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Energy productivity and greenhouse gas emission intensity in Dutch dairy farms: A Hicks–Moorsteen by-production approach under non-convexity and convexity with equivalence results

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Abstract

The agricultural sector is currently confronted with the challenge to reduce greenhouse gas (GHG) emissions, whilst maintaining or increasing production. Energy-saving technologies are often proposed as a partial solution, but the evidence on their ability to reduce GHG emissions remains mixed. Production economics provides methodological tools to analyse the nexus of agricultural production, energy use and GHG emissions. Convexity is predominantly maintained in agricultural production economics, despite various theoretical and empirical reasons to question it. Employing non-convex and convex frontier frameworks, this contribution evaluates energy productivity change (the ratio of aggregate output change to energy use change) and GHG emission intensity change (the ratio of GHG emission change to polluting input change) using Hicks-Moorsteen productivity formulations. We consider GHG emissions as by-products of the production process by using a multi-equation model. Given our empirical specification, non-convex and convex Hicks-Moorsteen indices can coincide under certain circumstances, which leads to a series of theoretical equivalence results. The empirical application focuses on 1,510 observations of Dutch dairy farms for the period of 2010–2019. The results show a positive association between energy productivity change and GHG emission intensity change, which calls into question the potential of on-farm, energy-efficiency-increasing measures to reduce GHG emission intensity.

KEYWORDS

convexity, dairy, energy, greenhouse gas emissions, non-convexity, productivity analysis

JEL CLASSIFICATION

D22, D24, Q12, Q53, Q54

1 | INTRODUCTION

The agricultural sector is currently facing the challenge to reduce greenhouse gas (GHG) emissions, whilst maintaining or increasing production. Agriculture contributes almost one quarter of total GHG emissions (FAO, 2014). Energy-saving technologies are often proposed as a way to reduce GHG emissions in agriculture (Schneider & Smith, 2009). They can in theory decrease GHG emissions per unit produced, since they can decrease the requirements for energy use, a polluting input, per unit produced. In practice, however, these energy-saving technologies do not necessarily lead to a decrease of energy per unit produced, because of slower technology adoption among laggards, which furthermore can still be associated with energy-wasting behaviour because of the rebound effect (Pan et al., 2021). Moreover, GHG emissions per unit of polluting inputs, consisting of not only energy, but also for example herd size, fertilisers and feed, can still increase.

Analysing energy productivity change and GHG emission intensity change can provide useful insights on the interplay between agricultural production, energy use and GHG emissions. Energy productivity change can be defined as the ratio of aggregate output change to energy use change, and GHG emission intensity can be defined as the ratio of GHG emission change to polluting input change. This paper develops an analytical framework to evaluate energy productivity change and GHG emission intensity change in the agricultural sector.

Production economics provides a suitable methodological toolbox to analyse energy productivity change and GHG emission intensity change. This field is concerned with the appropriate modelling of the production relationship between the inputs used and outputs produced. Energy use is one of the conventional inputs to produce conventional outputs. The axiomatic properties assigned to analyse the conversion of conventional inputs to conventional outputs have been thoroughly studied (e.g., Färe & Primont, 1995), which allows assessment of energy productivity growth. GHG emissions are pollutants that occur as by-products in the production process. Axiomatic treatment of pollutants has been heavily debated, but the multi-equation modelling approach proposed by Murty et al. (2012) is currently considered the most promising.[1] Such appropriate modelling permits assessment of GHG emission intensity growth.

In spite of these methodological advances, applications to the agricultural sector overwhelmingly use the basic convexity assumption when estimating the production technology. However, there are theoretical and empirical reasons to question the convexity assumption.

[1]Surveys on how to model pollutants are available in Dakpo et al. (2016), Ancev et al. (2017), and Dakpo and Ang (2019).

Theoretically, there can be indivisibilities in inputs and outputs, economies of scale and economies of specialisation (that play a role in the new growth theory: e.g., Romer, 1990 on non-rival inputs), as well as externalities. Seminal contributions to axiomatic production theory indicate that the cost function is convex in the outputs if and only if technology is convex (e.g., Jacobsen [1970, Corollary 5.5]). Thus, using contraposition, the cost function is non-convex if and only if technology is non-convex: Kerstens and Van de Woestyne (2021) illustrate that the gap between convex and non-convex costs may be very substantial.

Empirically, various studies in agricultural economics contain evidence about the potential relevance of non-convexities. Paris et al. (1970) report concave isoquants in the hay and concentrates inputs space for whole milk and skimmed milk. Brokken (1977) similarly summarises three studies revealing that there are concave isoquants in the concentrates and roughage inputs space in beef production. Bhide et al. (1980) also report at least partially concave isoquants in the concentrate and corn silage input space that best explain the relationship in beef gain production. Finally, Freeze and Hironaka (1990) report limited substitution of alfalfa hay and concentrate in beef feeding diets resulting in a forage-concentrate weight gain isoquant that are concave to the origin in the middle range. Despite the empirical relevance of non-convexities in experimental and agronomical data in agriculture, the large majority of the empirical applications assumes a convex technology. Recent exceptions empirically considering a non-convex technology include Ruijs et al. (2013), Ruijs et al. (2017), Ang and Kerstens (2017) and Ang et al. (2018). General reflections on the role of non-convexity in ecosystems and agriculture are found in Dasgupta and Mähler (2003) and Brown et al. (2011), among others.

Our contributions are fourfold. First, using a production economics perspective, we analyse energy productivity change and GHG emission intensity change side-by-side. A particular advantage of this approach is its appropriate consideration of, on the one hand, the conversion of conventional inputs to conventional outputs and, on the other hand, the GHG emissions occurring as a by-product in this process. Employing Hicks-Moorsteen productivity formulations (Bjurek, 1996), the aggregations in the various components are grounded in production theory. Following Murty et al. (2012), we consider GHG emissions as by-products of the production process using multi-equation modelling.

Second, in contrast to the prevailing literature, we assume a non-convex technology in addition to the more traditional convex technology. To this end, we estimate the production technology using a free disposal hull (FDH) (Deprins et al., 1984). FDH is a non-parametric approach that only relies on minimal assumptions. Such a non-convex technology has been rarely employed in a productivity index context. Examples of such studies include Diewert and Fox (2014), Kerstens and Van de Woestyne (2014a), Ang and Kerstens (2017) and Kerstens et al. (2018), among others.

Third, we show that convex and non-convex Hicks-Moorsteen index results can be identical under certain conditions, which is the case for several components in our empirical analysis. This leads to a series of new theoretical results on the conditions under which convex and non-convex Hicks-Moorsteen productivity indices coincide. While theoretical relations between, for instance, Hicks-Moorsteen and Malmquist productivity indices are wellestablished (see, e.g., Kerstens & Van de Woestyne [2014a, Section 2.4] for a survey), we are unaware of any theoretical results regarding the equivalence of a productivity index under convexity and non-convexity. To the best of our knowledge, our results are new to the productivity index literature.

Fourth, merging a comprehensive accountancy data set with a unique data set with GHG emission estimates, we illustrate our approach with an application to a large sample of Dutch dairy farms for the years 2010–2019. The European Energy Efficiency Directive focuses on increasing energy efficiency and reduction of the use of fossil fuels (Moerkerken et al., 2021). The Dutch dairy sector in particular has signed several covenants that target increases in energy-efficiency, which have been in place in the studied period. There have been (so far unsuccessful) calls for making the Dutch dairy chain energy neutral (Gebrezgabher et al., 2012). Furthermore, the dairy sector contributes substantially to GHG emissions in the Netherlands (Ruyssenaars et al., 2021). As a result, the Dutch dairy sector is a good candidate for a case study.

The remainder of the current paper unfolds as follows. Section 2 describes the theoretical framework, in which we provide a Hicks-Moorsteen formulation of energy productivity change and GHG emission intensity change. This is followed by the description of the non-convex method in Section 3, in which we establish the equivalence results between non-convex and convex Hicks-Moorsteen productivity indices, and by a brief description of the data set of Dutch dairy farms in Section 4. Subsequently, we show the empirical results in Section 5. Section 6 concludes.

2 | THEORETICAL FRAMEWORK

Balk (2003) states that total factor productivity (TFP) change, the most encompassing measure of productivity change, is the 'real' component of profitability change. Therefore, productivity is a key component of profitability and it is an important driver of changes in living standards. TFP growth can be conceived as an index number that captures any output growth that is unexplained by input growth (Hulten, 2001). Russell (2018) defines theoretical productivity indices as known and non-stochastic, but unspecified. The Malmquist productivity index (Caves et al., 1982) and the Hicks-Moorsteen productivity index (Bjurek, 1996) are prime examples. The Malmquist productivity index measures the local shift of the production frontier, while the Hicks-Moorsteen productivity index is a ratio of an aggregate output index to an aggregate input index. The current contribution focuses on the Hicks-Moorsteen productivity formulation.

Our Hicks-Moorsteen productivity formulation has two key advantages in comparison to the Malmquist productivity index formulation. First, the Hicks-Moorsteen TFP index is multiplicatively complete (O'Donnell, 2012). This permits separate analysis of output and input growth or decline, which can also be adapted to the environmental context (Abad & Ravelojaona, 2022). For our partial productivity formulations, this means that one can separately assess aggregate output change and energy use change, on the one hand, and GHG emission change and polluting input change, on the other hand. This is normally not possible using a Malmquist productivity formulation, although Abad and Ravelojaona (2021) demonstrate how to formulate a pollution-adjusted Malmquist productivity index consisting of a separate polluting productivity index and a separate non-polluting productivity index. Second, the Hicks-Moorsteen formulation is not susceptible to infeasibilities under weak conditions on technology (mainly strong disposability), which contrasts with the Malmquist productivity formulation (see Briec and Kerstens (2011)).[2]

2.1 | Basic notation

Let $\mathbf{x} \in \mathbb{R}_+^{n+o}$ be the vector of inputs being transformed to the vector of outputs $\mathbf{y} \in \mathbb{R}_+^m$. Let us additionally consider a production process that generates greenhouse gas emissions *ghg* as a by-product. We partition $\mathbf{x}$ into a sub-vector of polluting inputs $\mathbf{u} \in \mathbb{R}_+^n$ and sub-vector of

[2]When using weak disposability (another popular way to model bad outputs), infeasibilities can occur even with the Hicks-Moorsteen formulation. For instance, Zaim (2004) employs a Hicks-Moorsteen productivity index with weak disposal of bad outputs and reports infeasibilities for 8 out of 41 US states, despite using time windows that reduce the number of infeasibilities.

non-polluting inputs $\mathbf{v} \in \mathbb{R}_{+}^{o}$: $\mathbf{x} = (\mathbf{u}, \mathbf{v})$. Energy ($E$) is one of the polluting inputs; $\mathbf{z} \in \mathbb{R}_{+}^{n-1}$ is the sub-vector of non-energy polluting inputs, which implies $\mathbf{u} = (E, \mathbf{z})$.

2.2 | Energy productivity change

The parental conventional technology at time t is defined as follows:

$$T_t = \left\{ \left(\mathbf{x}_t, \mathbf{y}_t\right) \in \mathbb{R}_{+}^{n+m+o} \mid \mathbf{x}_t \text{ can produce } \mathbf{y}_t \right\}. \tag{1}$$

whereby the vector of inputs $\mathbf{x}$ contributes to generating the vector of outputs $\mathbf{y}$.

Here, $\mathbf{x} = (\mathbf{u}, \mathbf{v})$ and $\mathbf{u} = (E, \mathbf{z})$. Therefore, the technology (1) can be rewritten as follows:

$$T_t = \left\{ \left(E_t, \mathbf{z}_t, \mathbf{v}_t, \mathbf{y}_t\right) \in \mathbb{R}_{+}^{n+m+o} \mid (E_t, \mathbf{z}_t, \mathbf{v}_t) \text{ can produce } \mathbf{y}_t \right\}. \tag{2}$$

In line with, for example, Färe and Primont (1995), we make the following assumptions:

Axiom 1 *Closedness.* T_{t} *is closed.*

Axiom 2 *Boundedness.* T_{t} *is bounded.*

Axiom 3 *Free disposability of inputs and outputs. If* $\left(\mathbf{x}'_t, -\boldsymbol{y}'_t\right) \geq \left(\boldsymbol{x}_t, -\boldsymbol{y}_t\right)$ *then* $\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \in T_t \Rightarrow \left(\boldsymbol{x}'_t, \boldsymbol{y}'_t\right) \in T_t$.

Axiom 4 *Inaction. Inaction is possible:* $(\mathbf{0}^{\mathrm{n+o}}, \mathbf{0}^{\mathrm{m}}) \in \mathrm{T}_{\mathrm{t}}$.

Axiom 5 *Convexity.* T_{t} *is convex.*

Axioms 1–4 are always maintained throughout this contribution. Despite its widespread use in economics, the axiom of convexity is not always maintained in this contribution.[3]

We can represent technology T_t by the traditional output distance function:

$$D_t^{y}(E, \mathbf{z}, \mathbf{v}, \mathbf{y}) = \inf_{\phi} \left\{ \phi > 0 \mid \left(E, \mathbf{z}, \mathbf{v}, \frac{\mathbf{y}}{\phi} \right) \in T_t \right\} \tag{3}$$

that scales up outputs for given total input use, and a sub-vector energy distance function:

$$D_t^{E}(E, \mathbf{z}, \mathbf{v}, \mathbf{y}) = \sup_{\theta} \left\{ \theta > 0 \mid \left(\frac{E}{\theta}, \mathbf{z}, \mathbf{v}, \mathbf{y} \right) \in T_t \right\}. \tag{4}$$

that scales down the energy input, given non-energy inputs and outputs. We refer to Färe and Primont (1995) for the properties of these distance functions.

[3] The convex variable returns to scale technology does not satisfy inaction. Since technologies (1, 2) are equivalent, axioms 1 to 4 as well as 5 can also be rewritten for technology T_t in (2).

Using Malmquist aggregations (Caves et al., 1982; O'Donnell, 2012) of Equations (3) and (4), we can define aggregate output change between time s and t as:

$$YC_{t,t+1} = \sqrt{\frac{D^{y}_{t+1}\left(E_{t+1}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t+1}\right)}{D^{y}_{t+1}\left(E_{t+1}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t}\right)} \frac{D^{y}_{t}\left(E_{t}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t+1}\right)}{D^{y}_{t}\left(E_{t}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t}\right)}} \tag{5}$$

and energy use change between time s and t as:

$$EC_{t,t+1} = \sqrt{\frac{D^{E}_{t+1}\left(E_{t+1}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t+1}\right)}{D^{E}_{t+1}\left(E_{t}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t+1}\right)} \frac{D^{E}_{t}\left(E_{t+1}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t}\right)}{D^{E}_{t}\left(E_{t}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t}\right)}}. \tag{6}$$

Dividing the aggregate output change (5) by the (sub-vector) energy use change (6) yields a Hicks-Moorsteen productivity formulation (Bjurek, 1996; Caves et al., 1982) of energy productivity change between time periods s and t:

$$EPRODC_{t,t+1} = \frac{YC_{t,t+1}}{EC_{t,t+1}} = \frac{\sqrt{\frac{D^{y}_{t+1}\left(E_{t+1}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t+1}\right)}{D^{y}_{t+1}\left(E_{t+1}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t}\right)} \frac{D^{y}_{t}\left(E_{t}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t+1}\right)}{D^{y}_{t}\left(E_{t}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t}\right)}}}{\sqrt{\frac{D^{E}_{t+1}\left(E_{t+1}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t+1}\right)}{D^{E}_{t+1}\left(E_{t}, \mathbf{z}_{t+1}, \mathbf{v}_{t+1}, \mathbf{y}_{t+1}\right)} \frac{D^{E}_{t}\left(E_{t+1}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t}\right)}{D^{E}_{t}\left(E_{t}, \mathbf{z}_{t}, \mathbf{v}_{t}, \mathbf{y}_{t}\right)}}}. \tag{7}$$

Equation (7) represents a sub-vector and therefore partial productivity index focusing on energy use. Values above unity indicate energy productivity growth. This means that the growth rate of aggregate output exceeds that of energy use, which can be interpreted as a relative decoupling of production from energy use.

Note that a sub-vector approach to model energy productivity growth as in expression (7) has also been used by, for instance, Oude Lansink and Ondersteijn (2006) with an application to the Dutch glasshouse sector. But, these authors use a Malmquist productivity index formulation instead.

2.3 | GHG emission intensity change

Murty et al. (2012) show that pollutants such as GHG emissions can be explicitly modelled as a by-product. The *emission-generating* technology is defined as follows:

$$G_t = \left\{\left(\mathbf{u}_t, ghg_t\right) \in \mathbb{R}^{n+1}_{+} \mid \mathbf{u}_t \text{ can produce } ghg_t\right\}. \tag{8}$$

whereby the polluting inputs $\mathbf{u}$ produce the by-product of greenhouse gas emissions *ghg*.

Following Murty et al. (2012), we make the following assumption:

Axiom 6 *Closedness.* G_t *is closed.*

Axiom 7 *Boundedness.* G_t *is bounded.*

Axiom 8 *Costly disposability of greenhouse gas emissions and polluting inputs. If* $(\mathbf{u}_t, ghg_t) \in G_t$ *and* $ghg'_t \geq ghg_t$ *and* $\boldsymbol{u}'_t \leq \boldsymbol{u}_t$*, then* $\left(\boldsymbol{u}'_t, ghg'_t\right) \in G_t$.

Axiom 9 *Convexity.* G_t *is convex.*

Similar to the case of T_t, we do not always maintain the convexity assumption for G_t in the following.

We represent G_t by the polluting input distance function:

$$D_t^u(\mathbf{u}, ghg) = \inf_{\rho}\left\{ \rho > 0 | \left(\frac{\mathbf{u}}{\rho}, ghg\right) \in G_t \right\} \tag{9}$$

that scales up polluting inputs for a given total *ghg*, and a *ghg* emission distance function:

$$D_t^{ghg}(\mathbf{u}, ghg) = \sup_{\delta}\left\{ \delta > 0 | \left(\mathbf{u}, \frac{ghg}{\delta}\right) \in G_t \right\} \tag{10}$$

that scales down *ghg* as much as possible.

Analogous to Equations (5)–(7), we aggregate Equations (9) and (10) using Malmquist formulations (Caves et al., 1982; O'Donnell, 2012). We define polluting input change between time periods *s* and *t* as:

$$XPC_{t,t+1} = \sqrt{\frac{D_{t+1}^u\left(\mathbf{u}_{t+1}, ghg_{t+1}\right)}{D_{t+1}^u\left(\mathbf{u}_t, ghg_{t+1}\right)} \frac{D_t^u\left(\mathbf{u}_{t+1}, ghg_t\right)}{D_t^u\left(\mathbf{u}_t, ghg_t\right)}} \tag{11}$$

and GHG emission change between time periods *s* and *t* as:

$$GHGC_{t,t+1} = \sqrt{\frac{D_{t+1}^{ghg}\left(\mathbf{u}_{t+1}, ghg_{t+1}\right)}{D_{t+1}^{ghg}\left(\mathbf{u}_{t+1}, ghg_t\right)} \frac{D_t^{ghg}\left(\mathbf{u}_t, ghg_{t+1}\right)}{D_t^{ghg}\left(\mathbf{u}_t, ghg_t\right)}}. \tag{12}$$

Again, we refer to Färe and Primont (1995) for the properties of these distance functions.

Dividing Equation (12) by Equation (11) yields a Hicks-Moorsteen formulation of GHG emission intensity change between time periods *s* and *t*:

$$GHGIC_{t,t+1} = \frac{GHGC_{t,t+1}}{XPC_{t,t+1}} = \frac{\sqrt{\frac{D_{t+1}^u\left(\mathbf{u}_{t+1}, ghg_{t+1}\right)}{D_{t+1}^u\left(\mathbf{u}_t, ghg_{t+1}\right)} \frac{D_{t+1}^u\left(\mathbf{u}_{t+1}, ghg_t\right)}{D_t^u\left(\mathbf{u}_t, ghg_t\right)}}}{\sqrt{\frac{D_{t+1}^{ghg}\left(\mathbf{u}_{t+1}, ghg_{t+1}\right)}{D_{t+1}^{ghg}\left(\mathbf{u}_{t+1}, ghg_{t+1}\right)} \frac{D_t^{ghg}\left(\mathbf{u}_t, ghg_{t+1}\right)}{D_t^{ghg}\left(\mathbf{u}_t, ghg_t\right)}}} \tag{13}$$

Equation (13) compares GHG emission change to polluting input change. Values above one indicate intensification, which means that the growth rate of GHG emissions exceeds that of polluting inputs. Equation (13) can thus be regarded as the reciprocal of a productivity change measure: scores above unity are bad, while scores below unity are good. Observe that $XPC_{t,t+1}$ reduces $GHGIC_{t,t+1}$ and is thus *beneficial* with regard to the emission-generating technology. If the level of GHG emissions remains constant, while the level of polluting inputs has increased, then this indicates an improvement of environmental performance in the emission-generating technology, as reflected by a decrease in GHG emission intensity. However, in the conventional technology, an increase in the level of inputs (including polluting inputs) would be penalised in terms of productivity. This highlights the importance of not only considering improvements in the environmental performance in the emission-generating technology, but also in the economic performance in the conventional technology.

The separate theoretical consideration of the conventional technology and emission-generating technology in a productivity context follows Lamkowsky et al. (2021). This approach differs somewhat from the original approach of Murty et al. (2012). The latter authors focus on the development of environmental efficiency measures that appropriately take into account the emission-generating process generating pollution. To this end, they compute the average of efficiency in the conventional technology and efficiency in the emission-generating technology, which can be represented in the intersection of both technologies. The present contribution focuses on comparing partial productivity scores in the respective technologies, which makes separate consideration appropriate.

3 | EMPIRICAL SPECIFICATION OF NON-PARAMETRIC TECHNOLOGIES

Thus far we have been silent on the approximation of the conventional and emission-generating technologies. This paper employs convex and non-convex nonparametric approximations. There are I farms. Assuming convexity and variable returns to scale (VRS), the conventional technology at time t is approximated by:

$$\widehat{T}_t(\mathbf{x}_t, \mathbf{y}_t) = \left\{ (\mathbf{x}_t, \mathbf{y}_t) \mid \sum_{i=1}^{I} \lambda_{i,t}\mathbf{x}_{i,t} \le \mathbf{x}_t, \sum_{i=1}^{I} \lambda_{i,t}\mathbf{y}_{i,t} \ge \mathbf{y}_t, \sum_{i=1}^{I} \lambda_{i,t} = 1 \right\}. \tag{14}$$

A non-convex approximation is obtained by adding the binary integer constraint $\lambda_{i,t} \in \{0, 1\}$ on the activity vector.

Again assuming convex VRS, the emission-generating technology at time t is approximated by:

$$\widehat{G}_t(\mathbf{u}_t, ghg_t) = \left\{ (\mathbf{u}_t, ghg_t) \mid \sum_{i=1}^{I} \mu_{i,t}\mathbf{u}_{i,t} \ge \mathbf{u}_t, \sum_{i=1}^{I} \mu_{i,t}, ghg_{i,t} \le ghg_t, \sum_{i=1}^{I} \mu_{i,t} = 1 \right\}. \tag{15}$$

Again, a non-convex approximation is obtained by adding the binary integer constraint $\mu_{i,t} \in \{0, 1\}$ on the activity vector.

These approximations allow computation of all components of energy productivity change and GHG emission intensity change. Following the detailed explanation in Murty and Russell (2020, pp. 47–48), these separate approximations are also consistent with the original theoretical framework of Murty et al. (2012) that defines the by-production technology as the *intersection* of the conventional technology and the emission-generating technology. Appendix A (online) shows an overview of the required linear and binary mixed-integer linear programmes under the assumptions of convexity and non-convexity respectively.

The only alternative theoretical models that use a by-production framework to model bad outputs in both convex and non-convex ways are found in Abad and Briec (2019) and Abad and Ravelojaona (2021, 2022). These models are based on recent work to measure strong forms of hypercongestion for convex and non-convex technologies in Briec et al. (2016) who develop a limited form of strong disposability called S-disposability (see Briec et al. (2018) for an empirical illustration).[4] Abad and Briec (2019) and Yuan et al. (2021) are among the first to empirically implement a non-convex version of the Murty et al. (2012)

[4]Abad and Briec (2019) re-baptise this S-disposability assumption as a B-disposability assumption when modelling bad outputs.

by-production approach: these authors report substantial differences between convex and non-convex empirical results.

Convex and non-convex comparisons of the Hicks-Moorsteen productivity index are rare in the literature. Kerstens and Van de Woestyne (2014a, 2014b) compare Hicks-Moorsteen and Malmquist productivity indices under balanced and unbalanced panel data and under constant and variable returns to scale. These authors report substantial differences between convex and non-convex Hicks-Moorsteen productivity indices, but they do not report any formal testing. In an additive context, we are aware of only two further studies that report on the impact of convexity on the Luenberger-Hicks-Moorsteen productivity indicator: both Ang and Kerstens (2017) and Kerstens et al. (2018) report statistically significant differences between non-convex and convex estimates.

When computing non-convex and convex Hicks-Moorsteen productivity indices for our empirical specification, we find that several components coincide exactly. This leads to a series of new theoretical results stating that convex and non-convex (partial) Hicks-Moorsteen productivity indices coincide under specific conditions.

Theorem 1 *Assuming that there is just a single output* (m = *1), then the following statements are true under both convex and non-convex assumptions:*

$$\frac{D^y_{t+1}\left(E_{t+1},\mathbf{z}_{t+1},\mathbf{v}_{t+1},y_{t+1}\right)}{D^y_{t+1}\left(E_{t+1},\mathbf{z}_{t+1},\mathbf{v}_{t+1},y_{t}\right)}=\frac{D^y_{t}\left(E_{t},\mathbf{z}_{t},\mathbf{v}_{t},y_{t+1}\right)}{D^y_{t}\left(E_{t},\mathbf{z}_{t},\mathbf{v}_{t},y_{t}\right)}=\frac{y_{t+1}}{y_t}. \tag{16}$$

$$YC_{t,t+1}=\frac{y_{t+1}}{y_t}. \tag{17}$$

The proofs of Theorem 1 and the other statements are given in Appendix B, online.

Theorem 2 *The following statements are true under both convex and non-convex assumptions:*

$$\frac{D^E_{t+1}\left(E_{t+1},\mathbf{z}_{t+1},\mathbf{v}_{t+1},\mathbf{y}_{t+1}\right)}{D^E_{t+1}\left(E_{t},\mathbf{z}_{t+1},\mathbf{v}_{t+1},\mathbf{y}_{t+1}\right)}=\frac{D^E_{t}\left(E_{t+1},\mathbf{z}_{t},\mathbf{v}_{t},\mathbf{y}_{t}\right)}{D^E_{t}\left(E_{t},\mathbf{z}_{t},\mathbf{v}_{t},\mathbf{y}_{t}\right)}=\frac{E_{t+1}}{E_t}. \tag{18}$$

$$EC_{t,t+1}=\frac{E_{t+1}}{E_t}. \tag{19}$$

Corollary 1 *Assuming that there is just a single output* (m = *1), then the following statement is true under both convex and nonconvex assumptions:*

$$EPRODC_{t,t+1}=\frac{y_{t+1}E_t}{y_tE_{t+1}}. \tag{20}$$

The above results shows that with a single output, we can measure all components of the Hicks-Moorsteen index without having to solve any optimization models. In addition, the Hicks-Moorsteen index and its components are independent of the value of fixed inputs. As a consequence, in this particular case, the fixed inputs can be ignored. This closed-form specification provides opportunities for policy-oriented applications, that can dispense with more complex linear or binary mixed-integer linear programmes.

This simplification for computing a theoretical Hicks-Moorsteen productivity index is new to the productivity literature. It is wellknown that efficiency measures under a FDH technology can be obtained via implicit enumeration algorithms and that this leads to substantial time gains (see, e.g., Kerstens and Van de Woestyne (2014b)). However, it is exceptional to have implicit enumeration results that are also valid for convex technologies. To the best of our knowledge, the only other results concern the cost function and revenue function under constant returns to scale and a single output or a single input, respectively (see Briec et al. (2014)). However, the latter result concerns value functions, while here we have a result for a particular specification of the technology.

Theorem 3 *Assuming that there is just a single polluting input (*n = 1*), then the following statements are true under both convex and non-convex assumptions:*

$$\frac{D^u_{t+1}\left(u_{t+1}, ghg_{t+1}\right)}{D^u_{t+1}\left(u_t, ghg_{t+1}\right)} = \frac{D^u_t\left(u_{t+1}, ghg_t\right)}{D^u_t\left(u_t, ghg_t\right)} = \frac{u_{t+1}}{u_t}. \tag{21}$$

$$XPC_{t,t+1} = \frac{u_{t+1}}{u_t}. \tag{22}$$

Theorem 4 *The following statements are true under both convex and nonconvex assumptions:*

$$\frac{D^{ghg}_{t+1}\left(\boldsymbol{u}_{t+1}, ghg_{t+1}\right)}{D^{ghg}_{t+1}\left(\boldsymbol{u}_{t+1}, ghg_t\right)} = \frac{D^{ghg}_t\left(\boldsymbol{u}_t, ghg_{t+1}\right)}{D^{ghg}_t\left(\boldsymbol{u}_t, ghg_t\right)} = \frac{ghg_{t+1}}{ghg_t}. \tag{23}$$

$$GHGC_{t,t+1} = \frac{ghg_{t+1}}{ghg_t}. \tag{24}$$

Corollary 2 *Assuming that there is just a single polluting input (*n = 1*), then the following statement is true under both convex and nonc-onvex assumptions:*

$$GHGIC_{t,t+1} = \frac{u_{t+1} ghg_t}{u_t ghg_{t+1}}. \tag{25}$$

Observe that our empirical application considers *multiple* polluting inputs. Consequently, Theorem 3 and Corollary 2 do not strictly hold for our particular empirical application.

4 | DATA

We use a data set from the Farm Accountancy Data Network (FADN), which is merged with a data set containing computations of GHG emissions by Wageningen Economic Research (WEcR). The FADN data set is an unbalanced, but stratified panel. To obtain a homogeneous sample, the application focuses on the specialised dairy farms not producing any other on-farm output (thus, omitting farms that produce crop outputs). One clear outlier with an unrealistic value has been omitted. The final, merged data set contains 1,510 observations for the years 2010–2019.

We distinguish one output and six inputs. The output is the aggregate dairy output (in €), which consists of milk and meat. The three polluting inputs (**u**) are energy (in €), herd size (in livestock units) and other non-energy intermediate polluting inputs (in €). The latter consist of an aggregation of seed, feed, pesticide, fertilisers and other variable inputs. The three non-polluting inputs (**v**) are land (in hectares), labour (in annual working hours), and the aggregate capital depreciation of buildings and machinery (in €).

Dairy output, other non-energy intermediate polluting inputs and aggregate capital depreciation are computed as the ratio of the total monetary value to the respective dimensionless Törnqvist price index. The monetary value of energy is deflated by the respective dimensionless price index. As a result, the outputs and inputs expressed in monetary terms are implicit quantities, while livestock, land and labour are expressed as original quantities. Implicit quantities employ a common price index per year. This implies that differences in price are reflected as differences in implicit quantity. Outputs and inputs with a higher price are here assumed to have a higher quality and hence a higher price (Cox & Wohlgenant, 1986; Mairesse & Jaumandreu, 2005). All price indices are drawn from the Eurostat (2021) database. Finally, we consider GHG emissions (in kilograms). WEcR computes the GHG emissions by a consideration of the emission factors of all inputs and outputs, as well as a careful investigation of the agricultural production system. GHG emissions consist of CO_2 emissions, N_2O emissions and CH_4 emissions. Sources of GHG emissions include, for example, the production and purchasing of fertilisers, ruminal fermentation of cows, storage of manure, and energy use (Duurzame Zuivelketen, 2018).

In our empirical setting, we compute $EPRODC_{t,t+1}$ as follows: (i) the $YC_{t,t+1}$ component expands the output given all six inputs, and (ii) the $EC_{t,t+1}$ component reduces the single energy input solely given the five other inputs and the output. Additionally, $GHGIC_{t,t+1}$ is computed as follows: (i) the $XPC_{t,t+1}$ component reduces GHG emissions given the three polluting inputs, and (ii) the $GHGC_{t,t+1}$ component expands the three polluting inputs given GHG emissions.

The data on FADN and WEcR are proprietary, but their use can be requested at and negotiated with WEcR. The Supplementary Materials online provide the R code to compute $EPRODC_{t,t+1}$ and $GHGIC_{t,t+1}$.

Table 1 shows the detailed descriptive statistics. Despite the homogeneity of the sample, there is substantial heterogeneity in the inputs, output, and GHG emissions.

5 | EMPIRICAL RESULTS

This section describes our empirical results. We first show the results regarding energy productivity change and GHG emission intensity change, which is followed by a comparison between both. There are in total 1,008 annual growth rates. The non-convex and convex approximations are deterministic and as a result sensitive to potential outliers that may determine the production frontier. Following Ang and Kerstens (2016) and Serra et al. (2014) among others, we apply the super-efficiency approach of Banker and Chang (2006) as a robustness check. This involves the removal of the considered observation from the reference technology in the efficiency estimation. 'Super-efficient' farms have a score higher than unity or are infeasible to compute with respect to such a modified technology (Ray, 2008). Appendix C (online) shows the non-convex scores of energy productivity change and GHG emission intensity change for the sub-sample of observations with a feasible score between the 5th and 95th percentile for an output distance function formulation, employing non-convex approximation. These results without potential outliers are overall similar to those presented in the main body of the text.

5.1 | Energy productivity change

As mentioned in Section 3, the non-convex and convex approximations of all components of $EPRODC_{t,t+1}$ coincide.

TABLE 1 Descriptive statistics

Statistic	Mean	St. dev.
Dairy output (implicit quantity in €)	364,728	276,785
Labour (in annual working hours)	4,730	3,051
Land (in hectares)	58.158	35.635
Herd size (in livestock units)	151.870	100.799
Material non-energy input (implicit quantity in €)	144,716	115,273
Energy (implicit quantity in €)	7,239	5,246
Aggregate capital depreciation (implicit quantity in €)	50,624	41,545
Greenhouse gas emissions (in kilograms)	1,555,100	1,101,576
Dairy Törnqvist price index (dimensionless)	1.107	0.089
Material non-energy input Törnqvist price index (dimensionless)	1.132	0.072
Energy price index (dimensionless)	1.034	0.114
Aggregate capital Törnqvist price index (dimensionless)	1.068	0.061

Table 2 shows the annual energy productivity change, $EPRODC_{t,t+1}$ in Equation (7), and the components of aggregate output change, $YC_{t,t+1}$, and energy use change, $EC_{t,t+1}$. The average annual $EPRODC_{t,t+1}$ in the considered period is 1.034, which indicates an average growth rate of 3.4% per annum (p.a.). The median annual $EPRODC_{t,t+1}$ is 1.008, which indicates a slight median increase of 0.8% p.a. The mean is somewhat higher than the median, but overall close to the median. The average $EPRODC_{t,t+1}$ indicates growth of +17.6%, +8.5%, +10.7%, +13.7% and +11.7% in the periods of 2010–2011, 2011–2012, 2012–2013, 2016–2017 and 2017–2018, respectively. In the other periods, there is on average a decline in $EPRODC_{t,t+1}$, of which 2018–2019 (−12.8%) is the worst period. Finally, we note that $EC_{t,t+1}$ is more volatile and has a larger spread than $YC_{t,t+1}$.

The results on average annual energy productivity change, aggregate output change, and energy use change for the subsample without potential outliers are reported in Table C1 in Appendix C, online. These results are similar to the ones discussed here.

5.2 | GHG emission intensity change

As mentioned in Section 3, the non-convex and convex approximations of $GHGC_{t,t+1}$ coincide.

As our empirical application considers *multiple* polluting inputs, Theorem 3 and Corollary 2 do not hold for our empirical application. Therefore, the non-convex and convex approximations differ for $XPC_{t,t+1}$ and $GHGIC_{t,t+1}$.

Table 3 shows the annual GHG emission intensity change estimated using nonconvex approximation, $GHGIC^{NC}_{t,t+1}$ in Equation (13), and the components of polluting input change estimated using non-convex approximation, $XPC^{NC}_{t,t+1}$, and GHG emission change estimated using non-convex approximation, $GHGC^{NC}_{t,t+1}$. The average annual $GHGIC^{NC}_{t,t+1}$ in the considered period is 1.015, which indicates an average increase of 1.5% p.a. The median annual $GHGIC^{NC}_{t,t+1}$ is 1.005, which indicates a slight median increase of 0.5% p.a. The mean and median are thus rather close to one another. The average $GHGIC^{NC}_{t,t+1}$ indicates decline of 2.5% and 1.2% in 2013–2014 and 2014–2015, respectively. In all other periods, there is on average an increase in $GHGIC^{NC}_{t,t+1}$, of which 2012–2013 (+16.9%) stands out. Interestingly, average annual increases (decreases) in $EPRODC_{t,t+1}$ are counterbalanced by average annual increases (decreases) in $GHGIC^{NC}_{t,t+1}$. The trend of $GHGC^{NC}_{t,t+1}$ largely follows the trend of $XPC^{NC}_{t,t+1}$, except in 2018–2019, in which $XPC^{NC}_{t,t+1} > 1$ and $GHGC^{NC}_{t,t+1} < 1$. The positive association between $XPC^{NC}_{t,t+1}$ and $GHGC^{NC}_{t,t+1}$ is more pronounced than the one between $Y C_{t,t+1}$ and $EC_{t,t+1}$. This suggests

TABLE 2 Average annual energy productivity change, aggregate output change and energy use change

Period	$EPRODC_{t,t+1}$	$YC_{t,t+1}$	$EC_{t,t+1}$
2010–2011	1.176	1.021	0.895
2011–2012	1.085	1.031	1.010
2012–2013	1.107	1.039	0.989
2013–2014	0.941	0.965	1.083
2014–2015	0.975	1.066	1.123
2015–2016	0.938	1.067	1.206
2016–2017	1.137	1.035	0.941
2017–2018	1.117	0.998	0.926
2018–2019	0.872	1.031	1.227
Overall	1.034	1.029	1.050

TABLE 3 Average annual greenhouse gas emission intensity change, polluting input change and greenhouse gas emission change under nonconvex approximation

Period	$GHGIC^{NC}_{t,t+1}$	$XPC^{NC}_{t,t+1}$	$GHGC^{NC}_{t,t+1}$
2010–2011	1.019	1.000	1.018
2011–2012	1.017	1.025	1.041
2012–2013	1.164	1.050	1.223
2013–2014	0.975	1.055	1.028
2014–2015	0.988	1.057	1.041
2015–2016	1.006	1.071	1.075
2016–2017	1.021	0.977	0.996
2017–2018	1.028	0.954	0.979
2018–2019	0.957	1.017	0.972
Overall	1.015	1.028	1.040

that decoupling energy use from production occurs more frequently than decoupling GHG emissions from the use of polluting inputs. Finally, we note that $XPC^{NC}_{t,t+1}$ and $GHGC^{NC}_{t,t+1}$ are not so volatile and have a relatively low spread.

Table 4 shows the annual GHG emission intensity change estimated using convex approximation, $GHGIC^{C}_{t,t+1}$ in Equation (13), and the components of polluting input change estimated using convex approximation, $XPC^{C}_{t,t+1}$, and GHG emission change estimated using convex approximation, $GHGC^{C}_{t,t+1}$. As shown in the theoretical results, $GHGC^{C}_{t,t+1} = GHGC^{NC}_{t,t+1}$. There are differences in $GHGIC^{C}_{t,t+1}$ and $XPC^{C}_{t,t+1}$, albeit to a very minor extent.

The results on average annual GHG emission intensity change, polluting input change, and greenhouse gas emission change under non-convex approximation for the subsample without outliers are reported in Table C2 in Appendix C, online. Overall, these results are in line with the ones discussed here.

5.3 | Comparing energy productivity change to GHG emission intensity change

Given the similarity between the results estimated using non-convex and convex approximations, we only focus on the comparison between energy productivity change and GHG emission intensity change employing the non-convex approximation.

TABLE 4 Average annual greenhouse gas emission intensity change, polluting input change and greenhouse gas emission change under convex approximation

Period	$GHGIC^C_{t,t+1}$	$XPC^C_{t,t+1}$	$GHGC^C_{t,t+1}$
2010–2011	1.032	0.988	1.018
2011–2012	1.018	1.026	1.041
2012–2013	1.173	1.043	1.223
2013–2014	0.978	1.053	1.028
2014–2015	0.982	1.063	1.041
2015–2016	0.989	1.089	1.075
2016–2017	1.018	0.981	0.996
2017–2018	1.037	0.947	0.979
2018–2019	0.931	1.047	0.972
Overall	1.017	1.024	1.040

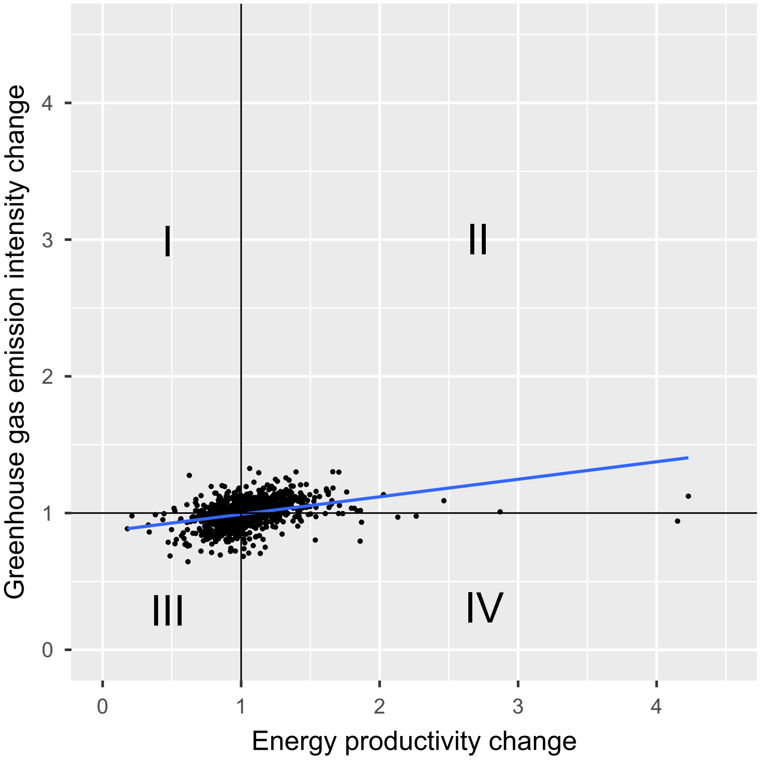

FIGURE 1 Scatter plot of energy productivity change versus greenhouse gas emission intensity change, estimated using non-convex approximation

Figure 1 shows a scatter plot that relates energy productivity change to GHG emission intensity change. It shows a positive association between energy productivity change and GHG emission intensity change, which suggests a trade-off between good performance in one technology and good performance in the other. This empirical finding is confirmed by a Pearson correlation of 0.345 and Spearman rank correlation of 0.486.

The large majority of farms score well either in terms of energy productivity change or in terms of GHG emission intensity change: quadrant II shows 400 observations with energy productivity growth and GHG emission intensity growth, while quadrant III shows 355 observations with energy productivity decline and GHG emission intensity decline. Quadrant I shows 177 observations with energy productivity decline and GHG emission intensity growth. Quadrant IV shows 176 observations with energy productivity growth and GHG emission intensity decline.

6 | CONCLUSIONS

Using a production economics perspective, this paper develops a framework to analyse energy productivity change and GHG emission intensity change. Both measures are computed employing a nonparametric, nonconvex and convex framework based on a Hicks-Moorsteen productivity formulation. The empirical application focuses on 1,510 observations of Dutch specialised dairy farms for the years 2010–2019. Given our specific empirical specification, we observe that energy productivity change and polluting input change are equivalent for nonconvex and convex approximations. We formulate theoretical conditions under which this equivalence holds.

The results are similar for non-convex and convex approximations. The average energy productivity growth is 3.4% p.a. in both approximations, while the GHG emission intensity increases by 1.5% p.a. in the non-convex approximation, and by 1.7% p.a. in the convex approximation. A robustness check for outliers is in line with our main results. Fluctuations over time are substantial for energy productivity change and more moderate for GHG emission intensity change. Energy productivity growth is positively associated with GHG emission intensity *growth* rather than GHG emission intensity *decline*.

We emphasise that these results should be interpreted as descriptive and exploratory rather than causal. Our identification strategy disallows verifying whether energy productivity growth *causes* GHG emission intensity growth. Moreover, change in one technology may imply adjustment in the other one, which is overlooked by the correlation analysis. Nonetheless, our findings do call into question the potential of on-farm, energy-efficiency-increasing measures to reduce GHG emission intensity.

We have five recommendations for future research. First, the flexibility of our proposed framework allows straightforward application to other empirical settings. Any change in partial or total factor productivity can be compared to a change in the performance in the emission-generating technology. Energy productivity change and GHG emission intensity change can be evaluated side-by-side in, for instance, the electric power plant sector. Another interesting avenue is the consideration of other pollutants such as phosphorus surplus and nitrogen surplus in the agricultural sector.

Second, the behavioural and technological drivers explaining the nexus of agricultural production, energy use and GHG emissions should be further investigated. In this way, policymakers are able to draft policies that effectively stimulate reduction of GHG emissions whilst increasing or maintaining agricultural production.

Third, one should extend the current analysis by also considering *in*direct energy use. This paper solely focuses on direct, purchased energy use. Indirect energy use also takes into account earlier chain stages of, most notably, fertilisers. Although policy-makers rather focus on reducing direct energy use by means of energy-efficiency-increasing initiatives, identifying sustainable pathways to reduce GHG emissions requires analysis beyond the farm level.

Fourth, our framework could be applied in a difference-based productivity indicator framework. Following the terminology of Diewert (2005), the current framework is based on ratio-based productivity 'indices'. However, when there are zero or negative values, difference-based 'indicators' are more apt (Balk et al., 2003). Difference-based productivity measures include Bennet (Chambers, 2002), Bennet-Lowe (Ang, 2019), Luenberger (Chambers, 2002) and Luenberger-Hicks-Moorsteen (Briec & Kerstens, 2004) indicators.

Fifth, we recommend to adapt the proposed framework to a statistical setting. Our non-parametric framework is inherently deterministic. Simar and Wilson (1999) show how to obtain statistically robust estimates using a bootstrapped Malmquist productivity formulation. An extension to a Hicks-Moorsteen index remains to be developed. Alternatively, one could employ stochastic frontier analysis (Aigner et al., 1977; Meeusen & Van Den Broeck, 1977).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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