Accounting for Undesirable Outputs in Irish Agricultural Productivity: A Non-Parametric Index Approach

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The common agricultural policy (CAP) pursues both productivity and sustainability objectives. Technologically induced productivity increases are also a frequent recommendation of economists to establish a sustainable agricultural sector. This recommendation might be misleading though if byproducts of intensive practices are ignored. This paper therefore integrates Nitrogen surpluses in productivity analysis of Irish agriculture for 2006 to 2016. The Malmquist-Luenberger productivity index (MLI) shows volatile and decreasing results, questioning the recommendation of relying on productivity gains. An index decomposition further suggests that reductions in byproduct are not driven by technological progress since they rather occur on inefficient farms.

Keywords: environmental productivity, Malmquist-Luenberger Productivity Index, undesirable output, farm survey data, non-parametric productivity analysis

INTRODUCTION

Against this background the presented study starts with a traditional productivity measure and adopts the non-parametric Malmquist productivity index (MPI) to measure the development of factor productivity of more than 430 Irish farms between 2006 and 2016. To integrate undesirable environmental outputs, productivity increases are then quantified by the (also non-parametric) Malmquist-Luenberger Index (MLI). The comparison of the results allows for a judgment on the compatibility of environmental and productivity goals of the EU. Since both indices can be decomposed into a technological change and an efficiency change component, we can further attribute the development of Irish (environmental) productivity to either new 'technology-centered on-farm solutions' or 'the adaptation of practices'.

It turns out that neither regular nor environmental productivity have increased between 2006 and 2016. In fact, both indices show a decreasing yet volatile trend in productivity. Towards the end of the period environmental productivity decouples from regular productivity indicating a more balanced consideration of environmental and purely economic concerns. The decomposition of the indices suggests that the decoupling is mainly attributable to average farmers' catching up to the best performers rather than benchmark farms increasing productivity through technological progress.

The remainder of the paper is as follows. Section 2 briefly discusses the theoretical framework and introduces the MPI and the MLI. Section 3 continues with the description of data and the application of both indices on the Irish agricultural system. The results will be presented in section 4 before the paper closes with the discussion of the results in section 5 and the concluding remarks in section 6.

METHODOLOGY

Non-parametric Efficiency Measures and the Malmquist Productivity Index

Non-parametric efficiency analysis is a well-established tool for determining efficiency in the context of agricultural productivity (e.g. Galluzzo (2018), Majiwa et al. (2018)). Its results are exclusively determined by the empirically observed data of the considered decision-making units (DMU) (here Irish farms). This is beneficial for the present study, as the aim is to determine productivity development of the whole agricultural sector by analyzing aggregate changes of real individual farm performance.

Performance measurement in non-parametric approaches relies on relative comparisons of decision-making units towards an efficiency frontier, which is constituted by DMUs that employ the maximum feasible combination of inputs and outputs. In the original and most commonly applied DEA models (e.g. Charnes et al. (1978), Banker et al. (1984)) this is achieved by measuring radial efficiency, hence using Shepard distance functions to calculate the efficiency scores for DMUs. Those models credit a DMU for either reducing the inputs required to produce a given amount of outputs, or vice versa, depending on the orientation chosen and the researchers interest.

Time-series analysis within non-parametric methods can be done using the Malmquist productivity index (MPI) (e.g. Caves et al. (1982)). The efficiency scores calculated are also based on Shepard distance functions projected to the reference technology (the efficiency frontier) and compared over two time periods. Figuratively speaking, the movement of efficiency frontiers over two or more periods indicates a shift in technology, either promoting or restricting a higher productivity level. For the inefficient DMUs lying below those frontiers the development of the relative distance towards old and new frontier is of interest. This distance provides information on the capacity of average performing DMUs to catch up to the best performers on the frontier.

For an input vector $x^t = \{x_1^t, x_2^t, \dots, x_m^t\}$, an output vector $y^t = \{y_1^t, y_2^t, \dots, y_n^t\}$ and a production possibility set $P^t = \{x^t,\ y^t\}$ the geometric mean of contiguous output-oriented MPI for t and t+1 is defined as (Grifell-Tatjé and Lovell, 1995):

$$MP_t^{t+1} = [\frac{D_0^t(x^{t+1}, y^{t+1}) D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t) D_0^{t+1}(x^t, y^t)}]^{\frac{1}{2}} \tag{1}$$

where the output oriented adjacent-period distance functions are defined as:

$$D_0^t(x^{t+1}, y^{t+1}) = \min\{\theta :\ y^{t+1} \,/\, \theta \epsilon P^t(x^{t+1})\}\ and$$
$$D_0^{t+1}(x^t, y^t) = \min\{\theta :\ y^t \,/ \theta \epsilon P^{t+1}(x^t)\} \tag{2}$$

We are not providing axioms, production set and linear programming problem at this point, since the MPI has been broadly covered in the literature (for further details see Caves et al. (1982), Färe et al. (1994), Grifell-Tatjé and Lovell (1995)). Also, our focus lies on measuring environmental productivity (and its relation towards regular productivity), thus the results of the Malmquist-Luenberger Index, which will be introduced with further details in the upcoming section.

The index equals 1, if productivity remains constant. Values larger (smaller) one indicate increasing (decreasing) productivity. Färe et al. (1994) further proposed to decompose the MPI into two exclusive components, namely changes in technology (shift of the frontier) and technical efficiency (changes in efficiency given a certain technology). The frontier shift accounts for the progress or regress of the technology and reflects changes of maximum feasible productional productivity over two time periods. It can be defined as follows:

$$MPTECH_t^{t+1} = [\frac{D_0^t(x^{t+1},y^{t+1})D_0^t(x^t,y^t)}{D_0^{t+1}(x^{t+1},y^{t+1})D_0^{t+1}(x^t,y^t)}]^{\frac{1}{2}} \tag{3}$$

The efficiency change component displays the development of relative efficiency between two periods, hence the distance between maximum feasible production in period t from observed production in t+1, by the following ratio:

$$MPEFFCH_t^{t+1} = [\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}]^{\frac{1}{2}} \tag{4}$$

This component illustrates that distances to maximum achievable outputs have either been reduced or increased compared to other time periods. In a sense it monitors the average performers' capability to keep pace with the best performers, respectively with technology development. In the literature it is therefore often referred to as 'catch-up effect'. One shortcoming of traditional DEA and MPI is its incapacity to deal with byproducts, or bad outputs. Some authors treat such undesirable outputs as inputs. However, in this case DMUs would be credited for producing the same level of desirable and undesirable output with fewer inputs rather than for reducing the actual byproducts (Färe and Grosskopf, 2003). For this reason we follow the approach proposed by Chung et al. (1997) and employ a Malmquist-Luenberger Productivity index, based on directional output distance functions (rather than a Shepard distance function), which allows for crediting increasing (maximizing) desirable and simultaneously decreasing (minimizing) undesirable outputs.

Considering Bad Outputs With Malmquist-Luenberger Index

Assuming that productional technologies do generate undesirable byproducts or pollutants, their output set consists of both desirable outputs, y^t, that should be increased (maximized), and undesirable outputs b^t, that should be decreased (minimized). To properly catch this trade-off within the efficiency measurement, we apply a directional output distance function approach, as proposed by Chung et al. (1997).

Using an input vector $x^t = \{x_1^t, x_2^t, \dots, x_m^t\}$ to produce both desirable outputs $y^t = \{y_1^t, y_2^t, \dots, y_n^t\}$ and undesirable outputs $b^t = \{b_1^t, b_2^t, \dots, b_n^t\}$ the production possibility set P^t is denoted as follows:

$$P(x) = \{(y, b)\text{: can produce } (y, b)\} \tag{5}$$

Färe et al. (2007) describe such a technology as environmental technology that needs to meet some additional conditions, along the standard axioms for productional technologies, as given in (6), (7) and (8).

$$\{0\} \epsilon P(x) \text{ for all } x \epsilon R_+^n \tag{6}$$

$$P(x) \text{ is compact } x \epsilon R_+^n \tag{7}$$

$$P(x) \subseteq P(x') \text{ if } x' \geq x \tag{8}$$

The axioms determine that inactivity must always be possible (6), finite inputs produce finite outputs (7) and inputs are freely disposable (8). Furthermore, to meet the requirements of an environmental technology, weak disposability of outputs (9) and null-jointness (10) must be fulfilled.

$$(y, b)\epsilon P(x) \text{ and } 0 \leq \theta \leq 1 \text{ imply } (\theta y, \theta b)\epsilon P(x) \quad (9)$$

$$(y, b)\epsilon P(x) \text{ and } 0 \leq \theta \leq 1 \text{ imply } (\theta y, \theta b)\epsilon P(x) \quad (10)$$

The assumption of weak disposability (9) states that proportional reductions within the output set are feasible given a certain input level. Contrary to the case of strong disposability this disposal is not costless though since environmental regulations are assumed. The null-jointness requirement (10) states that producing zero byproducts necessarily means producing no outputs at all. Finally, axiom (11) guarantees free disposability of the desirable outputs.

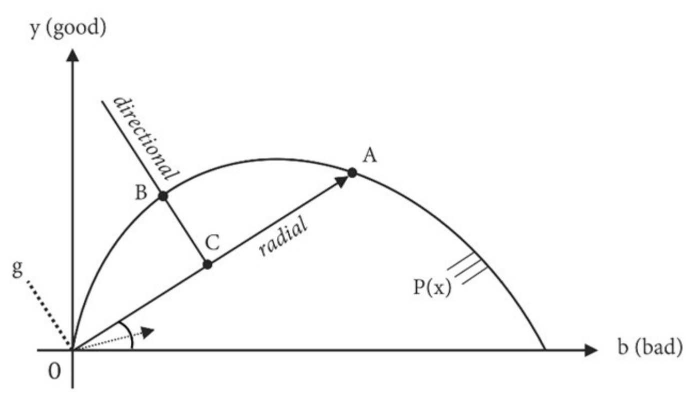
$$(y, b)\epsilon P(x) \text{ and } y' \leq y \text{ imply } (y', b)\epsilon P(x) \quad (11)$$

Given those requirements fulfilled the functional specification of the directional distance function is denoted by Chung et al. (1997) as:

$$D_0(x, y, b; g) = \sup\{\beta : (y, b) + \beta g \epsilon P(x)\} \quad (12)$$

As postulated, the output set given in Figure 1 starts at the origin and shows a joint disposability for the good output y and the bad output b.

FIGURE 1
DISTANCE FUNCTIONS (OWN REPRESENTATION BASED ON CHUNG ET AL. (1997)



Contrary to the basic DEA models, where the efficiency score is calculated radially with Shepard distance functions (0C/0A), the directional distance function approach determines a vector 0g, that directly points toward the combination on P(x), that both represents an equal proportional increase in good output and decrease in bad output. As denoted in (12) the value of the directional distance function for C would be positive given the positive value for 0g and the value for B would be zero since it lies on the frontier and therefore proves efficient. The Malmquist-Luenberger index adopts the directional distance function as introduced and allows for time series productivity analysis including undesirable outputs (MLI) (Chambers et al., 1996; Chung et al., 1997). Furthermore, just like the MPI, the MLI allows for a decomposition of the efficiency scores into a 'frontier shift' and 'catch-up' effect. Aparicio et al. (2013), however, convincingly argued that the decomposition could yield inconsistent results. To avoid this issue we follow their recommendation and complement axioms (6)-(12) by axiom (13) which states that if x can produce outputs (y, b) then it can also produce more bads to a certain point b(x).

$$If\ (y,b)\epsilon P(x) \text{ and } b \leq b' \leq \overline{b}(x), \text{then } (y,b')\epsilon P(x) \tag{13}$$

The output set that satisfies the properties introduced can thus be denoted as:

$$P(x) = (y,b): \begin{array}{rl} \sum_{k=1}^{K} z_k y_{km}^t \geq y_m^t, & m = 1,\dots,M \\ \sum_{k=1}^{K} z_k^t b_{ki}^t = b_i^t, & i = 1,\dots,I \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^t, & n = 1,\dots,N \\ z_k \geq 0, & k = 1,\dots,K \end{array} \tag{14}$$

Finally, the geometric mean of the adjacent output oriented MLI for t and t+1 is defined by equation (15) as:

$$ML_t^{t+1} = \left[\frac{(1+\overrightarrow{D_0^t}(x^t,y^t,b^t,-b^t))(1+\overrightarrow{D_0^{t+1}}(x^t,y^t,b^t;y^t,-b^t))}{(1+\overrightarrow{D_0^t}(x^{t+1},y^{t+1},b^{t+1},-b^{t+1}))(1+\overrightarrow{D_0^{t+1}}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}))}\right]^{\frac{1}{2}} \tag{15}$$

Again, values larger (smaller) one point to increases (decreases) of environmental productivity. Analogously to the MPI the MLI can further be decomposed into the technological change component (Eq. 16), and the efficiency change component (Eq. 17):

$$MLTECH_t^{t+1} = \left[\frac{(1+\overrightarrow{D_0^t}(x^t,y^t,b^t,-b^t))(1+\overrightarrow{D_0^{t+1}}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}))}{(1+\overrightarrow{D_0^t}(x^t,y^t,b^t,-b^t))(1+\overrightarrow{D_0^{t+1}}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}))}\right]^{\frac{1}{2}} \tag{16}$$

$$MLEFFCH_t^{t+1} = \left[\frac{1+\overrightarrow{D_0^t}(x^t,y^t,b^t,-b^t)}{1+\overrightarrow{D_0^{t+1}}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})}\right]^{\frac{1}{2}} \tag{17}$$

The index is computed by solving the linear programming problem of the directional distance function to maximize beta (Kumar, 2006):

$$\overrightarrow{D_0^{t+1}}(x^t,y^t,b^t;y^t,-b^t) = \max\beta \tag{18}$$

$$\begin{array}{rl} \sum_{k=1}^{K} z_k^t y_{km}^t \geq (1+\beta) y_{k'm}^t & m = 1,\dots,M \\ \sum_{k=1}^{K} z_k^t b_{ki}^t = (1-\beta) b_{k'}^t & i = 1,\dots I \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^t & n = 1,\dots N \\ z_k^t \geq 0 & k = 1,\dots,K \end{array}$$

For both indices constant returns to scale have been specified to allow for a comparison of the results. In so doing the MPI equal the MLI results when the bad output is set zero, since the output set as depicted in Fig. 1 'disappears'. Agricultural production could very well be represented by variable returns to scale, when using the MPI and thus the size of productivity gains and losses might be overestimated slightly in our results. Further there are some other inconsistencies attributed to non-parametric time series analysis in general, like not accounting for slacks (Chen, 2003), and potential infeasibility (Pastor and Lovell, 2005). But since the focus of our research goal was to identify the trend in productivity development over time and guarantee for a high comparison of all farms, systems and years the drawbacks lined out do not affect the validity of the conclusions to a great extent. Also, such a comparison between MPI and MLI has been done before, for example in the studies of Kumar (2006) or Majiwa et al. (2018). The comparison will thus allow us to answer the research question if environmental productivity has increased and to determine its relation to regular productivity. The calculation has been done with the Matlab package provided by Álvarez et al. (2017) to deal with the inconsistency issue pointed out earlier. Additionally, both indices require full balanced panel data since reference sets are calculated for all variables and years individually, which might reduce the data set applied substantially, which will be addressed in the upcoming section.

DATA

The applied data covers the period between 2006 and 2016 and originates from the Irish National Farm Survey, an annual survey of a sample of Irish farms carried out by Teagasc, the Irish Agriculture and Food Development Authority, operated as part of the Farm Accountancy Data Network (FADN) (Dillon et al., 2016). The sample data for 2016 adds up to 861 farms over all categories. The participating farms are selected annually in conjunction with the Irish central statistics office (CSO). The selected sample is representative of the whole national farm population and includes different farm systems, namely, dairying, cattle-rearing (the so-called suckler farms), cattle-other (or cattle-finishing farms), sheep, tillage and other. For this purpose, each farm is, based on standard output, assigned to one of these categories. Each farm is assigned a weighting factor based on the estimated farm population. Following this approach, the sample represents about 85.000 farms in Ireland (Dillon et al., 2016). Unfortunately, we cannot refer to the full sample. This is because both MPI and MLI require the same data set for the whole period, in particular complete data must be available for the very same farms (DMUs) over time. This limits the sample to 437 farms representing nearly 39,700 Irish farms (see table 1).

TABLE 1
SHARES OF FARM BUSINESS TYPES IN SAMPLE OF 2016

	Dairy	Cattle-Rearing	Cattle-other	Sheep	Tillage	Other	Total
Farms Represented (Nr.)	15,639	19,350	27,627	12,758	7,387	1,975	84,736
Full NFS Observations (Nr.)	314	139	209	117	64	18	861
Used NFS Observations (Nr.)	179	73	100	62	16	7	437
Represented by Sample (Nr.)	8,682	10,137	11,758	6,839	1,644	622	39,682
Represented by Sample (%)	56	52	43	54	22	31	47

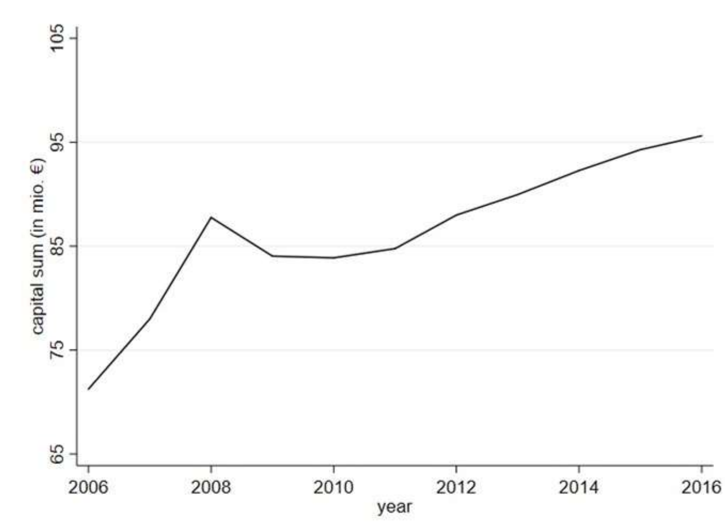
The analysis focuses on the case of Ireland for two reasons. For one the data base for farm level data is limited. The NFS farm survey data, provided by Teagasc, the Irish Food and Development Authority, contains agricultural inputs and outputs, as well as nitrogen farmgate balances for an 11-year period. For one, as already discussed it provides a rich empirical data base at farm level. Second, Irish agriculture serves as primary example for examining the effect of increasing productivity through technological progress and adaptation of practices. The agricultural sector is still vital for the whole Irish economy. For 2006, the first year of our sample, GDP at factor cost for the agri-food sector equaled 8.1% (Department of Agriculture, Fisheries and Food of Ireland, 2008a). Following the 'Agri Vision 2015 Action Plan' the former Irish minister Brendan Smith declared that Irish policies 'aim is to ensure that adequate resources will be available for improving the structures within the agriculture, [...], enhancing their competitiveness thus facilitating the continued development of a knowledge-based bio-economy' (Department of Agriculture, Fisheries and Food of Ireland, 2008b, p.3). In addition, the introduction of farm direct payments, Irish farms have increased investments extensively which should contribute to a higher productivity level achieved through technical progress (or the adaptation of best performers practices). Consequently, the Irish agricultural sector has been subject to various productivity studies and thus allows for a profound interpretation of this studies results. For index-based measures see e.g., Matthews (2000), for stochastic frontier analysis, O'Neill and Matthews (2001), or Matthews et al. (2007) and for non-parametric analysis Kelly et al. (2013) or Galluzzo (2018).

Production Inputs

In line with the literature in this field we consider land, labor and capital as primary inputs for agricultural production. Land is represented by the utilized agricultural area in hectare. The variable includes area under crops and pasture as well as the area of rough grazing (Dillon et al., 2016). Labor is given in total labor units (TLU). One person cannot exceed a value of one TLU, which equals about 1,800 hours of both paid and unpaid labor (Dillon et al., 2016).

Capital consists of investment in livestock, machinery, and buildings. The investment in livestock is calculated by the average of opening and closing valuation. The valuation of investment in machinery and buildings is based on the replacement cost methodology (Dillon et al., 2016). The annual development of the aggregated capital sum for the 437 selected farms is illustrated in Figure 2.

FIGURE 2
CAPITAL SUM DEVELOPMENT WITHIN SAMPLE



While the expenditures on investment in machinery have increased continuously, investment in livestock eventually takes off from 2010 on whereas investment in buildings rises less apart from a significant peak (17 % above average) in 2008. The aggregated capital sum thus follows a nearly linear trend starting at 71 million Euro in 2006 increasing up to a volume of 96 million Euro in 2016 marking a major investment boost of 35% for the agricultural sector in Ireland.

Obviously not all increases in investments equates technological progress. Nevertheless, the substantial capital built-up indicates farmers' preference for 'technology-centered on farm-solutions' and the adaptation of technology-driven practices to catch up with best performers (Velten et al., 2015). Regarding the main interest of our research question the capital sum can therefore be considered as a proxy for the application of new technologies. If technological progress indeed contributes towards a more environmentally efficient agricultural production an increasing capital sum should lead towards increasing environmental productivity. This is not to say that investments are purposefully directed towards more sustainable production patterns, but that farms' gross output does not increase on the cost of the environment.

Desirable and Undesirable Output

The desirable output, which is applied for both indices (MPI and MLI), is defined by farm gross output in US$. It is calculated as total sales less purchases, value of farm produce and changes in inventory of the individual farm. Since the farm gross output strongly depends on market prices, changes in resource productivity could be concealed by price volatility. Therefore, the farm gross output has been deflated by the CSO agricultural output price index, which accounts for price trends in the main farm produce such as cereals, cattle, calves, sheep, wool, and milk, among others. A joint deflation with one common index also guarantees for solid comparability of productivity differentiated according to farm system. The annual index stems from the Central Statistics Office of Ireland and is calculated as weighted averages of the monthly indices based on a Laspeyres formula with 2010 as base year.

For the application of the MLI an undesirable output must be selected. As mentioned already we apply nitrogen (N) farmgate balances (in kg N per hectare) as bad or undesirable output to account for environmental pressures created as byproduct of intensified practices linked to the goal of increasing productivity. The farmgate N balances are calculated by subtracting the total amount of nitrogen exports in kg from the imports in kg divided by the agricultural area usable in hectare. The imports refer to chemical fertilizers, concentrate feeds, forage crops, and livestock. The exports refer to milk, livestock sales, cash crops and wool (for further detail see Buckley et al. (2016)).

FIGURE 3
ABSOLUTE VALUE DEVELOPMENT OF OUTPUTS IN SAMPLE (BASE YEAR = 2006)

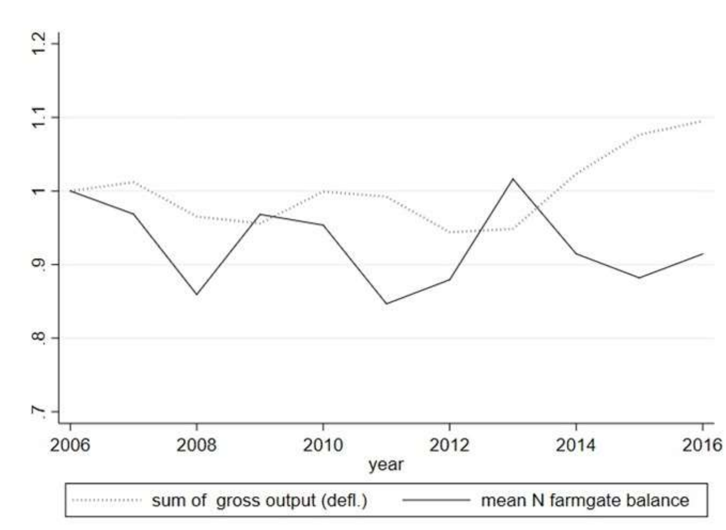


Figure 3 illustrates the development of the desirable and undesirable output for the considered period. A look at the annually aggregated output values reveals that indeed good output years also come along with good (N outtake) years and vice versa. Up until 2013 the development of the deflated gross output volume follows a rather negative to stagnating trend, while the mean for nitrogen farmgate balances seems volatile yet on average below the 2006 level. If this absolute development coincides with farm level results will be addressed in the following section where the indices results, and decomposition is presented.

RESULTS

Productivity Development

Interestingly and contrary to the intuitive notion, the findings indicate decreasing rather than increasing regular productivity. This particularly holds for the period between 2010 and 2013, where productivity decreased from a 95% to an 80% level compared to the base year 2006 (= 100%) (see table 2). This contrasts with the last 3 years, where we observe a slight recovery leading to a 92% productivity level in 2016 (compared to the base period).

The first major drop to 91% in 2008 can partly be explained by a moderate deflated gross output decrease of about 3% despite a peak in investment in buildings that lies 22% above period average. The cutbacks of 20% productivity in 2013 can be attributed to an input expansion in land (10% compared to 2006), investment in machinery (29%), livestock (21%) and buildings (32%) that came along a deflated gross output decrease of 5%.

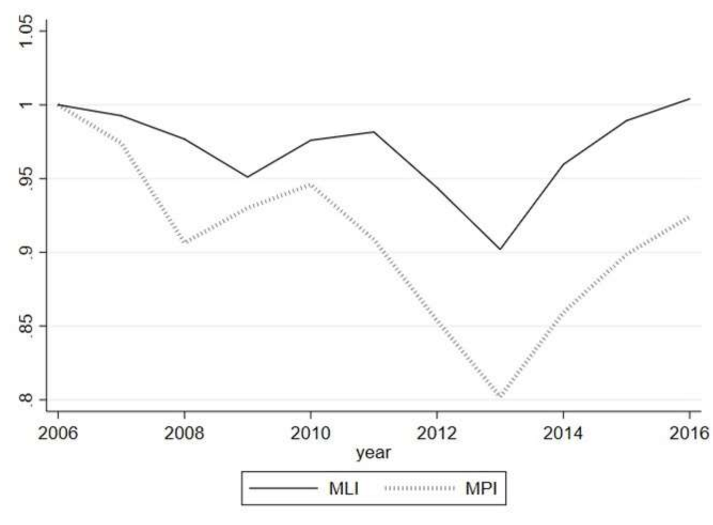
TABLE 2
MPI AND MLI RESULTS FROM 2006 TO 2016 FOR IRISH FARM BUSINESS TYPES

geomean	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Malmquist-Productivity-Index										
dairy	1.04	0.95	0.88	0.97	0.95	0.86	0.88	0.95	0.95	0.93
cattle-rearing	0.91	0.87	0.95	0.88	0.86	0.83	0.73	0.82	0.86	0.93
cattle-other	0.92	0.87	0.97	0.92	0.88	0.84	0.76	0.78	0.83	0.89
sheep	0.93	0.89	0.98	1.02	0.87	0.85	0.73	0.80	0.87	0.95
tillage	1.05	0.97	1.09	1.12	1.00	1.00	0.84	0.84	1.00	0.97
other	0.96	0.89	0.90	0.94	0.91	0.84	0.83	0.88	0.82	0.92
all types	0.97	0.91	0.93	0.95	0.91	0.85	0.80	0.86	0.90	0.92
Malmquist-Luenberger-Productivity-Index										
dairy	1.04	0.98	0.91	0.98	0.98	0.90	0.90	0.97	0.99	0.97
cattle-rearing	0.99	0.98	0.98	0.95	0.98	0.99	0.92	0.97	0.98	1.01
cattle-other	0.96	0.99	0.98	0.96	0.99	0.96	0.90	0.93	0.96	1.00
sheep	0.95	1.00	1.03	1.01	0.97	0.96	0.87	0.95	1.00	1.07
tillage	0.89	0.85	0.92	1.10	1.02	1.02	0.91	0.98	1.09	1.09
other	0.97	0.94	0.92	0.97	0.97	0.92	0.90	0.97	0.96	0.99
all types	0.99	0.98	0.95	0.98	0.98	0.94	0.90	0.96	0.99	1.00

The results for the different farm systems reveal a rather heterogeneous picture. Whereas tillage farming basically shows a constant productivity level over time, sheep farms and cattle systems show a more volatile trend with comparatively strong deflections in both directions. Dairy farming, arguably the most important sector of Irish agriculture, shows a comparatively stable trend with minor productivity losses over all years. Largest productivity losses of about 14% (compared to the base year) can be observed for the year 2012. Since then productivity levels have recovered slightly but did not reach the benchmark productivity level of the year 2006 at any time.

Obviously, the results could be affected by the choice of the base year, which could for whatever reason show unusually low or high productivity levels. However, a close look at the MPI reveals that changes in productivity levels occurred at different points of time. In particular, the largest losses or gains did not occur in the beginning of the considered period, which could be expected, if 2006 would have been indeed an extraordinary year. Thus, those findings of decreasing productivity levels are unlikely to be driven by the base year productivity level.

FIGURE 4
MEAN MLI AND MPI EFFICIENCY DEVELOPMENT



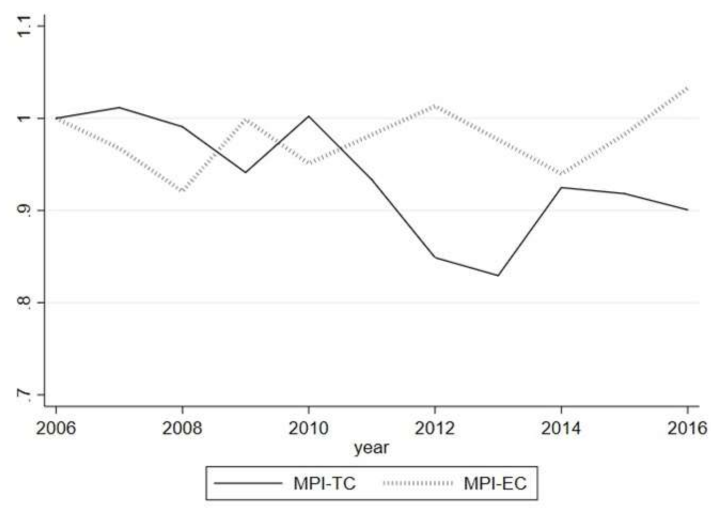
The findings for environmental productivity (based on the MLI) follow a similar trend. However, the inclusion of the environmental output clearly moderates losses in 2008 and between 2010 and 2013. These findings suggest a decoupling of farms' desirable and undesirable output. Thus, expansion of regular output is not at the cost of increasing nitrogen surpluses (at least costs are lower). Reasons for this trend could be manifold and include but are not limited to technological progress or changes in production patterns. In search of the main drivers for the decoupling of the MPI and the MLI, both indices are decomposed into a technological and efficiency change component in the next chapter.

Index Decomposition

Decomposition of the MPI

The decomposition of the MPI follows equations (3) and (4). As mentioned already, the technological change component measures the changes of the maximum feasible desirable output given a set of inputs. It therefore reflects the shift of the production frontier that is driven by the most efficient DMUs (farms) in the sample. To some extent the labeling is misleading, as shifts of the frontier are not only affected by technological development. They rather display the maximum achievable output with a given technology under consideration of external factors such as weather events, market conditions or political targets. While progress in technology is likely to shift the frontier upwards in the very long run, downward shifts may occur in the short and medium run, even if technology progresses. In contrast to the technological change component, which reflects the factor productivity of the benchmark DMUs, the efficiency change component measures the average farms' capability to catch up with the best performing farms on the frontier.

FIGURE 5
TECHNOLOGICAL CHANGE AND EFFICIENCY CHANGE OF THE MPI



As portrayed in Figure 5, the productivity losses found for the period 2010 and 2013, are stronger affected by the frontier-shift than the catch-up effect (for full results see Appendix A). In an annual analysis this must not be understood as loss in knowledge or innovative potential, which of course could not change as rapidly, but rather points to the fact that progress in technologies could not fully compensate for external restrictions in production conditions of the best performing farms.

The results for the efficiency change component of the MPI shows that average farmers have neither significantly in- nor decreased the distance to the best performers in the considered period. Even if we observe a minor 'catch-up' of 5% for the last period, the results of the MPI efficiency change component lie close to one and therefore suggest that the less productive farms have developed analogically to the group of the (best performing) farms that serve as a benchmark.

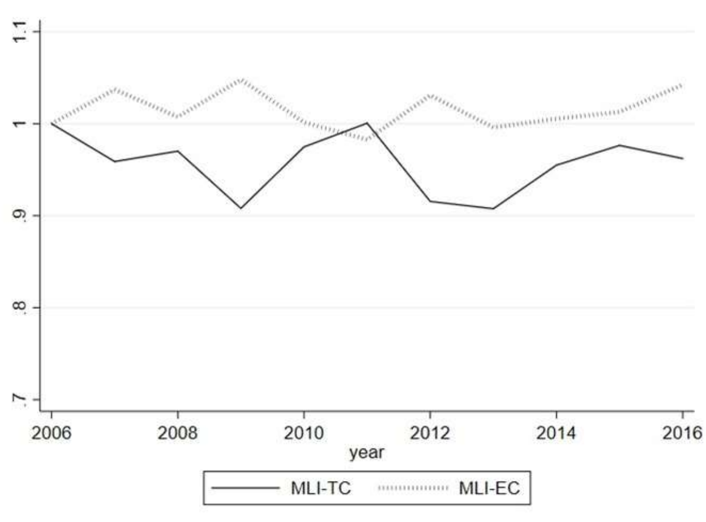
Considering the different farm systems, the MPI technological change component develops more or less equally for all sectors. The only exception is the year 2009 where productivity levels of tillage farms reaches a peak of 13% above the base level and deviate significantly from the other systems results. This particularly holds for dairy farms that experience a drop to only 88% of the 2006 productivity. Looking more closely at dairy farms, the sector's overall productivity losses over time (according to table 3) are clearly driven by the best performers' losses in factor productivity yielding a downward shift of the production frontier. This effect is only marginally compensated by a constant (yet small) catch up effect of dairy farms below the frontier. Whereas dairy farms show a constant development for the efficiency change component, tillage farming shows an extremely volatile development. In 2012 for example, a catch-up of 18% marks a sample high, whereas the value of 2014 marks a low with the catch-up falling to only 86%. Clearly, tillage farming shows the most volatile results. One presumption here could be that exogenous factors, such as the weather do impact tillage productivity stronger, than the other farm systems. However, tillage farming is also the least represented system in the sample (see table 1) and its results must therefore be treated with care.

Decomposition of the MLI

The decomposition of the MLI is carried out analogically (eq. (16) and (17)). This time, the technological change component of the MLI accounts for changes in efficient combination that equally increases desirable while decreasing undesirable output, given a set of inputs. The efficiency change component again measures the catch-up effect of average farmers.

Compared to the technological change index of the MPI, the overall trend for the MLI, depicted in Figure 6 is rather stagnating than decreasing. In particular, much smaller decreases for the technological change component of (only) up to 9% can be found between 2010 and 2013 – the period when we observe the largest decoupling of MPI and MLI.

FIGURE 6
TECHNOLOGICAL CHANGE AND EFFICIENCY CHANGE OF THE MLI



The decoupling of the overall index results is thus well reflected by the combination of a stagnating (not decreasing) frontier-shift and a positive catch-up (of the MLI). In 2011 the lead in technological change switches from economic productivity to environmental productivity. While for the whole period the MLI frontier-shift only lies 2% above the MPI results, for the years 2011 to 2016 the technological change level for the MPI lies at only 89% and thus way below the 95% level for environmental productivity. Nonetheless, even for the best performers development, it must be stated that over the years the environmental productivity level of 2006 is only reached once, in 2011. The positive effect of the decoupling is also influenced by the average performing farms. Over the years the positive MLI catch-up of about 2% dominates the MPI catch-up, which lies at minus 2%, reinforcing the frontier-shift effect on the overall indices decoupling.

For environmental productivity, all systems follow a similar path for the 'frontier-shift' coinciding largely with the overall MLI technological change component revealing no comparative advantage of a certain farm system.

DISCUSSION OF RESULTS

The results of the Malmquist-Productivity Index indicate that regular productivity generally decreased for the considered period (2006-2016). While the inputs land and labor only changed to a small extent, growth rates for price adjusted capital-based inputs (e.g. investment in buildings and machinery) have increased stronger compared to the price deflated gross output. Consequently, productivity levels deviate from the base level in 2006 by 10% on average (with a low of -20% and a high of -3%). The findings reveal a different and more stable picture for the environmental productivity measured with the MLI. Accounting for undesirable outputs by integrating nitrogen surpluses yields mean reductions from the productivity level in 2006 of about -3% compared to the base year (with a low of -10% and a high of +0.4%) Indeed on an aggregate level the increasing desirable outputs have been accompanied by slightly decreasing undesirable outputs, defined as mean nitrogen surplus. A more detailed analysis of farm systems shows a similar pattern.

The decomposition of the indices into the technological and efficiency change component shows that the decoupling of MPI and MLI is driven by both components. Over the whole period the technological change component for the MLI stays rather stable at 95%, whereas the MPI experiences a downward 'frontier-shift' from 2011 on. The decoupling is further intensified by the development of the efficiency change component. While respective values for the MLI even exceed the baseline level and compensate for some of the loss in technological change, the catch-up effect turns out to be negative for the MPI.

The generally decreasing MPI and MLI and the rather volatile development of the indices suggests that productivity is not only driven by technological progress on farm-level or the adaptation of certain practices but also depends on exogenous factors. Since the aggregated sums of inputs develop in a stable manner (even though the investment sum increased significantly) the volatility must be attributed to the development of the two outputs considered. Notably, tillage farming shows the largest deviations for environmental productivity catch-up. This might be explained by the greater exposition of this farm system to exogenous effects, such as the weather, impacting the amount of yields and the nutrient outtake on the other hand. As Figure 3 showed for absolute values, years with more good output generated seem to coincide with lower values for undesirable output. Future research should therefore focus on determining the impact of exogenous factors on agricultural productivity to clarify how realistic further productivity increases in the future really are. If indeed undesirable outputs in agricultural production enhance climate change, which encourages extreme weather events that impede an already stagnating productivity level, the inclusion of undesirable outputs seems even more important for an all-things-considered determination of productivity.

CONCLUSIONS

This paper provided an analysis of productivity that accounts for environmental pressures in agricultural production for the case of Ireland. We employed a non-parametric time series analysis indicator, the Malmquist-Luenberger Productivity Index, to make a judgment on environmental productivity development for the period between 2006 and 2016 (, which covers the majority of time since the implementation of direct payments until today). Farm survey data of over 400 farms represents about 47% (40,000 farms) of the total Irish agricultural sector. Besides the overall environmental productivity development, we wanted to examine if 'technology-centered, on-farm solutions', and the 'strategic emphasis on economic efficiency and adaptation of practices' can be proven empirically as a suitable strategy towards a more sustainable agricultural production as proposed in the literature (Velten et al., 2015). This is achieved by a comparison of environmental productivity results with regular productivity calculated with the MPI to analyze if efforts in environmental protection might rival (regular) productivity goals.

Based on our findings we draw the following conclusions regarding our research question. For the period 2006 to 2016 environmental productivity is found to decrease slightly (3%) for the case of Irish agriculture. The strategy of establishing a sustainable agricultural production by increasing productivity relies on increasing productivity. Given the chosen method and variables neither regular nor environmental productivity have increased. Even more important the results show a great vulnerability to exogenous factors even though we are accounting for price volatility with a deflated gross output.

This is supported by the results of the index decomposition. The claim of continuous technological progress on farm level harmonizing resource conservation and economic viability of farms cannot be found for the case of Ireland. The best performers show no vital gains of further good output expansion and bad output reduction. The decoupling of environmental productivity from regular productivity is mainly attributable to a higher efficiency change component. This suggests that the slightly decreasing values for Nitrogen surpluses much rather occurred on less efficient farms that might have adapted less intensive practices and thus closed the gap to the best performers.

The comparison of environmental and regular productivity indices suggests that environmental protection and increasing (regular) productivity are at least not rivaling goals. Since the MLI results decouple from the MPI results due to a stagnating technological change yet higher values for efficiency change, environmental productivity exceeds regular productivity. This way the environmental productivity indicator gets a grasp on the efforts of some (average) farms directed towards reduction of bad output (that the regular productivity indicator misses out on).

The empirical findings of this paper suggest that the proposal of increasing productivity to establish a sustainable agricultural sector is highly questionable. When environmental pressures are accounted for, the productivity indicator returns a highly volatile yet on the long run rather stagnating trend. A substantial contribution of technical progress on farm level that continuously contributes towards harmonizing yield and resources employed cannot be found. At least the EU agricultural policy objectives, promoting productivity and environmental protection do not seem to rival considering the comparison of regular and environmental productivity results. Indeed, a decoupling of the two indices shows that investments and efforts of less productive Irish farms are directed towards increasing environmental productivity. If this is the case then clearly any judgment on farm performance should consider environmental variables in a productivity indicator to make (even small portions of) environmental progress visible, enforce policy measures that credit farms for such efforts and further intertwine environmental and productivity objectives.

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APPENDIX

APPENDIX A
DECOMPOSITION OF THE MALMQUIST PRODUCTIVITY INDEX RESULTS

geomean	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Technological Change Component										
dairy	1.00	0.97	0.88	0.98	0.94	0.85	0.86	0.93	0.94	0.92
cattle-rearing	1.03	1.02	0.99	1.04	0.94	0.87	0.79	0.93	0.90	0.88
cattle-other	1.00	0.98	0.92	0.98	0.91	0.83	0.81	0.90	0.89	0.87
sheep	1.05	1.07	1.04	1.09	0.95	0.86	0.81	0.94	0.91	0.91
tillage	1.04	1.07	1.13	1.08	0.95	0.85	0.84	0.97	0.93	0.94
other	0.99	0.96	0.94	0.97	0.93	0.84	0.84	0.92	0.89	0.86
all types	1.01	0.99	0.94	1.00	0.93	0.85	0.83	0.92	0.92	0.90
Efficiency Change Component										
dairy	1.04	0.98	1.00	1.00	1.02	1.01	1.02	1.03	1.01	1.01
cattle-rearing	0.89	0.87	0.98	0.85	0.93	0.96	0.96	0.91	0.98	1.07
cattle-other	0.92	0.89	1.06	0.94	0.98	1.01	0.95	0.87	0.93	1.02
sheep	0.89	0.84	0.96	0.95	0.94	1.00	0.91	0.88	0.97	1.05
tillage	1.01	0.90	0.95	1.02	1.05	1.18	1.01	0.86	1.07	1.06
other	0.98	0.94	0.97	0.98	0.99	1.02	0.98	0.96	0.91	1.07
all types	0.97	0.92	1.00	0.95	0.98	1.01	0.98	0.94	0.98	1.03

APPENDIX B
DECOMPOSITION OF THE MALMQUIST-LUENBERGER PRODUCTIVITY RESULTS

geomean	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Technological Change Component										
dairy	1.00	0.98	0.90	0.99	0.99	0.90	0.91	0.96	0.99	0.95
cattle-rearing	0.93	0.96	0.91	0.96	1.01	0.94	0.91	0.96	0.96	0.96
cattle-other	0.95	0.99	0.93	0.97	1.02	0.93	0.91	0.95	0.96	0.96
sheep	0.91	0.96	0.92	0.95	0.98	0.90	0.89	0.94	0.98	0.99
tillage	0.91	0.89	0.89	0.99	0.99	0.88	0.89	0.95	0.99	0.96
other	0.94	0.95	0.88	0.97	1.00	0.91	0.92	0.96	0.96	0.92
all types	0.96	0.97	0.91	0.97	1.00	0.92	0.91	0.95	0.98	0.96
Efficiency Change Component										
dairy	1.04	1.00	1.01	0.99	0.99	1.00	1.00	1.02	1.00	1.02
cattle-rearing	1.06	1.02	1.08	0.98	0.97	1.04	1.01	1.01	1.03	1.05
cattle-other	1.01	1.01	1.05	0.99	0.97	1.04	0.99	0.98	1.00	1.04
sheep	1.05	1.04	1.13	1.06	0.99	1.06	0.98	1.01	1.02	1.07
tillage	0.98	0.96	1.03	1.09	1.04	1.15	1.02	1.03	1.09	1.16
other	1.04	0.99	1.05	1.01	0.97	1.01	0.98	1.01	0.99	1.08
all types	1.04	1.01	1.05	1.00	0.98	1.03	1.00	1.01	1.01	1.04