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ENERGY PRODUCTIVITY AND GREENHOUSE GAS EMISSION INTENSITY IN DUTCH DAIRY FARMS: A HICKS-MOORSTEEN BY-PRODUCTION APPROACH UNDER NONCONVEXITY

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ENERGY PRODUCTIVITY AND GREENHOUSE GAS EMISSION INTENSITY IN DUTCH DAIRY FARMS: A HICKS-MOORSTEEN BY-PRODUCTION APPROACH UNDER NONCONVEXITY

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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 a nonconvex, free disposal hull framework, this paper 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 means of multi-equation modelling. The application focuses on 1,510 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: productivity analysis, energy, greenhouse gas emissions, dairy, nonconvexity.
JEL classification: D22, D24, Q12, Q53, Q54.

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1. Introduction

The agricultural sector is currently facing the challenge to reduce GHG emissions, whilst maintaining or increasing production. Agriculture contributes to almost one quarter of total greenhouse gas (GHG) emissions (FAO, 2014). Energy-saving technologies are often proposed as a way to reduce GHG emissions in agriculture (Schneider and 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 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 and 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.

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 nonrival 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 nonconvex if and only if technology is nonconvex: Kerstens and Van de Woestyne (2021) illustrate that the gap between convex and nonconvex costs may be very substantial.

Empirically, various studies in agricultural economics contain evidence about the potential relevance of nonconvexities. 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

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

the empirical relevance of nonconvexities in agriculture, the large majority of the empirical applications assume a convex technology set. Recent exceptions empirically considering a nonconvex technology set include Ruijs et al. (2017), Ang and Kerstens (2017) and Ang et al. (2018).

Our contributions are threefold. 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 appropriately consider GHG emissions as by-products of the production process by means of multi-equation modelling.

Second, in contrast to the prevailing literature, we assume a nonconvex technology. To this end, we estimate the production technology using a free disposal hull (FDH) (Deprins et al., 1984). FDH is a nonparametric approach that only relies on minimal assumptions.

Third, 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. 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 contribution unfolds as follows. The next 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 nonconvex method in Section 3 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. The final 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 (see Hulten (2001)). Recently, Russell (2018) introduces the notion of theoretical productivity indices. A theoretical productivity index assumes that the technology is known and non-stochastic, but unspecified. Thus, this technology is most often approximated by a nonparametric multiple-input, multiple-output specification using some form of distance function. Key theoretical productivity indices are on the one hand the Malmquist productivity index (proposed by Caves et al. (1982)) and on the other hand the Hicks-Moorsteen productivity index (proposed by Bjurek (1996)). While the Malmquist productivity index fundamentally measures the local shift of the production frontier, the Hicks-Moorsteen productivity index is a ratio of an aggregate output index to an aggregate input index. Therefore, the more popular Malmquist productivity index measures local technical change but in general not TFP change, while the Hicks-Moorsteen productivity index has a TFP interpretation.

Our Hicks-Moorsteen productivity formulation has two key advantages in comparison to the Malmquist productivity index formulation. First, 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. This is not possible using a Malmquist productivity formulation. 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 non-polluting inputs $\mathbf{v} \in \mathbb{R}_+^o$: $\mathbf{x} = (\mathbf{u}, \mathbf{v})$. Energy ($E$) is one of the polluting inputs; $\mathbf{z} \in \mathbb{R}_+^{n+o-1}$ 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:

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

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

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

Axiom 1 (Closedness)**.** *P_t is closed.*

Axiom 2 (Free disposability of inputs and outputs)**.** *If $(\mathbf{x}'_t, -\mathbf{y}'_t) \geqslant (\mathbf{x}_t, -\mathbf{y}_t)$ then $(\mathbf{x}_t, \mathbf{y}_t) \in P_t \Rightarrow (\mathbf{x}'_t, \mathbf{y}'_t) \in P_t$.*

Axiom 3 (Inaction)**.** *Inaction is possible: $(\mathbf{0}^{n+o}, \mathbf{0}^m) \in P_t$.*

[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.

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

$$D_t^y(E,\mathbf{z},\mathbf{v},\mathbf{y}) = \inf_{\phi}\left\{\phi > 0 |(E,\mathbf{z},\mathbf{v},\frac{\mathbf{y}}{\phi}) \in P_t\right\} \tag{2}$$

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

$$D_t^E(E,\mathbf{z},\mathbf{v},\mathbf{y}) = \sup_{\theta}\left\{\theta > 0 |(\frac{E}{\theta},\mathbf{z},\mathbf{v},\mathbf{y}) \in P_t\right\}. \tag{3}$$

that scales down the energy input given non-energy inputs and outputs.

Using Malmquist aggregations (Caves et al., 1982; O'Donnell, 2012) of equations (2)-(3), we can define aggregate output change between time s and t as:

$$YC_{st} = \sqrt{\frac{D_s^y(E_s,\mathbf{z}_s,\mathbf{v}_s,\mathbf{y}_t)}{D_s^y(E_s,\mathbf{z}_s,\mathbf{z}_s,\mathbf{y}_s)}\frac{D_t^y(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_t)}{D_t^y(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_s)}} \tag{4}$$

and energy use change between time s and t as:

$$EC_{st} = \sqrt{\frac{D_s^E(E_t,\mathbf{z}_s,\mathbf{v}_s,\mathbf{y}_s)}{D_s^E(E_s,\mathbf{z}_s,\mathbf{z}_s,\mathbf{y}_s)}\frac{D_t^E(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_t)}{D_t^E(E_s,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_t)}}. \tag{5}$$

Dividing the aggregate output change (4) by the (sub-vector) energy use change (5) yields a Hicks-Moorsteen productivity formulation (Bjurek, 1996; Caves et al., 1982) of energy productivity change between time periods s and t:

$$EPRODC_{st} = \frac{YC_{st}}{EC_{st}} = \frac{\sqrt{\frac{D_s^y(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_s)}{D_s^y(E_s,\mathbf{z}_s,\mathbf{z}_s,\mathbf{y}_s)}\frac{D_t^y(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_t)}{D_t^y(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_s)}}}{\sqrt{\frac{D_s^E(E_t,\mathbf{z}_s,\mathbf{v}_s,\mathbf{y}_s)}{D_s^E(E_s,\mathbf{z}_s,\mathbf{z}_s,\mathbf{y}_s)}\frac{D_t^E(E_t,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_t)}{D_t^E(E_s,\mathbf{z}_t,\mathbf{v}_t,\mathbf{y}_t)}}}. \tag{6}$$

Equation (6) 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 (6) 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 *by-production* technology is defined as follows:

$$G_t = \left\{(\mathbf{u}_t, \mathbf{v}_t, ghg_t) \in \mathbb{R}_+^{n+1} | ghg_t \geqslant h(\mathbf{u}_t)\right\}. \tag{7}$$

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 4 (Costly disposability of greenhouse gas emissions)**.** *If* $(\mathbf{u}_t, \mathbf{v}_t, ghg_t) \in G_t$ *and* $ghg'_t \geqslant ghg_t$ *and* $\mathbf{u}'_t \leqslant \mathbf{u}_t$*, then* $(\mathbf{u}'_t, \mathbf{v}_t, ghg'_t) \in G_t$*.*

We represent G_t by the polluting input distance function:

$$D_t^u(\mathbf{u}, ghg) = \inf_\rho \left\{\rho > 0 | (\frac{\mathbf{u}}{\phi}, ghg) \in G_t\right\} \tag{8}$$

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

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

that scales down ghg as much as possible.

Analogous to equations (4)-(5) and (6), we aggregate equations (8)-(9) using Malmquist formulations (Caves et al., 1982; O'Donnell, 2012). We define polluting input change between time periods s and t as:

$$XPC_{st} = \sqrt{\frac{D_s^u(\mathbf{u}_s, ghg_t)}{D_s^u(\mathbf{u}_s, ghg_s)} \frac{D_t^u(\mathbf{u}_t, ghg_t)}{D_t^u(\mathbf{u}_s, ghg_t)}} \tag{10}$$

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

$$GHGC_{st} = \sqrt{\frac{D_s^{ghg}(\mathbf{u}_s, ghg_t)}{D_s^{ghg}(\mathbf{u}_s, ghg_s)} \frac{D_t^{ghg}(\mathbf{u}_t, ghg_t)}{D_t^{ghg}(\mathbf{u}_t, ghg_s)}}. \tag{11}$$

Dividing equation (11) by equation (10) yields a Hicks-Moorsteen formulation of GHG emission intensity change between time periods s and t:

$$(12)\qquad GHGIC_{st} = \frac{GHGC_{st}}{XPC_{st}} = \frac{\sqrt{\frac{D_s^{ghg}(\mathbf{u}_s, ghg_t)}{D_s^{ghg}(\mathbf{u}_s, ghg_s)} \frac{D_t^{ghg}(\mathbf{u}_t, ghg_t)}{D_t^{ghg}(\mathbf{u}_t, ghg_s)}}}{\sqrt{\frac{D_s^{u}(\mathbf{u}_s, ghg_t)}{D_s^{u}(\mathbf{u}_s, ghg_s)} \frac{D_t^{u}(\mathbf{u}_t, ghg_t)}{D_t^{u}(\mathbf{u}_s, ghg_t)}}}.$$

Equation (12) 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 (12) can thus be regarded as the reciprocal of a productivity change measure: scores above unity are bad, while scores below unity are good.

3. Empirical Approach: Free Disposal Hull

Thus far we have been silent on the approximation of the conventional and by-production technologies. This paper employs a nonconvex, nonparametric "Free Disposal Hull" (FDH) analysis (Deprins et al., 1984). There are I farms. Assuming variable returns to scale (VRS), the conventional technology of farm k is approximated by:

$$(13)\qquad \hat{P}_t(\mathbf{x}_{kt}, \mathbf{y}_{kt}) = \left\{ (\mathbf{x}_{kt}, \mathbf{y}_{kt}) | \sum_{i=1}^{I} \lambda_{it}\mathbf{x}_{it} \leqslant \mathbf{x}_{kt}, \sum_{i=1}^{I} \lambda_{it}\mathbf{y}_{it} \geqslant \mathbf{y}_{kt}, \sum_{i=1}^{I} \lambda_{it} = 1 \right\},$$

with $\lambda_{it} \in \{0, 1\}$ a binary integer constraint on the activity vector. Again assuming VRS, the by-production technology of farm k is approximated by:

$$(14)\qquad \hat{G}_t(\mathbf{u}_{kt}, GHG_{kt}) = \left\{ (\mathbf{u}_{kt}, GHG_{kt}) | \sum_{i=1}^{I} \mu_{it}\mathbf{u}_{it} \geqslant \mathbf{u}_{kt}, \sum_{i=1}^{I} \mu_{it} GHG_{it} \leqslant GHG_{kt}, \sum_{i=1}^{I} \mu_{it} = 1 \right\},$$

with $\mu_{it} \in \{0, 1\}$ again a binary integer constraint on the activity vector. These approximations allow computation of all components of energy productivity change and GHG emission intensity change. Appendix A shows an overview of the required binary mixed-integer linear programmes.

The only alternative theoretical models that use a by-production framework to model bad outputs in a convex and nonconvex way are found in Abad and Briec (2019) and Abad and Ravelojaona (2021). These models are based on recent work to measure strong forms of hypercongestion for convex and nonconvex technologies as in Briec et al. (2016) (see Briec et al. (2018) for an empirical illustration). Abad and Briec (2019) and Yuan et al. (2021) are among the first to empirically implement a nonconvex version of the Murty et al. (2012) by-production approach: these authors report substantial differences between convex and nonconvex empirical results.

4. Data

This contribution draws on 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 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 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 and Wohlgenant, 1986; Mairesse and Jaumandreu, 2005). All price indices are drawn from the Eurostat (2021) database. Finally, we consider GHG emissions (in kilograms).

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

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

5. Empirical Results

This section describes the 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.

5.1. **Energy productivity change.**

Table 2 shows the annual energy productivity change, $EPRODC_{st}$, and the components of aggregate output change, YC_{st}, and energy use change, EC_{st}. The average annual $EPRODC_{st}$ in the considered period is 1.027, which indicates an average growth rate of 2.7% *per annum* (*p.a.*). However, we note that this is in part driven by a few observations that have a very high growth rate. The median annual $EPRODC_{st}$ is only 0.992, which indicates a slight median decline of 0.8% *p.a.* instead. The average $EPRODC_{st}$ indicates growth of +12.9%, +6.4%, +13.8% and +19.8% in the periods of 2013 – 2014, 2014 – 2015, 2015 – 2016 and 2018 – 2019, respectively. In all other periods, there is on average a decline in $EPRODC_{st}$, of which 2010 – 2011 (−12.8%), 2016 – 2017 (−8.6%) and 2017 – 2018 (−6.3%) are the worst periods.

Remarkably, average annual growth of $EPRODC_{st}$ is driven by annual average decline in EC_{st}. It holds for every period that if $EPRODC_{st} > 1$, then $EC_{st} < 1$, and *vice versa*. $EPRODC_{st}$ follows the trend of YC_{st} for most periods, but not for 2014 – 2015, 2015 – 2016 and 2018 – 2019, where $EPRODC_{st} > 1$ and $YC_{st} < 1$. Finally, we remark that EC_{st} is more volatile and has a larger spread than YC_{st}.

5.2. **GHG emission intensity change.**

Table 3 shows the annual GHG emission intensity change, $GHGIC_{st}$, and the components of polluting input change, XPC_{st}, and GHG emission change, $GHGC_{st}$. The average annual $GHGIC_{st}$ in the considered period is 0.994, which indicates an average decline of 0.6% *p.a.* The median annual $GHGIC_{st}$ is 0.995, which indicates a slight median decline of 0.5% *p.a.* The mean and median are thus rather close to one another. The average $GHGIC_{st}$ indicates growth of +2.8%,

Table 2. Average Annual Energy Productivity Change, Aggregate Output Change and Energy Use Change

Period	$EPRODC_{st}$	YC_{st}	EC_{st}
2010-2011	0.882	0.988	1.154
2011-2012	0.988	0.979	1.056
2012-2013	0.955	0.967	1.066
2013-2014	1.129	1.042	0.975
2014-2015	1.064	0.950	0.917
2015-2016	1.138	0.945	0.875
2016-2017	0.914	0.973	1.100
2017-2018	0.937	1.014	1.119
2018-2019	1.198	0.976	0.844
Overall	1.027	0.981	1.007

+2.4%, +1.7% and +8.0% in the periods of $2013-2014$, $2014-2015$, $2015-2016$ and $2018-2019$, respectively. In all other periods, there is on average a decline in $GHGIC_{st}$, of which $2012-2013$ (-13.9%), $2017-2018$ (-3.1%) and $2010-2011$ (-2.7%) are the best periods. Interestingly, average annual increases (decreases) in $EPRODC_{st}$ are counterbalanced by average annual increases (decreases) in $GHGIC_{st}$. The trend of $GHGC_{st}$ largely follows the trend of XPC_{st}, except in $2010-2011$ and $2018-2019$, in which $XPC_{st} > 1$ and $GHGC_{st} < 1$, and $XPC_{st} < 1$ and $GHGC_{st} > 1$, respectively. The positive association between XPC_{st} and $GHGC_{st}$ is more pronounced than the one between YC_{st} and EC_{st}. This suggests that decoupling energy use from production occurs more frequently than decoupling GHG emissions from the use of polluting inputs. Finally, we note that XPC_{st} and $GHGC_{st}$ are not so volatile and have a relatively low spread.

TABLE 3. Average Annual Greenhouse Gas Emission Intensity Change, Polluting Input Change and Greenhouse Gas Emission Change

Period	$GHGIC_{st}$	XPC_{st}	$GHGC_{st}$
2010-2011	0.973	1.021	0.991
2011-2012	0.989	0.981	0.968
2012-2013	0.861	0.963	0.829
2013-2014	1.028	0.955	0.980
2014-2015	1.024	0.947	0.967
2015-2016	1.017	0.924	0.937
2016-2017	0.988	1.025	1.010
2017-2018	0.969	1.063	1.028
2018-2019	1.080	0.960	1.034
Overall	0.994	0.981	0.973

5.3. **Comparing energy productivity change to GHG emission intensity change.**

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 one. This empirical finding is confirmed by a Pearson correlation of 0.377 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 355 observations with energy productivity growth and GHG emission intensity growth, while quadrant III shows 400 observations with energy productivity decline and

GHG emission intensity decline. Quadrant III shows 176 observations with energy productivity decline and GHG emission intensity growth. Quadrant IV shows 177 observations with energy productivity growth and GHG emission intensity decline.

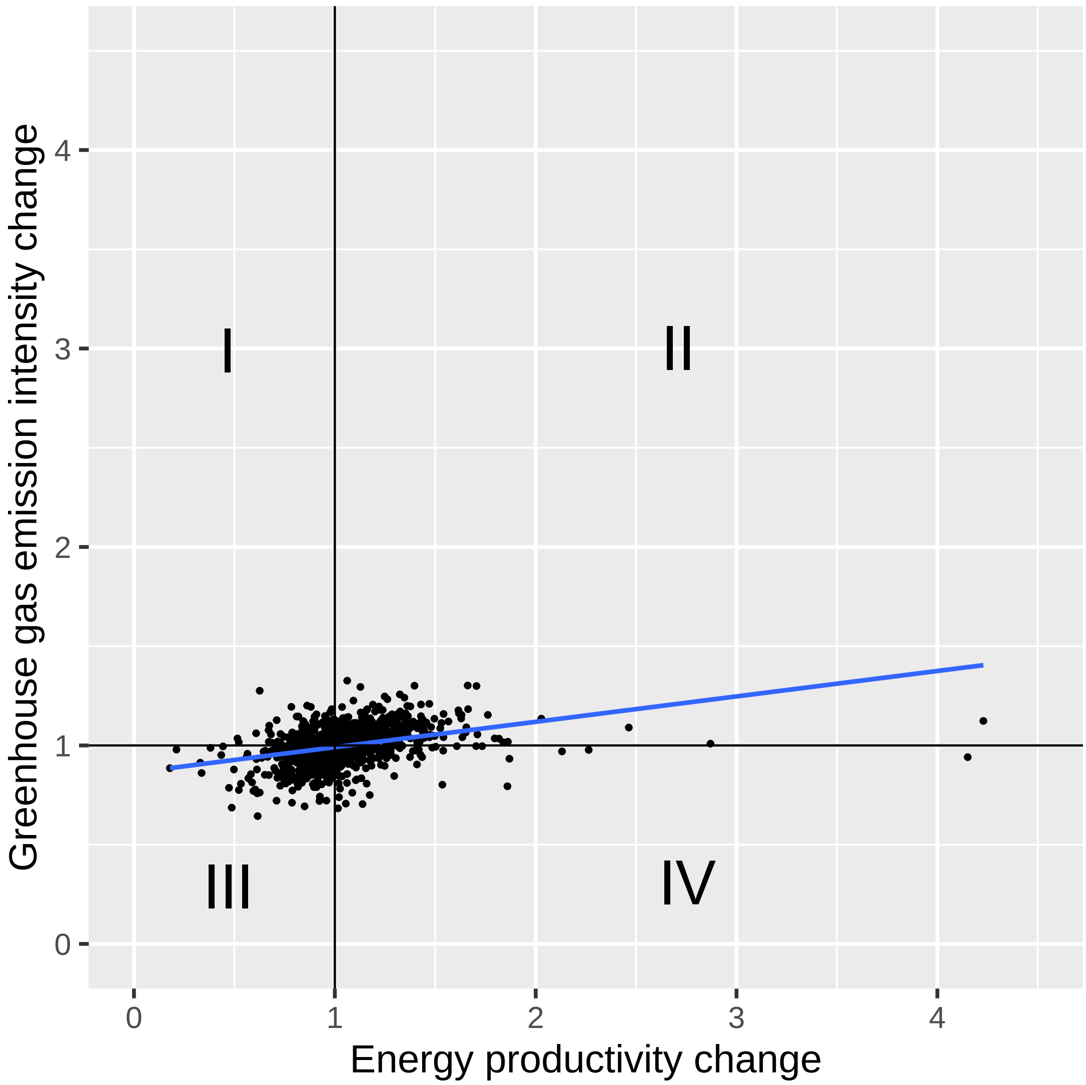

Figure 1. Scatter Plot of Energy Productivity Change vs. Greenhouse Gas Emission Intensity Change

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 framework based on a Hicks-Moorsteen productivity formulation. The empirical application focuses on 1,510 Dutch specialised dairy farms for the years 2010-2019.

The results show an average energy productivity growth of 2.7% *p.a.* and an average GHG emission intensity decline of 0.6% *p.a.* However, the former is in part driven by a few high-performing observations: the median energy productivity decreases by 0.8% *p.a.* Fluctuations over time are substantial for energy productivity change and more moderate for GHG emission intensity change. Remarkably, 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. 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 by-production 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, policy makers 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 and GHG emissions. This paper solely focuses on direct energy use and GHG emissions. Indirect energy use and GHG emissions also take 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 and Kerstens, 2004) indicators.

Fifth, we recommend to adapt the proposed framework to a statistical setting. Our nonparametric framework is inherently deterministic. Simar and Wilson (1999) show how to obtain statistically robust estimates using a bootstrapped Malmquist productivity formulation. Alternatively, one could employ stochastic frontier analysis (Aigner et al., 1977; Meeusen and Van Den Broeck, 1977).

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Appendix A. Binary Mixed-Integer Linear Programmes

A.1. Energy Productivity Change.

To assess YC_{st} defined in equation (4), we compute four binary mixed-integer linear programmes based on the output distance function defined in equation (2). With I observations in period s, and J observations in period t, we have for observation k:

$$
\text{(A1)} \quad
\begin{array}{rlcl}
 & D_s^y(E_{ks}, \mathbf{z}_{ks}, \mathbf{v}_{ks}, \mathbf{y}_{ks}) & = & \inf_{\phi>0, \lambda_{is}\in\{0,1\}} \phi \\
s.t. & \sum_{i=1}^{I} \lambda_{is} E_{is} & \leqslant & E_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{z}_{is} & \leqslant & \mathbf{z}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{v}_{is} & \leqslant & \mathbf{v}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{y}_{is} & \geqslant & \frac{\mathbf{y}_{ks}}{\phi}, \\
 & \sum_{i=1}^{I} \lambda_{is} & = & 1.
\end{array}
$$

$$
\text{(A2)} \quad
\begin{array}{rlcl}
 & D_s^y(E_{ks}, \mathbf{z}_{ks}, \mathbf{v}_{ks}, \mathbf{y}_{kt}) & = & \inf_{\phi>0, \lambda_{is}\in\{0,1\}} \phi \\
s.t. & \sum_{i=1}^{I} \lambda_{is} E_{is} & \leqslant & E_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{z}_{is} & \leqslant & \mathbf{z}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{v}_{is} & \leqslant & \mathbf{v}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{y}_{is} & \geqslant & \frac{\mathbf{y}_{kt}}{\phi}, \\
 & \sum_{i=1}^{I} \lambda_{is} & = & 1.
\end{array}
$$

$$
\text{(A3)} \quad
\begin{array}{rlcl}
 & D_t^y(E_{kt}, \mathbf{z}_{kt}, \mathbf{v}_{kt}, \mathbf{y}_{kt}) & = & \inf_{\phi>0, \lambda_{it}\in\{0,1\}} \phi \\
s.t. & \sum_{j=1}^{J} \lambda_{it} E_{it} & \leqslant & E_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{z}_{it} & \leqslant & \mathbf{z}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{v}_{it} & \leqslant & \mathbf{v}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{y}_{it} & \geqslant & \frac{\mathbf{y}_{kt}}{\phi}, \\
 & \sum_{j=1}^{J} \lambda_{it} & = & 1.
\end{array}
$$

$$
\text{(A4)} \qquad
\begin{array}{rlcl}
 & D_t^y(E_{kt}, \mathbf{z}_{kt}, \mathbf{v}_{kt}, \mathbf{y}_{ks}) & = & \inf_{\phi>0, \lambda_{it}\in\{0,1\}} \phi \\
s.t. & \sum_{j=1}^{J} \lambda_{it} E_{it} & \leqslant & E_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{z}_{it} & \leqslant & \mathbf{z}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{v}_{it} & \leqslant & \mathbf{v}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{y}_{it} & \geqslant & \frac{\mathbf{y}_{ks}}{\phi}, \\
 & \sum_{j=1}^{J} \lambda_{it} & = & 1.
\end{array}
$$

To assess EC_{st} defined in equation (5), we compute four binary mixed-integer linear programmes based on the energy distance function defined in equation (3). With I observations in period s, and J observations in period t, we have for observation k:

$$
\text{(A5)} \qquad
\begin{array}{rlcl}
 & D_s^E(E_{ks}, \mathbf{z}_{ks}, \mathbf{v}_{ks}, \mathbf{y}_{ks}) & = & \sup_{\theta>0, \lambda_{is}\in\{0,1\}} \theta \\
s.t. & \sum_{i=1}^{I} \lambda_{is} E_{is} & \leqslant & \frac{E_{ks}}{\theta}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{z}_{is} & \leqslant & \mathbf{z}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{v}_{is} & \leqslant & \mathbf{v}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{y}_{is} & \geqslant & \mathbf{y}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} & = & 1.
\end{array}
$$

$$
\text{(A6)} \qquad
\begin{array}{rlcl}
 & D_s^E(E_{kt}, \mathbf{z}_{ks}, \mathbf{v}_{ks}, \mathbf{y}_{ks}) & = & \sup_{\theta>0, \lambda_{is}\in\{0,1\}} \theta \\
s.t. & \sum_{i=1}^{I} \lambda_{is} E_{is} & \leqslant & \frac{E_{kt}}{\theta}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{z}_{is} & \leqslant & \mathbf{z}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{v}_{is} & \leqslant & \mathbf{v}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} \mathbf{y}_{is} & \geqslant & \mathbf{y}_{ks}, \\
 & \sum_{i=1}^{I} \lambda_{is} & = & 1.
\end{array}
$$

$$
\begin{array}{llll}
 & D_t^E(E_{kt}, \mathbf{z}_{kt}, \mathbf{v}_{kt}, \mathbf{y}_{kt}) & = & \sup_{\theta>0,\lambda_{it}\in\{0,1\}} \theta \\
s.t. & \sum_{j=1}^{J} \lambda_{it} E_{it} & \leqslant & \frac{E_{kt}}{\theta}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{z}_{it} & \leqslant & \mathbf{z}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{v}_{it} & \leqslant & \mathbf{v}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{y}_{it} & \geqslant & \mathbf{y}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} & = & 1.
\end{array} \tag{A7}
$$

$$
\begin{array}{llll}
 & D_t^E(E_{ks}, \mathbf{z}_{kt}, \mathbf{v}_{kt}, \mathbf{y}_{kt}) & = & \sup_{\theta>0,\lambda_{it}\in\{0,1\}} \theta \\
s.t. & \sum_{j=1}^{J} \lambda_{it} E_{it} & \leqslant & \frac{E_{ks}}{\theta}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{z}_{it} & \leqslant & \mathbf{z}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{v}_{it} & \leqslant & \mathbf{v}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} \mathbf{y}_{it} & \geqslant & \mathbf{y}_{kt}, \\
 & \sum_{j=1}^{J} \lambda_{it} & = & 1.
\end{array} \tag{A8}
$$

Combining the above eight mixed-integer programmes (A1)-(A8) yields $EPRODC_{st}$ defined in equation (6).

A.2. **Greenhouse Gas Emission Intensity Change.**

To assess XPC_{st} defined in equation (10), we compute four binary mixed-integer linear programmes based on the polluting input distance function defined in equation (9). With I observations in period s, and J observations in period t, we have for observation k:

$$
\begin{array}{llll}
 & D_s^u(\mathbf{u}_{ks}, ghg_{ks}) & = & \inf_{\rho>0,\mu_{is}\in\{0,1\}} \rho \\
s.t. & \sum_{i=1}^{I} \mu_{is} \mathbf{u}_{is} & \geqslant & \frac{\mathbf{u}_{ks}}{\rho}, \\
 & \sum_{i=1}^{I} \mu_{is} ghg_{is} & \leqslant & ghg_{ks}, \\
 & \sum_{i=1}^{I} \mu_{is} & = & 1.
\end{array} \tag{A9}
$$

$$
\begin{array}{lrcl}
 & D_s^u(\mathbf{u}_{kt}, ghg_{kt}) & = & \inf_{\rho>0, \mu_{is}\in\{0,1\}} \rho \\
s.t. & \sum_{i=1}^{I} \mu_{is}\mathbf{u}_{is} & \geqslant & \frac{\mathbf{u}_{kt}}{\rho}, \\
 & \sum_{i=1}^{I} \mu_{is} ghg_{is} & \leqslant & ghg_{kt}, \\
 & \sum_{i=1}^{I} \mu_{is} & = & 1.
\end{array} \tag{A10}
$$

$$
\begin{array}{lrcl}
 & D_t^u(\mathbf{u}_{kt}, ghg_{kt}) & = & \inf_{\rho>0, \mu_{it}\in\{0,1\}} \rho \\
s.t. & \sum_{j=1}^{J} \mu_{it}\mathbf{u}_{it} & \geqslant & \frac{\mathbf{u}_{kt}}{\rho}, \\
 & \sum_{j=1}^{J} \mu_{it} ghg_{it} & \leqslant & ghg_{ks}, \\
 & \sum_{j=1}^{J} \mu_{it} & = & 1.
\end{array} \tag{A11}
$$

$$
\begin{array}{lrcl}
 & D_t^u(\mathbf{u}_{ks}, ghg_{kt}) & = & \inf_{\rho>0, \mu_{it}\in\{0,1\}} \rho \\
s.t. & \sum_{j=1}^{J} \mu_{it}\mathbf{u}_{it} & \geqslant & \frac{\mathbf{u}_{ks}}{\rho}, \\
 & \sum_{j=1}^{J} \mu_{it} ghg_{it} & \leqslant & ghg_{ks}, \\
 & \sum_{j=1}^{J} \mu_{it} & = & 1.
\end{array} \tag{A12}
$$

To assess $GHGC_{st}$ defined in equation (11), we compute four binary mixed-integer linear programmes based on the ghg emission distance function defined in equation (9). With I observations in period s, and J observations in period t, we have for observation k:

$$
\begin{array}{lrcl}
 & D_s^{ghg}(\mathbf{u}_{ks}, ghg_{ks}) & = & \sup_{\delta>0, \mu_{is}\in\{0,1\}} \delta \\
s.t. & \sum_{i=1}^{I} \mu_{is}\mathbf{u}_{is} & \geqslant & \mathbf{u}_{ks}, \\
 & \sum_{i=1}^{I} \mu_{is} ghg_{is} & \leqslant & \frac{ghg_{ks}}{\delta}, \\
 & \sum_{i=1}^{I} \mu_{is} & = & 1.
\end{array} \tag{A13}
$$

$$
\text{(A14)} \qquad \begin{array}{rlcl}
 & D_s^{ghg}(\mathbf{u}_{ks}, ghg_{kt}) & = & \sup_{\delta>0, \mu_{is}\in\{0,1\}} \delta \\
s.t. & \sum_{i=1}^{I} \mu_{is}\mathbf{u}_{is} & \geqslant & \mathbf{u}_{ks}, \\
 & \sum_{i=1}^{I} \mu_{is} ghg_{is} & \leqslant & \frac{ghg_{kt}}{\delta}, \\
 & \sum_{i=1}^{I} \mu_{is} & = & 1.
\end{array}
$$

$$
\text{(A15)} \qquad \begin{array}{rlcl}
 & D_t^{ghg}(\mathbf{u}_{kt}, ghg_{kt}) & = & \sup_{\delta>0, \mu_{it}\in\{0,1\}} \delta \\
s.t. & \sum_{j=1}^{J} \mu_{it}\mathbf{u}_{it} & \geqslant & \mathbf{u}_{kt}, \\
 & \sum_{j=1}^{J} \mu_{it} ghg_{it} & \leqslant & \frac{ghg_{kt}}{\delta}, \\
 & \sum_{j=1}^{J} \mu_{it} & = & 1.
\end{array}
$$

$$
\text{(A16)} \qquad \begin{array}{rlcl}
 & D_t^{ghg}(\mathbf{u}_{kt}, ghg_{ks}) & = & \sup_{\delta>0, \mu_{is}\in\{0,1\}} \delta \\
s.t. & \sum_{j=1}^{J} \mu_{it}\mathbf{u}_{it} & \geqslant & \mathbf{u}_{kt}, \\
 & \sum_{j=1}^{J} \mu_{it} ghg_{it} & \leqslant & \frac{ghg_{ks}}{\delta}, \\
 & \sum_{j=1}^{J} \mu_{it} & = & 1.
\end{array}
$$

Combining the above eight binary mixed-integer linear programmes (A9)-(A16) yields $GHGIC_{st}$ defined in equation (12).