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Analysing Organic Eco-Scheme Uptake in Sweden

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LIST OF ABBREVIATIONS

AEI	Agri-Environmental Indicator
AECS	Agri-Environmental and Climate Scheme
AES	Agri-Environmental Scheme
BISS	Basic Income Scheme for Sustainability
CAP	Common Agricultural Policy
EU	European Union
EC	European Commission
ES	Eco-Scheme
LCA	Life Cycle Assessment
OECD	Organisation for Economic Co-operation and Development
OVB	Omitted Variable Bias
SFDI	Shannon Functional Diversity Index
SBA	Swedish Board of Agriculture
SFA	Swedish Forest Agency
SMHI	Swedish Meteorological and Hydrological Institute
SS	Statistics Sweden
TSLs	Two Stage Least Squares

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“And read carefully: don’t be content with a general overview — and don’t agree too quickly with every chatterer.” Marcus Aurelius’ Meditations 1:7.

1. Introduction

The Common Agricultural Policy (CAP), which is adopted and implemented by all member states in the European Union (EU) is the backbone of agricultural policy within the EU. For the period 2023-2027, the CAP introduces so called eco-schemes (ES) as part of the 1st pillar budget to further facilitate reaching climate and environmental objectives for European agriculture (Dupraz & Guyomard, 2019; Jongeneel & Gonzalez-Martinez, 2023; Poppe & Koutstaal, 2020). The previous CAP has been criticized for not allocating enough of the budget to environmental- and sustainability objectives (OECD, 2022), and the ES are introduced to further improve on this matter (European Parliament, 2021). The increased focus on environmental sustainability in agriculture is in line with the far-reaching strategies EU Green Deal and the Farm-to-Fork strategy. Fundamental to the ES are that they are compulsory for the member states to offer, but voluntary for the farmers to adopt (European Parliament, 2021).

The budget allocation for the ES in Sweden is around 600 million € or 6914 million SEK, which corresponds to roughly 11.5% of the budget for the strategic plan (The Swedish Government, 2022). In the Swedish strategic plan, there are three different ES; support for organic production, support for cover crops and spring cultivation, and support for planning of precision agriculture (The Swedish Government, 2022). Now, with the first year of ES having ended, the first evaluations with real observational data are possible to conduct. The need to evaluate the eco-schemes' effectiveness, efficiency and impact on environmentally related goals is hence urgent to facilitate design of policy modifications. This thesis focuses particularly on the how the introduction of the organic production ES has affected farmers' uptake of environmentally sustainable practices and their impact on environmental indicators in Sweden.

Evaluating the policy effects already after one year of the planned duration is early and limits the availability of relevant high-quality data. However, quick policy responses require examining the newly implemented measure as soon as possible. In the pursuit of developing good agricultural policy, this thesis conducts an early-stage evaluation of the organic ES implementation. Conducting an early-stage evaluation is important to enable the development of policy modifications that better fulfill the objectives during the rest of the policy duration. The novelty of this early-stage evaluation is one factor that legitimizes the chosen research topic for this thesis.

1.1 Problem Formulation

The Swedish strategic plan for CAP 2023-2027 includes three general goals where the second one concerns positive environmental externalities from agriculture including carbon sequestration, sustainable production and biodiversity (The Swedish Government, 2022). One official ex-ante evaluation of the strategic plan ordered by the Swedish Board of Agriculture has been presented (Denninger et al., 2021). The report concludes that there are insufficient evaluations of climate and environmental effects of the strategic plan. An additional ex-ante strategic environmental evaluation ordered by the Swedish Board of Agriculture proposes at least four improvements with regards to climate and environmental aspects where further analysis is required (Hilding-Rydevik et al., 2021). The highlighted lack of analysis of the environmental effects of ES compensations motivates and justifies the analysis in this thesis.

The analysis of support measure uptake is intricate in the case of ES as the schemes are developments of their predecessor measures in the previous CAP reform as Pillar 2 Agri-Environment and Climate Schemes (AECS). Notably, the ES compensation for organic production is a fusion of the two previous measures “compensation for organic production” and “transition to organic production” offered annually in contrast to the previous measures that required five-year contracts (Denninger et al., 2021). The fusion may have a risk-decreasing effect on farmers considering transitioning to organic production and could facilitate an increased support uptake (Ibid.), but no formal analysis on the effect on uptake has been conducted. It is also uncertain how moving environmental measures to Pillar 1, which is fully funded by the EU budget, affects the uptake in contrast to the AECS uptake belonging to Pillar 2 (Dupraz & Guyomard, 2019). One of the objectives of the EU Farm to Fork Strategy is an expansion of the European organic food production and expansion of the agricultural land cultivated organically to 25% of EU’s agricultural land (European Union, 2020). The coherence with such union strategies motivates and legitimizes the analysis performed in this thesis.

An expansion of the Swedish organic production at the expense of conventional agricultural expansion may come with unexpected and unwanted consequences (Denninger et al., 2021), which inspired this thesis to further examine the relation between proportion of organically farmed land and relevant environmental indicators.

1.2 Objective and Research Question

This thesis’ objective is to examine the effects of the introduction of the organic ES in the Swedish strategic plan for CAP 2023-2027 on farmers’ uptake of environmentally sustainable practices. It furthermore aims to put the findings into relation with reaching the EU’s

established climate and environmental objectives. Overall, the strive is to make a valuable contribution to the evaluation of the Swedish strategic plan for CAP 2023-2027 with regards to the first year of implemented eco-schemes.

The precise formulation of the research question is “*What are the effects of the new organic eco-scheme in CAP 2023-2027 on farmers’ uptake of organic agricultural practices and their environmental impacts in Sweden?*”.

1.3 Structure

This thesis is divided into different sections and sub-sections. Section two comprehensively summarizes the relevant academic literature on eco-schemes, their implementation in the EU and their effects on environmental performance indicators in European agriculture. Section three presents the data compilation process and the structure of the data. Section four presents the decisions relevant to the econometric modelling and the model specifications chosen to analyse the data. Section five presents the econometric model results and is followed by a discussion of the results in section six. The sixth section also proposes policy implications and further research. The final section summarises the findings and infers conclusions.

2. Literature Review

The ES discourse in academia is limited, most likely because of the novelty of the policy measure, which was first mentioned on the EU level in 2018. The current literature mostly consists of ex-ante analyses with simulations and predictions of outcomes of ES implementation in several member states. Furthermore, most journal articles on ES are explanatory and informational, rather than investigatory. Another category is empirical analysis based on changes after the implementation, but this category is unfortunately scarce as the availability of new data is restricted. First, this literature review covers the most prominent analyses and findings on the ES introduction published in academic journals and reports. Second, findings from the predecessor AECS are presented. Third, a section on environmental indicators in agriculture is added to give a background on the use of environmental indicators in agricultural policy analysis. Fourth, findings in the literature on environmental impacts of organic agriculture are presented.

2.1 Eco-Schemes in the Literature

Jongeneel and Gonzalez-Martinez (2023) highlight the heterogeneity in ES implementation among EU member states, as the member states have a far-reaching freedom to design their own implementation structure. A similar conclusion is made by Runge et al. (2022) who find that the number of individual ES offered among 15 member states ranges from 3 to 21. Nevertheless, ES may generally be described by an artificial market for ecosystem services with the national governments on the demand side and farmers on the supply side (Jongeneel & Gonzalez-Martinez, 2023). Given a price set by the government, farmers may decide to adopt a certain measure and production practice or not. The farmers whose additional costs incurred by following the environmentally sustainable practices are lower than the set price, will (in theory) adopt these measures and supply the ecosystem services. However, Latacz-Lohmann et al. (2022) present their concerns regarding over-subscription to certain ES as farmers are legally entitled to ES payments and cannot be denied participation in the offered schemes even when the demand for adopting these practices exceeds the allocated budget. In the Swedish context, the over-subscription concern could be irrelevant as the actual uptake rate of the ES are far below the goals established in the strategic plan and the payments size can be adjusted within a certain range to adapt to the demand (The Swedish Government, 2022).

Poppe & Koutstaal (2020) identify that the new ES could be perceived more attractive to farmers compared to the Basic Income Scheme for Sustainability (BISS) in Pillar 1 and their

conditionality requirements. The environmental cross-compliance requirements associated with the BISS support in the previous CAP version have shown to have low effects on environmental sustainability (Dupraz & Guyomard, 2019), and Poppe & Koutstaal (2020) suggest that the ES introduction constitutes a move from rules and compliance to monitoring and rewarding positive environmental results. They highlight the importance of ES giving the farmers the opportunity to improve the environmental sustainability of their enterprises and that the shift for voluntary measures to Pillar 1 can enable the adoption of more farmers and more land coverage.

Denninger et al. (2021), in the official ex-ante examination of the Swedish strategic plan, are positive to the new one-year contracts as they decrease the risks of the farmers as opposed to longer multi-year contracts. They expect an increased adoption and a larger coverage as an effect of the decreased risk. However, (Poppe & Koutstaal, 2020) are skeptical to the one-year contracts due to the loss of long-term targets and the implementation of long-term environmental strategies benefiting the environment.

2.2 Agri-Environmental and Climate Schemes in the Literature

In contrast to the availability of published works on ES, the pool of literature on the predecessors AECS and agri-environmental schemes (AES) is rich (Uthes & Matzdorf, 2013). Historically, measures designed to motivate farmers to engage in sustainable practices have been part of European policy since the 1980s (Ducos et al., 2009). Originally, such measures were separate from the CAP and voluntary for MS to offer. With the MacSharry CAP reform in 1992 and Agenda 2000, agri-environmental measures gradually became a part of CAP Pillar 2 and mandatory for MS to offer. However, European farmers have been reluctant to participate in the AES and the impact on European agriculture has been limited (Espinosa-Goded et al., 2010).

To facilitate a policy design that is more attractive to farmers, Espinosa-Goded et al. (2010) utilizes a choice experiment approach to analyze farmer's perceptions of design elements of the environmental measure. They find that farmers strongly prefer measures that do not restrict their current management strategies to a large extent, but higher compensation eases the reluctance to participate. In addition, Uthes & Matzdorf (2013) present factors limiting the attractiveness of the measure such as too strict and complicated management regimes, competition with other CAP measures and bureaucracy of agricultural authorities.

Instead of analyzing how the characteristics of the measure itself affects the uptake rate of the scheme, Lastra-Bravo et al. (2015) perform a meta-analysis identifying key characteristics of

the farmer affecting the willingness to participate in the EU AES. Their findings show that the main factors driving the adoption are compensation levels, higher off-farm income, age and education level, and the presence of a successor. Further on in this thesis, such factors are considered, if data are available, when analyzing the ES uptake. In contrast to the mentioned approaches to analyse farmers' participation, Bazzan et al. (2023) argue that contextual conditions, cooperation between stakeholders and trust-building mechanisms are necessary for successful implementation of European agri-environmental schemes. Attitudinal factors also play a critical role in farmer's willingness to adopt the schemes (Uthes & Matzdorf, 2013). These inherent attitudes could be skepticism towards authorities or unwillingness to try new practices.

2.3 Environmental Indicators for Agriculture

The Organisation for Economic Co-operation and Development (OECD) has developed a set of agri-environmental indicators (AEI) whose purpose is to serve as guidance for agricultural policy analysis (OECD, 1999; Parris, 2000). The environmental impacts of agriculture are of major concern for the objective of achieving sustainable food systems that can feed the global population without exhausting the natural resources required for production. The current OECD agri-environmental indicators are based on nitrogen balance, phosphorous balance, ammonia emissions, energy use and biofuel production, farm birds index, greenhouse gas emissions, pesticide sales, soil erosion, water quality, water resources, and agricultural land area (OECD, 2013). For the use in this thesis, relevant AEIs have to be identified and data compiled on municipality level. This proved to be challenging as the OECD AEI database only provides data on national level.

Schaak et al. (2023) suggest using the Shannon functional diversity index (SFDI), an alternative to the more commonly used Shannon index for crop diversity. In contrast to the original index where individual crops are treated separately, the functional version groups crops with similar characteristics with concern to environmental influence. The advantage of using the SFDI is that it accounts for crop species with more or less similar roles in the cropping ecosystem (Ibid.). Using the SFDI as an indicator of ecological biodiversity is suitable as a wider range of functional crop families could enhance the multifunctionality of the agroecosystem (Finney & Kaye, 2017).

2.4 Environmental Impact of Organic Agriculture

Comparing organic and conventional agriculture from an environmental perspective is beneficial when analyzing the individual impacts of the practices. Such comparisons can be made based on different units such as hectare-based or yield-based. It is thus important to pay

attention to the unit of comparison. In general, a multitude of findings support that environmental impacts per land area tend to be less in organic production but more in terms of production quantity (Meier et al., 2015; Tuomisto et al., 2012). In terms of yield of human metabolizable energy, the yield ratio of organic-to-conventional ranges from 0.43-0.74 over eight regions in Sweden (Connor, 2022). However, lower yields may be defended by lower harm on the environment. Additionally, Einarsson et al. (2022) claim that the results of Connor (2022) are inaccurate as they build upon the assumption that the organic and conventional crop mixes are fixed and the end-use of cereals is not considered. They argue that there is a high variation in organic farming practices and that different organic production systems can have very different environmental impacts.

(Meier et al., 2015) underscore further issues in the “organic VS conventional” literature. Often Life Cycle Assessment (LCA) is used to examine the environmental sustainability of products originating from organic and conventional agriculture. When reviewing 34 comparative LCA studies, the authors find that a wide range of resource efficiencies are reported for the two production practices respectively. Squalli & Adamkiewicz (2023) support that published literature in the organic academic discourse have mixed or even contradicting conclusions. However, environmental impacts per land area tend to be less in organic production but more in terms of production quantity. Nevertheless, comparative LCAs often fail to adequately distinguish the specific characteristics of organic and conventional agriculture, and the environmental impact categories often limited (Meier et al., 2015).

In a meta-analysis on studies comparing the environmental impacts of organic and conventional farming in Europe, (Tuomisto et al., 2012) find that organic farms tend to have higher soil organic matter, lower nitrogen leaching, and lower nitrogen oxide and ammonia emissions per land area. The same inferences cannot be made with environmental impact per production volume as reference point.

Without advocating for any of the agricultural production practices in particular, the EU has established the goal of increasing the share of organically farmed land. As such, this thesis analyzes the effectiveness and efficiency of the organic ES policy, not the specification of the policy objective itself.

3. Data

This section presents the nature of the data used and clarifies the data generation process. The choices of variables included in the regression model are discussed.

The compiled dataset is based on observations from Sweden's 290 municipalities from 2016-2023 and forms a balanced panel. For all municipalities, the key variable organic support uptake was requested and compiled from the Swedish Board of Agriculture (SBA).

Furthermore, data on explanatory variables related to agriculture such as yield levels, agricultural income, off-farm income, total arable land number of farms were compiled from the Swedish Board of Agriculture's statistical database. Data on normal values for temperature and precipitation levels were compiled from open weather station data from the Swedish Meteorological and Hydrological Institute (SMHI) and manually matched to the corresponding municipality. Data on population levels, total land- and water area were compiled from Statistics Sweden (SS) and forest related data were compiled from the Swedish Forest Agency (SFA).

3.1 General Data Description

The CAP ES for organic production, introduced the 1st of January 2023 nationwide, offers farmers financial support for organic agriculture. It is supposed to reduce the risks of practicing organic agriculture by compensating the additional costs associated with organic production (Denninger et al., 2021; The Swedish Government, 2022). Prior to the ES for organic production, compensation was offered through the AECS financed by the CAP Pillar 2 budget. The effects of switching the organic support scheme from Pillar 2 to Pillar 1 along with changing the name and some underlying parameters is not well understood. In 2022, before the introduction of ES, the average uptake rate of organic AECS of total arable land on municipality level ranged from 0 to 89.9% with a mean of 18.3%. In 2023, after the introduction of the organic ES, the application share of the total arable land ranged from 0 to 62.0% on municipality level with a mean of 17.0%. At first sight, the data may be interpreted to show a decrease in farmers' willingness to practice and apply for organic support. But confounding effects have to be considered and there could be an anticipation effect increasing the applications in the years leading up to the policy change. Hence, a more thorough investigation has to be conducted.

There was a considerable variation in the organic uptake rates between municipalities before the ES implementation, and so also after the implementation. Similar to Finkelstein (2005)

this geographic variation allows to identify the effect of the ES introduction separately from any underlying secular trend. Analogously to Finkelstein, a key criterion for using geographic variation in uptake rate to identify the impact of the ES introduction is that the previous AECS-equivalent was redundant of what the ES subsequently covered. This is to a large degree true in this case. With this reasoning, uptake rate of the previous AECS provides a good measure of the of the ES-equivalent uptake rate before the introduction of the actual policy.

Generally speaking, uptake rates for the organic support schemes are higher in small municipalities close to a bigger city and rural municipalities with poorer soil conditions and a high degree of perennial grass coverage. Lower uptake rates are generally found in municipalities with either excellent soil conditions, municipalities in cities with scarce arable land (naturally) and municipalities with really harsh climatic conditions. The geographic pattern in organic uptake is fairly stable over time.

Table 1: Variable Descriptions and Sources

Variable	Description	Unit	Source
Uptake rate	Fraction of land applying for organic ES of total cultivated land	Percent (%) of cultivated land	Own calculation based on compiled data
Organic area	Hectares of land applying for organic ES (after 22) and sum of land applying for organic compensation and transition to organic agriculture (before 2023)	Hectares (ha)	Requested from SBA
Total area	Total agricultural area in the municipality excluding natural pastures	Hectares (ha)	SBA
Number of farms	Number of registered farm enterprises		SBA
Average farm size	Agricultural area divided by number of farms	Hectares (ha)	Own calculation based on compiled data
Farm income	Taxed firm income	Swedish kronor (SEK)	SBA
Employment income	Taxed income from employment	Swedish kronor (SEK)	SBA
Average yield	Average harvest for conventional spring barley	Kilos per hectare (KG/ha)	SBA
Latitude	Latitude of the weather station best representing the municipality	Degrees north (°)	SMHI
Average temperature	Normal average temperature for the municipality	Degrees Celsius (°C)	SMHI
Average precipitation	Normal average precipitation for the municipality	Millimeters per year (mm/y)	SMHI
Population	Population in the municipality		SS
Population density	Population per km ²	Individuals per km ²	Own calculation based on compiled data
Pasture	Area of pasture land in the municipality	Hectares (ha)	SBA
Perennial grasses	Area of perennial grasses in the municipality	Hectares (ha)	SBA
SFDI	Shannon Functional Diversity Index for crop group diversity		Own calculation based on compiled data
Forest Owners	Forest Owners per municipality		SFA
Water area	Area of water bodies in the municipality	Km ²	SS
Water-Land-Ratio	Ratio of water to land in the municipality	%	Own calculation based on compiled data

Note: Data are compiled from 2016-2023. Abbreviations: Swedish Board of Agriculture (SBA), Statistics Sweden (SS), Swedish Meteorological and Hydrological Institute (SMHI), Swedish Forest Agency (SFA)

The municipality outcome variables chosen in this study are related to the environmental objectives of the ES. These AEI are coverage of cultivated perennial grasses, coverage of permanent pastures, and the SFDI. These indicators are chosen as they indicate different environmental qualities related to the environmental objectives of the Swedish strategic plan for CAP. Specifically the coverage of perennial grasses and the diversity index are in line with the results-indicators R14 and R31 in the Swedish strategic plan (The Swedish Government, 2022). The coverage of cultivated perennial grasses play an important role in reducing soil carbon depletion in the farming landscape and have additional benefits such as nitrogen fixation in the soil if legumes are included in the seed mix (J. Nilsson et al., 2023). The

coverage of pastures in the agricultural eco-systems is related to biodiversity and maintaining habitats for extinction threatened species (F. O. L. Nilsson, 2009). The SFDI is a common index used as an environmental indicator for biodiversity in the agricultural landscape. The choice of environmental indicators is deemed suitable for this thesis, but is not exhaustive. There are many more possible environmental indicators to analyse, but the novelty of this thesis comes with the disadvantage of scarce availability of data. Further environmental indicators to investigate in the future are proposed in the section 6.4 of the discussion.

In the variable Shannon Functional Diversity Index, eight crop groups were defined inspired by Nilsson et al. (2022) and are constructed as shown in table 2. The computation of the municipality level index score is based on the respective share of each crop group in the municipality according to the formula:

$$H^F = - \sum_{g=1}^k p_g * \ln(p_g) \quad (1)$$

Where k is the number of functional groups $g = 1, \dots, k$ and p_g is the area share of the functional group relative to the total agricultural area. The index ranges from 0 to $\ln(k)$ where 0 resembles a municipality with no crop group diversity and only one crop group dominates the agricultural landscape. The maximum value $\ln(k)$ represents a municipality where all k crop groups are cultivated in identical shares of the total available land (Schaak et al., 2023).

Table 2: Crop Group Descriptives

$g=1, \dots, k$	Crop family	Content
g ₁	Cereals	Wheat (Winter & Spring) Rye Barley (Winter & Spring) Oat Triticale (Winter & Spring) Mixed cereals
g ₂	Legumes	Yellow peas Field beans Green peas Brown Beans
g ₃	Forage crops	Perennial grasses (ley) Grass for seed harvest Green forage crops Maize
g ₄	Vegetables and sugar beets	Potatoes Starch potatoes Vegetables Sugar beets
g ₅	Oilseeds	Rapeseed (Winter & Spring) Turnip rapeseed (Winter & Spring) Flax
g ₆	Unspecified/other crops	Unspecified crops Other crops
g ₇	Energy crops	Trees for bioenergy
g ₈	Fallow	Fallow

The descriptive statistics of variables used in the econometric model are specified in table 3.

Table 3: Descriptive statistics of full data set

Variables	N	Mean	Std. Dev.	Min	Max
Uptake Rate	2320	0.17	0.14	0.00	1.21
Farm Size	2320	31.56	26.49	0.00	180.00
Farm Income	2320	86404.00	21208.24	40826.00	129469.00
Employment Income	2320	413803.00	24452.60	306735.00	462196.00
Yield	2320	4120.00	1302.75	1280.00	7400.00
Average Temperature	2320	-0.340	1.97	6.43	9.24
Latitude	2320	59.29	2.66	55.38	67.89
Average Precipitation	2320	688.50	147.30	396.20	1237.90
Population Density	2320	158.06	577.64	0.21	6420.39
Forest Owners	2320	1191.40	1051.85	0.00	7499.00
Water-Land-Ratio	2320	0.64	1.84	0.003	20.33
Perennial Grass	2320	3628.00	3663.00	0.00	36750.00
Pasture	2320	1580.20	2831.9	2.00	29730.00
SFDI	2320	0.91	0.32	0.00	1.55

One value stands out when observing the descriptive statistics, namely the maximum value of the organic support uptake rate. The reason why the maximum value of the organic support uptake rate is 1.21 or 121% is an outlier in a small semi-urban municipality where the area

applying for the support exceeds the existing arable land. To mitigate such anomalies, municipalities under a certain threshold of arable land are excluded from the regression analysis to avoid outliers found mostly in urban municipalities.

4. Methodology

This section formalizes the econometric approach applied in this thesis. To answer the research question stipulated in the introduction, the model design process has constituted a considerable effort to ensure the identification of the uptake effect of the ES introduction. Specific sub-sections are designated to the management of econometric challenges like unobserved heterogeneity, endogeneity and residual autocorrelation. The reasoning behind the choice of model specification is explained in depth and justified with literary foundation. The mechanics of the econometric approach are further specified in sub-section three.

Empirically, the strategy is to compare municipality outcomes before and after the ES introduction in areas of Sweden where the introduction had a larger effect on uptake rate of organic support, to areas where it had less of an effect. By nature, AECS uptake rates before the ES introduction are not randomly assigned. Hence, data on other confounding factors such as climatic conditions, geographical characteristics and municipality traits are necessary to explain the uptake rate variation across municipalities. The adequate econometric model is thus designed to identify the effect of the ES introduction by looking at the direction and significance of the changes in the level of the municipality specific environmental outcome variables around the time of the ES introduction in 2023.

In panel data econometrics, model designs are often centered around the dichotomy of fixed effect (FE) and random effects (RE) estimators. The specification test proposed by Hausman (1978) is commonly used to test whether a fixed or random effects model should be used but Baltagi (2005) argues that this is not an adequate approach. Instead, there are testable restrictions for the FE estimator that if satisfied motivates the adoption of the estimator (Ibid.). Mundlak (1978) argued that the RE estimator builds on the assumption of all regressors being exogenous with the individual effects. On the other hand, the FE model allows for some endogeneity in all regressors with the individual effects (Baltagi, 2005). In contrast to this polarized perspective, (Hausman & Taylor 1981) proposed a model allowing for some of the explanatory variables to be endogenous. There is a lot of literature on panel data estimation and how to manage endogeneity and the next sub-section aims to clarify the choices made for this thesis.

4.1 Endogeneity Management

First of all, the characteristics of the variable of interest *uptake rate of organic production support* are such that the level of this variable is made by farmers' choices. There is hence

reason to suspect that the uptake rate is correlated with the municipality-specific effects and the regression idiosyncratic error term due to individual municipality inherent traits. Inability to efficiently capture and account for these characteristics raises concern of omitted variable bias (OVB) and unobserved heterogeneity. If the uptake rate variable is correlated with the regression idiosyncratic error term, it is defined as an endogenous explanatory variable (Stock & Watson, 2020). There are no statistical procedures to directly test if an explanatory variable suspected of being endogenous is in fact correlated with the error term (Ullah et al., 2018). Additionally, “exogenous” variables may never truly be exogenous in non-experimental data (Ketokivi & McIntosh, 2017). Thus, researchers have to rely on their best judgement when dealing with the complexity of endogeneity and employ a rigorous statistical investigation accompanied by relevant literature analysis on research design.

In longitudinal data, endogeneity issues may also arise from correlated unobserved effects in addition to the non-zero correlation between idiosyncratic errors and explanatory variables (Semykina & Wooldridge, 2010). The latter can be caused by omission of relevant time-varying factors and require special consideration. The standard fixed effects procedure controls for omitted variables in time-invariant but entity-varying variables (Stock & Watson, 2020) so an extended framework has to be applied to mitigate or eliminate endogeneity issues related to the omission of time-varying variables. A portion of the unobserved heterogeneity can be controlled for by using the combination of entity fixed effects and time fixed effects regression (Ibid.). This is equivalent to controlling for entity-varying time-constant omitted variables such as cultural norms, and entity-constant time-varying variables such as national regulations or the organic support compensation in this case. Including both entity fixed effects and time fixed effects is a common approach in the economic literature, regardless the size of T and N, and is commonly called the “two-way fixed effects” (Wooldridge, 2021). Due to the expected unobserved heterogeneity, a two-way fixed effects approach is adequate and applied in this thesis to eliminate OVB arising from the issues mentioned.

However, the two-way fixed effect estimation doesn't solve the problem with the endogeneity in uptake rate. Such endogeneity would generate inconsistent and biased estimates (Baltagi, 2005). Hence, instrumental variable estimation with two stage FE is a common approach applied to deal with the issues associated with endogenous explanatory variables.

There are two formal conditions for a valid instrument in classical cross-sectional estimation. For an endogenous variable X, the instrumental variable Z must satisfy the following two requirements (Stock & Watson, 2020):

1. Instrument relevance: $\text{corr}(Z_i, X_i) \neq 0$.
2. Instrument exogeneity: $\text{corr}(Z_i, u_i) = 0$.

In the case with the organic ES uptake rate, a valid instrument for uptake rate in one municipality must be associated with reasons to practice organic agriculture, but must not be associated with the outcome variable in the second stage regression. Such suitable instruments are tested when performing the first stage regression to ensure that the instruments satisfy the underlying assumptions and are strong. Multiple instruments may together be jointly strong for a single endogenous variable.

Additional assumptions are required for instrument validity in panel data analysis as the error term contains an idiosyncratic part which is assumed to be IID, an entity-specific effect, and a time-specific effect. Hausman and Taylor (1981) propose a framework to manage both time- and entity-varying regressors and entity-varying regressors potentially correlated with the entity-specific effect. Such correlations make both OLS and generalized least squares (GLS) biased and inconsistent. The within estimator (FE) eliminates this issue by transforming the data to deviations from the entity-specific means. However, the within estimator is not efficient since variation within entities in the sample are lost (Ibid.). Amemiya and Macurdy (1986) propose an efficient instrumental variable estimator for error component models and Baltagi (2005) propose the efficient error component two stage least squares which requires the estimates of the variance components of the first stage.

In the following two stage procedure, the endogenous variable uptake rate is regressed on all instrumental variables and all exogenous variables in the first stage. The estimated values of the uptake rate in the first stage are substituted in the second stage regression to eliminate the endogeneity issue. The variables selected as instruments for uptake rate are the second lag of uptake rate itself, water-land-ratio in the municipality, population density and number of forest owners in the municipality. Special care is taken with regards to the second lag of uptake rate to ensure the assumption of no residual autocorrelation is not violated.

4.2 Residual autocorrelation

The presence of residual autocorrelation violates the classical assumptions of linear regression where errors terms must be independently and identically distributed errors. The consequence is biased and inefficient parameter estimates. For the purpose of this thesis, the potential residual correlation in the first stage regression is of particular interest as it dictates the validity of using the second lag of uptake as an instrument for uptake rate in time t .

If the error term in the first stage regression is autocorrelated, then the second lag of uptake rate is endogenous because the second lag of the error term is part of the second lag of uptake rate. However, if the autocorrelation function (ACF) and partial autocorrelation function (PACF) of residuals drop to zero after lag 1, then the second lag of uptake rate can be claimed to be exogenous and suitable as instrument. Such a scenario indicates that the residual can be represented as a moving average process of order one and is uncorrelated with the second lag of anything. The structure of the residual correlation has to be examined carefully and statistical tests for residual autocorrelation applied.

4.3 Model Specification

Considering the nature of the research question, the first stage regression has two specific purposes. To identify the year-specific effect on uptake rate and indicate the uptake effect of the new policy introduction (1), and generate estimated values of uptake rate that are exogenous in the second stage regression (2). With this in mind, the first stage regression is chosen to be a Mundlak (1978) specification including dummy year variables. In line with the Mundlak specification, the municipality specific means of the time-varying explanatory variables are included in the regression to address the potential bias arising from unobserved time-invariant heterogeneity. The second stage uses two-way FE estimation with the environmental performance indicator as dependent variable and the interaction between the first difference of estimated uptake and the year effects as explanatory variables of interest. The precise specification is:

First stage regression:

$$y_{it} = \beta X_{it} + \gamma \bar{X}_i + \delta W_i + \theta Z_{it} + \sigma \bar{Z}_i + \alpha_i + u_{it} \quad (2)$$

Where y_{it} is the uptake rate of organic support, X_{it} and \bar{X}_i are time-varying and the corresponding municipality-mean regressors. W_i are time invariant regressors and Z_{it} and \bar{Z}_i are time-varying instruments and their corresponding municipality-means. α_i and u_{it} are the time-invariant error and idiosyncratic error respectively. Even though this is an error component model, any correlation between the α_i and X_{it} has been absorbed by the intra-municipality means. The advantage of this approach is that the exogeneity assumption now only has to rely on the idiosyncratic error u_{it} .

The second stage regression is specified as:

$$\vartheta_{it} = \varphi_i + \rho_t + \sum_{t=2019}^{t=2023} \pi_t (\Delta \hat{y}_{it}) * D_t + \omega X_{it} + \varepsilon_{it} \quad (3)$$

Where ϑ_{it} is the dependent agri-environmental indicator, φ_i and ρ_t are municipality fixed effects and time fixed effects respectively. Dt are time dummy variables indicating the year. \hat{y}_{it} is the estimated uptake rate from the first stage regression.

The intuition of the model design is to compare the municipality level outcome variables in municipalities where the introduction of the ES had a large effect on the uptake rate to areas where the effect was low. That is the reason why the change in estimated uptake is used as regressor in the second stage. The key variables of interest are the interactions between the change in uptake rate and the year dummies. The coefficients of the interaction variable (π_t) indicate the estimated time pattern in the outcome variable in municipalities where the ES introduction had a larger impact on uptake rate, relative to municipalities where it had a smaller impact. These interaction coefficients can then be compared before and after the introduction of the ES and provide an estimate of ES' impact on the dependent variable. The model formulation does not privilege 2023 relative to other years for when any changes might occur as it allows the data to show anticipation effects.

For robustness, a Hausman-Taylor (Hausman & Taylor, 1981) model is also used to address the potential endogeneity issues. The model is specified accordingly:

$$y_{it} = \beta_1 X1_{it} + \beta_2 X2_{it} + \delta_1 Z1_i + \delta_2 Z2_i + \alpha_i + u_{it} \quad (4)$$

Where $X1_{it}$ is a ($n \times k_1$) matrix of observations on exogenous, time-varying variables assumed to be uncorrelated with both α_i and u_{it} . $X2_{it}$ is a ($n \times k_2$) matrix of observations on exogenous, time-varying variables assumed to be uncorrelated with u_{it} but possibly correlated with α_i . $Z1_i$ is a ($n \times g_1$) matrix of observations on exogenous, time-invariant variables assumed to be uncorrelated with both α_i and u_{it} . $Z2_i$ is a ($n \times g_2$) matrix of observations on exogenous, time-invariant variables assumed to be uncorrelated with u_{it} but possibly correlated with α_i . Addressing the municipality specific autocorrelation, the random effects transformation can be executed to modify the model to:

$$\widetilde{y}_{it} = \beta_1 \widetilde{X1}_{it} + \beta_2 \widetilde{X2}_{it} + \delta_1 \widetilde{Z1}_i + \delta_2 \widetilde{Z2}_i + \widetilde{\alpha}_i + \widetilde{u}_{it} \quad (5)$$

Where

$$\widetilde{X1}_{it} = X1_{it} - \hat{\gamma}_i \overline{X1}_i \quad (6)$$

and $\hat{\gamma}_i$ adjusts for the quasi-demeaning transformation. In contrast to the within transformation, $\widetilde{Z1}_i$ and $\widetilde{Z2}_i$ are not zero and δ_1 and δ_2 can be estimated. However, the time-invariant error is not eliminated and $\widetilde{\alpha}_i$ is correlated with the transformed $\widetilde{X2}_{it}$ and $\widetilde{Z2}_i$. The

mentioned correlation has to be managed with instrumental variables fulfilling the strict exogeneity and instrument relevance assumptions. The within-transformed $X2_{it}$ ($X2_{it} - \overline{X2_i}$) is a suitable instrument for $\overline{X2_{it}}$ as it is uncorrelated with α_i but correlated to $\overline{X2_{it}}$. For the potential time-invariant endogenous variable $\widetilde{Z2}_i$, within transformation is not appropriate since it will be eliminated if the municipality mean is subtracted. Here, the municipality-mean of the exogenous time-varying regressors ($\overline{X1_i}$) that are uncorrelated with the α_i , constitute adequate instruments.

Specifically for this thesis, the appropriate variables of each type of regressor are summarized in the table below.

Table 4: Hausman-Taylor estimation variables

Y_{it}	Environmental indicators SFDI, Perennial Grasses and Pasture
$X1_{it}$	D_i , Farm size, Farm Income, Employment Income and Yield Level, Population Density, Water-Land-Ratio, Forest Owners
$X2_{it}$	Uptake rate, instrumented by its demeaned version
$Z1_i$	Latitude, Average Precipitation and Average Temperature
$Z2_i$	Not applicable as we don't expect time-invariant endogenous regressors

5. Results

This chapter provides a summary of the results of the panel data estimation conducted in this thesis. Based on the reasoning about model selection provided in section 4, the regression results are divided into first stage regression output and the second stage performed on three different outcome variables. Additionally, the Hausman-Taylor model outcomes are presented in a separate table.

5.1 Regression Results

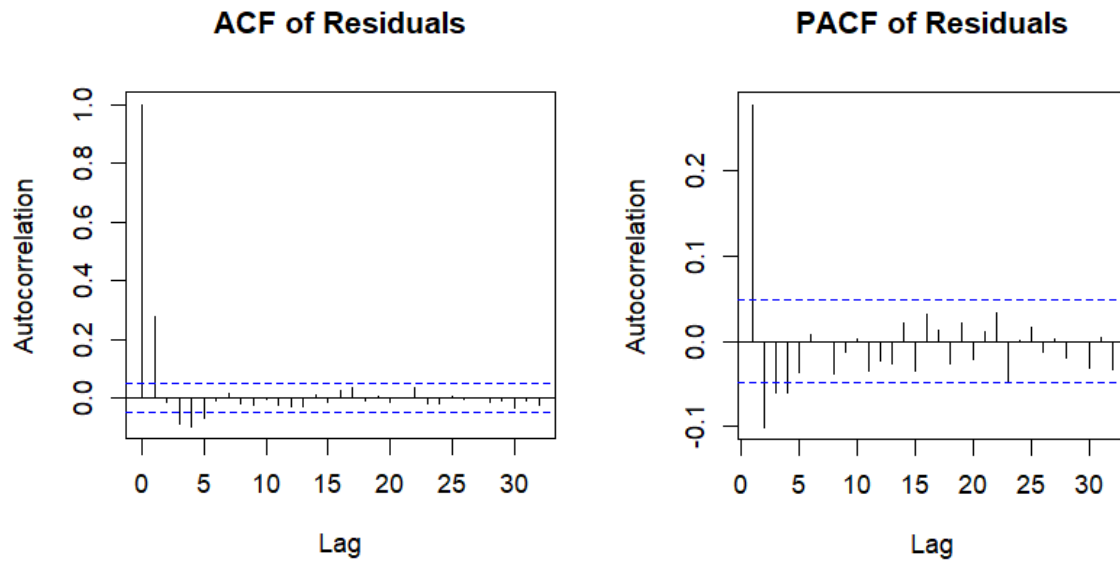
Table 5: First stage regression results.

<i>Dependent variable: Uptake Rate</i>		
Variable	Coefficient	Standard Error
<i>Time-varying:</i>		
D19	-0.009	(0.008)
D20	-0.024*	(0.014)
D21	-0.021*	(0.013)
D22	-0.009	(0.013)
D23	-0.021	(0.013)
Farm Size	0.001	(0.0004)
Farm Income	0.00000	(0.00000)
Yield	0.00000	(0.00000)
Employment Income	0.00000	(0.00000)
<i>Time-invariant:</i>		
Latitude	-0.002*	(0.001)
Average Temperature	-0.0002	(0.002)
Average Precipitation	0.00002	(0.00001)
<i>Instrumental variables:</i>		
Water-Land-Ratio	0.513***	(0.191)
Forest Owners	0.00001	(0.0001)
Population Density	0.0002	(0.0002)
L ² (Uptake rate)	0.264***	(0.029)
Constant	0.126	(0.111)
Observations (municipalities)	1,638 (273)	
Adjusted R ²	0.819	

*Notes: *p < .1, **p < .05, ***p < .01*

A lot of careful consideration has shaped the first stage regression to be as adequate as possible. Given statistical testing procedures, economic intuition and guidance from the literature and my supervisors, this first stage regression is the one I have most confidence in.

Figure 1: Residual Autocorrelation Function and Partial Autocorrelation Function



As can be seen in Figure 1, the second order residual autocorrelation is insignificant and the consecutive orders only show signs of negligible residual autocorrelation. Thus, the choice of the instrumental variable the second lag of uptake can be defended. Furthermore, the joint validity of the instruments is confirmed by the Stock and Staiger (1997) F-test rule of thumb. Additionally, the high R^2 value indicates a good fit for the estimated values of the uptake rate. Collectively, the measures taken to ensure the elimination of endogeneity concerns in the uptake rate variable indicate that the first stage regression is well suited to support the second stage which is the second (2) purpose of the first stage stipulated in section 4.3.

The first (1) purpose of the first stage regression stipulated in section 4.3 is to allow for the identification of the effect of the ES introduction in 2023 on uptake rate. All year-dummy variables are negative and only D20 and D21 are significant at the 5% level. The effect of the introduction of the organic support ES on uptake rate, shown by the D23 dummy variable, is insignificant and the arable land covered by organic support has not changed significantly due to the introduction of ES in the CAP 2023-2027 reform. By observing the years prior to the introduction, no prominent anticipation effects can be seen.

Table 6: Second stage regression results

Variables	Dependent variable:		
	SFDI	Perennial Grasses	Pasture
$\Delta\widehat{Upt}_{it}$	-0.270 (0.220)	2511.1*** (709.67)	872.27 (624.59)
$\Delta\widehat{Upt}_{it} * D20$	-0.368 (0.365)	-3039.0*** (1177.4)	-1358.5 (1036.3)
$\Delta\widehat{Upt}_{it} * D21$	1.751*** (0.523)	-2533.5 (1686.5)	-903.24 (1484.3)
$\Delta\widehat{Upt}_{it} * D22$	0.625* (0.321)	-2781*** (1034.3)	-854.45 (910.32)
$\Delta\widehat{Upt}_{it} * D23$	1.141*** (0.372)	-2827.5** (1199.9)	-1365.4 (1056.0)
Farm Size	-0.0017*** (4.70e-4)	-1.819 (1.518)	-1.711 (1.336)
Yield	2.42e-6 (2.86e-6)	0.0016 (0.0092)	-0.039*** (0.008)
Farm Income	1.32e-6** (6.31e-7)	1.8730e-04 (0.0020)	0.001 (0.002)
Employment Income	-1.77e-7 (5.27e-7)	0.0024 (0.0017)	7.3416e-04 (0.002)
Observations (groups)	1365 (273)	1365 (273)	1365 (273)
Adjusted R2	-0.22	-0.24	-0.25

Notes: * $p < .1$, ** $p < .05$, *** $p < .01$. Standard error within parenthesis.

The second stage regression is a two-way fixed effects taking into account both municipality-specific effects as well as time fixed effects. By including the interaction term between the change in estimated uptake rate and the year dummy-variables, it is possible to distinguish the effect of change in uptake in a specific year on the dependent variable. The coefficient of the interaction variable captures the additional effect of the change in uptake rate when the specific year is present. The reason why the year dummy-variable corresponding to 2019 is omitted is because taking the first difference of uptake rate eliminates yet another year of information in the panel. The time-invariant variables latitude, average precipitation and average temperature are eliminated by the model due to the within-transformation.

For the environmental indicator SFDI, the change in uptake rate in 2023 had a positive and significant effect on the 5% level. This is in line with the biodiversity objective of the introduction of the ES. The same can be said about the two years leading up to the ES introduction. The additional effect in 2023 specifically is more than in 2022 but less than in 2021. The additional effect has to be understood in relation to the main effect without year-interaction but also in relation to previous years. This issue is discussed further in the discussion section of this thesis. Furthermore, the time-varying variables farm size and farm income had a negative and positive significant effect on the SFDI respectively. Intuitively, these outcomes are reasonable as larger farms tend to be more industrialized and focus on larger production of fewer crops and a larger farm income could facilitate the interest in trying a wider range of crops.

The area of cultivated perennial grasses, as an environmental indicator of carbon and nitrogen sequestration, is decreased significantly due to the change in uptake rate in 2023. This negative interaction effect or additional effect specific to 2023 exceeds the positive main effect of change in uptake rate and the resulting combined effect is an overall decrease in perennial grasses in 2023 due to an increase in organic support uptake. Yet, the additional effect of the 2023 interaction does not indicate a break in the trend when considering the previous years before to ES introduction. None of the other time-varying variables show a significant effect on the area of perennial grasses cultivated in Sweden.

The area of pastures in the municipalities is not affected significantly by a change in uptake rate of organic support. Hence, the effect of the introduction of organic ES on the area of pastures is concluded to not be significantly different from zero.

Table 7: Hausman-Taylor regression results

	<i>Dependent variable:</i>		
	SFDI	Perennial Grasses	Pasture
Farm Size	-0.0003 (0.0004)	2.016 (1.238)	-1.494 (1.081)
Yield	0.00000** (0.00000)	-0.008 (0.006)	-0.008 (0.005)
Employment Income	-0.00000** (0.00000)	0.003*** (0.001)	-0.0003 (0.001)
Farm Income	-0.00000 (0.00000)	0.006*** (0.001)	0.004*** (0.001)
Uptake Rate	-0.079*** (0.023)	86.016 (70.724)	82.887 (61.699)
Latitude	0.043* (0.023)	124.023 (164.996)	-445.051*** (150.253)
Average Precipitation	-0.001*** (0.0002)	-3.335** (1.379)	-4.629*** (1.256)
Average Temperature	0.140*** (0.034)	765.584*** (234.801)	-24.671 (213.591)
Water-Land-Ratio	-0.016 (0.029)	233.099 (187.281)	385.170** (169.214)
Population Density	0.0001 (0.0001)	-0.616 (0.409)	-0.883** (0.359)
Forest Owners	-0.00003 (0.00003)	1.621*** (0.133)	0.481*** (0.118)
D17	0.008* (0.005)	-78.425*** (14.527)	-3.855 (12.676)
D18	0.006 (0.007)	-51.665** (20.460)	-5.528 (17.856)
D19	-0.032*** (0.010)	47.615 (32.351)	24.681 (28.232)
D20	-0.009 (0.016)	-114.628** (49.398)	3.122 (43.111)
D21	0.010 (0.015)	-148.483*** (45.861)	12.763 (40.027)
D22	0.034** (0.015)	-165.317*** (46.923)	23.758 (40.954)
D23	0.005 (0.015)	-182.089*** (46.177)	-18.734 (40.308)
Constant	-1.844 (1.588)	-9,709.718 (11,234.930)	30,561.010*** (10,230.480)
Observations	2,184	2,184	2,184
Municipalities	273	273	273
Adjusted R ²	0.194	0.219	0.048
F-Statistic	541.282***	630.649***	126.900***

Notes: * $p < .1$, ** $p < .05$, *** $p < .01$. Standard error within parenthesis.

Unlike the second stage reported in Table 6 using two-way fixed effects estimation, the Hausman-Taylor (1981) allows to identify the effect of the time-invariant variables as well. The model also estimates robust standard errors and the effect of uptake rate is identified using exogenous instruments. Residual autocorrelation is also managed with the model specification. In this specific model specification, the second lag of uptake is not used as an instrument for uptake, but rather the water-land-ratio, population density and number of forest owners are used as instruments. These instruments all fulfill the strong instrument condition of relevance as they are correlated to a certain degree with the uptake rate. Intuitively, they ought to only affect the environmental outcome variable indirectly through the uptake and have no direct effect. Not using the second lag of uptake rate as instrument allows for a longer time range to be used as there is no information lost through lagging variables or taking the first differences. In this specification, change in uptake rate is not used as regressors but rather the level of uptake rate.

The most interesting findings from the HT-model is that uptake rate overall has a negative and significant effect on SFDI and that the effects on area of perennial grasses and pastures are insignificant. In the perspective of policy analysis, European agricultural policy makers ought to be concerned and this issue will be discussed further in section 6. In the HT-model, the coefficients of the year-dummy variables should be interpreted as the average effect of each year on the dependent agri-environmental indicator variable, conditional on the other variables in the model and relative to the base year 2016. For the purpose of this thesis, the average effect on the environmental indicator associated with a specific year is irrelevant as the organic support uptake rate is controlled for. The relevant pathway analyzed is rather how the uptake rate of the organic support ES affects the environmental outcome variable directly, when controlling for other confounding factors.

6. Discussion

This section is divided into a discussion of the regression results, agricultural policy implications, limitations and suggestions for further research.

6.1 Discussion on regression results

Multiple interesting findings can be inferred from the regression results presented in section 5. The interpretation of the regression coefficients can seem complex at first, but this section aims to concretely summarize how the coefficients should be interpreted correctly. First of all, the year-dummy variables in the first stage regression are interpreted as the year-specific effect on the uptake rate relative to the base year 2018. The 2023 dummy variable is assumed to capture the effect of the introduction of the ES on the uptake rate and is insignificant. However, the magnitude of the coefficient is in the order of a few percentage points, which is in line with what we would expect as the uptake rate varies a few percentage points from year to year. This gives an indication that the first stage regression is correctly specified.

In the second stage regression, the main interest is in the interaction coefficients of year-dummies and change in uptake rate. Here there are three effects to be interpreted: the main effect shown by the coefficient on the change in uptake rate without time-interaction, the additional effect specific to the certain years in relation to the main effect, and the combined effect which is the sum of the main effect and the additional effect. By using the change in uptake rate, municipalities where the change is zero or negligible between years will essentially not be accounted for but the environmental effect of the change in uptake rate itself will be isolated. Comparing these interaction coefficients before and after the ES introduction in 2023 gives a measure of the efficiency of the ES on influencing the environmental indicator with respect to the uptake rate. An interaction coefficient in 2023 significantly different from the previous years would indicate that the ES is either more or less efficient in achieving its environmental objectives in terms of the uptake itself, compared to its predecessor policy measure.

Finally, the coefficients in the HT-model should be interpreted as the average effect of the regressors on the environmental outcome variable while holding all other variables constant. The year-dummy variables in the HT-model show the average year-specific effect on the outcome variable, conditional on the other regressors. Collectively, the first stage regression, the second stage regression and the HT-regression complement each other to facilitate establishing correct and reliable conclusions.

Comparing the second stage regression results focusing on the change in uptake rate and the HT-model focusing on the uptake rate level, the HT-model indicates a negative significant average effect of increased uptake rate on SFDI. The finding from the second stage regression supports this finding and shows a negative main effect of a change in uptake rate, although insignificant. However, the specific effect on SFDI associated with a change in uptake rate in 2023 is positive and significant. Nonetheless, the additional positive effect associated with the introduction of ES in 2023 is not differential in comparison to the years prior to the ES introduction in 2021 and 2022. There is no clear trend break which suggests that the organic support ES is not more efficient in terms of uptake in improving the agricultural biodiversity compared to its predecessor. Table 7 highlights the relevant coefficients discussed.

Table 7: Coefficient Comparisons with SFDI as Regressand

HT-model		Second stage	
Variable	Coefficient (S.E)	Variable	Coefficient (S.E)
<i>Uptake Rate</i>	-0.079*** (0.023)	$\Delta\widehat{Upt}_{it}$	-0.270 (0.220)
		$\Delta\widehat{Upt}_{it} * D23$	1.141*** (0.372)
		$\Delta\widehat{Upt}_{it} * D22$	0.625* (0.321)
		$\Delta\widehat{Upt}_{it} * D21$	1.751*** (0.523)

In terms of maintaining perennial grasses in the agricultural eco-system contributing to soil carbon- and nitrogen preservation, the uptake of the organic ES has a positive non-significant average effect as shown by the HT-model which is in line with a positive main effect of a change in uptake rate shown by the second stage regression, although significant. However, the additional effect specific to 2023 is negative and significant but not distinguishing compared to the years prior during the ES' predecessor. Collectively, the findings suggest that the area of perennial grasses may increase due to organic agriculture, but the introduction of ES in 2023 has not increased the ability to do so compared to its predecessor. Table 8 highlights the relevant coefficients discussed.

Table 8: Coefficient Comparisons with Perennial Grasses as Regressand

HT-model		Second stage	
Variable	Coefficient (S.E)	Variable	Coefficient (S.E)
<i>Uptake Rate</i>	86.016 (70.724)	$\Delta\widehat{Upt}_{it}$	2511.1*** (709.67)
		$\Delta\widehat{Upt}_{it} * D23$	-2827.5** (1199.9)
		$\Delta\widehat{Upt}_{it} * D22$	-2781*** (1034.3)
		$\Delta\widehat{Upt}_{it} * D21$	-2533.5 (1686.5)

The area of pastures contributing to biodiversity and the preservation of agricultural landscapes are not affected significantly on average by the uptake of organic agriculture according to the HT-model. The second stage regression supports this conclusion, and the specific effect attributed to the change in organic uptake rate in 2023 is insignificant.

The results from the econometric analysis can be summarized into four main findings. First, the introduction of the organic ES in 2023 has no significant average effect on the uptake of organic production support in Sweden. Second, the uptake of organic agriculture has a negative average impact on the SFDI in Sweden and the change in uptake rate specific to the ES introduction does not mitigate this issue more than its predecessor. Third, an increase in uptake of organic agriculture in Sweden may positively affect the area of perennial grasses, but the change of uptake rate associated specifically with the ES introduction is neither more nor less efficient in doing so, compared to its predecessor. Fourth, pasture as an agri-environmental indicator is not affected by the practice of organic agriculture and the introduction of ES in 2023 has not changed that situation in Sweden.

6.2 Policy implications

Given the four main findings in the previous sub-section, there are several areas in which European and Swedish agricultural policy makers can improve. The expected increase (Denninger et al., 2021) in uptake of organic farming practices due to the introduction of the ES did not arrive in 2023. A more thorough investigation of farmers' perceptions on the short-term contracts ought to be conducted. Furthermore, increased organically farmed land negatively or insignificantly affects the three agri-environmental indicators studied in this thesis. This should raise concern as large budget spendings are designated to organic farming with the objective of environmental preservation. The impacts of organic farming on agri-environmental indicators should be examined further and policies designed accordingly.

6.3 Limitations

One of the main limitations of this thesis is the novelty of the researched issue. With only one year having passed since the introduction of the ES in CAP 2023-2027, only short-term impacts can be analyzed. The long-term impacts are yet to come and there could be delayed effects of the ES introduction. Nevertheless, this thesis provides an early-stage evaluation suggesting useful improvements of the organic ES in the Swedish strategic plan for CAP 2023-2027.

6.4 Further research

There are many environmental indicators used in agricultural policy impact evaluation and this thesis has only investigated a few of them. The evaluation of environmental impact of

organic support uptake is desirable and hence more indicators ought to be examined. My suggestions are to extend from the land-use perspective applied in this thesis and explore effects on soil nutrient balances, pesticide use and sales, on-farm energy consumption, soil erosion, water quality and use, acidification and eutrophication. To comprehensively summarize the environmental impact of a certain agricultural practice is complicated and involves a multitude of measurements, but only when understanding these complex systems can policies truly be effective and efficient.

7. Concluding Remarks

The newly introduced Eco-Schemes in the European CAP 2023-2027 have high ambitions of improving the sustainability of European agriculture. Both potential benefits with the ES introduction have been presented (Dupraz & Guyomard, 2019; Jongeneel & Gonzalez-Martinez, 2023; Poppe & Koutstaal, 2020), but also risks (Hilding-Rydevik et al., 2021; Latacz-Lohmann et al., 2022). Due to the novelty of the policy measure, conducting an early-stage policy evaluation is fundamental to re-design and improve the measure for the coming years of the current CAP reform.

In terms of providing an answer to the research question “*What are the effects of the new organic Eco-Scheme in CAP 2023-2027 on farmers' uptake of organic agricultural practices and their environmental impacts in Sweden?*”, several conclusions can be drawn. First, the introduction of the organic ES in 2023 has no significant average effect on the uptake of organic production support in Sweden. Second, the uptake of organic agriculture has a negative average impact on the SFDI in Sweden and the change in uptake rate specific to the ES introduction does not mitigate this issue more than its predecessor. Third, an increase in uptake of organic agriculture in Sweden may positively affect the area of perennial grasses, but the change of uptake rate associated specifically with the ES introduction is neither more nor less efficient in doing so, compared to its predecessor. Fourth, pasture as an agri-environmental indicator is not affected by the practice of organic agriculture and the introduction of ES in 2023 has not changed that situation in Sweden.

Agricultural policy development is challenging and the mechanisms through which the policy affects social, economic and environmental sustainability have to be well understood in the context of implementation. This thesis has primarily covered the environmental aspects of the organic ES introduction in Sweden, and serves as guidance for agricultural policy makers in the pursuit of developing agricultural policies that are truly effective and efficient.

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PERSONAL DECLARATION

I hereby certify on my honor to have carried out and written this master thesis self-dependently without utilizing additional tools than the specified ones. The text is derived from clearly identified published or unpublished sources. Furthermore, I declare that all the sources of information and tools used are indicated. Finally, this thesis has not been previously submitted in the context of another examination.

Uppsala, 2024-07-30

A handwritten signature in black ink, appearing to read "Samuel Bäckström". The signature is written in a cursive style with a prominent horizontal line across the middle of the name.

Analysing Organic Eco-Scheme Uptake in Sweden

Carl Samuel Bäckelin

In 2023, a new agricultural policy measure was introduced to the European Union's Common Agricultural Policy called Eco-Schemes. Member states have the opportunity to design the Eco-Schemes at national level and Sweden implemented an Eco-Scheme supporting organic agriculture to replace a previous measure for organic production support. The organic Eco-Scheme differs in its design compared to its predecessor and the transition to the new policy is not well understood. Hence, there is a need to analyse the effects of the introduction on farmers' uptake of organic practices and the resulting environmental implications. The precise formulation of the research question is "*What are the effects of the new organic Eco-Scheme in CAP 2023-2027 on farmers' uptake of organic agricultural practices and their environmental impacts in Sweden?*"

The econometric analysis of the research question includes a two-stage panel data model and a Hausman-Taylor model with instrumental variables. The findings are summarized in four conclusions. First, the introduction of the organic Eco-Scheme in 2023 has no significant average effect on the uptake of organic production support in Sweden. Second, the uptake of organic agriculture has a negative average impact on the Shannon-Functional-Diversity-Index in Sweden and the change in uptake rate specific to the Eco-Scheme introduction does not mitigate this issue more than its predecessor. Third, an increase in uptake of organic agriculture in Sweden may positively affect the area of perennial grasses, but the change of uptake rate associated specifically with the Eco-Scheme introduction is neither more nor less efficient in doing so, compared to its predecessor. Fourth, pasture as an agri-environmental indicator is not affected by the practice of organic agriculture and the introduction of Eco-Scheme in 2023 has not changed that situation in Sweden.

This thesis has primarily covered the environmental aspects of the organic Eco-Schemes introduction in Sweden, and serves as guidance for agricultural policy makers in the pursuit of developing agricultural policies that are truly effective and efficient.