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Measuring dynamic biased technical change in Lithuanian cereal farms

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Abstract

Changes in substitutability among inputs and outputs can help farms adapt to economic, technological, or societal changes. However, measurement of technical bias has only been carried out in a static framework, ignoring the confounding effects of technical bias due to adjustment costs. This paper integrates two streams of literature, that is one measuring dynamic inefficiency and the other measuring technical bias, thereby offering non-parametric measures of technical bias for dynamic production technology. The dynamic framework explains the changes in the extent of output foregone to enable investments. The proposed framework is applied to a panel of data of Lithuanian cereal farms over the period 2004–2014. The results show technical change was, on average, more biased toward increasing output rather than investment. Technical change has been more focused on labor-usage, relative to land and intermediate consumption in the same period.

KEYWORDS

biased technical change, cereal farms, dynamic Luenberger indicator, total factor productivity

1 | INTRODUCTION

Productive technology is likely to change over time due to shifts in economic, social, and technological environments. One of the earliest attempts to formalise such linkages was the theory of induced innovation (Ruttan & Hayami, 1984), which hypothesized that the evolution of a productive technology over time is driven by the relative abundance of inputs used in the production of outputs (Chambers, 1988). Productivity growth, resource allocation, and economic returns are likely to be impacted by technical change (TC), which in turn may be biased toward reducing the use of the relatively scarce inputs (Song, Zheng, & Wang, 2017).

Support schemes prevail in agriculture across many countries—for example, the common agricultural policy (CAP) in the European Union (EU)—because of the multifunctionality of agriculture. Among multiple support measures, those related to investments are linked to changes in capital assets and modernization in general (Minviel & Latruffe, 2017). Thus, it is important to identify the effects of support policies on the underlying technology. Biased TC refers to changes in productive technology with respect to (a) input substitution which can be influenced by the support policies and (b) the relationships between investment and output production which depend on investment decisions and adjustment costs.

Färe, Grifell-Tatjé, Grosskopf, and Knox Lovell (1997) devised the bias-corrected Malmquist productivity index, which allows quantification of the input- and output-related bias in TC in the context of a radial distance function. This measure was applied more widely in the literature, and specifically by Baležentis (2014) to a sample of Lithuanian family farms.[1] Briec, Chambers, Färe, and Peypoch (2006) developed a measure for neutral TC in the context of a directional distance function, which was extended by Briec and Peypoch (2007) to measuring biased TC through a Luenberger productivity indicator. This approach was applied by several authors, such as Barros, Guironnet, and Peypoch (2011), Peypoch and Sbai (2011), and Barros and Peypoch (2012) for the analysis of productivity growth of, respectively, the French higher education system, Moroccan hotels, and African seaports. A major shortcoming of the existing literature on measuring biased TC is the assumption of a static context in which decision-making units can adjust input and output quantities without adjustment costs. As hypothesized by Eisner and Strotz (1963), this assumption is unlikely to hold for quasi-fixed factors such as capital. The more recently introduced dynamic approach to measure efficiency and productivity addresses this shortcoming by explicitly accounting for the presence of adjustment costs associated with investments. Silva and Stefanou proposed a characterization of the dynamic adjustment costs technology (Silva and Stefanou, 2003), and later developed dynamic measures of technical, allocative, and cost-efficiency in the context of a radial distance function (Silva and Stefanou, 2007).[2] Silva, Oude Lansink, and Stefanou (2015) established dynamic duality within the directional distance function context to measure dynamic technical, allocative, and cost-efficiency. A dynamic approach to measuring total factor productivity (TFP) growth and its components (technical efficiency change, TC, and scale efficiency change) was developed by Oude Lansink, Stefanou, and Serra (2015) and applied by Kapelko, Oude Lansink, and Stefanou (2015a) and Kapelko, Oude Lansink, and Stefanou (2015b). This dynamic approach is of particular interest here, as it enables measuring TC while accounting for adjustment costs associated with investments. Extending this approach to the measurement of biased TC would address the aforementioned limitations of the existing (static) literature on measuring biased TC.

Central and Eastern European countries have long been and still are, in the process of transforming their agricultural sectors following the establishment of the EU. The transformation is accompanied by substantial investments in new capital and structural changes in the agricultural labor force. This suggests that it is important to account for adjustment costs due to both investments and biased TC in response to the rapidly changing business environment.

Therefore, this paper extends the dynamic Luenberger productivity indicator to measure dynamic biased TC and to quantify the output-, investment-, and input-related bias. The empirical model focuses on a sample of Lithuanian cereal farms over the period 2004–2014. Indeed, the latter farming type has become relatively more important following Lithuania's accession to the EU. The results suggest non-neutral (labor-using) TC in Lithuanian family farms over the study period. Moreover, on average, more farms showed output-producing TC, implying that Lithuanian farms were more concerned about increasing output rather than increasing investments.

[1]Baležentis (2014) applied the Malmquist productivity index to a sample of Lithuanian family farms. The present paper differs in a number of ways: (a) we employ the dynamic setting (i.e. dynamic production technology is assumed to maintain links between technologies for different time periods), (b) we use an input distance function and Luenberger productivity indicator to accommodate the dynamic setting, (c) a new data set is applied which focuses on the major farm type in Lithuania.

[2]Yet another strand for dynamic efficiency analysis is that by Nemoto and Goto (1999, 2003). However, their approach does not explicitly model changes in the quasi-fixed inputs.

Section 2 develops the dynamic bias-corrected Luenberger productivity indicator. Section 3 presents the data used and Section 4 discusses the results.

2 | METHODS

This paper aims to define a framework for the analysis of technical bias within the setting of dynamic efficiency. This section introduces dynamic efficiency measures, integrates them into the measurement of change in the TFP, and presents the analysis of technical bias in a dynamic setting.

2.1 | Measures of dynamic efficiency

Dynamic efficiency measures differ from static ones as they consider changes in the levels of capital stock for two consecutive time periods. This is facilitated by accounting for gross investments in production technology.

Following Silva et al. (2015), we can define the dynamic production technology at a period t in terms of the input requirement set:

$$V(y^t|K^t) = \{(x^t, I^t): (x^t, I^t) \text{ can produce } y^t \text{ given } K^t\}, \tag{1}$$

where $y^t \in \mathfrak{R}^M_{++}$ is the output vector, $x^t \in \mathfrak{R}^N_{+}$ the vector of variable inputs, $K^t \in \mathfrak{R}^F_{++}$ the vector of capital, and $I^t \in \mathfrak{R}^F_{+}$ the vector of gross investments in capital. The latter setting implies that the attainable level of output not only depends on variable and quasi-fixed inputs but also on investments in quasi-fixed inputs. The adjustment costs are, therefore, included in the model under the respective assumptions regarding monotonicity of $V(\cdot)$, cf. Silva and Stefanou (2003).

In the dynamic efficiency setting, the production technology is recovered by projecting an observation on the production frontier, that is by contracting inputs and expanding investments. This study uses a dynamic directional input distance function to approximate the underlying technology.[3] The directional input distance function is defined as follows:

$$D_t(y^t, K^t, x^t, I^t) = \begin{cases} \max\{\beta: (x^t - \beta g_x, I^t + \beta g_I) \in V(y^t|K^t)\}, & \exists\, \beta: (x^t - \beta g_x, I^t + \beta g_I) \in V(y^t|K^t) \\ \infty, & \text{otherwise} \end{cases}, \tag{2}$$

where $(g_x, g_I) \in \mathfrak{R}^N_{++} \times \mathfrak{R}^F_{++}$ is the directional vector defining the path for the projection of (x^t, I^t) toward the production frontier.

The production technology represented by $V(\cdot)$ distinguishes investments and capital, where the latter involves the accumulated (and partly depreciated) investments from previous years. Hence, the dynamic production technology accounts for past investments through the inclusion of capital in the directional distance function (Kapelko, Oude Lansink, & Stefanou, 2014; Serra, Oude Lansink, & Stefanou, 2011; Silva et al., 2015). Noteworthy, adjustment costs associated with investments are reflected in the use of inputs. Hence, higher investments require at least the same quantity of inputs to maintain the same level of outputs (or require lower output levels when keeping inputs constant). This is reflected in the characteristics of the input distance function which is increasing in inputs, decreasing in investments and decreasing in output. Given the properties of $V(\cdot)$ defined by Silva and Stefanou (2003) and Silva et al. (2015), the input distance function defined in Equation (2) is increasing in inputs (if $\tilde{x}^t \geq x^t$ then $D_t(y^t, K^t, \tilde{x}^t, I^t) > D_t(y^t, K^t, x^t, I^t)$), decreasing in investments (if $\tilde{I}^t \leq I^t$ then $D_t(y^t, K^t, x^t, \tilde{I}^t) > D_t(y^t, K^t, x^t, I^t)$) and decreasing in outputs (if $\tilde{y}^t \geq y^t$, then $D_t(\tilde{y}^t, K^t, x^t, I^t) < D_t(y^t, K^t, x^t, I^t)$).

[3]The choice of the directional vector is at the discretion of the researcher. In the case of Lithuanian agriculture, there are no clear arguments in favor of either input or output orientation.

Empirically, the measure given by Equation (2) is implemented using Data Envelopment Analysis (DEA; see e.g., Silva et al., 2015). Let us consider K firms (decision-making units), indexed over $k = 1, 2, \ldots, K$ and operating during period t. Then, the following linear programming problem yields the values of the directional distance function for an arbitrary observation $k' = 1, 2, \ldots, K$:

$$
\begin{aligned}
& D_t(y^t, K^t, x^t, I^t; g_x, g_I) = \max \beta \\
& \text{s.t.} \\
& \sum_{k=1}^{K} \lambda_k y_{m,k}^t \geq y_{m,k'}^t,\ m = 1, 2, \ldots, M; \\
& \sum_{k=1}^{K} \lambda_k x_{n,k}^t \leq x_{n,k'}^t - \beta g_{x,n},\ n = 1, 2, \ldots, N; \\
& \sum_{k=1}^{K} \lambda_k \left(I_{k,f}^t - \delta_f K_{k,f}^t \right) \geq I_{k',f}^t - \delta_f K_{k',f}^t + \beta g_{I,f},\ f = 1, 2, \ldots, F; \\
& \lambda_k \geq 0,\ k = 1, 2, \ldots, K
\end{aligned}
, \quad (3)
$$

where λ_k are intensity variables and δ_f are input-specific depreciation rates. Note that Equation (3) assumes a constant-returns-to-scale technology.[4] Furthermore, Equation (3) yields a contemporaneous measure of distance to the frontier. TFP growth is computed by solving four dynamic directional distance functions. Equation (3) is solved for period t and period $t + 1$. Furthermore, the distance of an observation from period t toward the frontier of the period $t + 1$, $D_{t+1}(y^t, K^t, x^t, I^t; g_x, g_I)$ is computed by manipulating the left-hand side of constraints in Equation (3):

$$
\begin{aligned}
& D_{t+1}(y^t, K^t, x^t, I^t; g_x, g_I) = \max \beta \\
& \text{s.t.} \\
& \sum_{k=1}^{K} \lambda_k y_{m,k}^{t+1} \geq y_{m,k'}^t,\ m = 1, 2, \ldots, M; \\
& \sum_{k=1}^{K} \lambda_k x_{n,k}^{t+1} \leq x_{n,k'}^t - \beta g_{x,n},\ n = 1, 2, \ldots, N; \\
& \sum_{k=1}^{K} \lambda_k \left(I_{k,f}^{t+1} - \delta_f K_{k,f}^{t+1} \right) \geq I_{k',f}^t - \delta_f K_{k',f}^t + \beta g_{I,f},\ f = 1, 2, \ldots, F; \\
& \lambda_k \geq 0,\ k = 1, 2, \ldots, K
\end{aligned}
, \quad (4)
$$

where K corresponds to the number of observations in the period $t + 1$. Similarly, the distance of an observation from period $t + 1$ to the frontier of period t can be computed.

Another issue regarding practical implementation of the (dynamic) directional efficiency measures is the value of the directional vector. In the setting of dynamic efficiency, this issue becomes especially important given the occurrence of zero investments in (some) quasi-fixed inputs. Following Kapelko et al. (2014), we set $(g_x, g_I) = (x, 0.2K)$, that is the directional vectors for inputs and investments are represented by the actual input quantity and 20% of the initial capital stock, respectively.

Note that even though we chose the input distance function for the analysis, our major interest is the change of the underlying production technology, and we can evaluate output, input and investment bias. Therefore, the choice of the direction of optimization is not important.

[4]Indeed, estimation of variable-returns-to-scale technology would allow one to capture scale inefficiency and introduce respective components in the decomposition of productivity change. However, this paper is focused on the bias in TC, rather than scale efficiency considerations.

2.2 | TFP change in the dynamic setting

The measures of dynamic efficiency given by Equations (3) and (4) can be employed to gauge the changes in TFP. O'Donnell (2018) presented a number of different measures of productivity change. In this paper, we selected the Luenberger productivity indicator for several reasons. First, the Luenberger productivity indicator allows for the simultaneous contraction of inputs and expansion of investments, which makes the implementation of the dynamic measures computationally feasible. The latter property can also be maintained by employing, for example, a Malmquist-Luenberger index or a hyperbolic Malmquist index. However, the Luenberger productivity indicator allows specifying the elements of the directional vector, whereas the former two indices rely on directional vectors consisting of observed input/output quantities (i.e., proportional contractions and expansions of outputs). Second, as some of the variables in the dynamic setting may approach zero, the Luenberger productivity indicator allows handling these values by assigning non-zero elements of the directional vector to the relevant variables. Note that the Luenberger productivity indicator does not require price data, as is the case for the Lowe indicator, for example. The Luenberger productivity indicator[5] (Chambers, Chung, & Färe, 1996) can be applied together with the dynamic directional distance function as proposed by Oude Lansink et al. (2015).

The dynamic Luenberger productivity indicator measures the change in productivity with respect to dynamic production technology of periods $t + 1$ and t

$$L = \frac{1}{2}([D_{t+1}(y^t, K^t, x^t, I^t; g_x, g_I) - D_{t+1}(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I)] + [D_t(y^t, K^t, x^t, I^t; g_x, g_I) - D_t(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I)]), \tag{5}$$

where the first and second terms in Equation (5) capture productivity change against the dynamic production technology of period t and $t + 1$, respectively. Note that the indicator is based on a constant-returns-to-scale technology. Positive (resp. negative) values of L indicate gain (resp. loss) in TFP. For instance, $L = 0.1$ indicates that, due to an increase in TFP, input use can be contracted by 10% and investments increased by 2% of the capital stock (i.e., 0.1×0.2) for a given output.

The dynamic Luenberger productivity indicator (L) can be decomposed to identify the contributions of dynamic technical efficiency change and TC

$$L = \text{EC} + \text{TC}, \tag{6}$$

where EC captures firm-specific gains in TFP (i.e., a catch-up effect) and TC measures the frontier shift. Efficiency change is simply defined as the change in distance to a contemporaneous frontier

$$\text{EC} = D_t(y^t, K^t, x^t, I^t; g_x, g_I) - D_{t+1}(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I), \tag{7}$$

so that $\text{EC} > 0$ indicates gains in TFP due to firm-specific decisions. Technical change is measured against observations from both period t and period $t + 1$

$$\text{TC} = \frac{1}{2}([D_{t+1}(y^t, K^t, x^t, I^t; g_x, g_I) - D_t(y^t, K^t, x^t, I^t; g_x, g_I)] + [D_{t+1}(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I) - D_t(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I)]), \tag{8}$$

where $\text{TC} > 0$ indicates an increase in TFP due to the movement of the production frontier. Again, in the dynamic setting, EC and TC measure the extent to which inputs can be contracted and investments augmented while keeping output fixed.

[5]O'Donnell (2012) noted that the Luenberger productivity indicator is not additively complete, which precludes it being termed a TFP indicator.

2.3 | Technical bias in the dynamic setting

Färe et al. (1997) defined the decomposition of the Malmquist productivity index under Hicks non-neutral TC. Subsequently, Briec and Peypoch (2007) proposed the corresponding decomposition of the Luenberger productivity indicator. Specifically, additional terms are introduced to capture TFP change due to shifts in marginal rates of technical substitution (MRTS). The additional terms are input bias (IB), output bias (OB), and magnitude of technical change (MTC). As such, one can analyse the changes in frontier shape in terms of input or output pairs.

By applying dynamic efficiency measures, one can analyse the changes in factor substitutability in the direction of input contraction and investment expansion. The approach proposed in this paper differs from the conventional one in that investment and output quantities are treated in the same manner. That is, OB accounts for changes in substitutability among outputs of the productive technology and investments in quasi-fixed inputs. Therefore, it is possible to assess the changes in investment for the frontier firms. Indeed, in the output space, OB is measured in the direction of investment expansion. The dynamic OB component is defined as follows:

$$\begin{aligned}\mathrm{OB} = \frac{1}{2}(&[D_t(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I) - D_{t+1}(y^{t+1}, K^{t+1}, x^{t+1}, I^{t+1}; g_x, g_I)] \\ &+ [D_{t+1}(y^t, K^t, x^{t+1}, I^t; g_x, g_I) - D_t(y^t, K^t, x^{t+1}, I^t; g_x, g_I)]),\end{aligned} \tag{9}$$

where the first term measures the shift of the frontier through $(y^{t+1}, K^{t+1}, I^{t+1})$ in the direction of (g_x, g_I) and the second one through (y^t, K^t, I^t) in the direction of (g_x, g_I).

Similarly, the dynamic IB component captures the changes in input substitutability as represented by changes in MRTS. The calculation is carried out by keeping the output level fixed at period t and manipulating input quantities

$$\begin{aligned}\mathrm{IB} = \frac{1}{2}(&[D_{t+1}(y^t, K^t, x^t, I^t; g_x, g_I) - D_t(y^t, K^t, x^t, I^t; g_x, g_I)] \\ &+ [D_t(y^t, K^t, x^{t+1}, I^t; g_x, g_I) - D_{t+1}(y^t, K^t, x^{t+1}, I^t; g_x, g_I)]),\end{aligned} \tag{10}$$

where the first and the second terms measure the change in MRTS in the direction of (g_x, g_I) through x^t and x^{t+1}, respectively, with outputs and investments fixed at period t. Note that, IB = 0 and OB = 0 imply no IB and OB, respectively. Finally, the magnitude of technical change, MTC, is defined as follows:

$$\mathrm{MTC} = D_t(y^t, K^t, x^t, I^t; g_x, g_I) - D_{t+1}(y^t, K^t, x^t, I^t; g_x, g_I). \tag{11}$$

The latter component measures the shift of the production frontier through the observations of the period t. Indeed, the components are given by Equations (9)–(11) add up to a negated TC component:

$$\mathrm{IB} + \mathrm{OB} + \mathrm{MTC} = -\mathrm{TC}. \tag{12}$$

Even though the changes in TFP can now be explained in terms of technical bias, some additional considerations are needed to identify the exact nature of the underlying bias. Particularly, one is often interested in whether TC is factor-using or factor-saving. Similarly, TC can be output-producing and, in the framework of dynamic efficiency, investment-producing. Such types of analysis can be facilitated by looking at changes in the ratios of two inputs and the ratio of output and investment. Tables 1 and 2 present the possible types of bias.

To further illustrate the rationale behind the definition of different types of OB given in Table 1, let us consider investment-output space (Figure 1). For simplicity, assume input use and capital assets remain at the same level for both periods t and $t+1$, that is $(K^t, x^t) = (K^{t+1}, x^{t+1})$, whereas the investment-output bundle changes from $\left(I_f^t, y_m^t\right)$ to $\left(I_f^{t+1}, y_m^{t+1}\right)$ so that the ratio of investment to output decreases (i.e., the ratio of output to investment increases).

TABLE 1 The types of OB (Barros & Peypoch, 2012)

	OB > 0	OB < 0
$\frac{y_m^t}{I_f^t} < \frac{y_m^{t+1}}{I_f^{t+1}}$	I_f-producing TC	y_m-producing TC
$\frac{y_m^t}{I_f^t} > \frac{y_m^{t+1}}{I_f^{t+1}}$	y_m-producing TC	I_f-producing TC

Abbreviations: OB, output bias; TC, technical change.

TABLE 2 The types of IB (Barros & Peypoch, 2012)

	IB > 0	IB < 0
$\frac{x_n^t}{x_p^t} > \frac{x_n^{t+1}}{x_p^{t+1}}$	x_n-using/x_p-saving TC	x_p-using/x_n-saving TC
$\frac{x_n^t}{x_p^t} < \frac{x_n^{t+1}}{x_p^{t+1}}$	x_p-using/x_n-saving TC	x_n-using/x_p-saving TC

Abbreviations: IB, input bias; TC, technical change.

This is depicted as a movement from point A toward point B in Figure 1. The investment-output possibilities are bound by the set O_t for the period t.

A Hicks-neutral TC would render a proportional movement toward O_{t+1} in the direction of g_I, as defined by the concept of neutral translation (Briec et al., 2006). In this case, OB = 0.5·([BE − BG] − [AD − AC]) = CD − EG = 0, which indicates neutral TC. In case of an investment producing TC, the frontier shifts to the boundary of O_{t+1}^I. Therefore, OB = 0.5·([BE − BF] − [AD − AC]) = CD − EF > 0. Given a decrease in the investment-to-output ratio, we have $(y_m^t/I_f^t) < (y_m^{t+1}/I_f^{t+1})$, and Table 1 suggests an I_f-generating TC. Similarly, under output-producing TC, the frontier would be defined by O_{t+1}^y and, thus, OB = 0.5·([BE − BH] − [AD − AC]) = CD − EH < 0. According to Table 1, $(y_m^t/I_f^t) < (y_m^{t+1}/I_f^{t+1})$ and OB < 0 imply a y_m-producing TC.

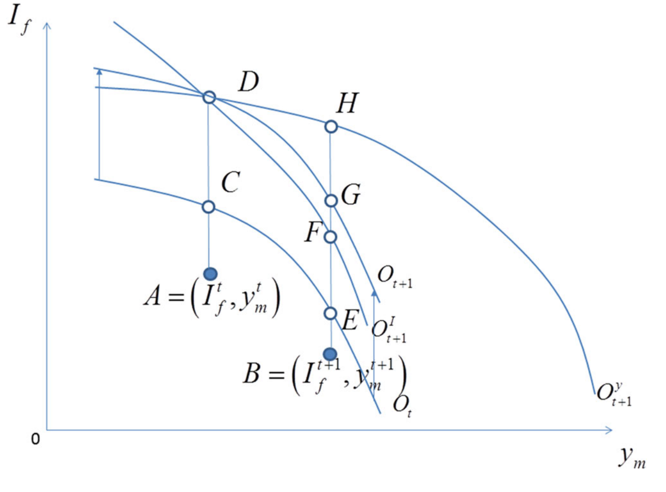

FIGURE 1 Output bias in investment-output space [Color figure can be viewed at wileyonlinelibrary.com]

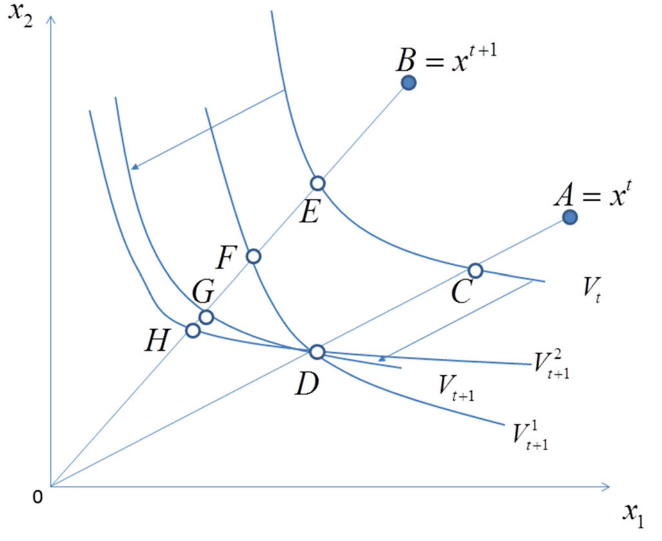

FIGURE 2 Input bias in input space [Color figure can be viewed at wileyonlinelibrary.com]

To illustrate IB, let us consider a two-input case (Figure 2). The ratio x_2/x_1 increases over time. This is represented by a movement from point A to point B in Figure 2. In this case, assume that output, capital assets, and investments remain the same for the two periods, that is $(y^t, K^t, I^t) = (y^{t+1}, K^{t+1}, I^{t+1})$.

The isoquant for the period t is given by V_t. A neutral TC occurs if the isoquant shifts to V_{t+1}. In that case, $\mathrm{IB} = 0.5 \cdot ([\mathrm{AD} - \mathrm{AC}] + [\mathrm{BE} - \mathrm{BG}]) = \mathrm{CD} - \mathrm{EG} = 0$. In case an x_2-using TC prevails, the frontier shifts to V_{t+1}^2 and IB become negative: $\mathrm{IB} = 0.5 \cdot ([\mathrm{AD} - \mathrm{AC}] + [\mathrm{BE} - \mathrm{BH}]) = \mathrm{CD} - \mathrm{EH} < 0$. Therefore, Table 2 suggests IB < 0 and increased intensity of the use of x_2, entailing an x_2-using TC. In case of an x_1-using TC, the frontier shifts to V_{t+1}^1. Accordingly, $\mathrm{IB} = 0.5 \cdot ([\mathrm{AD} - \mathrm{AC}] + [\mathrm{BE} - \mathrm{BF}]) = \mathrm{CD} - \mathrm{EF} > 0$. Thus, as the ratio x_2/x_1 increases, Table 2 suggests an x_1-using TC.

3 | DATA

This study used data from the Farm Accountancy Data Network (FADN) in Lithuania. We analysed specialized cereal and rapeseed farms of farming type 15 under regulation 1242/2008 EC (type 13 under regulation 2003/369 EC) over the years 2004–2014. This implies that more than two-thirds of the total agricultural output comes from cereal and rapeseed production on these farms.

We follow the common practice of measuring technical efficiency and productivity change in Central and Eastern European countries (Bojnec & Latruffe, 2013; Latruffe, Balcombe, Davidova, & Zawalinska, 2004; Latruffe, Fogarasi, & Desjeux, 2012) and distinguish four inputs, that is land, labor, intermediate consumption, and capital asset variables. However, some alterations are carried out To accommodate the dynamic setting. The productive technology is defined in terms of three variable inputs (land, labor, and intermediate consumption),[6] one quasi-fixed input (capital assets) with associated gross investments, and one output (total agricultural output). Land input is the agricultural area measured in hectares. Labor input comprises both family and hired

[6]Note that, for example, Silva et al. (2015) treat labor as a fixed input.

TABLE 3 Descriptive statistics for the model variables

Indicator	Labor input	Land input	Intermediate consumption	Capital assets	Gross investments	Deprecia-tion	Agricultural output
Dimension	*AWU*	*ha*	*100,000 LTL of 2010*				
Mean	2.6	219	2.58	4.29	1.55	0.68	3.69
Median	1.9	149	1.42	1.96	0.44	0.32	2.02
SD	2.3	225	3.40	6.14	2.81	0.95	4.80
Minimum	0.3	10	0.06	0.005	0	0.0005	0.06
Maximum	28.2	1,968	34.62	61.92	43.39	12.94	47.13

Note: 1 EUR = 3.4528 LTL.
Abbreviations: LTL, Lithuanian Litas; SD, standard deviation.

labor and is measured in annual work units (AWU), each corresponding to 2036 working hours.[7] Intermediate consumption encompasses specific production costs along with overheads (in Lithuanian Litas,[8] LTL). Capital assets include the book value of machinery and buildings at the beginning of the year (in LTL). Gross investments represent the flow of investments during the respective year (in LTL). Total agricultural output captures crop, livestock, and other agricultural outputs (in LTL).[9]

To compute the implicit quantities of capital assets and total agricultural output, Törnqvist price indices were computed. Specifically, the machinery price index and the construction inputs price index for nonresidential buildings were employed to construct the Törnqvist price index for capital asset input. The aggregate capital asset variable was then deflated by the latter price index. Similarly, respective agricultural output price indices were used to construct the Törnqvist price index for total agricultural output. The price indices were provided by Eurostat (2016) and Statistics Lithuania (2016).

Investments and depreciation were deflated by the Törnqvist price index for capital asset input. Intermediate consumption was deflated by the agricultural input price index for goods and services currently consumed. The price indices were provided by Eurostat (2016).

We applied the procedure suggested by Kapelko et al. (2014) to identify outlying observations. The latter approach is implemented by computing the ratios of output over each of the inputs. If the ratio falls outside the interval defined by the median plus/minus two standard deviations, then the observation is considered to be an outlier. Furthermore, observations with negative gross investment and capital prices exceeding 100% were removed from the sample. This resulted in a reduction of the initial sample from 4,580 observations down to 3,671 observations for 1,346 farms.[10] The sample covers approximately 334 farms per year and 2.7 years per farm on average. Both the initial and resulting data are rotating panels. Table 3 presents the descriptive statistics for the resulting sample.

Given we apply the dynamic framework, only observations covering two consecutive years for a certain farm can be used in the analysis. In our case, a total of 1,787 observations (containing data on input, output, and investment for two consecutive periods) was available for the empirical analysis. However, the whole sample was used to construct the frontiers for different years.

[7]The literature on modeling labor input in efficiency and productivity analyses treats labor both as a fixed input (Dakpo & Lansink, 2019) or as a variable input (Dakpo, Desjeux, Jeanneaux, & Latruffe, 2019). Indeed, the model could be refined by considering family and hired labor separately; however, such accurate data are not available for Central and Eastern European countries. It is common to have farms that use both family and hired labor. Hence, we think that the assumption of labor being a variable input is justified.

[8]1 Lithuanian Litas (LTL) equalled 0.2896 EUR when the currency was revoked at the beginning of 2015.

[9]The total agricultural output is not disaggregated, as crop output constitutes the largest component of total agricultural output. Specifically, crop output constituted more than 95% of total agricultural output in cereal and rapeseed farms in 2014 (Lithuanian Institute of Agrarian Economics, 2015).

[10]The high share of outliers can be explained by noisy data, which to a certain extent stems from the fact that the FADN system has been running since 2004 in Lithuania.

4 | RESULTS

4.1 | Productivity change in the dynamic setting

The change in dynamic productivity of Lithuanian grain and oilseed farms was rather uneven during 2004–2014, as suggested by the minimum and maximum values of −18.7% and 18.7%, respectively. The average value of the dynamic Luenberger productivity indicator was −1.3%. Decomposition of the latter value indicates that technical efficiency change had no impact, on average, on the change in productivity; TC was the main driver of the decrease in productivity. This suggests that Lithuanian grain farms have experienced a deterioration in production technology during the study period.

A more detailed analysis of the dynamics in productivity is presented in Figure 3. The period of 2004–2005 saw a slight increase in TFP of 0.3% as a result of technical progress (3.1%) and a negative contribution of technical efficiency change (−2.8%). During 2005–2006, both TC and technical efficiency change contributed negatively to TFP change (with the latter being more severe) due to unfavorable weather conditions during the corresponding period.

The frontier moved outward during 2007–2009, which was indicated by a positive and increasing TC component (2.4% and 8.1% for 2007–2008 and 2008–2009, respectively). However, the losses in technical efficiency amounted to 5.7% and 8.7% for the two subperiods and thus resulted in a (slightly) negative change in productivity. These developments might reflect the impact of the global economic crisis in those years. Even though higher yields pushed the production frontier outward, tightened bank lending policies made some farms unable to maintain proper investment flows, thereby reducing their dynamic technical efficiency (note that investment is expanded in the dynamic setting). However, not all farms were subject to credit constraints and, thus, affected by changes in bank policies.

The subperiod of 2009–2010 marked an increase in productivity of 3.3%, which was due to gains in technical efficiency (5.1%). This might have been caused by relaxed lending policies, which allowed investing into capital assets at higher rates. The TC component, though, played a negative role (−1.9%) due to decreasing yields. With

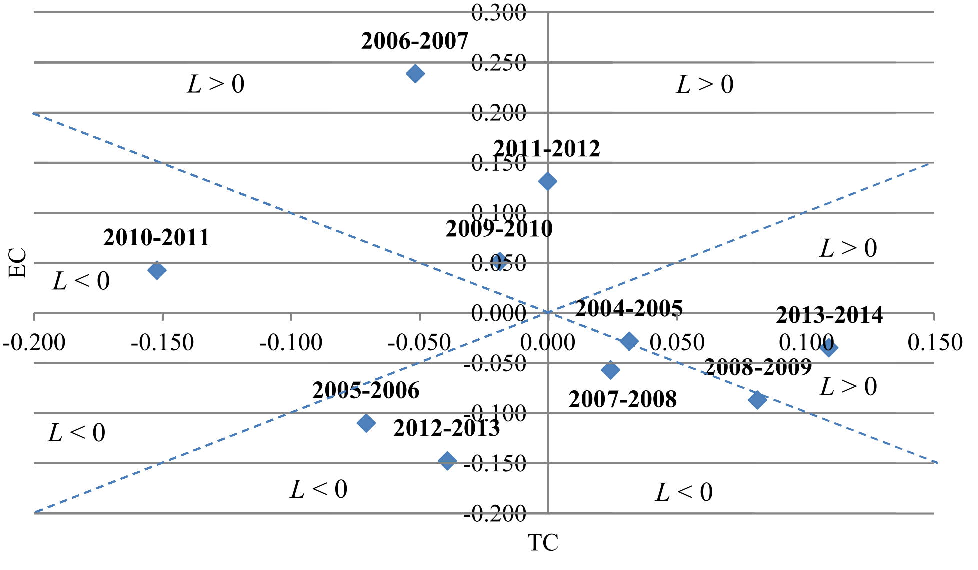

FIGURE 3 EC and TC components for the Luenberger productivity indicator. The dashed lines indicate equal magnitudes of EC and TC. EC, efficiency change; TC, technical change [Color figure can be viewed at wileyonlinelibrary.com]

yields remaining rather low, the production frontier continued to move inward throughout the period 2010–2011, as represented by a negative TC component of −15.2%. In this period, TFP went down by 10.9%.

During the period 2011–2012, productivity rose by 13.1%, a change that was solely driven by technical efficiency improvements. The whole period of 2012–2014 saw an increase in the area sown under wheat, with 627–708 thousand ha compared to 551 thousand ha in 2011. Such changes in the areas under crops might have negatively affected productivity growth. The subperiod of 2012–2013 showed a steep decline in productivity of 18.7%, with contributions from both technical efficiency change (−14.8%) and TC (−3.9%). Indeed, the year 2013 was characterized by unfavorable weather conditions, as represented by a decrease in yields. Furthermore, the growth in farm credit was subdued in 2012–2014. Correspondingly, dynamic technical efficiency might have been negatively affected by insufficient investments. Even though technical efficiency change remained negative (−3.5%), it was offset by positive TC (10.9%).

The average changes in productivity as well as its components are listed in Table 4. Besides decomposition into TC and EC components, we also decomposed the TC component.

The decomposition of the TC component into IB, OB, and MTC, consistent with Equations (9)–(11), gives insight into the nature of the TC. Table 4 shows that MT dominates the other components of TC. Specifically, the mean contribution of MT is −2.6% over 2004–2014, whereas IB and OB together account for 1.3%. However, IB and OB combined are greater than the mean EC or TC. This finding suggests a non-neutral TC in Lithuanian grain farms. In our case, IB captures the changes in MRTS among variable inputs, whereas OB accounts for those between agricultural output and investments. Therefore, an analysis of the nature of the underlying technical bias might shed more light on changes in factor substitution as well as on preferences regarding (long-term) investments or (short-run) output growth.

4.2 | Technical bias

Next, we look at the evolution of technical bias. To do so, we need to consider observations with well-defined data for ratios of inputs and ratios of output to investments. While there are no data availability issues for the input use, some observations have zero investments, yielding an undefined output ratio. As a result, 1,341 observations are considered for the analysis of technical bias. The bias of TC is assessed by considering the share of observations featuring specific types of bias. Furthermore, each type of bias can be accompanied by a corresponding or opposite

TABLE 4 The dynamics in the Luenberger productivity indicator and its components

			Technical change			
	L	EC	Overall TC	Output bias	Input bias	Magnitude of TC
2004–2005	0.003	−0.028	0.031	0.008	−0.001	0.024
2005–2006	−0.181	−0.110	−0.071	0.010	0.007	−0.087
2006–2007	0.187	0.239	−0.052	−0.009	0.012	−0.055
2007–2008	−0.033	−0.057	0.024	−0.001	−0.001	0.026
2008–2009	−0.006	−0.087	0.081	0.007	0.008	0.067
2009–2010	0.033	0.051	−0.019	0.005	0.013	−0.037
2010–2011	−0.109	0.043	−0.152	0.010	0.007	−0.170
2011–2012	0.131	0.131	0.000	0.022	0.005	−0.027
2012–2013	−0.187	−0.148	−0.039	0.001	0.011	−0.051
2013–2014	0.074	−0.035	0.109	0.010	0.001	0.098
Average	−0.013	0.000	−0.013	0.006	0.007	−0.026

Abbreviations: EC, efficiency change; L, productivity change; TC, technical change .

TABLE 5 Technical bias in terms of land and labor substitutability

	Land-saving, labor-using TC		Land-using, labor-saving TC	
	Share of obs. with particular bias	Increase in labor use intensity	Share of obs. with particular bias	Increase in land use intensity
2004–2005	0.63	0.53	0.37	0.43
2005–2006	0.52	0.65	0.48	0.70
2006–2007	0.57	0.69	0.43	0.79
2007–2008	0.43	0.40	0.57	0.54
2008–2009	0.44	0.47	0.56	0.69
2009–2010	0.59	0.61	0.41	0.71
2010–2011	0.54	0.65	0.46	0.58
2011–2012	0.41	0.73	0.59	0.53
2012–2013	0.52	0.75	0.48	0.76
2013–2014	0.50	0.58	0.50	0.63
Whole sample	0.52	0.61	0.48	0.65

Note: The figures are the shares of observations within each time period specific for a particular bias or factor intensity change.

change in input intensity, for example, a certain farm might experience labor-using TC and increased labor intensity. This provides insight into the degree to which farms followed the technical bias, as the bias itself is only a manifestation of behavior of the frontier farms. Tables 5–8 present the corresponding figures for different combinations of inputs or outputs.

The results in Table 5 suggest that land-using and labor-saving TC prevailed in Lithuanian grain and oilseed farms in the period 2004–2014 (in total, 52% of observations showed land-saving, labor-using TC). However, the general trend is that the share of land-saving and labor-using farms decreased by 1 percentage point per annum. The latter implies that farms are likely to dispose of labor when expanding their utilized agricultural area in the

TABLE 6 Technical bias in terms of land and intermediate consumption substitutability

	Land-saving, intermediate consumption-using TC		Land-using, intermediate consumption-saving TC	
	Share of obs. with particular bias	Increase in intermediate consumption use intensity	Share of obs. with particular bias	Increase in land use intensity
2004–2005	0.39	0.73	0.61	0.34
2005–2006	0.45	0.59	0.55	0.74
2006–2007	0.81	0.80	0.19	0.45
2007–2008	0.22	0.64	0.78	0.44
2008–2009	0.54	0.75	0.46	0.40
2009–2010	0.36	0.37	0.64	0.80
2010–2011	0.47	0.71	0.53	0.55
2011–2012	0.49	0.92	0.51	0.32
2012–2013	0.69	0.83	0.31	0.59
2013–2014	0.50	0.72	0.50	0.49
Whole sample	0.50	0.71	0.50	0.54

TABLE 7 Technical bias in terms of labor and intermediate consumption substitutability

	Labor-saving, intermediate consumption-using TC		Labor-using, intermediate consumption-saving TC	
	Share of obs. with particular bias	Increase in intermediate consumption use intensity	Share of obs. with particular bias	Increase in labor use intensity
2004–2005	0.36	0.68	0.64	0.39
2005–2006	0.43	0.63	0.57	0.71
2006–2007	0.60	0.77	0.40	0.67
2007–2008	0.37	0.54	0.63	0.44
2008–2009	0.53	0.77	0.47	0.39
2009–2010	0.36	0.47	0.64	0.75
2010–2011	0.40	0.69	0.60	0.57
2011–2012	0.48	0.83	0.52	0.42
2012–2013	0.63	0.84	0.37	0.61
2013–2014	0.47	0.70	0.53	0.52
Whole sample	0.46	0.70	0.54	0.57

future. This is in line with the theory of induced innovations (Hayami & Ruttan, 1971). Specifically in the past decade, the rural labor supply has tightened in Lithuania due to both demographic transition and migration, whereas increasing farm size poses an additional demand for the hired labor force. As a result, the price of labor has increased, calling for the implementation of labor-saving technologies. However, as can be seen from Table 5, the frontier shift indicates labor-using TC. Comparing the FADN data for 2007 and 2014, one can note a decrease in the labor force from 1.79 AWU down to 1.75 AWU for the average cereal farm, whereas the corresponding values for all types of farming were 1.87 and 1.73 AWU. Therefore, the labor force growth rate amounted to approximately −2% in cereal farms, whereas a growth rate of approximately −8% was observed in the whole farming sector. This indicates that the trend of increased labor use and intensity might prevail in some cereal farms. One possible explanation for this observation is the introduction of CAP support in Lithuania, as direct payments

TABLE 8 Technical bias in terms of investment and output substitutability

	Investment-producing TC		Output-producing TC	
	Share of obs. with particular bias	Increase in investment intensity	Share of obs. with particular bias	Increase in output/investment ratio
2004–2005	0.55	0.65	0.45	0.55
2005–2006	0.41	0.83	0.59	0.69
2006–2007	0.60	0.39	0.40	0.29
2007–2008	0.55	0.53	0.45	0.60
2008–2009	0.44	0.58	0.56	0.61
2009–2010	0.39	0.55	0.61	0.66
2010–2011	0.47	0.56	0.53	0.58
2011–2012	0.37	0.78	0.63	0.80
2012–2013	0.56	0.75	0.44	0.53
2013–2014	0.38	0.69	0.63	0.80
Whole sample	0.47	0.61	0.53	0.62

for organic cereal farming are higher than those for conventional farming. As organic farming is more labor-intensive than conventional farming, the aforementioned policies contribute more to labor-intensive TCs. Another reason for labor-using TC is the increase in area sown under rape, which is a more labor-intensive crop than wheat or other cereal crops.[11] Labor-using TC has not been followed by changes in factor intensity to the same extent as labor-saving TC has. For 61% of the observations with a labor-using bias, the labor intensity actually increased, whereas 65% of farms under labor-saving bias showed a decrease in labor intensity.

The results in Table 6 show that farms were evenly split in terms of changes in substitutability between land and intermediate consumption. However, the proportions varied across time periods. Note that the subperiods of 2005–2006 and 2009–2011 marked decreasing yields and negative TC. During those periods, the share of farms experiencing land-saving and intermediate consumption-using TC dropped to 36–47%, that is most of the farms experienced intermediate consumption-saving and land-using TC. This implies that the use of fertilizers, pesticides, and other intermediate inputs contributed less to output growth than did an increase in the farm area. With regard to the changes in input intensities, intermediate consumption-using TC was accompanied much more frequently with an increased intensity of intermediate consumption (relative to land) than the TC biased in the opposite direction: 71% of observations with intermediate consumption-using TC actually increased the intermediate consumption intensity (relative to land), whereas only 54% of intermediate consumption-saving observations were accompanied by a decreasing intermediate consumption intensity (relative to land). Indeed, this is reasonable in the Lithuanian context, as expenses for intermediate consumption per hectare are lower than in Denmark and Germany, for example. The trend analysis for shares of farms under different types of bias suggests a 1 percentage point increase in the share of farms under land-saving and intermediate consumption-using TC. Hence, it is expected that grain production will become more intensive in terms of fertilizer and pesticide application.

Table 7 presents the results on changes in substitutability between labor and intermediate consumption. Sample-wide results suggest that the farms generally experienced labor-using and intermediate consumption-saving TC (54% of the sample observations). However, such TC is not likely to persist under the aforementioned circumstances of demographic transition and increased labor prices. Indeed, the trend fitted to the shares of observations under different types of TC indicates that the share of farms under labor-using and intermediate consumption-saving has decreased by approximately 1 percentage point from 2004 to 2014. Moreover, the share of observations featuring an increase in labor use intensity (against intermediate consumption) is much lower than the share featuring a decrease: 57% against 70% for the whole sample in 2004–2014. Accordingly, application of advanced chemicals is likely to induce a decrease in labor input.

Up to now, we have looked into IB, which is quite common in the literature. In the setting of dynamic efficiency, the direction for projections toward the production frontier is different, namely, contraction of inputs and expansion of investments. Table 8 presents the results on OB. In the dynamic context of this paper, the two "outputs" considered are the total agricultural output and investments in capital assets. Therefore, an output-producing bias implies that the frontier is shifted outward so that farms are able to produce more output while maintaining the same level of investments. In contrast, an investment-generating bias indicates that TC enables farms to increase their investments relative to output. Therefore, the OB disentangles the potential for expanding output vis-a-vis investment.

The empirical results suggest that farms under output-producing TC constituted a larger share of the observations (53%). This suggests that more output was being produced for the same level of investment in capital assets in the case of positive TC. Indeed, the trend analysis implies that the share of farms under investment-producing TC decreased by 1 percentage point per year on average during the period 2004–2014. Such a

[11]See Table 2 in Baležentis and Kriščiukaitienė (2016) for more details on the dynamics of areas sown under different crops in Lithuania.

persistent trend suggests that Lithuanian cereal farms were more concerned about increasing output rather than increasing their investments during the study period.

The share of observations under different types of output and investment bias varied across subperiods. The period of 2004–2008 showed a higher share of farms experiencing production-biased investment TC, namely, 55–60%. In the period after 2008, however, this figure dropped, indicating a shift in the bias of TC toward the production of output rather than increasing investments.

The period of 2006–2011 is characterized by relatively limited (compared to other periods) changes in the investment-to-output ratio (investment intensity). This can be seen in Table 8, which shows the shares of observations experiencing an increase in investment intensity or an increase in output/investment ratio. This implies that the frontier farms tended to focus on different objectives (in terms of output production or investment) compared to the non-frontier farms. Following the serious drought in 2006, most frontier farms focused on output expansion. The non-efficient farms adjusted to such TC gradually, as can be seen from the growing share of observations with an increased output/investment ratio (Table 8). Indeed, the orientation toward output-producing bias might have been induced by the direct payment scheme, where unlimited amounts of agricultural area are subject to financial support. Under these circumstances, cereal farms opt for extensive development. In contrast, the earlier investment into machinery (partially due to investment support) had expanded the capacity of operation, and thus the focus on output expansion rather than investments appears quite natural in the Lithuanian cereal farming. The changes in the shares of observations corresponding to investment bias and output-producing bias were closely related. Furthermore, the mean values for the whole sample were also similar, namely 61% and 62% for investment-producing and output-producing TCs, respectively.

Besides analysing input and OB in a pair-wise manner, one can also identify different patterns in TC. Table 9 shows the average values of bias indicators (unity implies a certain bias) across each type of bias. Each column in the table contains the respective means for a certain type of bias. Each row represents a split of observations for a single combination of inputs or outputs.

The results in Table 9 can be interpreted by considering two groups of observations in terms of their TC bias. For example, the first group is characterized by land-using and labor-saving TC and the second group by land-saving and labor-using TC. These groups are represented by subcolumns in Table 9. Of the observations belonging to the first group (i.e., land-using and labor-saving TC), 56% also experienced land-using and intermediate consumption-saving TC. From the observations within the second group (i.e., land-saving and labor-using TC), only 45% showed land-using and intermediate consumption-saving TC. The mean values are significantly different. Similarly, looking at observations with land-saving and intermediate consumption-using TC, one can note that 42% of these observations indeed showed land-using and labor-saving TC. However, the shares of observations facing contradictory types of bias were much lower for combinations of all inputs except land. Specifically, looking at labor-using and intermediate consumption-saving TC, only 29% of observations exhibited land-using and

TABLE 9 Relationships among different types of bias (proportions of observations within each combination of bias)

	Land-using, labor-saving TC		Land-using, int. consumption-saving TC		Labor-using, int. consumption-saving TC		Investment-producing TC	
Land-using, labor-saving TC	1	0	**0.53**	**0.42**	**0.29**	**0.69**	0.48	0.47
Land-using, int. consumption-saving TC	**0.56**	**0.45**	1	0	**0.73**	**0.23**	0.51	0.49
Labor-using, int. consumption-saving TC	**0.34**	**0.73**	**0.79**	**0.29**	1	0	0.56	0.52
Investment-producing TC	0.61	0.59	0.61	0.59	0.62	0.58	1	0

Note: Figures in bold indicate that the two adjacent cells within the same row are significantly different ($p < 0.01$, two-way *t*-test).

labor-saving TC. Similar results apply to other combinations of inputs, where land is not considered. Therefore, the direction of land-use bias against other inputs varied more than that of labor and intermediate consumption bias. This indicates that substitutability between land and other inputs was rather uncertain and depended on the input mix (i.e., specifics of the production technology).

The results show that the nature of bias related to inputs is generally consistent across different pairs of inputs. However, Table 9 suggests there is no relationship between input and OB. Specifically, the shares of observations featuring a particular input-bias were not significantly different across investment-producing and output-producing observations. This indicates that a farm's capital investment decisions are not related to the bias in TC among inputs.

5 | CONCLUSIONS

This paper extended the dynamic Luenberger productivity indicator to measure dynamic TC and to identify the bias related to input, output, and investment in quasi-fixed factors. The bias-corrected Luenberger productivity indicator was applied to a sample of Lithuanian cereal farms over the period 2004–2014.

The results suggest a decrease in productivity in Lithuanian cereal farms over the period 2004–2014. Specifically, the average change is −1.3% for the study period and was mainly driven by negative TC; technical efficiency change made a negligible contribution to productivity growth. Further decomposition of the TC component revealed that input and output/investment bias each contributed to an average annual increase in productivity of 0.6–0.73% for the study period. This positive effect was offset by a negative contribution of TC. These findings suggest the presence of non-neutral TC in Lithuanian family farms.

The analysis of the input and OB in TC suggests Lithuanian cereal farms faced labor-using TC relative to land and intermediate consumption. This urges the implementation of labor-saving technologies in the most productive (frontier-shaping) farms. However, during the study period, the income of cereal farms was relatively high (compared to the other types of farming in Lithuania) and possibly this provided a disincentive for the adoption of labor-saving technologies. Hence, relatively high incomes from both sales of crops and subsidies may have enabled a labor-intensive mode of production and may have given insufficient incentives for further improvement of production technology. However, in the long run, further improvements are likely needed to cope with the rising price of labor and to maintain the competitiveness of the sector.

The analysis of OB revealed that the period 2004–2008 mainly marks an investment-generating TC, whereas the period 2008–2014 was characterized by an output-producing TC. This implies investments have become relatively more expensive during the study period in terms of output foregone. Also, the more restrictive lending policies that were implemented in the aftermath of the global financial crisis may have increased the costs of investments vis-a-vis outputs. However, investments are needed in the long run to facilitate the adoption of new and more productive technologies. Policy makers can encourage such investments by providing credit guarantees and introducing fiscal support measures. The analysis of farmers' investment decisions and unraveling why investments lag behind is an interesting avenue for future research as well.

The present study has several limitations. First, a deterministic framework was applied to implement the dynamic measures of technical bias. Second, this study focused on Lithuanian cereal farms. Third, determinants of the technical bias were not modeled. Thus, further research could be developed along the following lines. Parametric and semiparametric techniques could be employed to better account for the stochastic nature of agricultural production in the estimation of the underlying production technology and its technical bias. Statistical inference could be carried out for deterministic measures. Such techniques as propensity score matching could be applied to identify possible differences in technical bias across farms (not) participating in various support schemes. Finally, the analysis could be extended to other countries and farming types and results could be compared.

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