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The Sources of Slow Declines in Agricultural Nutrient Leakage: Evidence From Sweden

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ABSTRACT

We apply index decomposition methods to decompose nitrogen and phosphorus leakage trends from Swedish arable land. The results show considerable heterogeneity; changes in nutrient pollution coefficients (kg leakage/SEK of crop value produced) and crop rotations caused leakage to increase in some areas and decrease in others. Crucially, we find only modest pollution-decreasing technique effects, mainly driven by increased yields rather than reductions in per-hectare nutrient leakage. We argue that lax regulation of agricultural pollutants is one determining factor behind these results. Despite an increased focus on environmental considerations in agricultural policy, the cost of emitting has remained low.

JEL Classification: Q15, Q53

1 | Introduction

The present agricultural policy landscape is largely a result of historical trajectories (De Schutter 2017; Conti et al. 2021). In the early 1970s, strong population growth together with weak progress in productivity came to shape a 'productionist' policy approach in many parts of the world, largely neglecting agriculture's impact on the environment. Over recent decades, there has been a shift to promoting production techniques that provide environmental services other than food and reduce polluting emissions (Swinton et al. 2006; Zhang et al. 2007)—but progress has been relatively modest. In this paper, we focus on nitrogen (N) and phosphorus (P) leakage from agricultural land, which continues to exceed critical levels in most EU regions (European Environment Agency 2019) and other parts of the world. There is consensus among scholars that current agricultural N and P loads to the environment constitute a severe global issue that requires rapid action (Kanter, Bartolini, et al. 2020; Kanter, Chodos, et al. 2020; Richardson et al. 2023). To better target policy measures, an important initial step is to understand what lies behind the leakage trends, which is the objective of this paper. We apply state-of-the-art decomposition methods (Levinson 2009, 2015) adapted to the agricultural sector to break down N and P leakage from Swedish arable land between 1995 and 2011 into possible sources behind the leakage trends observed. The results could guide policymakers regarding why past environmental policy measures have not had a more substantial effect, and what type of regulation is required to push the leakage of N and P from arable land to sustainable levels.

Following the seminal work by Grossman and Krueger (1991), a general practise among economists has become to decompose the possible sources of changes in pollution flows into *scale, technique and composition effects* [see for instance Shapiro and Walker (2018)]. We follow this convention, but to adapt the analysis to the arable farming sector, we subdivide the scale effect into *extensive* and *intensive* scale effects, denoting the sum of these as the *compound scale effect*. The first effect relates to the hectares cultivated, while the second pertains to crop yields. Our novel approach contributes to the agricultural economics literature on structural change by analysing the impact of structural change on agricultural pollution. Most existing studies in this area typically focus on the other direction, such as the effect of climate change and subsidies on farm structure [see, for instance, Etwire et al. (2019), Neuenfeldt et al. (2019), Wimmer et al. (2024)]. To illustrate how the four effects of the decomposition analysis operate in the context of nutrient leakage and arable farming, consider the simple hypothetical example in the next paragraph.

Imagine the world consisting of a single field split between the cultivation of barley and wheat—causing polluting flows of nutrient leakage to surrounding waters—and an uncultivated part. We notice that the nutrient leakage from the cultivated area has decreased by 5% over the past 10 years, and decided to study the sources behind this change. First, we observe that the farmer decreased the size of the cultivated area by 3%. If neither cultivation technologies nor area shares of crops changed over the study period, this would imply a 3% decline in nutrient leakage, defined as the *extensive scale effect*. But total harvests (in value terms) actually increased by 1% over the period, hence there must have been an overall intensity increase of 4% (= 1 − (−3)) throughout the field. Again, holding everything else fixed (including leakage per kg crop produced), this would lead to a 4% increase in nutrient leakage, which constitutes the *intensive scale effect*. Furthermore, by analysing cultivation technologies used, we note that the farmer moved towards precision farming (Finger et al. 2019), leading to a decrease in kg nutrient leakage per SEK of crop value produced. Empirically validated models of the relationship between cultivation technologies and leakage show that these changes—all else equal—would lead to a nutrient leakage decline of 4%, defined as the *technique effect*. Finally, we observe that the farmer increased the area share of wheat, which had a negative impact on nutrient leakage since wheat production generates less nutrient leakage per hectare than barley. By utilising what we already know, we can calculate the size of this *composition effect* as: $-5-(1-4)=-2$. That is, if the compound scale effect and the technique effect were held constant, nutrient leakage would decline by 2% over the period. Hence, in general terms, the scale effect has to do with changes in the overall scale of production, the technique effect with changes in the farmers' production technologies such as changes in sowing time, catch crop usage and N use efficiency, and the composition effect with alterations in the mix of commodities produced, together explaining changes in pollution flows over time.

Previous decomposition literature studying manufacturing industries and air pollutants shows that scale effects generally increase pollution (Levinson 2009, 2015; Brunel 2017; Ustyuzhanina 2021). At the same time, technique effects lead to substantial reductions, resulting in overall steady air pollution reductions from manufacturing over time. With regard to Swedish crop farming, the data shows that the area of arable land in Sweden follows a decreasing trend, from 3.8 million hectares (ha) in 1919 to 2.6 million hectares in 2011 (Swedish Board of Agriculture, Statistics Sweden 2012)[1] and, with a few exceptions, total harvests (in tonnes) for the most common crops have declined since 1990 (calculated using data from the Swedish Board of Agriculture's statistical database, www.statistik.sjv.se). Given absent or small scale effects, and if technological progress followed the same pattern as in the manufacturing sector, we would expect to see a steep and continuous fall of N and P leakage from Swedish arable land. Instead, the gross load of N and P—i.e., N and P passing through the root zone on agricultural land reaching surface water and groundwater before retention processes exert their effect—displays a fluctuating trend over our study period, 1995–2011.[2]

The fluctuations in the nutrient trends are concerning as agriculture is responsible for most of the gross anthropogenic load of nutrients to the sea in Sweden: around 40% and 50% of N and P, respectively, originate from agricultural land (Hansson et al. 2019). And, regardless of the measures implemented so far, Sweden has not reached its environmental quality objective concerning eutrophication ('Zero Eutrophication') nor the environmental goals in the EU Water Framework Directive (Directive 2000/60/EC) (The Eutrophication Inquiry 2020). This pattern conforms to global trends: the planetary boundaries literature argues that aggregate biochemical flows of N and P from agriculture are far beyond sustainable levels (Richardson et al. 2023). Hence, the results of our decomposition analysis are relevant beyond Sweden's borders.

Decomposition methods are very helpful to gain a basic understanding of the sources behind pollution trends. However, these methods are not well established in the agricultural economics literature, nor have they been widely used to study the sources behind N and P loads from agriculture. One reason behind the latter observation is likely due to the difficulty of identifying and measuring diffuse pollutants, which is why the few existing studies use indirect measures of nutrient leakage, e.g., fertiliser consumption (Cai et al. 2018; Fujii et al. 2016). The closest related study that we have identified is one by Wier and Hasler (1999). They apply the related 'input–output structural method' to decompose the total change in N loading from various economic sectors in Denmark into emission factor effects, input mix effects and effects from the mix and level of final commodity demand. Agricultural N loading was assessed by estimating a nitrogen budget for Danish agriculture and then calculating the residual from all N inputs and outputs. Wier and Hasler (1999) conclude that Danish agriculture was responsible for the main bulk of N discharge over the study period (the mid-1960s to the late 1980s), mainly explained by increased leaching per unit of production.

In this study, we use soil and crop-specific spatial data on annual leakage measured in kg N or P per hectare of arable land to decompose N and P leakage from Swedish arable land. The data, referred to as leakage rates, was simulated by a soil science calculation system (Johnsson et al. 2022) and has not been used in an economic context before. The calculation system consists of two model packages, one for each of N and P, parameterised and tested by cross-checking with measurement data on nutrients from several different field trials under various conditions using different production techniques. We also use annual data on crop prices (SEK/kg), yields (kg harvest/ha and year)—controlled for temporary weather conditions—and area shares (ha) for the crops produced during the period analysed. Our results show that composition effects play an important role in explaining changes in N and P leakage over time. Moreover, we find no evidence of industry-wide technological improvements reducing leakage coefficients. Where leakage per SEK of crop value falls, it is largely due to higher productivity per hectare, not lower leakage per hectare.

The rest of the paper consists of six sections. Section 2 describes the index decomposition method, and Section 3 presents the data and its application in the analysis. Section 4 reports the results, followed by Section 5, which provides robustness checks. Section 6 discusses the results in the context of the existing environmental and agricultural economics literature and their policy implications. Lastly, Section 7 concludes.

2 | Methods

In the following sections, we present the formal decomposition method and the indexes used to calculate the technique effect.

2.1 | The Decomposition Method

The decomposition methodology allows us to attribute changes in total N and P leakage from arable land to *intensive* and *extensive scale effects*, *technique effects* and *composition effects*. Formally, following Levinson (2009, 2015), we define the total leakage, Z, of N or P in each region and year (with region and time subscripts omitted to ease notation) as the sum of leakage generated from each crop variety produced, z_i (for $i = 1, \ 2 \ldots n$). In turn, this equals the sum of each crop variety's value share, $\left(\theta_i = v_i / V\right)$, multiplied by a leakage coefficient reflecting (N or P) leakage per SEK of value shipped from the production of a specific crop, $\left(\phi_i = z_i / v_i\right)$, that is

$$Z = \sum_i z_i = \sum_i v_i \phi_i = V \sum_i \phi_i \theta_i. \tag{1}$$

The total value of agricultural crop produced, V, could be further disaggregated by defining total hectares cultivated, α (equal to the sum of hectares cultivated per crop) and average crop value generated per hectare, $Y = V / \alpha$. Hence, for each region, we have that

$$Z = V \sum_i \phi_i \theta_i = \alpha \left(\frac{V}{\alpha}\right) \sum_i \phi_i \theta_i = \alpha Y \sum_i \phi_i \theta_i. \tag{2}$$

Expressing Equation (2) in vector notation, it transforms to

$$Z = \alpha Y \phi' \theta, \tag{3}$$

where ϕ and θ are $n \times 1$ vectors containing the leakage coefficients and respective value shares for each of the n crop varieties. By totally differentiating Equation (3), we obtain the following expression:

$$dZ = Y \phi' \theta d\alpha + \alpha \phi' \theta dY + \alpha Y \theta' d\phi + \alpha Y \phi' d\theta. \tag{4}$$

Equation (4) lets us describe the change in total leakage of N or P, dZ, in a region as a function of (1) extensive scale effects, (2) intensive scale effects, (3) technique effects and (4) composition effects, represented by the four terms on the right-hand side. We estimate the magnitude of the four respective effects by considering the change in Z from altering one effect while holding the other three constant. The two scale effects and the technique effect are calculated directly, while the composition effect is calculated as a residual. From considering Equation (1), the residual composition effect is retrieved by calculating the predicted total leakage, $\hat{Z}$, holding each crop variety's value share, θ_i, constant:

$$\hat{Z} = V \sum_i \phi_i \bar{\theta}_i. \tag{5}$$

Any change in $\hat{Z}$ over time is exclusively explained by the compound scale and technique effects, meaning that the difference between the actual leakage, Z, and $\hat{Z}$ must be attributed to the composition effect.

One effect is always the residual in this particular methodological approach, as all four effects should sum to the total change in leakage, dZ, over the years studied, ensuring aggregation consistency. In practice, we could have calculated the composition effect directly and the technique effect as a residual, as is done in the early manufacturing decomposition literature due to a lack of annual pollution data [e.g., in Levinson (2009)]. We do not pursue this option, as we have disaggregated annual leakage rate data and are particularly interested in technique effects. If the technique effect was calculated as the residual, any unobserved changes would be attributed to it, which we want to avoid. There are several index decomposition approaches to choose from, each with inherent advantages and disadvantages. Ang and Zhang (2000) and Ang (2015) survey the most common methods, discussing their uses and properties. One method that has gained significant popularity over the last couple of decades is a variant of the logarithmic mean Divisia index method, known as 'LMDI I', owing to its attractive properties: being perfect in decomposition (i.e., without any residual term) and consistent in aggregation (Ang and Liu 2001). We assess the impact of using the multiplicative LMDI I. A comparison of results reveals mostly small deviations from our main findings. (Detailed results are presented in Section 5.2).

2.2 | Index Calculations for Directly Calculating the Technique Effect

To calculate the technique effect, we follow Levinson (2015) and apply the widely adopted additive Laspeyres and the additive Paasche index methods, whose original purposes are to measure current prices or quantities in relation to those of a selected base period. These indexes isolate the impact of a variable by allowing that specific variable to change, while holding the other variables at their respective base-year values (Ang and Zhang 2000). The reason for constructing both of these indexes is that, while the Laspeyres index traditionally tends to overstate the role of the technique effect, the Paasche index tends to understate it; hence, constructing both of these indexes serves as a robustness check. It also gives additional insight into the potential bounds of the technique effect.

Following the standard definition used in the manufacturing decomposition literature, the Laspeyres index entails, in our context, comparing the actual leakage of N and P in 1995 to what the current leakage would have been had the crop-specific leakage coefficients changed since 1995, but the compound scale and composition remained unchanged.

By defining the base year 1995 as year 0, we calculate the Laspeyres indexes, with leakage coefficients instead of prices or quantities, for each region, nutrient (N and P) and year (t) according to the following equation:

$$I_t^L = \frac{\sum_{i=1}^{n} \phi_{i,t} \cdot v_{i,0}}{\sum_{i=1}^{n} \phi_{i,0} \cdot v_{i,0}}, \tag{6}$$

where $\phi_{i,t}$ is the leakage coefficient for crop i in year t (the year of comparison), $v_{i,0}$ is the total value generated from crop i in the base year, 0, and $\phi_{i,0}$ is the leakage coefficient for crop i in the base year. From Equation (6), a positive (leakage-increasing) technique effect ($I_t^L > I_0^L$) is defined by increases in leakage coefficients between the base year 0, and t, weighted by crop production revenues in year 0.

Calculating the Paasche indexes follows the same procedure as above except that current-period weighting is used instead, resulting in the following equivalent equation for the Paasche index:

$$I_t^P = \frac{\sum_{i=1}^{n} \phi_{i,t} \cdot v_{i,t}}{\sum_{i=1}^{n} \phi_{i,0} \cdot v_{i,t}}. \tag{7}$$

Using these indexes enables explicit analysis of the role of changes in leakage coefficients in the observed leakage trends. Appendix A, in S1, provides further details on how the indexes are used to calculate the technique effect in our specific context.

3 | Data

This section presents the data, its sources, the data management and aggregation processes and the final datasets used to perform the decomposition analysis.

3.1 | Area Cultivated, Yields, and Crop Prices

To calculate the total value of crop production in each region over the entire study period, we use year and region-specific information on the area distribution of crops and crop yields, provided by Statistics Sweden (www.scb.se). Statistics Sweden is responsible for official, and other government statistics in Sweden. We obtain these data from Blombäck et al. (2014), and references therein, since the same information also serves as a part of the total input data for the leakage rate simulations. Moreover, we use nominal crop prices from 2005 (roughly in the middle of the study period) to calculate production values for each crop and year in the main analysis, and actual deflated crop prices in an alternative analysis as a robustness check (reported in Appendix B, S1). Large fluctuations in crop prices over time are the fundamental motivation behind this approach. Prices of agricultural commodities are historically more volatile compared to, e.g., manufacturing prices (Jacks et al. 2011). That is, the prices fluctuate unrelated to the characteristics of the commodities, e.g., due to temporary weather conditions and policy, which could distort the interpretation of the results.

We obtain crop price data and output price indexes from the Swedish Board of Agriculture's statistical database (www.statistik.sjv.se). The Swedish Board of Agriculture provides annual average prices for the most significant groups of crops in terms of total value (SEK) generated (Swedish Board of Agriculture 2021). (Additional descriptions of how the crop price data is collected and managed are provided in Appendix C, S1). There is no price data available for ley since ley is, above all, used as an intermediate input in the farmer's production process, i.e., as fodder to livestock, as opposed to being sold on a market. Instead, we use a constant average ley price (SEK/kg dry matter) calculated based on a sample of values from 2005.[3] To test the robustness of this assumption, we analysed how the results were affected by using either the minimum or maximum ley price observed, and the results were similar to our main analysis.

3.2 | Leakage Rates

By using simulated nutrient leakage data (Blombäck et al. 2014, and references therein), we are able to derive year, region, crop and soil-specific leakage coefficients (kg N or P/SEK and year), allowing us to calculate the technique effect directly—and separately from composition effects. Evidently, the first-best choice would be to use actual measurement data of nutrient discharges from Swedish arable land but, unfortunately, there is no such comprehensive data available, the reason being that N and P leakage constitute non-point source pollutants. That is, nutrient leakage does not originate from a single discrete source but from several diffuse ones and is spatially distributed in many ways, e.g., through leaching, land runoff and precipitation, making it hard (and costly) to determine from which specific field the leakage originates. To overcome this problem, scholars have developed advanced soil science modelling systems to attribute measured downstream nutrient flows to specific sources. The data on N and P leakage used in this study have been simulated from such a modelling system, called NLeCCS (Nutrient Leaching Coefficient Calculation System) (Johnsson et al. 2022), first developed in the 1990s but undergoing continuous improvement.

The data generated by NLeCCS estimates the *actual* N and P leakage from Swedish arable land in a given year, as this cannot be measured directly for the reasons previously mentioned. If the simulations are perfect, they should replicate the measurement data, where such data is available. To accomplish this, a vast amount of relevant (actual) data is used to parameterise the model system and to make it accurately estimate how different factors affect actual leakage levels of N and P (Johnsson et al. 2022). The simulated leakage rates are chiefly used to evaluate the fulfilment of the Swedish eutrophication target and for official reporting of Sweden's nutrient load on surrounding seas to the Helsinki Commission HELCOM (an intergovernmental organisation and a regional sea convention in the Baltic Sea area). Hence, they must serve as good proxies for actual nutrient flows by capturing how such physical flows respond to changes in the field and its surroundings, e.g., when new production technologies are introduced. Note that this study is limited to arable land, but in principle, all land gives rise to nutrient leakage, so decreasing the arable land area to zero does not imply zero nutrient leakage. In the official reporting of total N and P leakage from Swedish agricultural land, this is accounted for by including the 'background leakage' from agricultural land (Johnsson et al. 2022). The calculation system has been developed by testing it vis-à-vis results from conducted field experiments in different parts of the country (Johnsson et al. 2022). Field experiment outcomes have also been utilised to enable simulation of how the different kinds of cultivation measures and techniques used in Swedish crop farming, e.g., tillage measures, buffer strip usage and fertilisation techniques, affect leakage of N and P from arable land.

The N leakage represents the annual root-zone leakage, and for P, both annual root-zone leakage and loss through surface runoff. Put differently, the leakage consists of N and P that have left the agricultural system, regarded as the arable land's gross load of N and P on surface water and groundwater before retention processes. The leakage is simulated using a long period of weather data to mimic the normal expected climate, and based on this, annual leakage rates are calculated as multi-year averages (Johnsson et al. 2022). This methodological approach allows for filtering out the extensive impact on leakage levels from temporary weather conditions. Hence, leakage rates calculated using this approach serve as a preferred basis for analysing the effect of different cultivation measures on N and P losses, whereas comparing actual nutrient leakage between individual years could be misleading.

In practice, to estimate the nutrient leakage in NLeCCS, Sweden is divided into 22 leakage regions depending on regional characteristics, e.g., long-term climate, crop varieties, harvests and fertilisation and cultivation regimes. For each region, year-specific leakage rates are calculated for several combinations of crops (11 varieties including fallow), soil-texture classes (10 types), slope classes (3 types) and soil-P content (3 types: low, medium, high) (Johnsson et al. 2008). The latter two are only relevant for P, included by calculating leakage rates for different field slopes and soil P concentrations. Subsequently, leakage equations are estimated using multiple linear regression, allowing for inclusion of the impact of ground slope and P soil content for the leakage of P from arable land (Johnsson et al. 2022).

Input data to the simulations consist of annual regional-level statistics on, for example, yields, average yearly precipitation and fertiliser and manure applications, crop distribution per soil type, total hectares of catch crops, buffer zones and where spring tillage is applied. Some data, for example on nitrogen fixation, are only available on a more aggregate level and have therefore been adapted to the 22 region disaggregation. Thus, the leakage rates account for changes in individual farm behaviour, but only at an aggregate level, since they ultimately constitute averages. The yield data (from Statistics Sweden) is constructed from actual yields observed, but controlled for temporary weather conditions, meaning they are the yields to be expected given normal weather conditions. Hence, the expected yields change from year to year depending on changes in cultivation trends (e.g., alterations in farming techniques, crop varieties and fertilisation regimes), but not from, for example, a temporary heat wave (Johnsson et al. 2022). By using the expected yields data as 'target yields' in NLeCCS, yields are subsequently estimated endogenously by the model. Again, the main goal is to make the modelling system mimic what *actually* happens within the Swedish arable farming sector, and thus to nutrient leakage levels, over the years.

The role of livestock in arable land leakage is indirectly considered through the leakage calculations: first, the distribution of ley (consisting of pastures and meadows used to produce, for example, silage for livestock) indicates animal density, which impacts total leakage levels in different regions; second, statistics on regional-level average fertilisation regimes are used as input data in the simulations, and a higher share of land applied with manure implies a higher presence of livestock (Johnsson et al. 2022). Specifically, for each crop and region, information about the area shares applied with (i) mineral fertilisation, and (ii) manure fertilisation with complementary mineral fertilisation, is used. The area not fertilised is distributed proportionally between these two forms. N and P flow from point sources at the farm, such as dunghills, are not included and should not induce additional leakage since these are strictly regulated. The leakage calculations also include hectares of organically farmed arable land, where an increase in the share of organic arable land affects simulated leakage rates through a decrease in commercial fertiliser usage and an increase in manure applications. By 2011, almost 12% of arable land was cultivated using organic practices.

The leakage data is expressed in kg per hectare and year, and comparable calculations are available for 1995, 1999, 2005, 2007[4], 2009 and 2011, allowing us to see trends and trend changes over the study period. Data for 2019 exists but is not comparable to earlier data due to significant modelling advancements made after 2011. However, the leakage pattern has remained relatively stable between 2011 and 2019, and leakage rate reductions mainly occurred between 1995 and 2005, underscoring the relevance of the present analysis. The data includes leakage rates for the 10 most common crops produced in Sweden in terms of the number of hectares: spring barley, winter wheat, ley (temporary meadows for mowing or for pasture), sugar beets, winter rape, oats, spring wheat, rye, spring rape and potatoes (food and starch potatoes), and for fallow. The leakage rates for fallow equals the mean leakage from stubble and green fallow. Overall, the data covers around 92% of the total area of arable land in Sweden during the study period. Crops produced on $<1\%$ of the total area of arable land, unspecified crops, land used to crop grass for seed, and unused ley or arable pasture are not included in the leakage rate simulations due to their low prevalence.

Note that fallow land does not generate any direct revenue and is in this study purely regarded as a farming technique to allow for the land to recover and thereby improve the profitability of the cropping system, which indeed is its original purpose. Section 5.1 includes a discussion of this assumption. Accordingly, we attribute the N and P leakage from fallow to the production of the crops (except for ley, since fallow is not typically in the same crop rotation as ley) based on the crops' respective area shares.

3.3 | Leakage Groups

Initially, we perform the decomposition analysis—using both the Laspeyres and the Paasche indexes—on a regional level for the 22 different leakage regions. The regions were subsequently grouped according to the official classification of Sweden into three national areas ('RO') depending on natural conditions that significantly influence agricultural viability [Figure 7, Johnsson et al. (2022)]. The baseline grouping was then further refined by disaggregation into five groups[5], enhancing the group consistency concerning crop types, yield levels and results (Figure 1 presents the final groups). The main motivation for aggregating the regions into groups is to present results that are as disaggregated and informative as possible while minimising the need to exclude data for computational reasons; sometimes, crops are only cultivated for one or a couple of years, leading to zeros in the data, which bias the index calculations for the technique effect. By merging regions into the preferred groups, we almost entirely solve this problem because the regions then complement each other such that a crop is always produced in at least one region every year. As a result, we do not have to make as many adjustments to the data. The only adjustment in the group-wise decomposition analysis was to exclude three crops cultivated for one year: winter rape from Group C, winter rape from Group D, and potatoes from Group E. They accounted for 1.17%, 0.15% and 0.01% of the total area of arable land in their respective groups during the year cultivated. To present decomposition results for each of the 22 regions separately, we would have to exclude significantly more data to avoid the zero problem. This approach would make the results unclear and also less informative as some regions contribute only a small share of Sweden's total agricultural production.

After merging the regional data into the five groups, we perform the decomposition analysis (again), but for each group instead. The

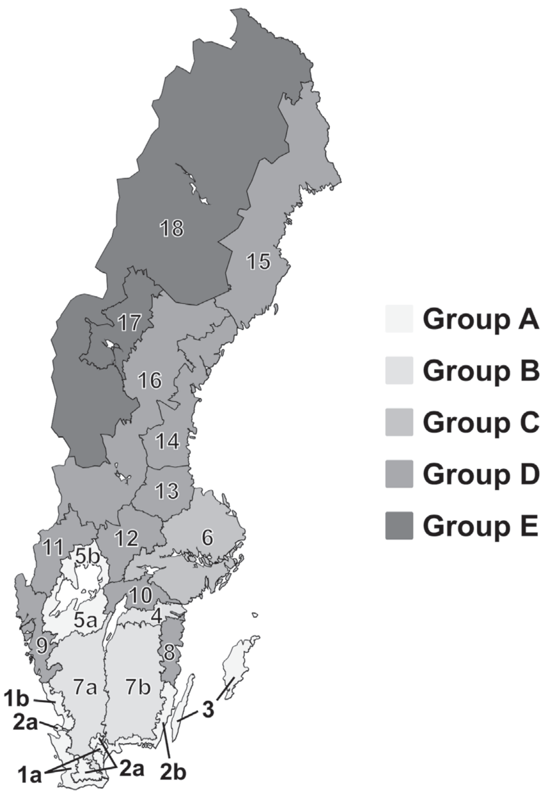

FIGURE 1 | Leakage regions and groups. *Source:* Redesigned based on Figure 7 in Johnsson et al. (2022). NLeCCS—a system for calculating nutrient leakage from arable land, p. 13.

TABLE 1 | Division of groups, area shares (percentage of the total number of hectares), value shares (percentage of total production value in SEK), and the number of crops produced during the period.

Group divisions	Area share (%)	Value share (%)	No. of crops
Group A: 1a, 1b, 2a, 2b, 3, 5a, 5b	38	46	10
Group B: 4, 7a, 7b	18	19	9
Group C: 6	21	16	7
Group D: 8, 9, 10, 11, 12, 13, 14, 15, 16	21	18	8
Group E: 17, 18	2	1	2

division of groups together with their respective area shares, value shares and number of crops produced are reported in Table 1. Region 6 stands out from the rest of the regions with its increase in N leakage 1995–2011 and is, therefore, its own group. We also decompose the leakage of N and P for Sweden as a whole, which did not require any crop exclusion since each crop was always produced in at least one region during a particular year.

3.4 | Final Datasets and Data Application

Table 2 presents the final dataset for Group A, containing all the information required to perform the decomposition analysis of N and P for this group. The structure of the final datasets is consistent for all groups, and also across different levels of analysis—regional, group-wise, or national—the only difference is the level of data aggregation. In this section, we detail how the data is applied and how the different effects in the decomposition analysis are calculated using the dataset for Group A. (Complete datasets at the group and national levels, along with the decomposition analysis using the Laspeyres index method, are available in Data S1). We start by calculating the technique effect, which isolates the impact on nutrient leakage levels from changes in the farmers' production technologies over time. To calculate the information needed to deduce the technique effect for N and P, we started by condensing the data (presented in Section 3) to the same level, i.e., according to year, crop and region. The leakage rates are, however, more disaggregated as they constitute a matrix with soil-type specific leakage rates (for each year, crop and region). Since the other data needed to perform the decomposition analysis is more aggregated—because there is no yield data at the soil-type level—we aggregated the leakage rates for the different soil types and each pollutant into weighted averages. Thus, the leakage rates constitute weighted averages, according to prevalence (area shares) of different soil texture classes, over the leakage rates in a region. These weighted leakage rates for N and P were then used to calculate the region's total annual leakage per crop. In turn, total regional leakage levels were aggregated according to the groups presented in Table 1 to construct crop, year and group-specific leakage coefficients, $\phi_{i,t}$. These coefficients were subsequently used in the index calculations (Equations 6 and 7). The index calculation results for group A are displayed in Columns a and b (Laspeyres), and Columns c and d (Paasche), in Table 2. To obtain the final expression for the technique effect, we subtract 1 (the index value in the baseline year) from each year's index value and then multiply the result by 100 to express it in percentages. The resulting value is interpreted as the technique effect's contribution to the change in leakage between a particular year and the baseline year (1995). For instance, following these calculations, the technique effect contributed to an 18.0% reduction in total N leakage from arable land in Group A between 1995 and 2005 since $(0.820 - 1) \times 100 = -18.0$.

The intensive scale effect is calculated by comparing the value generated per hectare (in SEK) in each year to the value per hectare in 1995 (the baseline year). For example, between 1995 and 1999, the intensive effect contributed to a 1.3% decline in total N and P leakage since $((6666/6754) - 1) \times 100 = -1.3$. The procedures for calculating the extensive scale effect and the percentage changes in total N and P leakage relative to the 1995 levels, dZ_t, are the same. However, for these calculations, we use the annual data on total hectares cultivated (Column h) and total leakage (Columns f and g). Note that the compound scale effect equals the sum of intensive and extensive scale effects. Finally, we subtract the scale effects and the technique effect from dZ_t to derive the residual composition effect for each year. The composition effect shows what the N and P leakage trends would have looked like in each year of analysis, had scale and technique effects remained at their 1995 values, but the mix of crops produced would have been allowed to change according to what is observed in the data (as illustrated in Equation 5).

4 | Results

Table 3 presents the results of decomposing the N leakage from arable land between the two endpoints in the data: 1995 and 2011. For the technique effect, both Laspeyres and Paasche indexes are reported. Since the composition effect is calculated as a residual, its magnitude depends on the choice of the index used for estimating the technique effect.

From considering Figure 1 together with Table 3, a quite clear geographical pattern in the results may be detected. In Group A, which contains the regions with Sweden's most fertile soils, we observe a modest negative technique effect of 17.3% (Laspeyres index) and 15.5% (Paasche index) between 1995 and 2011, ceteris paribus (Columns 3 and 4 in Table 3). In other words, if scale (extensive and intensive) and composition were held constant over this period, N leakage would have declined by around 15%–17%. While the technique effect is negative, the composition effect is positive, indicating that the group shifted towards producing more leakage-intensive crops. Holding scale and technique effects constant, annual leakage of N would have increased by 5.7% according to he Laspeyres index and 4.0% according to the Paasche index.

TABLE 2 | Final dataset used to perform the decomposition analysis for Group A.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Year	I_t^L **(N)**	I_t^L **(P)**	I_t^P **(N)**	I_t^P **(P)**	**Value/ha (SEK)**	**N leakage (t)**	**P leakage (t)**	**Area (ha)**
1995	1	1	1	1	6754	31,709	412	978,748
1999	0.979	0.973	0.967	0.970	6666	31,397	417	961,774
2005	0.820	0.922	0.816	0.909	6805	27,086	398	958,305
2007	0.861	1.024	0.839	0.987	5950	26,806	403	953,222
2009	0.823	1.001	0.797	0.966	6304	27,160	410	942,684
2011	0.827	0.888	0.845	0.896	7294	28,077	391	907,080

TABLE 3 | Decomposition of N leakage from arable land, 1995–2011.

	(1)	(2a)	(2b)	(3)	(4)	(5)	(6)
				Laspeyres	**Paasche**	**Laspeyres**	**Paasche**
	Δ Total leakage	**Ext. scale**	**Int. scale**	**Technique**		**Composition**	
Group A	−0.115	−0.073	+0.074	−0.173	−0.155	+0.057	+0.040
Group B	−0.176	−0.118	+0.115	−0.102	−0.042	−0.071	−0.131
Group C	+0.102	−0.053	+0.111	+0.155	+0.209	−0.111	−0.165
Group D	−0.210	−0.073	+0.049	+0.086	+0.078	−0.272	−0.264
Group E	−0.183	−0.107	+0.011	−0.039	−0.049	−0.048	−0.037
Sweden	−0.120	−0.076	+0.081	−0.093	−0.068	−0.031	−0.057

Note: Column 1 reports the percentage change in N leakage from arable land for each group and Sweden as a whole compared to 1995. The total leakage is decomposed into extensive scale (2a), intensive scale (2b), technique and composition effects by applying the Laspeyres (3 and 5) and the Paasche (4 and 6) index methods.

Since we use relative prices in the calculations, this reflects actual production shifts and is not a result of price changes.

In Group B, both technique and composition effects contributed to an overall decrease in N leakage 1995–2011, although the technique effect is even weaker than in Group A. The pattern of leakage-decreasing technique effects switches strongly for Group C, for which we see a positive technique effect of 15.5% by the Laspeyres index and 20.9% by the Paasche index (all else equal). The technique effect is positive also for Group D, but the most salient is the negative composition effect of −27.2% and −26.4%, respectively, responsible for the absolute majority of the decline in leakage of N. For Group E, which only accounted for 1% of the total value produced, both technique and composition effects are small and lie between −3.7% and −4.9%. Contrary to the other groups, a down-scaling of the crop sector is the most determinant source of the change in N leakage in Group E, driven by negative extensive scale effects (decreased area of arable land), and the total change in N leakage was −18.3%. On a national level, the intensive scale effect was positive, while the extensive scale, technique and composition effects contributed to the total decline in N leakage of 12.0%. (Note that the compound scale effect was close to zero).

Table 4 reports the results from the decomposition of P leakage from Swedish arable land between the data endpoints (1995 and 2011). The overall pattern is very similar to the one we observe for N, but the percentage decrease in P leakage was weaker compared to N for Groups A, B, D, and E and total leakage decreased for all groups regarding P, including for Group C. In general, technique effects were even more modest in magnitude for P, but signs of the effects were nevertheless the same as in the decomposition analysis of N for all groups except for Group C, where the technique effect was negative (−1.3%) using the Laspeyres index. In other words, we do not observe particularly sharp distinctions in what explains the change in N and P leakage within a specific group. The same holds for Sweden as a whole, but the decline in P was smaller than for N, and so are the effects. For additional insights into the sources driving changes in leakage over time, see Figure 2. It shows the decomposition of changes in N (Panel a) and P (Panel b) leakage between each observational year, and the baseline year 1995, for Sweden as a whole (using the Laspeyres index). For example, Panels a and b suggest that something changed the Swedish crop farmers' decision environment between 2005 and 2007 leading to: a negative (leakage-decreasing) intensive scale effect (for both N and P);

TABLE 4 | Decomposition of P leakage from arable land, 1995–2011.

	(1)	(2a)	(2b)	(3)	(4)	(5)	(6)
				Laspeyres	Paasche	Laspeyres	Paasche
	Δ Total leakage	Ext. scale	Int. scale	Technique		Composition	
Group A	−0.052	−0.073	+0.074	−0.112	−0.104	+0.059	+0.052
Group B	−0.115	−0.118	+0.115	−0.067	−0.041	−0.045	−0.071
Group C	−0.052	−0.053	+0.111	−0.013	+0.001	−0.098	−0.111
Group D	−0.153	−0.073	+0.049	+0.060	+0.039	−0.189	−0.168
Group E	−0.177	−0.107	+0.011	−0.015	−0.026	−0.066	−0.055
Sweden	−0.090	−0.076	+0.081	−0.071	−0.056	−0.024	−0.040

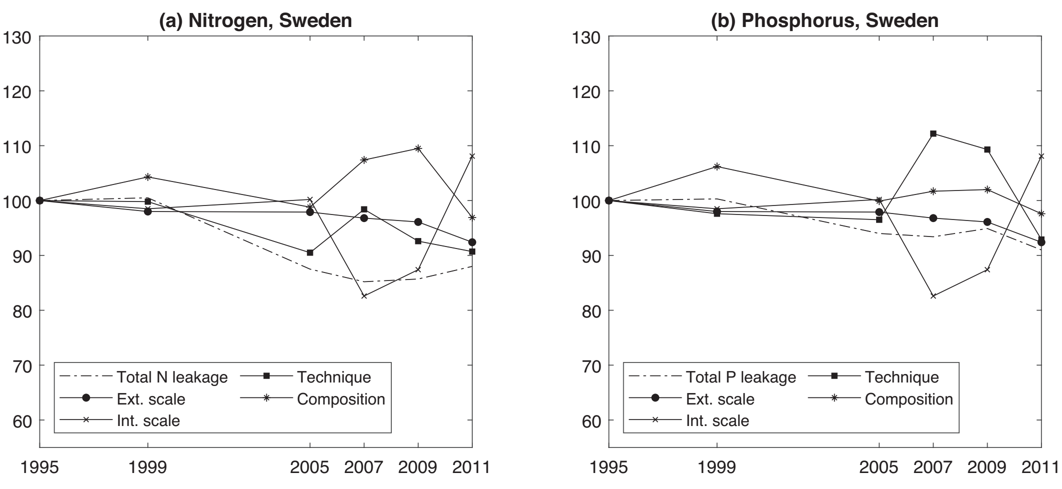

FIGURE 2 | Decomposition of N and P leakage from Swedish arable land, 1995–2011, on an aggregated level. Values are indexed such that 1995 = 100. The technique effect is calculated using the Laspeyres index.

TABLE 5 | Group-wise changes in hectares (ha) of fallow land, arable land and arable land excluding fallow along with percentage changes in total area of arable land for each group 2007–2009.

Change 2007–2009	Group A	Group B	Group C	Group D	Group E
Δ ha fallow land	−51,048	−20,393	−33,138	−21,940	−774
Δ ha arable land	−10,538	+3104	+5433	−13,521	−1737
Δ ha arable land excl. fallow	+40,510	+23,497	+38,571	+8419	−963
% Δ ha arable land	−1.1	+0.7	+1.1	−2.5	−4.1

Note: Own calculations based on the same data as is used in the decomposition analysis (Blombäck et al. 2014, and references therein).

a positive (leakage-increasing) composition effect for N; and a positive (leakage-increasing) technique effect concerning P.

On the impact of the direct estimate of the technique effect from using the Laspeyres or the Paasche index methodology, we observe some mixed results. Tables 3 and 4 report that the Laspeyres index gives larger improvements (smaller deterioration) in leakage coefficients (kg N or P/SEK produced and year) compared to Paasche for Groups A, B and C. The case is the opposite regarding Groups D and E. Analogous to what Levinson (2015) finds for US manufacturing, it implies that leakage coefficients decreased the most for the crops whose value shares grew the most, in terms of shares of total output value, in Groups D and E. The reverse holds for A, B and C.

Concerning scale effects, we observe the same pattern throughout the country, i.e., negative extensive, and positive intensive, scale effects with compound scale effects close to zero except for Groups C and E where they are +5.8 and −9.6, respectively. (The sign pattern is the same for the alternative decomposition analysis using actual deflated crop prices, but the size of the intensive scale effect differs). On a national level, the area of arable land decreased by 7.6% over the study period (extensive scale effect), but the compound scale effect is slightly positive (0.5%), explained by an overall intensity increase on Swedish arable land of 8.1%. There are two possible explanations behind these results: (i) Swedish farmers became more productive over time, i.e., they managed to produce more (kg) output per hectare, or (ii) the farmers shifted to producing crops with relatively higher prices. An analysis of crop yield changes for the different regions, and of the nominal crop prices in 2005, suggests that the first explanation is likely the most critical, but the latter also has some impact.

5 | Robustness

In this section, we analyse the results' sensitivity to assumptions made and methodological choices. First, we study how fallow land is handled in the analysis. Second, we perform the decomposition analysis using an alternative index approach.

5.1 | Including Leakage From Fallow Land

The total leakage of N and P from fallow land is attributed to the production of crops (except for ley), which allows us to account for its leakage in the decomposition analysis. The justification behind this assumption is that fallow mainly is a cultivation measure to improve the profitability of the cropping system. But, during the study period, arable land could also lie fallow for other reasons, such as to fulfil requirements in the CAP. Until 2008, the EU had a requirement that a certain amount of arable land used for food and fodder production should lie fallow or, alternatively, be used for the production of, for example, energy or protein crops (Swedish Board of Agriculture 2008). Some farmers with particularly profitable cereal production chose to convert old meadows or utilise buffer strips and headlands for perennial fallow instead (Swedish Board of Agriculture 2006). If the removal of the set-aside requirement in 2008 caused such areas to drop out of the data set, and if the leakage from these areas was significant, the observed reduction in N and P leakage could lead to misleading conclusions regarding the clean-up of nutrients from agriculture. An evaluation by the Swedish Board of Agriculture (Swedish Board of Agriculture 2008) shows, however, that the absolute majority of fallow land area was not determined by the mandatory set-aside obligation but by the profitability of production. Table 5 shows that between 2007 and 2009, a large part of the decrease in fallow land was met by an increase in cropland, and the total amount of arable land increased in absolute terms for Groups B and C (accounting for 39% of the total area of arable land). In sum, a share of the fallow land likely dropped out of the data set because it was converted to land uses not counted as arable land, but this circumstance was probably limited and happened only in certain regions.

5.2 | Implications of Using the Multiplicative LMDI I Methodology

To further analyse the robustness of our main results (Tables 3 and 4) with respect to the choice of index method, we perform a decomposition analysis for N and P in this section using the multiplicative LMDI I method (data and MATLAB code are available in 'Data S1'). Similar to the Laspeyres and Paasche indexes, the LMDI I method allows for consistent aggregation of effects. In addition, it satisfies the necessary conditions for perfect decomposition, whereby the results do not include a residual term (Ang and Liu 2001). The formula for calculating each respective effect, with all results expressed in index form (this is only the case regarding the technique effect in our main analysis), can be written as

$$G_{x_t} = \exp\left[\sum_i \frac{L\left(Z_i^t, Z_i^0\right)}{L\left(Z^t, Z^0\right)} \ln\left(\frac{x_i^t}{x_i^0}\right)\right], \tag{8}$$

where G_{x_t} is the value of effect x in year t, and Z_i^0 represents the total leakage from crop i in the baseline year (1995 in our case). It follows that Z^0 denotes the group's total leakage of N or P in that same year. The ratio $\left(x_i^t / x_i^0\right)$ contains the specific data used to calculate each effect (according to what is explained in Equation 3).[6] In addition, $L(\cdot)$ is the logarithmic average of two positive numbers, a and b, given by

$$L(a,b) = \begin{cases} \dfrac{a-b}{\ln a - \ln b} & \text{for } a \neq b \\ a & \text{for } a = b \end{cases}$$

facilitating consistency in the aggregation of effects, i.e., ensuring that the product of all indexed effects yields the total change in leakage between the two time periods studied.

A comparison of the LMDI I and Laspeyres index decomposition results reveals overall good consistency, regardless of the index type applied, with no changes in value signs (Tables 6 and 7). For most effects and groups, deviations are smaller than one percentage point. The results are particularly consistent concerning extensive and intensive scale effects (where underlying data is aggregated to the group level). The largest deviation is found for group B concerning N, where the technique effect is 2.9 percentage points smaller (in absolute terms) for the LMDI compared to the Laspeyres index. Nevertheless, the overall deviations are relatively minor, and contrary to what is often highlighted as a limitation of the Laspeyres method, using the Laspeyres index methodology does not consistently leave a larger residual term compared to the LMDI I method.

6 | Discussion

This section discusses the potential reasons behind the spatially heterogeneous results and the comparatively weak technique effects.

6.1 | Explanatory Factors Behind the Spatial Heterogeneity

Our results demonstrate that the scope of the technique effect, and whether it was leakage-increasing or decreasing, depends on which geographical location is under study. Results from Johnsson et al. (2008), studying a more limited period (1995–2005), provide some insights into why this might be. They show that changes in N efficiency were one of the main reasons behind the geographical variation in technique effects regarding N. In groups A and B, where overall technique effects were distinctly negative (see Table 3), annual yields increased for most crops, while fertiliser inputs typically stayed constant. In contrast, annual yields for most crops were stable or declined over the period in groups C and D—in which technique effects contributed to a surge in N leakage—whereas fertiliser input increased or remained unchanged. The introduction of catch crops also explains a significant part of the region-wise variation in technique effects for N, where an intensified use of catch crops contributed to declining N leakage (Johnsson et al. 2008). Concerning P leakage, the results are not as clear, but variations are potentially explained by changes in fertilisation supply and buffer strip usage across regions.

TABLE 6 | Comparison of N decomposition results 1995–2011 using the Laspeyres index and the multiplicative LMDI I methods.

	Δ Total leakage	Ext. scale		Int. scale		Technique		Composition	
		Laspeyres	LMDI I	Laspeyres	LMDI I	Laspeyres	LMDI I	Laspeyres	LMDI I
Group A	−0.115	−0.073	−0.072	+0.074	+0.079	−0.173	−0.163	+0.057	+0.058
Group B	−0.176	−0.118	−0.115	+0.115	+0.127	−0.102	−0.073	−0.071	−0.109
Group C	+0.102	−0.053	−0.054	+0.111	+0.117	+0.155	+0.177	−0.111	−0.113
Group D	−0.210	−0.073	−0.072	+0.049	+0.052	+0.086	+0.079	−0.272	−0.251
Group E	−0.183	−0.107	−0.102	+0.011	+0.006	−0.039	−0.044	−0.048	−0.054
Sweden	−0.120	−0.076	−0.075	+0.081	+0.086	−0.093	−0.081	−0.031	−0.047

TABLE 7 | Comparison of P decomposition results 1995–2011 using the Laspeyres index and the multiplicative LMDI I methods.

	Δ Total leakage	Ext. scale		Int. scale		Technique		Composition	
		Laspeyres	LMDI I	Laspeyres	LMDI I	Laspeyres	LMDI I	Laspeyres	LMDI I
Group A	−0.052	−0.073	−0.073	+0.074	+0.079	−0.112	−0.108	+0.059	+0.062
Group B	−0.115	−0.118	−0.116	+0.115	+0.129	−0.067	−0.054	−0.045	−0.062
Group C	−0.052	−0.053	−0.055	+0.111	+0.118	−0.013	−0.006	−0.098	−0.098
Group D	−0.153	−0.073	−0.072	+0.049	+0.052	+0.060	+0.046	−0.189	−0.171
Group E	−0.177	−0.107	−0.102	+0.011	+0.006	−0.015	−0.020	−0.066	−0.070
Sweden	−0.090	−0.076	−0.075	+0.081	+0.087	−0.071	−0.063	−0.024	−0.034

Additionally, an analysis of yield statistics reveals that divergent trends in annual yields played a central role in explaining the heterogeneity in technique effects for both N and P over the entire study period (1995–2011). Yield changes depend on many factors, including shifts in production technologies. Farmers' technology choices, in turn, are shaped by multiple influences; behavioural differences among farmers may be a key underlying explanation for the spatial heterogeneity observed in the scope and direction of the technique effect. The existing literature has shown that factors such as culture and personal values play a crucial role in farmers' production decisions (Wuepper et al. 2023), including their willingness to adopt less polluting production techniques, and the compensation rate required for such adoption (Zemo and Termansen 2022). Regional variations in the availability, type and quality of extension services are also likely to have a significant impact.

Another explanation behind the different sizes and directions of effects could be spatially-specific policy changes, affecting cultivation choices. In Sweden, nutrient usage within agriculture is mainly regulated through legislation of which the EU Nitrates Directive (Council Directive 91/676/EEC) is a central governing legal document. It states that areas that drain into polluted waters or waters at risk of pollution due to agricultural activities should be appointed Nitrogen Vulnerable Zones (NVZs) (www.environment.ec.europa.eu) (indirectly relevant for P too), giving rise to spatially heterogeneous environmental regulations, e.g., regarding where and when fertilisation is allowed. However, a comparison of the group-level results from the decomposition analysis and areas designated as NVZs since 2003 (when the NVZs increased from their 1995 level) shows no clear relationship. For example, in groups A and C, almost the entire area constituted NVZs in 2003 but technique and composition effects go in different directions in the two groups. In addition, in most parts of group B and in groups D (except for regions 8 and 9) and E, we have no NVZs but, nevertheless, the effects differ substantially. This suggests that the NVZs have little impact on the aggregate pattern in farmers' production choices.

6.2 | Why Do We Observe Weak Technique Effects Within Agriculture?

The results show no indication of industry-wide technological improvements leading to cuts in nutrient leakage coefficients. For the crops and regions where we do see falling leakage per SEK of crop value produced, this is to a great extent attributed to increased productivity per hectare, and not reduced leakage per hectare. Since the decomposition analysis results are descriptive rather than causal, they do not provide insights into the impact of specific policies on pollution levels. Nor can we infer dynamic interactions or non-linear relationships between factors. Although the decomposition does not explain why changes occur, possible reasons can be discussed. Here, we explore three conjectural explanations for why the Swedish crop sector exhibits modest pollution-decreasing technique effects, corresponding to an average technique effect of at most 0.6% per year for N and 0.5% for P. These are tentative explanations—grounded in theory and existing evidence—but require further research for confirmation. The first potential reason is biased technological change, i.e., an exogenous bias in technological development (not linked to policy) towards clean technology in some sectors, such as manufacturing, but not in agriculture. The second is that considerable nutrient pollution regulations have been imposed in agriculture, but the sector's marginal abatement cost (MAC) curves are steep. More precisely, the elasticity of pollution flows to the cost of polluting is low, resulting in a poor response of agricultural leakage levels to stricter regulation. And, the third explanation—which we argue for—is that policy raising the cost of polluting remained comparatively lax in the agricultural sector.

Regarding the source of technological change, extensive empirical evidence shows that directed price signals have been determinant for making manufacturing firms engage in clean-technology innovation and move away from pollution-intensive production processes (Popp 2002; Aghion et al. 2016; Shapiro and Walker 2018). For instance, Shapiro and Walker (2018) show that progressively more stringent environmental regulations for criteria air pollutants in the Clean Air Act, rather than exogenous bias in technological change, account for most of the pollution cuts in the US 1990–2008. While the implicit tax for criteria pollutants doubled over this period, the shadow price for the unregulated pollutant CO_2 stayed more or less constant, and so did CO_2 emission levels.

If there had been a bias in technological change towards clean production technologies in the agricultural sector, we could, for example, have expected to observe a widespread adoption of precision agriculture. Precision agriculture involves using new technologies and data to account for the natural variabilities across the field to tailor management to site, crop and environmental characteristics (Finger et al. 2019). The concept of precision agriculture gained prominence in the early 1990s, yet no substantial regulations or support schemes were introduced under the CAP between 1995 and 2011 to encourage its adoption. Despite considerable interest from European (and American) policymakers and researchers, its uptake remained limited, with no widespread adoption across Europe during the study period (Noor et al. 2005; Zarco-Tejada et al. 2014). Large-scale implementation of precision farming technologies in the agricultural sector is still lacking (Finger et al. 2019).

Turning to the second possible reason explored, previous studies do not suggest generally steep MAC curves within the agricultural sector; MAC curves concerning nutrients are typically convex, i.e., the rate of abatement costs increase as the abatement level rises (Johansson et al. 2004; Helin et al. 2006; Schmidt et al. 2021). From using farm-optimisation models and a sample of 3400 heterogeneous Swiss farms, Schmidt et al. (2021) find that a 20% reduction of N surplus from Swiss agriculture (~20 thousand tonnes) would cost around USD 6/kg N under a quota scheme, whereas a 50% reduction (~55 thousand tonnes) implied a marginal abatement cost of approximately USD 36/kg N reduced. The authors conclude that abatement costs for reducing N surplus differ greatly depending on farm type; average MACs were lowest for arable farms, i.e., farms predominantly cropping cereals, and highest for special-crop farms (growing vegetables, fruit and vines). MAC curves for arable farms—which we study—were flat and began slightly below zero on average as a result of optimisation, i.e., some farms could reduce their N surplus without income losses. In essence, flat MAC curves within a specific sector imply that the pollution elasticity to the cost of polluting is high, i.e., pollution flows respond strongly to a tightening of environmental policy.

The arguments outlined above suggest that the third potential reason may be important in explaining the weak technique effects observed, i.e., continued lax regulation of nutrient leakage from arable farming. This is an interesting finding given that Sweden's efforts to make the agricultural sector more sustainable are relatively ambitious compared to the global average [see the database provided by Wuepper et al. (2024)]. With respect to the policy framework governing nutrient pollution from agriculture (mainly regulated by the EU Nitrates Directive as previously mentioned), there have been many policy additions and adjustments affecting Swedish farmers over the study period, but there is little or no evidence that these have significantly increased farmers' incentives to reduce N and P leakage. Rather, the existing literature suggests that inadequate regulation of agricultural pollutants is an important cause behind the modest technique effects (Elofsson 2012; Ollikainen et al. 2019; Brady et al. 2022). Specifically, the general design of nutrient reduction programmes—and implementation of existing abatement measures—is considered poor, and available policy instruments, such as voluntary agri-environmental schemes, are not judged cost-effective (Ollikainen et al. 2019; Brady et al. 2022). The conclusions are similar regarding US agriculture; Kanter and Searchinger (2018) argue that voluntary adoption of production techniques that reduce nitrogen pollution has not caused any significant improvements and is not likely to accomplish the efficiency improvements needed. Meanwhile, agricultural economics literature using bio-economic modelling to examine the impacts of changes in fertiliser input prices on crop farmers' economic decisions and nutrient leakage, such as Mérel et al. (2014), finds that introducing nitrogen taxes on fertiliser use could achieve significant reductions in nitrogen leaching at a low social cost.

The above policy discussion raises an important question: why has stricter regulation, e.g., more direct price signals, not been implemented to address nutrient discharge from agriculture? A possible explanation is that the historical 'productionist' approach in agricultural policy is obstructing a transition to a more sustainable agri-food sector today (De Schutter 2017; Conti et al. 2021). It has been shown that historical strategic choices and conditions are hard to let go of, i.e., a strong path-dependency or lock-in effect is prevailing, stemming from the co-evolution and dependency of different parts of the food system. Another contributing factor is the inherent characteristics of diffuse pollutants, which invoke challenges to policymakers, including high monitoring costs. This relates to the underlying information asymmetry between emitters of non-point source pollution and environmental regulators concerning volumes emitted and abatement efforts (Xepapadeas 2011; Kanter, Chodos, et al. 2020). Environmental damages of non-point source pollutants are also expected to differ across locations (Keiser and Shapiro 2019). Therefore, uniform policies to reduce nutrient pollution, e.g., taxes, might need to be complemented by policies tailored to local conditions and individual pollution elasticities, as suggested in previous literature (Goetz et al. 2006; Keiser and Shapiro 2019; Brady et al. 2022). Beyond physical spatial differences, it is also important to consider behavioural heterogeneity among farmers, as it influences their production decisions and, consequently, the impact and effectiveness of agri-environmental policies (Dessart et al. 2019; Wuepper et al. 2023).

7 | Concluding Remarks

The persistently high loads of N and P from agriculture to the environment are a much considered global issue, yet we see little progress. In this paper, we use spatially disaggregated leakage rate data to decompose the sources behind N and P leakage trends from Swedish arable land, 1995–2011. By illuminating why N and P leakage from arable land is not decreasing more rapidly, the results could contribute to better-targeted policy measures within and outside of Sweden.

We demonstrate considerable differences between regions concerning magnitudes and directions of technique and composition effects. Crucially, we do not observe a general reduction in per hectare leakage of N and P from arable land in Sweden. Compared to other sectors of the economy, such as manufacturing, our results indicate that technique effects in the agricultural sector are substantially weaker in terms of decreasing impacts on pollution. We argue that a failure to efficiently regulate pollution from agriculture is one of the central explanations behind this difference, which supports the literature stressing that the direction of technological change responds strongly to economic incentives. Directed regulation and taxation are needed to ensure a shift towards cleaner technologies. For such policies to be effective, they may also need to be accompanied by regulations tailored to farm-specific characteristics.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The main data and code files are available in 'Data S1', and the complete material is readily available upon request. These data were retrieved from the following publicly available reports: Johnsson et al. (2008), Johnsson et al. (2009), Mårtensson et al. (2010), and Blombäck et al. (2011, 2014).

Endnotes

[1] Arable land is defined as the area of land with temporary crops as part of crop rotations, temporary meadows for mowing or for pasture

and land temporarily fallow. The area of arable land included in our analysis accounted for around 85% of total agricultural land in Sweden during the years studied (own calculations based on data from Statistics Sweden, www.scb.se).

[2]The gross load of N from Swedish agricultural land decreased by approximately 10% from 1995 to 2009 but rose again by around 3.7% from 2009 to 2011 (Ejhed et al. 2011). The gross load of P declined by almost 9% between 1995 and 2011 in total but increased during a period between those years. After 2005, there was only a small reduction in the discharge of P.

[3]The average ley price is calculated based on 18 observations retrieved from a study analysing ley cropping revenues (used as fodder) from a series of field trials with ley lying for 3 years.

[4]The N and P leakage rates have been interpolated linearly for 2007 because comparable simulations of leakage rates were not available for this year.

[5]A decomposition (using the Laspeyres index) at the three-group level was also performed, with results presented in Appendix D, S1. Since the data aggregation—and therefore the calculations—differ, the results are not directly comparable to the analysis at the five-group level but we still find significant heterogeneity across groups, with technique effects being small or even leakage-increasing in some parts of the country. The five-group analysis is preferred as it offers more disaggregated and clear results.

[6]Hence, we have (x^t / x^0) in Equation 8 instead of (x_i^t / x_i^0), when calculating extensive and intensive scale effects since the underlying data is at the group, and not crop, level.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.