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Cost of abating excess nitrogen on wheat plots in France: An assessment with multi-technology modelling

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Abstract

We use a multi-equation model of polluting technologies to evaluate excess nitrogen's marginal abatement cost (MAC). The MAC is estimated using the convex non-parametric quantile regression. The empirical application is conducted at the plot level for wheat production in France in 2017. Results show a median shadow price for excess nitrogen of about €21 per kilogram. If the current European Union's Nitrates Directive (which sets a 170-kg constraint on organic nitrogen per hectare) were extended to mineral nitrogen, this would allow a reduction of total excess nitrogen by 9.5%, but this would be accompanied by a 3.1% decrease in wheat revenue.

KEYWORDS

convex quantile, excess nitrogen, marginal abatement cost, multi-equation, shadow price

JEL CLASSIFICATION

C61, D24, Q51

1 | INTRODUCTION

Although nutrients, such as nitrogen, are crucial for plant growth, overuse can cause adverse environmental effects (Vilmin et al., 2018). For instance, nutrients may be drained by rain or irrigation and introduced into rivers or groundwater aquifers where their high concentration damages water quality (Haruvy et al., 1997). In addition to nitrogen runoff in water, excess nitrogen can also occur as nitrous oxide (N_2O), a very potent greenhouse gas with a significant impact on ozone depletion (Ravishankara et al., 2009), and as ammonia (NH_3) emissions which can have adverse effects ‘on air quality, ecosystem productivity, and human health’ (Mikkelsen, 2009). Thus, the consequences of nitrogen excess are pervasive due to environmental, health and water quality issues.[1] In the United States, Dodds et al. (2009) estimated damages associated with eutrophication[2] in fresh water to be approximately US$2.2 billion annually. These costs range between US$105 million and US$160 million in England and Wales annually (Pretty et al., 2003). In the case of France, 'eutrophication of coastal waters is estimated to cost between 70 million and 1 billion Euros while additional water treatment costs are estimated to lie between 540 million and 1.2 billion Euros (approximately doubled if bottled water usage is included)' (Moxey, 2012, p. 18).

As nitrogen pollution is not priced, farmers may not internalise it in their decision-making process and use non-(socially) optimal fertiliser levels. We contribute to the literature on nitrogen pollution valuation by estimating a nitrogen excess value using plot-level data and physical quantities of nitrogen. We estimate nitrogen excess's shadow price using production technologies where nitrogen excess is considered a bad output. The shadow price derived under this framework can be closely related to an abatement cost or, more explicitly, to the profit foregone when reducing nitrogen pollution. This information on nitrogen abatement costs can help policy-makers adjust the payments proposed to farmers under agri-environmental schemes such as those in the frame of the European Common Agricultural Policy (CAP). It can also serve as the basis for tradeable nitrogen quotas. While the European Union's Nitrates Directive, aiming to reduce nitrogen use in agriculture through zoning, imposes a limit on organic nitrogen only, we compute here nitrogen's shadow price for mineral fertilisers. This enables us to illustrate what could happen in environmental and economic terms for farms at the plot level if the Nitrates Directive were extended to mineral nitrogen.

Few papers have calculated nitrogen shadow prices in agriculture. Some studies are based on productivity approaches where nitrogen pollution is treated as an undesirable output under the weak disposability assumption (Färe & Grosskopf, 2003) or as an input under the strong disposability assumption (Hailu & Veeman, 2001). Using those two disposability assumptions, Shaik et al. (2002) applied the input and output distance function approach and data envelopment analysis (DEA) to aggregated state data for Nebraska (USA) during 1936–1997. Their study obtained excess nitrogen from agriculture with nutrient mass balance accounting (nitrogen input use minus nitrogen removed from crops). The excess nitrogen was then valued using farms' deflated revenue and cost. In a series of papers, Reinhard et al. (1999, 2000, 2002) examined nitrogen surplus efficiency in the case of Dutch dairy farms. Nitrogen surplus is considered as an additional strongly disposable input in a stochastic frontier analysis (SFA) framework. The environmental efficiency is derived by solving two equations and assuming that a farm that is output technically efficient is also environmentally efficient. Although trade-offs (elasticities) between nitrogen surplus and output production are sometimes provided in the above-mentioned studies, there is no mention of shadow prices. Using a hedonic output index based approach, Malikov et al. (2018) reconsidered the shadow price of Dutch dairy farms' nitrogen surplus. Mamardashvili et al. (2016) considered a parametric hyperbolic distance function for assessing the nitrogen surplus shadow price in Swiss dairy farms.[3] For French dairy farms, Berre et al. (2013) evaluated the shadow price of nitrogen excess from the farmer's and the society's perspective using DEA and assuming weak disposability for the bad output. In another approach, Piot-Lepetit and Vermersch (1998) considered organic nitrogen associated with animal breeding as a weakly/strongly disposable output to evaluate its shadow price in the case of French pig farms using DEA. Khataza et al. (2017)

[1]Nitrogen excess can also result in soil acidification (Galloway et al., 2008).

[2]Eutrophication is defined as 'an increase in the rate of supply of organic matter to an ecosystem' (Nixon, 1995, p. 201). More specifically, it describes an increase in nutrients (nitrogen and phosphorous) into a particular body of water (Richardson & Jørgensen, 1996). The consequences of eutrophication include rapid algae growth along with a wide range of impacts on aquatic ecosystems (Dupas et al., 2015; Smith et al., 2006).

[3]The same approach was also used in Adenuga et al. (2019) for dairy farms in the case of Ireland.

assessed the shadow price of symbiotic nitrogen against commercial nitrogen for a sample of maize-legume intercropped plots in Malawi in 2013/2014 by considering a parametric directional distance function. Their study obtained the quantity of symbiotic nitrogen using the harvest-index method.[4]

Our approach differs from the previous studies by using a novel way of modelling bad output under the multi-technologies' framework (Førsund, 2017; Murty et al., 2012). The basic idea of this approach is that the system is divided into two sub-technologies where one produces the desired output, and the other generates the detrimental output. This multi-equation modelling of polluting technologies offers the advantage of consistency with the materials balance principles. It also overcomes current issues of modelling frameworks, such as inappropriate trade-offs between bad outputs and inputs generating pollution (Dakpo et al., 2016). Moreover, from a methodological point of view, we extend the convex non-parametric quantile regression (known to be robust to heteroscedasticity) proposed by Banker (1988)[5] and Wang et al. (2014) to provide a distribution of shadow prices. The quantile approach offers the advantage of investigating differential characteristics of the frontiers as close as possible to every observation accounting for their inefficiency.[6]

The originality of our approach is that we apply the analysis at the plot level. Most productivity studies dealing with bad outputs in agriculture consider the farm level or the sectoral level. Here we consider a more disaggregated plot level, as this is the level where the environment is at stake in the case of nitrogen pollution. There may not be nitrogen excess on a specific farm when considering the farm as a whole. Nevertheless, some plots may still have high excess, implying potential nitrogen losses to the environment that need to be addressed. More specifically, farms with homogeneous plot practices will exhibit an overall similar nitrogen balance. However, with heterogeneous plot practices, the overall balance will hide plots with nitrogen excess. Therefore, plot-level analysis considers the heterogeneity of nutrient management practices within the same farm operation. As farmers can freely allocate inputs across plots, from an environmental perspective, input misallocation may be hidden at the farm-level analysis. Moreover, several essential management practices for nitrogen pollution occur at the plot level (e.g., crop rotation). They account for soil and weather conditions that may be different depending on the geographical distribution of the farm's plots. Also, for the balance to be reliable, evaluation should be run at the plot level because of manure export/import and fertiliser inventory change. In addition, as stressed by Sun et al. (2016), adjustments following policy measures can be felt immediately at the plot level through a reduced fertiliser application rate, while it takes more time at the farm and sectoral level due to the sluggish adjustment of land allocation across crops.

The rest of the paper is organised as follows. The following section presents the methodological background of the multi-equation modelling framework and the approach to obtaining trade-offs, shadow prices and marginal abatement costs. Then, the following sections describe the empirical strategy and data and explain the results. Finally, the last section concludes.

2 | METHODOLOGY

This section presents the methodological framework for multi-technologies (or multi-equations) dealing with detrimental outputs and the derivation of shadow prices and marginal abatement costs. The following subsection introduces multi-equation technologies.

[4]Other modelling strategies can be found in Polman and Thijssen (2002) and Helming and Reinhard (2009).

[5]The author used the terminology stochastic DEA instead of convex non-parametric quantile.

[6]In the classic framework where only one frontier is estimated, shadow prices can only be evaluated for efficient observations, thus ignoring the presence of inefficiency (Kuosmanen & Zhou, 2021).

2.1 | Multi-equation modelling of pollution-generating technologies

To obtain shadow prices, we use the multi-equation modelling framework of pollution-generating technologies discussed in several papers (Dakpo & Ang, 2019; Førsund, 2017; Førsund, 2021; Ray et al., 2017), which finds its origin in Frisch (1965). This modelling has been used to measure performance while accounting for environmental pollution from firms (Boussemart et al., 2019; Lozano, 2015; Murty & Nagpal, 2019; Zhao, 2016), and to a lesser extent from farms (Chambers et al., 2014; Dakpo et al., 2017).

For the operationalisation of such modelling, inputs are split into two groups: 'materials inputs', which generate pollution, and 'service inputs', which do not. This input separation is a core aspect of multi-equation modelling (Førsund, 2017; Murty et al., 2012). Mathematically, let $(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) \in \mathbb{R}^{K+L+1}$ be the vector of materials inputs ($\mathbf{x}_{\boldsymbol{M}}$), service inputs ($\mathbf{x}_s$)[7] and the good marketed output (y) which is wheat production in the following application. We denote z the level of nitrogen excess, which is the bad output of the model. The overall production can be represented as the intersection of two distinct sub-technologies, one for producing good output (Ψ_y) and the other for the generation of nitrogen excess, namely the bad (or undesirable) output (Ψ_z). Formally:

$$\Psi = \Psi_y \cap \Psi_z, \tag{1}$$

where:

$$\Psi_y = \left\{(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y, z) \in \mathbb{R}^{K+L+2} \mid f(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) \leq 0\right\}, \tag{2}$$

$$\Psi_z = \left\{(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y, z) \in \mathbb{R}^{K+L+2} \mid g(\mathbf{x}_{\boldsymbol{M}}, z) \geq 0\right\}, \tag{3}$$

with f and g continuously differentiable transformation functions.

Contrary to Førsund (2017), we do not introduce the service inputs in the nitrogen excess generation sub-technology (Ψ_z) since those inputs do not have direct impacts on nitrogen excess.[8] Hence, the conceptual framework presented here almost strictly follows the one developed in Murty et al. (2012). Moreover, we also assume that the good output sub-technology (Ψ_y) is independent of z, which implies that nitrogen excess does not have any direct impact on wheat production. Graphically, the different sub-technologies are represented in Figure 1. Under the good output sub-technology, the classic disposability assumptions are maintained, while under the nitrogen excess sub-technology, Murty et al. (2012) suggested a costly disposability assumption of this bad output.

The disposability assumptions imply the following monotonicity conditions:

i. for the good output sub-technology

$$f_y(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) \geq 0 \wedge f_{x_M}(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) \leq 0 \wedge f_{x_S}(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) \leq 0 \tag{4}$$

2 for the nitrogen excess sub-technology

$$g_{x_M}(\mathbf{x}_{\boldsymbol{M}}, z) > 0 \wedge g_z(\mathbf{x}_{\boldsymbol{M}}, z) < 0 \tag{5}$$

[7] In the case of nitrogen excess, service inputs may include land, labour and pesticide use, none of which can directly generate nitrogen excess.

[8] See also Førsund (2021) for more discussion on the representation of the bad output sub-technology.

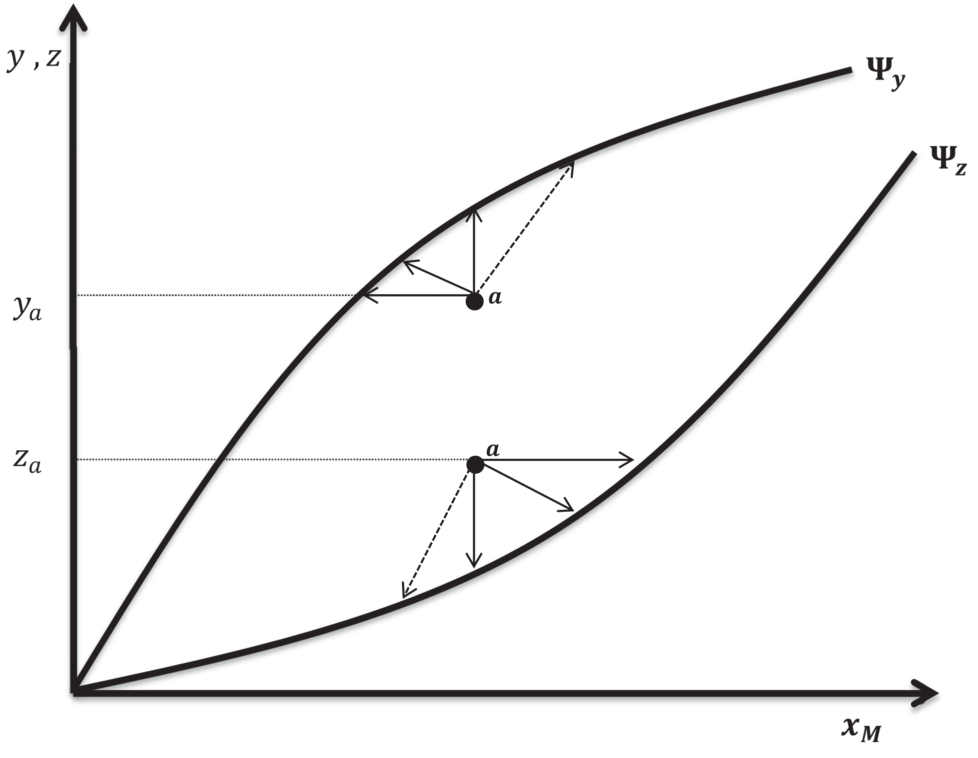

FIGURE 1 Multi-equation technology representation. Ψ_y is the sub-technology for the good output y, and Ψ_z is the sub-technology for the bad output z. *Source*: Adapted from Dakpo et al. (2017).

From the monotonicity conditions in (4) and (5), different trade-offs involving the bad output can be assessed, which is the first step in shadow pricing nitrogen excess, as explained below. The following subsection details how trade-offs can be estimated and shadow prices derived.

2.2 | Trade-offs estimation and shadow prices derivation

We are interested in determining the different trade-offs involving bad output. To this end, let us consider the transformation functions of Equations (2) and (3) at a weak efficient point $(\hat{\mathbf{x}}_{\boldsymbol{M}}, \hat{\mathbf{x}}_{\boldsymbol{S}}, \hat{y}, \hat{z})$:[9]

$$\begin{aligned} f(\hat{\mathbf{x}}_{\boldsymbol{M}}, \hat{\mathbf{x}}_{\boldsymbol{S}}, \hat{y}) = 0 \\ g(\hat{\mathbf{x}}_{\boldsymbol{M}}, \hat{z}) = 0 \end{aligned} \tag{6}$$

The implicit function theorem implies that there exists a local neighbourhood around $\left(\hat{\mathbf{x}}_{\boldsymbol{M},-\boldsymbol{k}}, \hat{z}\right) \in \mathbb{R}^K$ such that:[10]

$$x_{M,k} = h\left(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, z\right) = g^{-1}\left(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, z\right). \tag{7}$$

[9]The shadow prices are derived at the hyperplanes of each technology. Even in the presence of inefficiency: $f(\mathbf{x}_M, \mathbf{x}_S, y) + c = 0$ and $g(\mathbf{x}_M, z) - d = 0$, the inefficiency components c and d do not matter in deriving the shadow prices (because these components are constant). Hence, we adopt the strategy of estimating the quantile production frontier.

[10]$\mathbf{x}_{M,-k}$ represents the vector of all materials inputs except input k.

Then, substituting (7) into $f(\mathbf{x}_M, \mathbf{x}_S, y) = 0$ yields:

$$\check{f}\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, y, z\right) = f\left(h\left(\mathbf{x}_{M,-k}, z\right), \mathbf{x}_{M,-k}, \mathbf{x}_S, y\right) = 0. \tag{8}$$

If $f_y(\hat{\mathbf{x}}_M, \hat{\mathbf{x}}_S, \hat{y}) > 0$ then there exists a neighbourhood around $\left(\hat{\mathbf{x}}_{M,-k}, \hat{\mathbf{x}}_S, \hat{z}\right) \in \mathbb{R}^{K+L}$ such that $y = \psi\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, z\right)$, and the trade-off between the desirable (good) and undesirable (bad) output at the weakly efficient point $(\hat{\mathbf{x}}_M, \hat{\mathbf{x}}_S, \hat{y}, \hat{z})$ is given by:

$$\frac{\partial \psi\left(\hat{\mathbf{x}}_{M,-k}, \hat{\mathbf{x}}_S, \hat{z}\right)}{\partial z} = -\frac{f_{x_{M,k}}(\hat{\mathbf{x}}_M, \hat{\mathbf{x}}_S, \hat{y}) h_z\left(\hat{\mathbf{x}}_{M,-k}, \hat{z}\right)}{f_y(\hat{\mathbf{x}}_M, \hat{\mathbf{x}}_S, \hat{y})} \geq 0. \tag{9}$$

Note that this trade-off is non-negative, since $f_y(\mathbf{x}_M, \mathbf{x}_S, y) \geq 0$, $h_z\left(\mathbf{x}_{M,-k}, z\right) = -\frac{g_z(\mathbf{x}_M, z)}{g_{x_{M,k}}(\mathbf{x}_M, z)} > 0$, and $f_{x_{M,k}}(\mathbf{x}_M, \mathbf{x}_S, y) \leq 0$. Holding $\mathbf{x}_{M,-k}$ and $\mathbf{x}_S$ fixed, an increase in bad output z is attributable to an increase in materials input $x_{M,k}\left(h_z\left(\mathbf{x}_{M,-k}, z\right) > 0\right)$. Under the good output sub-technology Ψ_y, there is a non-negative relationship between $x_{M,k}$ and $y\left(-\frac{f_{x_{M,k}}(\mathbf{x}_M, \mathbf{x}_S, y)}{f_y(\mathbf{x}_M, \mathbf{x}_S, y)} \geq 0\right)$.

Using (7) and (8), the technology Ψ can be reformulated as:

$$\check{\Psi} = \left\{(\mathbf{x}_M, \mathbf{x}_S, y, z) \in \mathbb{R}^{K+L+2} \mid \check{f}\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, y, z\right) \leq 0 \wedge x_{M,k} \geq h\left(\mathbf{x}_{M,-k}, z\right)\right\}, \tag{10}$$

and the function $\check{f}$ can be used to analyse the trade-off between service input $x_{S,l}$ and undesirable output z. This trade-off is given by:

$$-\frac{\check{f}_z\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, y, z\right)}{\check{f}_{x_{S,l}}\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, y, z\right)} = -\frac{f_{x_{M,k}}(\mathbf{x}_M, \mathbf{x}_S, y) h_z\left(\mathbf{x}_{M,-k}, z\right)}{f_{x_{S,l}}(\mathbf{x}_M, \mathbf{x}_S, y)} \leq 0. \tag{11}$$

The non-positive trade-off between the service input and the undesirable output shown in (11) reflects the fact that an increase in those inputs can mitigate the level of pollution under fixed levels of inputs $\mathbf{x}_{M,-k}$ and of desirable output y.

Finally, the last set of trade-offs that can be derived from (10) is the one between the undesirable output z and materials input $j \neq k$. This trade-off is given by:

$$-\frac{\check{f}_z\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, y, z\right)}{\check{f}_{x_{M,j}}\left(\mathbf{x}_{M,-k}, \mathbf{x}_S, y, z\right)} = -\frac{f_{x_{M,j}}(\mathbf{x}_M, \mathbf{x}_S, y) + f_{x_{M,k}}(\mathbf{x}_M, \mathbf{x}_S, y) h_j\left(\mathbf{x}_{M,-k}, z\right)}{f_{x_{M,k}}(\mathbf{x}_M, \mathbf{x}_S, y) h_z\left(\mathbf{x}_{M,-k}, z\right)}. \tag{12}$$

The sign of the trade-off in (12) is ambiguous as $-\frac{f_{x_{M,j}}(\mathbf{x}_M, \mathbf{x}_S, y)}{f_{x_{M,k}}(\mathbf{x}_M, \mathbf{x}_S, y) h_z(\mathbf{x}_{M,-k}, z)} \leq 0$ and $-\frac{h_j(\mathbf{x}_{M,-k}, z)}{h_z(\mathbf{x}_{M,-k}, z)} > 0$. The costly disposability of materials input implies that an increase in $x_{M,j}$ has a composite effect on the undesirable output z for a fixed level of service inputs $\mathbf{x}_S$, good output y and other materials inputs $\mathbf{x}_{M,-k,-j}$. An increase in $x_{M,j}$ generates the standard positive effect on $z\left(-\frac{h_j(\mathbf{x}_{M,-k}, z)}{h_z(\mathbf{x}_{M,-k}, z)} > 0\right)$. On the other hand, a non-positive effect arises because, to maintain the level of desirable output unchanged, the materials input $x_{M,k}$ must decrease.

The combination of the trade-offs in (9), (11) and (12) is sufficient to characterise the production technology Ψ fully. In the following subsection, we present the derivation of the economically relevant shadow prices and discuss the derivation of marginal abatement costs for nitrogen excess.

2.3 | Shadow prices and marginal abatement costs

Let us specify the revenue function:

$$R\left(P_y, w_z, \mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}\right) = \max_{\substack{y,z \\ s.t.\, f(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)\leq 0 \\ g(\mathbf{x}_{\boldsymbol{M}},z)\geq 0}} P_y y - w_z z \tag{13}$$

where P_y is the observed price of the good output and w_z is the shadow price of nitrogen excess that needs to be determined.

Using (8), this revenue function is also equivalent to:

$$\begin{aligned} R\left(P_y, w_z, \mathbf{x}_{\mathbf{M}}, \mathbf{x}_{\boldsymbol{S}}\right) &= \max_{y,z} P_y y - w_z z \\ s.t. f\left(h\left(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, z\right), \mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, \mathbf{x}_{\boldsymbol{S}}, y\right) &\leq 0 \end{aligned} \tag{14}$$

The Lagrangian of programme (14) is:

$$\mathcal{L} = P_y y - w_z z + \lambda\left[f\left(h\left(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, z\right), \mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, \mathbf{x}_{\boldsymbol{S}}, y\right) - 0\right]. \tag{15}$$

The first-order conditions are:

$$\begin{aligned} \frac{\delta \mathcal{L}}{\delta y} &= P_y + \lambda f_y(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) = 0 \\ \frac{\delta \mathcal{L}}{\delta z} &= -w_z + \lambda f_{x_{M,k}}(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}, y) h_z\left(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, z\right) = 0 \end{aligned} \tag{16}$$

Solving the two equations in (16) yields:[11]

$$\begin{aligned} w_z &= -P_y \frac{f_{x_{M,k}}(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y) h_z(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}},z)}{f_y(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)} \\ w_z &= P_y \frac{f_{x_{M,k}}(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)}{f_y(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)} \frac{g_{z(\mathbf{x}_{\boldsymbol{M}},z)}}{g_{x_{M,k}(\mathbf{x}_{\boldsymbol{M}},z)}} \end{aligned} \tag{17}$$

From another perspective, let us consider a cost-minimisation behaviour. In this case, we have:

$$\begin{aligned} C\left(\boldsymbol{v}_{\mathbf{x}_{\boldsymbol{S}}}, w_z, \mathrm{y}, \mathbf{x}_{\boldsymbol{M}}\right) &= \min_{x_s,z} \boldsymbol{v}_{\mathbf{x}_{\boldsymbol{S}}} \mathbf{x}_{\boldsymbol{S}} + w_z z \\ s.t. f\left(h\left(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, z\right), \mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}}, \mathbf{x}_{\boldsymbol{S}}, y\right) &\leq 0 \end{aligned} \tag{18}$$

Solving the problem in (18) yields:

$$\begin{aligned} w_z &= v_{x_{S,l}} \frac{f_{x_{M,k}}(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y) h_z(\mathbf{x}_{\boldsymbol{M},-\boldsymbol{k}},z)}{f_{x_{S,l}}(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)} \\ w_z &= -v_{x_{S,l}} \frac{f_{x_{M,k}}(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)}{f_{x_{S,l}}(\mathbf{x}_{\boldsymbol{M}},\mathbf{x}_{\boldsymbol{S}},y)} \frac{g_{z(\mathbf{x}_{\boldsymbol{M}},z)}}{g_{x_{M,k}(\mathbf{x}_{\boldsymbol{M}},z)}} \end{aligned} \tag{19}$$

[11]This shadow price is very similar to that developed in the literature using distance functions (Färe et al., 2005).

Now recall that $\left(\mathbf{x}_{\boldsymbol{M}}, \mathbf{x}_{\boldsymbol{S}}\right) \in \mathbb{R}^{K+L}$, which means that the shadow price of nitrogen excess in Equations (17) and (19) may not be unique. Depending on the number of materials and service inputs $K + L$ different values can be obtained for w_z. From a rational point of view, a manager will never choose the costliest strategy. For this reason, following Kuosmanen and Zhou (2021), we decided to retain the minimum value among all the possible shadow prices obtained empirically for each observation.

Mathematically, the retained shadow price, which we call the marginal abatement cost (MAC), is obtained as follows:

$$MAC = \min_{k,l}\left\{ P_y \frac{f_{x_{M,k}}}{f_y}\frac{g_z}{g_{x_{M,k}}}; -v_{x_{S,l}}\frac{f_{x_{M,k}}}{f_{x_{S,l}}}\frac{g_z}{g_{x_{M,k}}}\right\} \tag{20}$$

Practically, to estimate the production technology Ψ we rely on the structural approach where both sub-technologies are estimated.[12] Each technology is separately estimated using the convex non-parametric quantile regression, described in the following subsection.

2.4 | Convex non-parametric quantile regression

The convex non-parametric quantile regression in the framework of performance benchmarking was initially discussed by Banker (1988) under the name of stochastic data envelopment analysis (SDEA). The sum of weighted error terms is minimised subject to Afriat inequalities, which impose the monotonicity properties. A more recent discussion of the SDEA model can be found in Wang et al. (2014), who use the term concave non-parametric quantile regression (CNQR) for the case of a production function.[13] This approach is flexible since no assumption is made about the functional form of the production function. Only the monotonicity and convexity properties are maintained in this stochastic framework.

In the case of the good output sub-technology Ψ_y, the model can be written as follows:

$$\begin{gathered}\min_{\alpha,\beta,\theta,e^+,e^-} \sum_{i=1}^{N}\left[\tau e_i^+ + (1-\tau)e_i^-\right]\\ y_i = \alpha_i + \mathbf{x}'_{\boldsymbol{iM}}\boldsymbol{\beta_{iM}} + \mathbf{x}'_{\boldsymbol{iS}}\boldsymbol{\beta_{iS}} + \mathbf{r}'_{\boldsymbol{i}}\theta_i + e_i^+ - e_i^-\\ \alpha_i + \mathbf{x}'_{\boldsymbol{iM}}\boldsymbol{\beta_{iM}} + \mathbf{x}'_{\boldsymbol{iS}}\boldsymbol{\beta_{iS}} \le \alpha_j + \mathbf{x}'_{\boldsymbol{iM}}\boldsymbol{\beta_{jM}} + \mathbf{x}'_{\boldsymbol{iS}}\boldsymbol{\beta_{jS}}\\ \boldsymbol{\beta_{iM}}, \boldsymbol{\beta_{iS}} \ge 0; e_i^+, e_i^- \ge 0; i, j = 1, \dots, N\end{gathered} \tag{21}$$

where i and j denote decision-making units. The presence of the intercepts α implies variable returns to scale (VRS). To avoid potential omitted variables' bias, control variables $\mathbf{r}$ are added to the production function.[14]

In the case of the bad output sub-technology, we have adapted the model such that the production technology is bounded below, as follows:

$$\begin{gathered}\min_{\gamma,\delta,\kappa,u^+,u^-} \sum_{i=1}^{N}\left[\left(1-\tilde{\tau}\right)u_i^+ + \tilde{\tau}u_i^-\right]\\ z_i = \gamma_i + \mathbf{x}'_{\boldsymbol{iM}}\boldsymbol{\delta_{iM}} + \mathbf{r}'_{\boldsymbol{i}}\kappa_i + u_i^+ - u_i^-\\ \gamma_i + \mathbf{x}'_{\boldsymbol{iM}}\boldsymbol{\delta_{iM}} \ge \gamma_j + \mathbf{x}'_{\boldsymbol{iM}}\boldsymbol{\delta_{jM}}\\ \boldsymbol{\delta_{iM}} \ge 0; u_i^+, u_i^- \ge 0; i, j = 1, \dots, N\end{gathered} \tag{22}$$

[12]Considering all the trade-offs aforementioned, it is possible to estimate a reduced form for Ψ. This strategy has been followed by Puggioni and Stefanou (2019).

[13]Another possible approach is the convex non-parametric least squares (CNLS); see Kuosmanen (2008) and Kuosmanen and Johnson (2010).

[14]We thank one reviewer for underlining this point.

where the parameter γ also implies here VRS, and $\mathbf{r}$ represents a vector of additional control variables.

Using the previous developments and the models in (21) and (22), the different shadow prices of excess nitrogen can be evaluated using:[15]

$$w_z = -P_y \frac{\beta_{iM,k}}{\delta_{iM,k}} \quad \text{or} \quad w_z = -v_{x_{S,l}} \frac{\beta_{iM,k}}{\beta_{iS,l}} \frac{1}{\delta_{iM,k}} \tag{23}$$

3 | DATA AND ESTIMATION STRATEGY

3.1 | Data

The data used in our case study come from the 2017 agricultural production methods survey (SAPM)[16] in France, managed by the French Ministry of Agriculture. SAPMs are surveys to inform agricultural practices, mainly fertiliser use and pest control. The surveys are conducted every 5 years on randomly selected plots in France for various crops. In addition to inputs used and crop output, the database also registers information about crop rotations and other practices (tillage, irrigation, sowing, etc.).[17] For homogeneity, we focus only on plots where winter wheat was produced in 2017. The single good output (y) is the wheat produced on the plot. The inputs are measured at the plot level. The three inputs are plot area in hectares, treatment frequency index (TFI), and mineral nitrogen in kilograms. Mineral nitrogen is treated as the sole pollution-generating input ($\mathbf{x}_M$) while plot area and TFI are service inputs ($\mathbf{x}_S$). The plot's nitrogen excess is computed by the available nitrogen on the plot (nitrogen from fertilisers applied and nitrogen remaining from the pre-crop, including grass) minus exported nitrogen (based on the crop nitrogen requirements and the crop yield).[18] We exclude plots with zero mineral nitrogen for the model to be estimated. To avoid omitted variables' bias, four control variables ($\mathbf{r}$) are included in the estimation, namely: r_1 is a dummy variable indicating whether the farmer uses a growth regulator; r_2 is a dummy variable indicating whether the farmer knows crop protein content; r_3 equals one if the plot is located in a disadvantaged area and zero if not; and finally, r_4 is the number of tillages in the last 2 years on the same plot. All these control variables help account for practices affecting wheat yield and nitrogen excess. For example, plant growth regulators can affect root morphology and increase nitrogen absorption capacity.

Table 1 displays descriptive statistics of the data. The analysis is conducted on a sample of 662 wheat plots. Plots have an average area of 7.7 hectares and produce 52.5 tonnes of wheat, implying an average yield of about 6.5 tonnes per hectare, about 10% lower than the average national yield.[19] Mineral nitrogen per hectare rises to 179 kg per hectare, while excess nitrogen (the bad output z) is about 42 kg per hectare, representing slightly more than 23% of the applied nitrogen. For comparison, Jacquet et al. (2011) for field crop farms in France in 2006 obtained a nitrogen surplus of around 26 kg per hectare. In Switzerland, Schmidt et al. (2021) calculated nitrogen surpluses depending on the farm's main specialisation, ranging from 37.5 kg (for mixed dairy and arable farms) to 157.6 kg (for specialist dairy farms) per hectare. In Italy, Semaan et al. (2007) indicate figures for nitrogen application and leaching

[15]The trade-offs shown in Equation (12) are not considered here, as in our empirical framework we only have one polluting input.
[16]'Enquêtes pratiques culturales, enquêtes PK'.
[17]More details on the SAPM surveys can be found in https://www.casd.eu/en/source/field-crop-cultural-practices/.
[18]Jacquet et al. (2011) also computed nitrogen excess with data from a similar survey in 2006 but did not account for pre-crop nitrogen stock.
[19]See FAOSTAT.

TABLE 1 Descriptive statistics of the data.

Variable	Mean	Median	Standard deviation	Coefficient of variation (standard deviation/mean)
Wheat output (tonnes)	52.5	37.2	53.0	0.99
Plot area (ha)	7.7	5.6	7.6	1.02
Treatment frequency index (TFI)	4.4	4.2	1.8	2.46
Mineral nitrogen use (kg)	1423.9	1023.6	1437.5	0.99
Nitrogen excess (kg)	279.8	168.0	311.2	0.90
Use of growth regulator (dummy)	0.31	0.00	0.46	0.67
Knowledge of crop protein content (dummy)	0.66	1.00	0.48	1.38
Location in a disadvantaged area (dummy)	0.91	1.00	0.29	3.17
Number of tillages in the last 2 years	1.15	1.00	0.83	1.37
Number of plots	662			

that amount to a nitrogen balance between 89 and 53 kg per hectare of wheat, depending on the type of management. Pesticide quantities are measured in TFI, a measure of the volume of pesticides farmers apply on their plots and based on the recommended (standard) dose of the product's marketing authorisation. In the case of our sample, TFI is, on average, 4.4 per plot. The coefficients of variation are high for all the variables, suggesting substantial heterogeneity in the data.

3.2 | Estimation strategy

Models (21) and (22) involve many variables and constraints. For instance, in the case of the model in (21), $662 \times 10 = 6620$ parameters[20] are estimated considering 662 equality constraints and $662^2 = 438,244$ inequality constraints. The model's high number of inequality constraints imposes an extreme computational burden. To counter this, we adopt one of the efficient algorithms discussed by Lee et al. (2013) in the case of the CNLS for our quantile models. For simplicity, we only detail the algorithm for model (21) since the extension to model (22) is relatively trivial. Moreover, the algorithm focuses mainly on reducing the number of inequality constraints in a multi-stage approach.

Step 1. The algorithm starts by choosing a set of initial inequality constraints. Though two possibilities are presented by Lee et al. (2013), we retain the sweet spot approach. For each observation i the concavity constraints of all observations with distance to i lower than a threshold are selected to be initially included in the model.[21] Practically, Lee et al. (2013) suggested a threshold set to the 3rd percentile. This first step is based on the fact that closer observations are more likely to satisfy the relevant concavity restrictions. The model is then run with the selected inequality and equality constraints.

Step 2. The algorithm continues by selecting the violated concavity constraints to be included in the optimisation programme. Three possibilities were suggested by Lee et al. (2013), among which one is retained. For each observation i, the most violated constraint among the N (662) concavity constraints with respect to observation i is selected and added to the previously solved programme. This strategy adds at most N concavity constraints. The algorithm is iterated till no violated constraints are found.

[20]Two noise components, three input marginal productivities, the intercept term, and the four control variables.

[21]The distance is computed using the matrix of all input variables.

TABLE 2 Elasticities distribution.

Variables	Mean	First quartile	Median	Third quartile
Wheat production sub-technology				
Plot area	0.50	0.31	0.43	0.61
TFI	0.11	0.03	0.05	0.11
Mineral nitrogen	0.56	0.41	0.63	0.74
Excess nitrogen sub-technology				
Mineral nitrogen	1.36	0.68	0.84	0.98
Response elasticities to a 1% increase in excess nitrogen				
Wheat production	0.80	0.34	0.70	0.98
Plot area	−2.86	−0.63	−1.81	−3.03
TFI	−9.15	−0.48	−1.79	−5.23

4 | RESULTS

4.1 | Trade-offs and elasticities

To estimate the production technology using the convex non-parametric quantile regression, Banker (1988) sets τ to 0.5, which is equivalent to the median regression. Here, to fully account for the heterogeneity in the sample, we use several values for $\tau \in [0.05, 0.95]$ (with increments of 0.05). Let N^+ represent the number of observations with strictly positive residual $\left(e^+ > 0\right)$, and N^- the number of observations with strictly negative residual ($e^- > 0$). It is worth noting that, as usual in quantile regression, the value of τ satisfies the following properties as the sample size runs to infinity:

$$\frac{N^+}{N} \to 1 - \tau \wedge \frac{N^-}{N} \to \tau$$

The 'optimal' quantile selected is the one yielding the closest hyperplane (minimum absolute residual) for each observation.

Table 2 displays the distribution of elasticities associated with the trade-offs derived, as explained in the methodology section, along with the input elasticities obtained for each sub-technology. For simplicity and robustness, we focus on the median values. Under the wheat production sub-technology, fertiliser (mineral nitrogen) has the highest elasticity, 0.62%. It is followed by the plot area elasticity of 0.43%, and pesticides have the lowest elasticity of 0.05%.[22] The high elasticity of fertiliser use indicates that wheat production is highly responsive to a change in mineral fertilisers. It also suggests that any policy aiming at reducing the use of mineral fertilisers should consider the impact on output and, consequently, on profit. In the excess nitrogen sub-technology, the sole input mineral nitrogen has a median input elasticity of 0.84%, revealing that mineral fertilisers are the main contributor. [23]

Table 2 also shows that at the median, wheat production and nitrogen excess elasticity is 0.70% for fixed plot area and pesticide use. This indicates that an increase of excess nitrogen by 1% implies an increase in wheat production by only 0.70%. Under the excess nitrogen sub-technology, the 1% increase in this output is obtained by increasing mineral nitrogen by 1.19% (1/0.84). The

[22]Similar results were obtained in the case of Dutch arable farms in 2003–2007 with land area and pesticides elasticities about 0.363 and 0.084 (for herbicides), respectively (Skevas et al., 2014).

[23]Marginal productivities results can be found in the Appendix S1.

TABLE 3 Marginal abatement cost (MAC) of excess nitrogen.

Cost	Mean	First quartile	Median	Third quartile
MAC	28.2	13.1	20.9	41.9
Cost per hectare (€) of reducing excess nitrogen by 25%	183.3	105.9	183.8	227.3
Cost per hectare (€) of reducing excess nitrogen by 50%	366.7	211.9	367.6	454.6
Cost per hectare (€) of reducing excess nitrogen by 75%	550.0	317.8	551.4	681.9
Cost per hectare (€) of reducing excess nitrogen by 100%	733.3	423.8	735.1	909.2

elasticities associated with plot area and TFI are negative, meaning substitution possibilities can reduce excess nitrogen. For plot area and TFI, the median elasticities of excess nitrogen are −1.81% and −1.79%, respectively. These elasticities imply that for a 1% increase in excess nitrogen, the same level of wheat production can be kept if the plot area is reduced by 1.81% or if pesticide TFI is reduced by 1.79% at the median.

4.2 | Marginal abatement cost (MAC)

As presented in Equation (20), the MAC of excess nitrogen is obtained as the minimum value of all possible shadow prices. Computing the shadow prices requires output and input prices not available in the database. Therefore, official statistics are used: we set wheat price $\left(P_y\right)$ to €154 per tonne (Oppel, 2017) and land price to €7420 per hectare.[24] Due to the nature of the pesticide input, the number of treatments (TFI), and not the actual volume (and toxicity) of pesticides, prices for this input were not considered. For this reason, the shadow prices are computed using only wheat and land prices.

For all the observations, the cheapest strategy to reduce excess nitrogen is to reduce wheat production rather than purchasing additional land. Table 3 summarises the MAC distribution and shows that the wheat plot sample's median MAC of excess nitrogen is €20.9 per kilogram. In other words, the last unit of excess nitrogen returns €20.9 of wheat revenue, about 136 kg of wheat produced. Moreover, the additional unit of excess nitrogen implies a median value of 5.9 kg of mineral nitrogen. The median MAC slightly contrasts with the higher average value of MAC (about €28 per kilogram). Again, this reflects the significant heterogeneity in the sample and supports the use of quantile regression.

Few studies estimate shadow prices for excess nitrogen. Shaik et al. (2002, p. 429) found shadow prices between US$0.91 and 2.21 per pound (1 pound is about 0.45 kilograms), depending on the disposability assumptions imposed, for Nebraska in 1936–1997. According to the authors, these prices represent 'the opportunity cost in terms of revenue to reduce one pound of nitrogen pollution while maintaining agricultural production' at the state level. Khataza et al. (2017) found shadow price values ranging in the confidence interval of US$1.01 to 22.23 per kilogram. These authors carried out their study at the plot level but only considered biological nitrogen derived from a legume-based cropping system, which was evaluated against commercial nitrogen. In other words, in their study, the shadow price indicated the gain for the farmer if biological nitrogen were used as a substitute for fertiliser nitrogen. It is worth mentioning that it is difficult to draw clear comparisons across studies due to the differences in objectives and methodologies used. The next subsection presents the results of different scenarios in reducing excess nitrogen.

[24]Land price is obtained from https://www.safer.fr/app/uploads/2019/02/2018pdt_synthese.pdf.

4.3 | Simulated cost of abating excess nitrogen

We conducted illustrative simulations to evaluate the distribution of the per hectare cost of reducing the excess nitrogen. The reduction levels considered are 25%, 50%, 75% and 100%. The results of these simulations in Table 3 reveal that the median cost to offset the excess nitrogen fully (100% reduction) is €735.1 per hectare. This cost is €183.8 per hectare for a 25% reduction.

These simulations show how our methodological approach could help policy design. There are no restrictions on the level of mineral fertilisers that farmers apply in the European Union. On the contrary, the Nitrates Directive only targets organic nitrogen and restricts it to 170 kg per hectare of utilised agricultural area. If the same restrictions were to be extended to mineral nitrogen, our approach could help quantify the changes in environmental terms (excess nitrogen) and economic terms (wheat production). In our sample, 63.3% of the plots are above the 170 kg limit of mineral nitrogen per hectare. Setting this limit would reduce our sample's total excess nitrogen by 9.5% on average. This reduction in excess nitrogen would be accompanied by a decrease in wheat production of 3.1%. For example, if the policy were more stringent, with limits of 150 or 100 kg of mineral nitrogen per hectare, 82.9% and 97.6% of our sample would be above these limits, respectively. These new restrictions would be associated with a 17.1% and 39.8% decrease in excess nitrogen and a drop in wheat production of 6.9% and 21%, respectively.

5 | CONCLUSION

This article estimates excess nitrogen's MAC (or shadow prices) with an original approach using multi-equation technology applied at the plot level. We use convex non-parametric quantile regression and multi-equation modelling to represent the pollution-generating technology. Under this framework, the overall technology comprises two sub-technologies, one associated with wheat production and the other with excess nitrogen generation. The results for wheat production in 2017 in France reveal a median shadow price of €20.9 per kilogram. This indicates that the last unit of excess nitrogen returns €20.9 of wheat revenue or 136 kg of wheat output. Across the plot sample, the shadow prices are exponentially higher for lower levels of excess nitrogen per hectare.

This analysis provides valuable insights for policies that mitigate the nitrogen excesses from farming. If the current European Union's Nitrates Directive (which sets a 170-kg constraint on organic nitrogen per hectare) were extended to mineral nitrogen, this would impact 63% of the sample's plots, which are currently above this limit. Such a policy measure would allow a reduction of total excess nitrogen by 9.5% over the sample. However, this favourable environmental impact would be accompanied by an unfavourable economic impact of a 3.1% decrease in wheat revenue. This would have to be considered when designing payments provided to farmers within agri-environmental schemes against specific farming practices that allow reduced mineral fertilisers.

Further research could consider both mineral and organic nitrogen input. From a practical point of view, this would entail substitution possibilities between the two types of nitrogen fertiliser, offering farmers another strategy to reduce excess nitrogen. Although our database did not allow this, accounting for all forms of nitrogen input applied on plots would give a comprehensive view of farmers' behaviour and help better target policy design.

It should be kept in mind that our analysis was conducted at the plot level, whereas policies (including the European Union's Nitrates Directive) are at the whole farm level. The latter implies that setting a limit on the farm's total use of fertilisers does not necessarily mean that all farm plots comply with this limit. However, it makes sense from an agronomic and environmental point of view to consider nitrogen use at the plot level. Our approach shows that it is possible to design policy instruments at the plot level to reduce pollution from farming, but this would require specific data. In general, agronomic information is detailed but economic information is not available in plot-level data or for too small a sample for economic analyses. In particular, the price of output (wheat in our example) and expenses on mineral fertilisers for each plot would be needed to fine-tune the shadow price computation and investigate alternative policy measures, such as a tax on mineral fertilisers.

Further analyses could compare the yield loss incurred by farmers in the case of an extension of the Nitrates Directive and the case of a tax on fertilisers. Collecting additional economic information in the SAPM survey would be possible, as would matching SAPM data with economic databases such as the Farm Accountancy Data Network (FADN). In France, such matching is rarely carried out. It has, for example, been done to investigate pesticide reduction (Jacquet et al., 2011) but remains to be implemented in the case of fertilisers.

Overall, plot-level analysis can complement farm-level analysis, even more when information about the variation among plots within farms exists. Having such information implies extensive surveys where all farm plots are investigated.

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