidity	-9.1E-05	-1.6E-04	-2.2E-05	-1.4E-04	-2.1E-04	-6.2E-05
Debt/asset ratio	-0.019	-0.022	-0.015	-0.019	-0.023	-0.015
Land tenure	0.008	0.005	0.011	0.007	0.004	0.011
Pasture	0.009	0.004	0.014	0.008	0.003	0.012
Somatic Cell Count	-5.0E-05	-1.3E-04	2.8E-05	1.05E-05	-7.6E-05	9.92E-05
Precipitation_autumn	-0.002	-0.004	-9.0E-05	0.001	-0.001	0.004
Precipitation_spring	4.6E-04	-0.001	0.002	-0.001	-0.002	3.5E-04
Precipitation_summer	-0.001	-0.002	4.5E-04	-0.001	-0.002	4.5E-04
Precipitation_winter	0.038	0.034	0.041	0.041	0.037	0.044
Temperature_autumn	-0.003	-0.004	-0.003	-0.002	-0.003	-0.002
Temperature_spring	0.004	0.003	0.005	0.005	0.005	0.006
Temperature_summer	-0.005	-0.006	-0.004	-0.008	-0.009	-0.006
Temperature_winter	-0.001	-0.001	-3.5E-04	-2.6E-05	-3.8E-04	3.4E-04
MPP	-0.002	-0.005	4.0E-04	-0.004	-0.008	-2.2E-04
W_Farm subsidies	-	-	-	-0.010	-0.011	-0.008
W_Non-farm income	-	-	-	0.002	-1.1E-05	0.004
W_Liquidity	-	-	-	-0.001	-0.001	-0.001
W_Family savings	-	-	-	0.003	0.002	0.003
W_Debt/asset ratio	-	-	-	0.006	0.005	0.008
W_Land tenure	-	-	-	-0.003	-0.004	-0.001
W_Pasture	-	-	-	-0.001	-0.002	-0.001
W_Somatic Cell Count	-	-	-	-0.001	-0.001	-0.001

Table 6: Results of the non-spatial random effects (RE) and SLX models to explain dynamic technical change

	Non-spatial RE			SLX		
		90% CI			90% CI	
	Coef.	Lower bound	Upper bound	Coef.	Lower bound	Upper bound
Farm subsidies	0.001	0.001	0.001	0.001	0.001	0.001
Non-farm income	-2.0E-04	-2.7E-04	-1.2E-04	-2.1E-04	-2.9E-04	-1.3E-04
Family savings	-3.5E-05	-7.0E-05	6.3E-07	2.9E-05	-8.7E-06	6.6E-05
Liquidity	3.6E-04	3.3E-04	3.9E-04	3.2E-04	2.9E-04	3.5E-04
Debt/asset ratio	-0.016	-0.017	-0.014	-0.019	-0.02	-0.017
Land tenure	-0.005	-0.006	-0.004	-0.006	-0.007	-0.005
Pasture	0.005	0.003	0.007	0.003	0.001	0.005
Somatic Cell Count	-2.0E-04	-2.3E-04	-1.6E-04	-1.3E-04	-1.7E-04	-1E-04
Precipitation_autumn	0.001	3.8E-04	0.002	0.008	0.008	0.009
Precipitation_spring	4.3E-04	-4.9E-05	0.001	4.3E-04	-4.9E-05	0.001
Precipitation_summer	0.002	0.001	0.002	0.001	4.4E-04	0.002
Precipitation_winter	0.015	0.013	0.016	0.02	0.018	0.021
Temperature_autumn	0.001	4.8E-04	0.001	0.001	0.001	0.001
Temperature_spring	0.001	0.001	0.002	0.003	0.003	0.004
Temperature_summer	-0.005	-0.006	-0.005	-0.007	-0.008	-0.007
Temperature_winter	-2.9E-04	-4.2E-04	1.5E-04	9.9E-05	-4.5E-05	2.4E-04
MPP	-0.006	-0.007	-0.005	-0.004	-0.005	-0.002
W_Farm subsidies	-	-	-	-0.013	-0.013	-0.012
W_Non-farm income	-	-	-	0.003	0.002	0.003
W_Liquidity	-	-	-	-0.001	-0.001	-0.001
W_Family savings	-	-	-	0.001	0.001	0.002
W_Debt/asset ratio	-	-	-	0.010	0.009	0.010
W_Land tenure	-	-	-	-0.003	-0.004	-0.003
W_Pasture	-	-	-	-0.001	-0.001	-0.001
W_Somatic Cell Count	-	-	-	-1.4E-04	-2.8E-04	5.8E-06

Table 7: Results of the non-spatial random effects (RE) and SLX models to explain dynamic scale inefficiency change

	Non-spatial RE			SLX		
		90% CI			90% CI	
	Coef.	Lower bound	Upper bound	Coef.	Lower bound	Upper bound
Farm subsidies	-0.002	-0.003	-0.002	-0.002	-0.003	-0.001
Non-farm income	0.001	3.2E-04	0.001	0.001	0.001	0.001
Family savings	1.7E-04	-1.6E-05	3.6E-04	1.5E-04	-6.2E-05	3.6E-04
Liquidity	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Debt/asset ratio	0.006	-0.002	0.015	0.007	-0.002	0.016
Land tenure	0.005	-0.002	0.012	0.005	-0.003	0.012
Pasture	0.006	-0.004	0.016	2.7E-04	-0.011	0.011
Somatic Cell Count	2.5E-05	-1.5E-04	2.0E-04	7.1E-05	-1.3E-04	2.7E-04
Precipitation_autumn	0.001	-0.003	0.005	-0.008	-0.014	-0.003
Precipitation_spring	7.2E-05	-0.002	0.002	0.003	2.7E-04	0.006
Precipitation_summer	-0.003	-0.006	2.6E-05	-0.001	-0.004	0.003
Precipitation_winter	-0.003	-0.01	0.004	-0.009	-0.017	-0.001
Temperature_autumn	-0.003	-0.004	-0.002	-0.004	-0.006	-0.003
Temperature_spring	6.6E-05	-0.001	0.001	-0.002	-0.004	-0.001
Temperature_summer	0.004	0.001	0.006	0.006	0.003	0.009
Temperature_winter	0.001	-1.4E-04	0.001	4.3E-04	-4.2E-04	0.001
MPP	0.013	0.008	0.019	0.015	0.006	0.024
W_Farm subsidies	-	-	-	0.002	-0.003	0.007
W_Non-farm income	-	-	-	-0.001	-0.005	0.003
W_Liquidity	-	-	-	1.5E-04	-0.001	0.001
W_Family savings	-	-	-	-0.002	-0.003	-2.5E-04
W_Debt/asset ratio	-	-	-	-0.004	-0.013	0.001
W_Land tenure	-	-	-	0.005	-0.002	0.009
W_Pasture	-	-	-	-7.8E-06	-0.001	0.001
W_Somatic Cell Count	-	-	-	-0.001	-0.002	-5.2E-05