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Modeling conversion to organic agriculture with an EU-wide farm model

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Abstract. This paper analyses the impacts of the Farm to Fork strategy (F2F) target of 25% organic farmland by 2030 in the EU using a farm level model. Two approaches are deployed to model conversion to organic agriculture. The first one, the endogenous approach, operates under the assumption that farm conversions to organic production result from assessing the utility difference between organic and conventional production systems. The exogenous approach relies on econometric estimation of the likelihood of farms to convert to organic driven by a combination of monetary and non-monetary drivers. The simulated impacts of the F2F target at the EU level vary depending on the chosen methodology. Gross income changes range from +3.8% under the endogenous approach to -1.3% under the exogenous approach. Both approaches forecast decreased production (-0.5% to -15%) for most crops and animal products upon achieving the organic target.

Keywords: organic farming, farm model, IFM-CAP, Farm to Fork strategy, EU Green Deal, EU.
JEL Codes: Q12, Q57.

1. INTRODUCTION

The Farm to Fork (F2F) strategy of the EU Green Deal (European Commission, 2019, 2021) aims to stimulate the transition to a sustainable food system that is fair, healthy, and environmentally friendly. Among other proposed solutions, such as nutrient surplus reduction, pesticide risk reduction, antimicrobial use reduction, or increase of biodiversity, one of the key tools to achieve the transition is to promote the expansion of organic farming. The F2F strategy sets the target of 25% of the EU's agricultural area under organic farming by 2030 (European Commission, 2020). Currently, only 9% of the utilized agricultural area is under organic farming in the EU. Therefore, to achieve the F2F goal, a sizable agricultural area (17%) would need to convert from conventional to organic agriculture.

Organic farming is significantly different from conventional farming, particularly regarding management practices and productivity (Alvarez, 2021; Baker et al., 2020; Bonfiglio et al., 2022; Reganold & Wachter, 2016; Watson C.A. et al., 2002). For this reason, the conversion of a large share of the agri-

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cultural area to organic farming may have a significant effect on the EU agri-food system. More specifically, while organic farming is generally perceived to have positive environmental impacts, concerns exist about potential decreases in food production when shifting from conventional to organic farming methods (Meemken & Qaim, 2018; Reganold & Wachter, 2016; Seufert & Ramankutty, 2017; Timsina, 2018). The potential production decrease associated with reaching the F2F target raises the issue of food security both in the EU and globally, given that EU is a major food producer and exporter. The main contribution of this paper is to shed light on these issues by developing (individual) farm level modeling of EU-wide organic conversion in order to bring quantitative insights into the potential production effects of reaching the 25% organic target in the EU.

Four main modeling approaches have been applied in the literature to simulate the impacts of conversion to organic farming: (i) spatially explicit agronomic/biophysical models, (ii) partial equilibrium agro-economic models, (iii) individual or representative agro-economic farm models[1], and (iv) non-conventional models. In the first approach, the interplay between nutrient inputs, spatially explicit biophysical characteristics and outputs are explored to analyze the impacts of the conversion to organic production on the whole food system. The geographic scope of this approach spans from the regional level to world coverage by applying different spatial resolution depending on the study objectives (Barbieri et al., 2019; Jones & Richard Crane, 2014; Lee et al., 2020; Muller et al., 2017). The second approach relies on partial equilibrium models, which depict the behavioral interactions of economic agents within the agriculture sector at the regional, country or global level (Barreiro Hurle et al., 2021; Bremmer et al., 2021). In the third approach, the study scale is either the individual (Acs et al., 2007, 2009; Kerselaers et al., 2007) or representative farms (Smith et al., 2018), where the allocation of activities is usually modeled as a constrained optimization problem. This approach captures more disaggregated behavioral choices. Finally, the last approach relies on non-conventional modeling methods like agent-based modeling and system dynamics (Rozman et al., 2013; Xu et al., 2018).

Each of these modeling approaches has several limitations in modelling organic conversion. The main limitation of the agronomic/biophysical models is that they do not consider the economic dimension of conversion, neither at the farm level nor at the aggregate regional or country level. Hence, they cannot capture the organic conversion of specific farms. They usually assume full conversion of the modeled food system and then compare it with the situation before the conversion (Barbieri et al., 2019; Muller et al., 2017). Although partial equilibrium agro-economic models consider the economic dimension of organic conversion by construction they do not capture micro behavior at the farm level. Instead, they attempt to model organic production and input relationships by adjusting general productivity parameters (e.g., yields, input use) and/or introducing organic-related aggregate production constraints. Representative farm models suffer from similar limitations as the food system and partial equilibrium agro-economic models. However, they can capture in greater detail some organic farm practices and their differences across farm types. They also usually assume full conversion to organic production of all modeled farm types (Smith et al., 2018). Finally, regarding the non-conventional models, agent-based models can capture the organic conversion and specific aspects of organic farm practices in more detail. However, they are not applied at a larger geographical scale due to their high data requirements (Kremmydas et al., 2018). In contrast, system dynamic models may represent well the interactions between the elements of the system and provide answers to strategic decisions, but they cannot model details of organic conversion and organic farm practices (Richardson, 2011).

Applying an individual farm-level model for modeling organic conversion has several advantages. First, since organic conversion choice and organic production practices are farm-specific, applying an individual farm-level approach can offer a more accurate representation of organic farming without imposing strong assumptions on farmers' behavior. For example, detailed agronomic and behavioral constraints representing the technological differences between the two systems (conventional and organic) can be introduced. Second, individual farm models incorporate individual farms and technology representation, enabling the selection of specific farms that are more likely to convert. A

[1] The main distinction between 'representative' and 'individual' farm modelling considered in this paper refers to the representation of production and endowments structure of farms. The 'representative' farm model considers a virtual farm aggregating the production and endowments of several farms. It represents production and endowments structure averaged over all farms across considered dimensions (e.g. by production specialization, farm size, regional level). The 'individual' farm model refers to the production and endowments of a real (individual) farm. Note that in statistical terms when representative sampling is deployed, an individual farm included in the sample is representative of the larger farm population from which it is drawn in a way that it reflects the characteristics of the farm population (so that the sample can accurately represent the whole population). Thus, the farms used in the model are individual farms that represent the EU farming population. However they are not average 'representative' farms that are used in models that aggregate many farms into one (e.g. the CAPRI model).

third advantage is their effectiveness in modeling policy incentives, especially those targeting environmental and organic production. Indeed, the Common Agricultural Policy (CAP), among others, includes farm-specific environmental measures (including support for organic production) which aim to improve the environmental and climate performance of the EU farming sector. Finally, an individual farm-level model can provide distributional effects across the farm population, allowing for more nuanced impact analyses for policy making (Buysse et al., 2007; Ciaian et al., 2013).

However, the individual farm models applied in the literature to simulate conversion to organic production exhibit several limitations. First, they rely solely on expert knowledge, which restricts their applicability to a broader geographical scale, such as the entire EU. Indeed, they are either applied to a single farm (Acs et al., 2007) or a single country (Kerselaers et al., 2007). Moreover, these models do not develop a methodology for selecting specific farms to undergo conversion; instead, they assume the conversion of all farms.

This paper aims to fill the gap in the existing literature on individual farm modelling of organic conversion. Specifically, it focuses on the challenges of adjusting an EU-wide model – IFM-CAP (Individual Farm Model for Common Agricultural Policy Analysis) – to account for changes in farm performance and management practices associated with organic production. Achieving these model adjustments requires conducting several econometric estimations to identify the difference in performance between organic and conventional production across individual farms in all EU countries. This is due to the scarcity of readily available expert knowledge for such a wide geographic area encompassing a heterogeneous range of production systems. To fully leverage the farm-level model, we consider behavioral constraints that are relevant to organic farming such as crop rotation, nitrogen management, maximum stocking density, feed self-sufficiency and minimum share of fodder in the diet, respecting the heterogeneity across the EU farms. Additionally, to simulate the effects of the F2F organic target on farm income, production (quantities and value) and production costs, we consider two alternative approaches to select specific farms for conversion to organic production. This differs from the modeling approaches applied in the existing literature, which typically assume 100% conversion. The first approach, referred to as 'endogenous' approach, is based on profitability (utility maximization) differences between organic and conventional production systems. Under this approach, the subset of the most profitable farms are assumed to convert to organic farming. The second approach, referred to as 'exogenous' approach, employs a probabilistic framework to econometrically estimate the likelihood of farms converting to organic production. The underlying idea is that conventional farms sharing characteristics similar to organic farms are more likely to convert to organic farming. In econometric estimation, we take into account both monetary (e.g. subsidies, intensity of input use) and non-monetary factors (e.g. farm structural characteristics) that are often found in the literature to affect the likelihood of farmers adopting organic agriculture (Canavari et al., 2022; Sapbamrer, 2021; Serebrennikov et al., 2020; Willock et al., 1999).[2] Using Farm Accountancy Data Network (FADN), we conduct a comparative assessment of multiple probability models to identify the best-performing approach, which is then utilized for the selection of a subset of farms converting to organic production.

The paper is structured as follows. The next section describes the methodology of modelling organic production in the IFM-CAP. Section 3 presents the methodology applied for the selection of converting farms to organic production. Section 4 describes the simulated results, while Section 6 concludes.

2. MODELING ORGANIC PRODUCTION IN THE IFM-CAP MODEL

The IFM-CAP model is a static positive mathematical programming model, which solves a set of microeconomic models reproducing the behavior of individual farms (Kremmydas et al., 2022). The model assumes that farmers maximize their expected utility of income subject to technical and policy constraints related to resource endowments, production relationships, and CAP policy. IFM-CAP models 81,107 individual farms from the 2017 FADN database[3], covering all 27 Member States (MS). Its calibration against the 2017 FADN data is performed with a Positive Mathematical Programming (PMP) approach. The IFM-CAP model has been used in various past studies for ex-ante CAP policy assessments at the EU level (European Commission, 2018a; Louhichi et al., 2017, 2018; Petsakos et al., 2022).

[2] For more details see Supplementary material Part A.

[3] The FADN is a European system of farm surveys that take place every year and collect structural and accountancy information on EU farms, such as farm structure and yield, output, land use, inputs, costs, subsidies, income, and financial indicators. The FADN data is unique in the sense that it is the only source of harmonized and representative farm-level microeconomic data for the whole European Union. Farms are selected to take part in the survey based on stratified sampling frames established for each EU region.

The generic mathematical formulation for an individual farm that follows conventional production system is as follows:[4]

$$\max_{x_i,\zeta_{i,m}\geq 0} \mathrm{E}[U] = \sum_i E[gm_i]x_i + e - \sum_{i\in crops} x_i\left(d_i + 0.5\sum_j Q_{i,j}x_j\right) - \sum_{i\in animals} x_i\zeta_{i,m}\left(d^F_{i,m} + 0.5\sum_m Q^F_{i,m}\zeta_{i,m}\right) - 0.5\varphi\sum_{i,j} x_i\Omega_{i,j}x_j \tag{1}$$

subject to:

$$\sum_m A^F_{n,m,v}\zeta_{i,m} \lesseqgtr b^F_{i,n,v}\ \left[\theta^F_{i,n,v}\right] \tag{2}$$

where $i \in$ set of "animal activities"

$$\sum_i A_{t,i}x_i \leq b_t\ [\theta_t] \tag{3}$$

where i,j indices denote the agricultural (crop and livestock) activities, m denotes marketable commodities (i.e., feed purchased and farm output sold in the market or used as animal feed),[5] t represents the resource and policy constraints related to activities (e.g., agricultural land, greening obligations), while v denotes animal feeding constraints and n the different types of nutrients or energy requirements. Regarding the decision variables, x_i is the level of activity i (hectares and head) and $\zeta_{i,m}$ is the amount of feed m given to animal activity i (tons per head). Regarding the rest of the elements, E[gm_i] is the expected gross margin for activity i (EUR/ha or EUR/head), e denotes decoupled payments (EUR), d_i is the intercept of the activity-specific behavioural (implicit cost) function (the linear PMP terms), $Q_{i,j}$ is its slope (the nonlinear PMP terms - a diagonal positive semi-definite matrix), $d^F{}_{i,m}$ is the linear term of the behavioural function related to animal feeding, $Q^F{}_{i,m}$ is the nonlinear part of the same function (a diagonal positive semi-definite matrix), φ is the farmer's constant absolute risk aversion (CARA) coefficient and Ω_{ij} is the covariance matrix of activity revenues per hectare or per head. Inequality (2) represents the general structure of the animal feeding constraints, where $A^F{}_{n,m,v}$ is a matrix of coefficients representing the content of nutrient n in feed m, while $b^F{}_{i,n,v}$ is the quantity limit of nutrient n given to animal i (lower or upper, or satisfied as equality),[6] and $\theta^F{}_{i,n,v}$ is the shadow price of the v-th feeding constraint. $A_{t,i}$ are coefficients for resource and policy constraints, b_t are available resource levels and upper bounds for policy constraints, while θ_t are their corresponding shadow prices.

The expected activity gross margin is defined as:

$$\mathrm{E}[gm_i] = \sum_m p_m(1-\xi_m)y_{i,m} + v_i - C_i \tag{4}$$

where $y_{i,m}$ is the expected yield of output from activity i, p_m denotes the expected price for commodity m (including for feed and young animals), ξ_m are estimated production losses, v_i are coupled payments linked to activity i, and C_i are the accounting variable costs. The calculation of variable costs differs between crop and animal activities. For crops, $C_i = \Sigma_k c_{i,k}$, k are intermediate inputs (i.e. fertilizer, seeds, crop protection, etc.) and $c_{i,k}$ are the per hectare costs of each input type. For animals, $C_i = \Sigma_{m\in Feed} p_m\zeta_{i,m}$, feed m given to animal activity i is evaluated at price p_m.

The model formulation for organic production system changes as follows (the changes are highlighted in bold letters):

$$\max_{x_i,\zeta_{i,m}\geq 0} \mathbf{E}[\boldsymbol{U}]' = \sum_i \boldsymbol{E}[\boldsymbol{gm_i}]'x_i + e - \sum_i x_i\left(d_i + 0.5\sum_j Q_{i,j}x_j\right) - \sum_{i\in animals} x_i\zeta_{i,m}\left(d^F_{i,m} - 0.5\sum_m Q^F_{i,m}\zeta_{i,m}\right) - 0.5\varphi\sum_{i,j} x_i\Omega_{i,j}x_j \tag{5}$$

where:

$$\boldsymbol{E}[\boldsymbol{gm_i}]' = \sum_m \{p_m(\mathbf{1}+\boldsymbol{p^G_m})\}(1-\xi_m)\{y_{i,m}(\mathbf{1}+\boldsymbol{y^G_{i,m}})\} + v_i - \boldsymbol{C'_i} \tag{6}$$

for crops,

$$\boldsymbol{C'_i} = \sum_k c_{i,k}(\mathbf{1}+\boldsymbol{c^G_{i,k}}) \tag{7}$$

for animals,

$$\boldsymbol{C'_i} = \sum_{m\in Feed} p_m(\mathbf{1}+\boldsymbol{p^G_m})\zeta_{i,m} \tag{8}$$

subject to:

[4] The optimization problem is specific to each farm. However, for simplicity we have suppressed the index for farms, *f*, in all equations.

[5] Mathematically this means that the set of feeds in IFM-CAP, and the set of farm outputs, some of which can be used as feeds themselves, are subsets of the set of all marketable commodities included in the model.

[6] This equation ensures that animal-specific nutrient demands (requirements) are met from on-farm produced or purchased feed (supply). Balancing feed supply (availability) and demand (requirements) is done through nutrient values. Additionally, we set lower and upper thresholds for feed in animal diets for each animal category to align feed allocation with animals' physiological requirements and prevent overuse or underuse of specific feeds in the diet (Kremmydas et al., 2022).

$$\sum_{m} \mathrm{A}^{F}_{n,m,v}\left(\mathbf{1} + \mathbf{A}^{F,G}_{n,m,v}\right)\zeta_{i,m} \lesseqqgtr b^{F}_{i,n,v}\ \left[\boldsymbol{\theta}^{F}_{i,n,v}\right] \tag{9}$$

where $i \in$ set of "animal activities"

$$\sum_{i} \boldsymbol{A}_{t',i} x_i \leq b_{t'}\ [\boldsymbol{\theta}_{t'}] \tag{10}$$

The following are the main model differences between conventional and organic management:

- The parameters $p^G{}_m$, $y^G{}_{i,m}$, $c^G{}_{i,k}$ and $A^{F,G}{}_{n,m,v}$ capture percentage differences between conventional and organic farming in prices, yields, costs and the content of nutrients in feeds, respectively.
- A modified set of technical constraints, t', is considered in equation (10), which adds farm practices specific to organic farming, namely crop rotation, nitrogen management, maximum stocking density, feed self-sufficiency and minimum share of fodder in the diet. Additionally, the CAP greening constraints are removed because organic farms are exempted from complying with the greening requirements.

The next sections provide a more detailed description of these model changes introduced in IFM-CAP for organic farming.

2.1 Output prices and yields of organic crops

The findings from the literature indicate that in general, organic farms tend to achieve lower crop yields and to obtain price premiums compared to conventional farms (Alvarez, 2021; De Ponti et al., 2012; Offermann & Nieberg, 2000; Seufert et al., 2012). To account for these effects, we apply a log-linear econometric specification to estimate the relative difference in the expected output prices and yields of crops between organic and conventional production systems. The advantage of the econometric approach is that we can control for a series of factors potentially affecting prices and yields, which can bias the estimated results if not accounted for. As covariates, we use a set of farm structural characteristics such as farm specialization, farm size, altitude of the farm, presence of natural constraints, the share of irrigated land and time dummy. To isolate the effect of organic farming on yields and prices, we do not include proxies of input use in the econometric estimations due to their high correlation with the organic status of the farm. Their inclusion in the estimated equation would likely bias downwards the estimates (particularly yield gaps).[7]

The estimations are based on FADN data for 2007-2016, covering the whole EU. We perform estimations for main crop products and for different geographical regions (FADN regions) to account for heterogeneity in technology, local characteristics, and farming systems. The estimated price and yield differences are then pooled together by five macro-regions: Central Europe North, Central Europe South, Northern Europe, Southern Europe and UK & Ireland. The median values[8] are extracted for each macro-region and used as price, $p^G{}_m$, and yield, $y^G{}_{i,m}$, differences between conventional and organic farming in the IFM-CAP model.

Overall, the estimated results show that organic farms attain higher output prices and lower yields than conventional farms. For most crops and macro-regions, the difference in prices varies between around 10% and 60%, while for yields, between -5% and -45%. The highest absolute difference in prices and yields is observed in UK & Ireland and Central Europe North, while the smallest differences tend to be in Southern Europe.[9]

2.2 Variable cost of organic crop production

Due to different technologies applied by organic and conventional farms, variable crop production costs are expected to differ between the two farming systems. Therefore, we conduct econometric estimations for four types of variable cost categories (per-hectare) – seeds, fertilizers, crop protection, and other crop-specific costs – to identify the differences induced by different technologies applied by the two farming systems. A linear econometric model was used to estimate these differentials between organic and conventional farms. The estimations are based on FADN data for 2007-2016, covering the whole EU.[10] Given that technologies and production mixes are expected to differ between farm types and regions, we econometrically estimate cost differences for each FADN region and for each production specialization separately. The estimated percentage difference in costs, $c^G{}_{i,k}$, between organic and conventional farms for each cost category, region, and farm specialization are then used to adjust the costs for converted farms in IFM-CAP.

Overall, the estimates indicate that organic farms generally have lower variable costs than conventional farms across most farm specializations and cost categories. This is particularly the case for fertilizers and

[7] For more details on the summary statistics of costs, prices and yields, distribution of organic farms, and econometric models see supplementary material Part B.

[8] The median price and yield differences between conventional and organic farming are expected to be robust against potential data outliers and model misspecification.

[9] For more information see Table A1 and Table A2 in Appendix.

[10] For more details, see the part of 'Part B: Econometric estimations' in the supplementary material.

crop protection costs. However, more mixed results are obtained for seeds and other crop-specific costs, where higher values for organic farms than conventional farms are more common across different farm specializations.[11]

2.3 Organic livestock output and feed prices, yields and feed efficiency

Similar as in the case of crops, for dairy milk, we estimated the differences in prices and yields between organic and conventional farming using FADN data for 2007-2016, covering the whole EU. Data for other livestock activities are not directly available in the FADN. These activities are derived from the livestock module in IFM-CAP (Kremmydas et al., 2022). Thus, for other livestock activities, we performed an econometric analysis of yield and price differences between conventional and organic farms using derived data from the livestock module in IFM-CAP for the period 2012-2016. As in the case of crops, the estimations were done by using the log-linear regression models of livestock yields and prices (for different FADN regions) by accounting for a set of explanatory variables relating to farm characteristics and to the characteristics of the operating environment. Note that in some cases (e.g. poultry meat) when data did not allow to conduct econometric estimations (e.g. small sample size), we relied on literature estimates from the meta-analysis conducted by Gaudaré et al. (2021). Their study compared the evidence from literature on the productivity and feed-use efficiency between conventional and organic livestock animals.

Overall, organic livestock farms have higher output prices and lower yields than conventional farms. For most crops and macro-regions, the difference in prices varies between around 5% and 50%, while for yields, between -1% and -25%. The highest absolute difference in prices seem to be in Northern Europe, while the smallest differences tend to be in Central Europe South, Southern Europe and UK & Ireland. For yields, there is no clear pattern across macro-regions.[12]

IFM-CAP models explicitly animal feed in terms of its physical quantity and nutrient value by balancing feed demand (determined by animal nutrient requirements) and feed supply/availability (determined by on-farm produced and purchased feed and its feed nutrients content). The utility maximization problem then determines endogenously the most cost-efficient selection of specific feeds in each animal's diets (Kremmydas et al., 2022)[13]. In line with the prerequisite to use organic feeds in organic livestock farms, we use price differences between organic and conventional feed, p^{G}_{m}, estimated for crops in the previous section for organic purchased feeds. Since most organic crop prices are usually higher than conventional crop prices, the cost of purchased feed is expected to be greater in organic than in conventional farms. Further, according to the Gaudaré et al. (2021), organic livestock farming shows lower feed efficiency by between 6% and 20% as compared to conventional farms. Following this evidence, we apply a 13% decrease in organic feed efficiency in IFM-CAP, $A^{F,G}_{n,m,v}$, by reducing nutrient content in the organic feed as compared to conventional feed. The lower feed efficiency for organic farms may be explained, among others, by differences in feeding strategies (e.g., a higher share of rough fodders in animal diets in organic compared to conventional farming) and differences in herd management practices as compared to conventional farms (e.g., more extended resting period between lactations for dairy).

2.4 Behavioral constraints of organic farms

As indicated in equation (10), we consider five behavioral constraints in IFM-CAP identified in the literature to characterize the organic production system and differentiate it from the conventional system: crop rotation, nitrogen management, maximum stocking density, feed self-sufficiency, and minimum share of fodder in the diet (Barbieri et al., 2017; Reimer et al., 2020; Gaudaré et al., 2021).

Crop rotation

In organic farming, crop rotation is used to manage the nutrient balance in the soil, address weed problems and prevent soil diseases and insect pests. It also facilitates farmers to substitute for chemical fertilizers and

[11] For more information see Table A3 in Appendix.

[12] For more information see Table A4 and Table A5 in Appendix.

[13] Livestock costs and feed requirements per head in IFM-CAP are derived based on FADN data and external data sources. This was applied because FADN does not contain all relevant information needed to parameterize the feed in IFM-CAP (in contrast to crop activities). FADN contains only aggregated economic data on feed availability and costs at farm level. The disaggregated feed data such as feed use by each animal category, nutrient content of feed, animal nutrient requirements are not available in FADN. The High Posterior Density (HPD) estimation approach was used to estimate animal-level feed data by combining FADN and external data, where external data are used only as prior information in the estimation approach. The estimation approach combines these different data sources by taking into consideration the minimization of deviation of estimated data values from the available prior information, the minimization of feed costs, balancing between feed nutrient requirements of livestock and feed availability, and data constraints to ensure that the sum of animal-level feed costs is as close as possible to the aggregated cost values reported in FADN. For more details see (Kremmydas et al., 2022).

plant protection, which is strictly limited in the organic production system (Reganold & Wachter, 2016; Baker et al., 2020). Ideally, modeling crop rotation requires a multi-annual model with detailed agronomic information at the plot level (Castellazzi et al., 2008; Dury et al., 2012). Since the IFM-CAP model is a comparative static model and does not consider time dynamics, we model differences in crop rotation between organic and conventional management indirectly by introducing empirically estimated farm-specific flexibility cropping constraints for main crops as follows:[14]

$$S_c^{org} \leq (1 + r_c) \cdot S_c^{conv} \quad \forall\ c \tag{11}$$

Where S_c^{org} is the share of main crop c in total area of farm converted to organic production, S_c^{conv} is the observed share of main crop c on conventional farm, and r_c is a crop-specific coefficient representing the reduction of the main crop share due to the farm converting to organic.

The motivation for applying flexibility constraint (11) comes from the observation that organic rotations are more complex and diversified than conventional ones. For example,(Barbieri et al., 2017) based on a meta-analysis of literature evidence comparing crop rotation differences between organic and conventional farming, Barbieri et al. (2017) estimated that, on average, at the global scale, organic rotations last for 4.5 ± 1.7 years. This duration is approximately 15% longer than their conventional counterparts and include 48% more crop categories.

The flexibility cropping constraints (11) represent the extensification of the main crops' area allowed under the organic production system in IFM-CAP. It sets the crop specific maximum thresholds that a crop can represent in the total farm area such that to replicate the distribution observed on organic farms. This modeling of crop rotation means that the most frequent crops of the rotation will be cultivated less frequently by organic farms than by conventional farms reflecting the observed distribution. The r_c coefficient is estimated based on FADN data[15] aiming to shift the distribution of the area shares of the crops of the converted farms towards the distribution of area shares empirically observed among organic farms.

[14] We introduce the flexibility constraint for the following main crops: soft wheat, durum wheat, barley, grain maize, fodder maize, rape seed, sugar beet, sun flower, potatoes.

[15] For more details on the estimation methodology, see supplementary material Part C.

Nitrogen management

The organic farm's nitrogen management is expected to impact the area devoted to the cultivation of nitrogen-fixing crops. Organic farms are expected to cultivate more nitrogen-fixing crops than conventional farms, primarily to maintain land fertility through the ability of these crops to fix nitrogen from the air and thus provide a source of nitrogen that could serve as a substitute for inorganic fertilizers (Barbieri et al., 2017). Additionally, the EU organic regulation 848/2018 requires the cultivation of leguminous crops by organic farms to maintain the soil's fertility and biological activity. Farms can also use other practices for nitrogen management, such as green and animal manure, leaving land fallow or grassland (Chmelíková et al., 2021; Lin et al., 2016).

Modeling the farm's nitrogen management is relatively complex and requires information unavailable in FADN (Küstermann et al., 2010; Thomas, 2003). Moreover, this is further complicated because nitrogen management practices could be very heterogeneous across organic farms, with some not using nitrogen-fixing crops. Indeed, according to FADN data, around 40% of organic farms did not cultivate nitrogen-fixing in the EU in 2017, varying between 19% and 77% across different farm specializations. Instead, according to FADN data, organic farms without nitrogen-fixing crops have a significantly higher share of fallow land and grassland in the total land than farms that cultivate nitrogen-fixing crops. This higher share is likely explained by the fact that the farms without nitrogen-fixing crops maintain land fertility through animal manure, fallow land, or grassland management.

To model nutrient management in IFM-CAP, we apply a simplified approach to model nitrogen management. We combine the agronomic knowledge with a data-driven approach to approximate the changes that converted farms need to undertake in their area allocation to account for nutrient management practices. More specifically, we assume that farms that convert to organic farming will cultivate a more significant share of their arable area with nitrogen management related crops[16] determined by the following flexibility constraint:

$$\sum_{c \in N} (S_c^{org}) \geq (1 + \eta) \cdot \sum_{c \in N} (S_c^{conv}) \tag{12}$$

Where, N is the set of the crops related to nitrogen management, S_c^{org} and S_c^{conv} are the area shares of crop

[16] The nitrogen related crops in IFM-CAP are soybean, pulses, other fodder, permanent grassland and fallow land.

c in total farm area when in the organic and conventional status, respectively, and η is a farm specific coefficient representing the increase of nitrogen related area in organic farming compared to conventional ones.

The constraints (12) defines the minimum area share of nitrogen related crops that organic farms need to maintain on farm. These minimum area shares are farm specific and are defined in such a way that the distribution of the nitrogen-fixing, fallow and grassland area shares of the converted farms shifts such that to resemble the observed ones on organic farms in FADN.[17]

Maximum stocking density requirements

The EU organic regulation (European Commission, 2018) requires that the total stocking density does not "exceed the limit of 170 kg of nitrogen per year and hectare". The regulation also indicates the number of livestock units (LSU) per hectare.

Based on this, we introduce the maximum stocking density constraint in the IFM-CAP for organic farms specifying that the total livestock units multiplied by the maximum number of hectares allowed per one livestock unit[18] across all animal categories of the farm cannot exceed the total farm area. This constraint requires the converted farms to adjust their number of animals to the available farm area such that to respect the maximum thresholds set by the EU organic regulation.

Feed self-sufficiency

The organic production system is characterized by a high degree of self-sufficiency of animal feed to reduce the risks of uncertain availability of organic feed on the market (especially for fodder). It also allows to sustain a better nutrient management at the farm level (Lampkin et al., 2017). To account for this aspect of an organic production system, we consider a feed self-sufficiency constraint in IFM-CAP. The constraint is based on the requirement set by the EU organic regulations regarding the animals' feed sourcing. The legislation requires a minimum percentage of the animal's feed to come from on-farm production: 60% for bovine and ovine and caprine and 30% for porcine and poultry (European Commission, 2008, 2018b). In IFM-CAP, we constraint the maximum share of purchased feed at the farm level in line with the thresholds provided in the EU organic regulations (e.g., 40% for bovines). The constraint ensures that the purchased feed (expressed in dry matter terms) does not exceed the maximum share of the total feed use at the farm level.

Minimum share of fodder in diet

Organic farms usually use a higher proportion of fodder in animal feed due to the lower possibility of acquiring organic concentrate feed on the market (lower diversity and higher prices than for conventional feed) and the rules set by the EU organic regulation (Flaten & Lien, 2009; Gaudaré et al., 2021; Lampkin et al., 2017). The EU organic regulations (European Commission, 2008, 2018b) require that all animals should have access to roughage. For bovine, ovine, and caprine animals, the percentage of dry matter that should come from roughage, fresh or dried fodder, or silage is 60%. However, this percentage may be reduced to 50% for female animals in milk production for a maximum period of three months in early lactation. In addition, the regulation specifies that roughage, fresh or dried fodder, or silage should be added to the daily ration for porcine and poultry, but without providing a specific minimum share.

Following the EU organic regulations, we introduce a constraint in IFM-CAP that defines the minimum share of fodder in the animal diet (represented in dry matter) for each farm animal. We use a minimum share 57.5% fodder for bovine, ovine and caprine animals[19] and 0.5% for porcine and poultry animals[20].

3. THE SELECTION OF CONVERTING FARMS

Alongside modelling the effects of organic conversion at the farm level, the selection of specific farms that convert to organic production system needs to be considered in an individual farm model. This is particularly relevant for policies that aims to achieve a partial conversion to organic such as the F2F strategy which sets the 25% area target. To the best of our knowledge, there is no consistent theoretical framework available in the literature that would provide modelling framework for selecting the farm that will convert. We consider two alternative selection approaches that build on different

[17] For more details on the estimation of the minimum shares see the supplementary material Part C.

[18] For more information see Table A6 in Appendix.

[19] This share is calculated as follows: [60% for nine months]*(9/12) + [50% for three months]*(3/12)

[20] Note that the 0.5% share for porcine and poultry is set ad-hoc since a specific value is not provided in the regulation. This share is based on literature findings indicating that porcine and poultry in organic farms often have a proportion of their diet in form of roughage (e.g. Hermansen et al., 2004; Sossidou et al., 2015).

grounds. One is based on IFM-CAP modeling results (utility maximization) and is referred to as 'endogenous' approach. The second one is based on external drivers affecting organic conversion determined outside the IFM-CAP model referred to as 'exogenous' approach.

3.1 Endogenous selection

In the endogenous approach, we assume that the propensity to convert is proportional to the utility difference between conventional production system and organic production system. The endogenous selection approach solely relies on the IFM-CAP model simulation results. First, we simulate the utility obtained with the conventional farming practices in place by solving the utility maximization problem outlined in equations (1) to (4), $U^{conv} = \mathrm{E}[U]$. Second, we run the utility maximization problem of organic production provided in equations (5) to (10), $U^{f}_{org} = E_f[U]$'. Finally, we order farms in decreasing order in terms of utility difference between organic and conventional farming obtained for each farm, $\Delta U = U^{org} - U^{conv}$. The best-performing farms are selected to convert to the organic production system. The number of selected converting farms depends on the simulated scenario (e.g. on the organic area target considered).

3.2 Exogenous selection

The exogenous approach is based on estimation of the likelihood of individual farms converting to the organic farming using FADN data. This approach does not rely on IFM-CAP model simulation results but is exogenously introduced in the model based on results obtain from econometric estimations. Our main assumption is that the likelihood of conversion depends on the similarity of conventional farms with respect to organic ones: conventional farms that are more similar to organic ones – in terms of farm characteristics, performance, behavior and the environment in which they operate – are assumed to be more likely convert to organic farming. Farms that are already similar to organic ones will find it less costly to make additional changes to their production methods to make it in line with the organic farming requirements.

Using probability models, we estimate the conversion likelihood for all farms included in the IFM-CAP base year (i.e., for FADN farms in 2017). We apply seven different probability models commonly used in the literature to estimate organic farm conversion: (i) linear probability model (LP), (ii) the linear probability model with stepwise selection algorithm (LP + SSA),[21] (iii) the logit model (LOGIT), (iv) the logit model using the covariates of model LP + SSA (LOGIT + SSA), (v) the probit model (PROBIT), (vi) the probit model using the covariates of model LP + SSA (PROBIT + SSA), and (vii) the random forest algorithm (RANDOM FOREST) (Basnet et al., 2018; Burton et al., 1999; Chatzimichael et al., 2014; Chmielinski et al., 2019; Djokoto et al., 2016; Genius et al., 2006; Hattam & Holloway, 2005; Läpple & Rensburg, 2011; Lohr & Salomonsson, 2000; Malá & Malý, 2013; Parra López & Calatrava Requena, 2005; Serebrennikov et al., 2020). The dependent variable used in all models is binary taking value of 1 if the farm is organic and 0 if the farm is conventional (non-organic). The choice of explanatory variables used in these models has been guided by previous empirical literature that suggested that several drivers may impact farmers' decision to convert to organic farming. These drivers include quantifiable monetary factors, such as subsidies and input expenditures, as well as non-monetary factors, such as structural characteristics, access to farm organic buyers/markets, and farmer believes and attitudes towards the environment[22] (Canavari et al., 2022; Sapbamrer, 2021; Serebrennikov et al., 2020; Willock et al., 1999)[23]. The set of selected covariates have been constructed using FADN data for 2014-2017 period to proxy these monetary and non-monetary drivers[24].

We compare the results obtained from all estimated probability models and choose the predictions generated by the model with the best prediction accuracy. FADN farms (in each MS or at the EU level, depending

[21] A stepwise selection algorithm based on the AIC criterion is applied to the full specification of the LP model. This selection algorithm allows reducing the number of covariates used in the estimation phase and, possibly, increasing the accuracy (goodness of fit) of the predictions. This reduced equation is then used to re-estimate the linear model, the logit and the probit model.

[22] For more details see supplementary material Part A.

[23] Note that unlike studies typically done in the literature on adoption of organic farming (Bravo-monroy et al., 2016; Darnhofer et al., 2005; Fairweather, 1999; Hattam & Holloway, 2005; Kallas et al., 2009; Lohr & Salomonsson, 2000; Parra López & Calatrava Requena, 2005; Yu et al., 2014), our approach is a prediction exercise. Our aim is to assign a probability of conversion to FADN farms rather than apply an explanatory model of conversion (Shmueli, 2010).

[24] More specifically, the monetary covariates considered in the estimations capture the amount of subsidies received, the performance of organic farms in the region relative to conventional ones, regional land prices, input expenditure. On the other hand, non-monetary covariates capture different farm characteristics such as the structural characteristics of the farm, production specialization, the characteristics of the geographical location in which farm operates, the type of farm activities, crop biodiversity index, yield gaps, labor use, and the presence of organic farming in the region. For the full list of covariates, see part D of the supplementary material.

on the type of simulated policy target)[25] are then ranked according to their estimated likelihood of converting to the organic status, and those with the highest probability are assumed to convert to organic production.[26] This implies that the selection of farms that convert to organic production in the exogenous approach is not necessarily those that gain the most in terms of profit (utility) but instead, those are estimated to be most likely converting determined by the various monetary and non-monetary related factors considered in the estimations.

The prediction accuracy of the seven estimated models varies between 0.51 and 0.99, with most models across MS and EU having an accuracy greater than 0.8.[27] For the majority of MS, as well as for the EU as a whole[28], the random forest algorithm outperformed the other six models in terms of prediction accuracy. Exceptions are Luxemburg and Ireland, for which the Logit model and the Logit model with a stepwise selection algorithm have shown a higher prediction accuracy, respectively. The prediction accuracy for the selected model is greater than 0.88 across MS and EU.

4. RESULTS

We apply the modified IFM-CAP model defined by equations (5) - (10) to simulate the 25% target set in the F2F strategy. We consider the implementation of the target both at the MS and EU levels. The 'MS level' implementation considers reaching the 25% target for each EU MS. The 'EU level' implementation means that the 25% target is set at the EU level and thus, some MS may have an organic area share lower or greater than 25%. We use those two scenarios because the actual policy implementation seems not to be clearly defined. While the target is set at the EU level, Member States have the primary obligation to implement it, but the target is not mandatory for them (European Commission, 2020). Thus, the two considered scenarios represent bounds within which the impact of the target is expected to lie.

The simulated impact of the organic target were compared against a reference, or 'baseline' scenario which represents the base year situation without organic conversion (i.e. 2017). The baseline simulations are based on equations (1)-(4).

4.1 Comparison of the farms selected in the endogenous and exogenous approaches

Table 1 shows the share of farms ranked in the first two quantiles (Q1 and Q2) of the distribution selected for organic conversion that overlaps in both the endogenous and exogenous approaches. In general, the two selection approaches select different farms to convert. In both the endogenous and exogenous approaches, there is only 5% overlap of farms selected for conversion in the first quantile (Q1), and only 25% overlap in the first two quantiles (Q1Q2) of the distribution. The discrepancy in these results arise from the selection criteria used by the two approaches. The profit maximization rule in the endogenous approach selects the most performant farms for organic conversion, most of which, as shown in Table 1, are different from the farms selected in the exogenous approach where the selection is based on the similarity of farms in monetary and non-monetary characteristics, such as farm structural characteristics.

When we break down the converting farms by farm specialization, we find that only for a few farm specializations, most farms selected in both approaches overlap (more than 60% in Q1 and Q2), namely specialist olives, specialist wine and permanent crops combined. This implies that drivers considered in the exogenous approach are relatively well aligned with the performance related rule in the endogenous approach for these farm groups. On the contrary, in specialist orchards, specialist granivores, specialist milk, mixed crops and livestock and specialist cereals, oilseed, protein crops, the majority of farms selected in one approach are generally not selected in the other approach and vice versa (more than 80% in Q1 and Q2). In other farm specializations, there is a 30% to 50% overlap in the selected farms between the two approaches for Q1 and Q2 quantiles. A similar pattern holds when we break down the converting farms by economic size. For all economic size classes, farms selected in one approach are generally not selected in the other: only between 21% and 31% of selected farms in Q1 and Q2 overlap in both approaches (Table 1).

Additionally, as reported in Table A9 in Appendix[29], the endogenous approach tends to select for organic conversion mainly farms specialized in field crops, specialist horticulture and mixed crops and livestock, while

[25] The estimated MS conversion probabilities are more appropriate when modeling the policy target set at the MS level. In contrast, the EU level conversion probabilities are more appropriate when modeling the policy target set at the EU level.
[26] For more details see supplementary material Part D.
[27] The performance metric of the seven models and the best performing model for MS and EU level estimations are reported in Table A8 in Appendix.
[28] Due to its computation complexity, the stepwise selection algorithm is not performed with the sample of EU as whole.

[29] Table A9 in Appendix shows the share of the selected farms by specialization, economic size and selection approach.

Table 1. Share of same farms in the endogenous and exogenous approaches ranked top of the conversion selection list in the EU by farm specialization and economic farm size.

	Share of selected farms overlapping in both approaches in Q1 (%)	Share of selected farms overlapping in both approaches in Q1 and Q2 (%)
Farm specialization		
Specialist cereals, oilseed, protein crops (15)	1%	18%
Specialist other field crops (16)	3%	32%
Specialist horticulture (20)	6%	38%
Specialist wine (35)	26%	74%
Specialist orchards - fruits (36)	1%	7%
Specialist olives (37)	49%	97%
Permanent crops combined (38)	12%	67%
Specialist milk (45)	1%	10%
Specialist sheep and goats (48)	6%	34%
Specialist cattle (49)	0%	10%
Specialist granivores (50)	1%	7%
Mixed crops (60)	8%	49%
Mixed livestock (70)	5%	15%
Mixed crops and livestock (80)	2%	14%
Economic farm size		
Small farms	5%	31%
Medium sized farms	5%	26%
Large farms	4%	21%
Total	5%	25%

Notes: The table shows the share of overlapping farms ranked in Q1 and Q2 in both endogenous and exogenous approaches. Q1 and Q2 refer to the first and second quantile of the ordered distribution of the two approaches. The farms that belong to the top two quantiles are likely to be selected to convert to organic farming.
Small farms: includes commercial farms with a standard output of less or equal to 25,000 euros; Medium farms: standard output greater than 25,000 euros and less or equal than 100,000 euros; Large farms: standard output greater than 100,000 euros.

the exogenous approach makes a more balanced selection, although it still favours certain farm types, such as farms specializing in permanent crops, field crops, specialist milk and mixed livestock farms over other specializations (particularly when compared to specialist other field crops, specialist cattle and other mixed crops). In terms of economic farm size, both approaches tend to select primarily small farms.

4.2 The economic impacts of the 25% organic target

Simulation results show that the aggregate farm income[30] in the EU increases compared to baseline in the endogenous approach and decreases in the exogenous approach (Table 2).[31] These results are expected because the endogenous approach selects farms for conversions based solely on profitability, resulting in only the best-performing farms converting and thus leading to higher farm income as compared to the baseline scenario. In contrast, the exogenous approach selects farms for conversion based on factors not always directly related to profitability (particularly non-monetary ones), meaning that the converting farms may not necessarily be the most profitable ones. For the target set at the EU level, the aggregate farm income in the EU increases compared to the baseline by 3.8% in the endogenous approach and decreases by 1.2% in the exogenous approach. For the targets set at MS level, the farm income change is slightly smaller (3.6% in the endogenous approach and -1.3% in the exogenous approach) compared to the EU-level target (Table 2).

The income effects are determined by changes in the output value and production costs. In the endogenous approach, both F2F target scenarios lead to an increase

[30] Farm income is calculated as the difference between total revenues (output value and subsidies, excluding organic payments) and variable costs (e.g., fertilisers, pesticides, seeds, feeding).

[31] Note that the farm income change does not include organic payments for the converted farms. This implies that a decrease in income represents a proxy for the minimum budgetary support required to offset the income loss.

Table 2. Simulated impacts of MS and EU organic targets on aggregate farm income, output value and costs in the EU (% change to the baseline)

	Targets set at EU level		Targets set at MS level	
	Endogenous	Exogenous	Endogenous	Exogenous
Farm income (excl. organic payments)	+3.8%	-1.2%	+3.6%	-1.3%
Output Value	+2.9%	-2.3%	+2.8%	-2.2%
Crops specific costs	-5.3%	-2.7%	-4.9%	-3.7%
Livestock feed costs	+0.7%	-5.1%	+0.7%	-4.0%

in the aggregate output value compared to the baseline: 2.9% for the EU target and 2.8% for the MS target. The output value increases is driven by the organic price premium, which more than offsets the reduction in the output quantity resulting from the switch to organic production. In contrast, the exogenous approach results in a decrease in the aggregate output value for both MS and EU level targets: -2.3% for the EU target and -2.2% for the MS target. This implies that, in the exogenous approach, the organic price premium does not fully offset the reduction in the output quantity caused by the switch to organic production (Table 2).

Regarding production costs, they generally decrease across the simulated scenarios compared to the baseline. The exception is livestock feed costs for the endogenous approach, which show a slight increase (Table 2). The cost reduction across simulated scenarios is primarily driven by lower expenditure on fertilizers and plant protection in the organic production system. In the endogenous approach, the cost reduction reinforces the increase in output value thus contributing to an improvement in farm income in both F2F target scenarios. The production cost reduction in the exogenous approach is not sufficient to offset the decrease in output value, resulting in lower farm income in these scenarios compared to the baseline.

Overall, the EU-level target results in slightly more favourable aggregate income change (either more positive or less negative) for farms compared to the MS target, with a stronger effect observed in the endogenous approach. This outcome can be attributed to the differences in the farm selection process for conversion between the two scenarios: the EU target selects from a combined pool of all EU farms, whereas the MS target involves farm selection split by MS sub-pools. In other word, the EU target allows a more profitable allocation of organic land, enabling countries in which organic farming is more profitable to exceed the 25% target, while other countries remain below this threshold.

When considering farm income across farm specializations, the impacts of the F2F target are relatively highly heterogeneous, with effects varying in magnitude and direction. For example, the specialist wine, specialist other field crops, and mixed livestock tend to perform better than the other specializations. Similar to above, when comparing the income performance between the endogenous and exogenous approaches, the former approach generally yields more favourable results across different farm specializations, but both approaches result in heterogeneous impacts across farm groups. On the other hand, the income effects are more consistent in magnitude and direction across economic size classes. Under the endogenous approach, all economic size classes experience an improvement in income, while the exogenous approach results in negative impacts. Small and/or large farms tend to be more affected than medium-sized farms (Table 3). These income effects across farm types depend on a combination of performance-related factors that undergo change when farms convert to the organic production system. These factors encompass changes in yields, organic price premiums, and variable costs. The estimations provided in Section 2 reveal that they vary across regions, products, and farm types. The actual income effect of the F2F target is, therefore, contingent on the importance of specific product and cost types within different farm groups. Additionally, the proportion of farmers selected for conversion within a specific group plays a significant role. Specifically, farms groups with organic conversion resulting in lower yield reductions (e.g. permanent crops, fodder crops), higher price premiums (e.g. vegetables, sugar beet, pork, poultry and sheep/goats meat), greater cost reductions (e.g. specialist other field crops, specialist cereals, oilseed, protein crops, mixed livestock) and smaller proportion of converted farms (e.g. mixed crops, specialist cattle, large farms) tend to experience lower adverse impact or achieve more favorable income effects compared to other farm groups. However, the varying importance of these factors and the offsetting effects between them (e.g. reduction in variable costs versus reduction in yields) across farm groups determine the actual income outcome, which makes it complex to identify more specific income patterns across farm groups.

Table 3. Simulated impacts of MS and EU organic targets on aggregate farm income in the EU by farm specialization and economic size (% change to the baseline).

	Targets set at the EU level		Targets set at MS level	
	Endogenous	Exogenous	Endogenous	Exogenous
Farm specialization				
Specialist cereals, oilseed, protein crops (15)	4.7%	-0.4%	4.2%	-0.3%
Specialist other field crops (16)	6.4%	0.1%	5.8%	0.0%
Specialist horticulture (20)	2.9%	1.1%	2.8%	0.2%
Specialist wine (35)	10.1%	4.5%	9.4%	4.7%
Specialist orchards - fruits (36)	0.1%	-5.1%	0.1%	-5.7%
Specialist olives (37)	2.4%	2.5%	2.3%	1.3%
Permanent crops combined (38)	1.6%	0.5%	1.5%	-0.3%
Specialist milk (45)	0.3%	-2.0%	0.3%	-1.7%
Specialist sheep and goats (48)	2.2%	-3.8%	1.7%	-2.4%
Specialist cattle (49)	0.1%	-2.2%	0.0%	-3.3%
Specialist granivores (50)	7.6%	-5.6%	7.4%	-6.0%
Mixed crops (60)	4.2%	0.2%	3.7%	-0.6%
Mixed livestock (70)	7.4%	0.2%	7.3%	0.3%
Mixed crops and livestock (80)	10.6%	-1.4%	10.5%	-1.1%
Economic farm size				
Small farms	3.70%	-0.60%	-1.50%	3.40%
Medium sized farms	3.30%	-1.10%	-1.00%	3.00%
Large farms	4.10%	-1.40%	-1.30%	3.90%

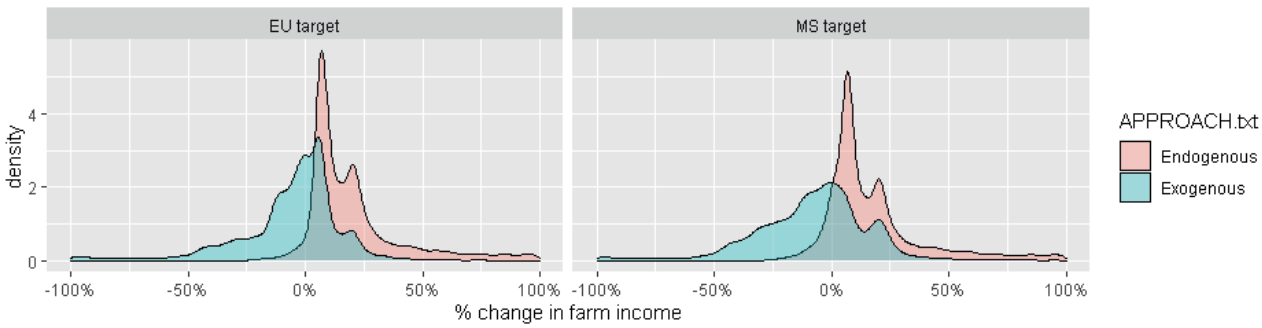

Figure 1. Probability density of the farm income change of converted farms in the EU in the MS and EU organic targets (% change to the baseline).

Figure 1 shows more disaggregated results on the distribution of the farm income change among converted farms for both the MS and EU organic targets, as well as for the two conversion selection approaches. The distribution of farm income change in the endogenous approach is shifted to the right, with most farms (more than 90% of converted farms) experiencing an improvement in income in both targets. In contrast, the distribution for the exogenous approach is shifted to the left and the negative income change tends to predominate among converted farms (for more than 50% of converted farms) in both targets. As discussed previously, these results are explained by the fact that the endogenous approach selects better-performing farms for conversion, whereas the exogenous approach considers both monetary and non-monetary factors, resulting in the selection of less profitable farms, as shown in Figure 1.

Table 4 shows more detailed results on the changes in aggregate production quantity for the main crop and animal products. As expected, the production quantity decreases for most crop and animal products (between -0.5% and -15%) in the simulated scenarios compared to

Table 4. Simulated impacts of MS and EU level organic targets on aggregate production quantity in the EU (% change to the baseline).

	Targets set at the EU level		Targets set at MS level	
	Endogenous	Exogenous	Endogenous	Exogenous
Soft wheat	-8.7%	-3.5%	-7.8%	-5.8%
Barley	-9.0%	-3.4%	-9.2%	-5.2%
Other cereals	-1.0%	-2.3%	-2.6%	-3.5%
Grain maize	-6.2%	-3.5%	-4.8%	-4.8%
Soybean	0.4%	0.6%	0.7%	0.5%
Pulses	-3.8%	-2.5%	-4.1%	-5.3%
Sunflower seed	2.7%	-1.2%	4.3%	-2.6%
Rape seed	-2.2%	-1.7%	-1.1%	-6.4%
Potatoes	-11.7%	-5.6%	-12.0%	-9.8%
Vegetables	-4.9%	-4.7%	-5.2%	-6.7%
Fodder maize	-1.4%	-4.2%	-2.8%	-6.5%
Fodder other	1.4%	-0.5%	1.5%	-0.2%
Permanent grass	-0.3%	-1.9%	-1.2%	-3.1%
Table wine	-10.2%	-5.0%	-9.4%	-3.9%
Apples and pears	-0.4%	-8.4%	-0.5%	-13.1%
Berry species	-0.7%	-6.4%	-1.0%	-22.2%
Citrus fruits	-0.4%	-8.9%	-0.4%	-5.7%
Olive oil	-4.2%	-5.2%	-3.9%	-2.2%
Cow milk for sales	-0.2%	-2.8%	-0.7%	-3.3%
Beef	-0.9%	-4.3%	-1.6%	-5.7%
Sheep & goat milk	-0.7%	-16.8%	-0.4%	-11.4%
Sheep & goat meat	-0.1%	-7.1%	-0.2%	-6.2%
Pork meat	0.0%	-4.2%	-0.3%	-5.2%
Poultry meat	-0.4%	-12.6%	-0.4%	-7.8%
Eggs	-3.9%	-9.0%	-3.8%	-10.5%

baseline due to the generally lower yields achieved following farm conversion to an organic production system. These changes tend to be more pronounced for the MS target than for the EU target, contributing to the more adverse income effects observed for the MS target compared to the EU target reported in Table 2.

Production effects are somehow different between the endogenous and exogenous approaches, with permanent crops and animal products having smaller decreases in the former than the latter approach. This result is expected because, by design, the endogenous approach selects better-performing farms for conversion compared to the exogenous approach. For arable crops, the results are mixed between the endogenous and exogenous approaches, although the production changes tend to be greater in the former than the latter approach (Table 4). These differences in production changes are driven by the types of farms selected in a given approach. In the endogenous approach, farms specialized in some arable crops (e.g. field crops) are selected to a greater extent than in the exogenous approach. The reverse is valid for some permanent crops and animal activities (e.g. specialist wine and specialist milk), where a greater share of farms tend to be selected in the exogenous than in the endogenous approach. Additionally, the exogenous approach selects farms for conversion that share similar non-monetary characteristics with organic farms, including factors related to production structure. Consequently, they are expected to be less affected by certain organic requirements, such as crop rotation and nitrogen management, resulting in a smaller adjustment in arable crop area and overall production levels. In contrast, the endogenous approach selects the best-performing farms for conversion, which may not necessarily resemble organic farms in these non-monetary characteristics. This, among other factors, is expected to have a less adverse impact on the economic variables of these farms (e.g., potentially resulting in lower yield reductions). However, it leads to a more significant adjustment in the allocation of arable crop area (and thus overall production levels) to ensure compliance with crop rotation and nitrogen management requirements.

Among specific products, only soybean, sunflower and other fodder exhibit production increases in at least endogenous approach. These positive effects are largely driven by the rotation requirement in organic farming to replace main crops with smaller ones, such as soybean and sunflower. Additionally, the feed self-sufficiency condition requires a higher proportion of on-farm feed production for animals, such as soybean or other fodder, in organic farming. In contrast, most other products experience a decrease in production quantity across all scenarios. In the case of the animal sector, all products are negatively affected, with less heterogeneity observed compared to the crop sector (Table 4). This reduced variability in production changes across animal products may result from lower variation in the organic production-related parameters across different animal activities, especially yield decreases in organic animal production. Furthermore, organic behavior constraints may have a less differential impact across animal categories compared to crops[32].

5. DISCUSSION AND CONCLUSIONS

This paper presents the modelling of organic farm conversion in an individual farm-level model (IFM-CAP) aiming to study the methodological challenges related to modelling specific farm selection into organic production and the parametrization of the converted farms. The developed model is applied to simulate economic impacts of the organic area targets adopted in the EU's F2F strategy. The paper's main contribution to the literature lies in providing a framework for modeling organic farm conversion within an EU-wide individual farm model (IFM-CAP) and bringing quantitative insights into the potential income and production effects of reaching the 25% organic target in the EU.

The results show that the simulated economic impacts based on individual farm model for the F2F organic target strongly depends on modelling assumptions, with implications that appear to be more significant than whether the organic target is set in the EU or MS level. Model simulations of the F2F organic target using the exogenous approach – under which the combination of monetary and non-monetary drivers determine farm conversion – result in more adverse aggregate farm income effects and a greater decrease in aggregate production value compared to the endogenous approach – under which profitability drives the farm conversion. These divergent result are driven by the fact that each approach tends to select different farms for conversion. In the endogenous approach, conversion to organic production significantly increases farm income for many farms that undergo conversion (for more than 90% of converted farms). Conversely, the exogenous approach shows negative income change for most converted farms (for over 50% of converted farms). While the F2F target may not necessarily have an adverse effect on the aggregate production value (especially in the endogenous approach) due to the organic price premiums offsetting the impact, the lower yields in organic production systems are expected to lead to a decrease in production quantity for most EU crop and animal products, ranging from -0.5% to -15%.

The literature on the profitability of organic farms presents mixed findings, often suggesting that organic farms have similar profitability levels to conventional farms. This implies that price premiums of organic products may offset the higher costs and lower yields associated with organic production (Alvarez, 2021; De Ponti et al., 2012; Offermann & Nieberg, 2000; Seufert et al., 2012). Hence, the positive income effect simulated in the endogenous approach raises the question about its accuracy in modeling farmers' conversion decisions. Moreover, the fact that farms are conventional in the baseline, yet the organic production is profitable in the endogenous approach, further highlights concerns about potential inaccuracies in capturing farmers' conversion decisions. This may suggest that certain behavioral effects of organic conversion, such as non-monetary factors that entail costs and benefits for converting farms (e.g., farmers' education and experience, willingness to adopt new technologies, access to organic markets), may not have been adequately accounted for.

In contrast, the exogenous approach aligns more closely with the literature's findings on simulated income changes and the role of non-monetary factors as essential drivers of farm conversion decisions to organic production (Canavari et al., 2022; Sapbamrer, 2021; Serebrennikov et al., 2020; Willock et al., 1999). However, the exogenous approach may reduce the role of profitability in influencing farmers' conversion decisions, as conversion probabilities are estimated based on both non-monetary and monetary factors. Consequently, this approach leads to lower responsiveness of the organic conversion to changes in profit-related incentives such as organic price premiums or subsidies. For instance, scenario simulations run with varying levels of organic payments is expected to yield a relatively minor response in terms of organic conversion under the exogenous approach, while the endogenous approach demonstrates

[32] For example, the maximum stocking density requirement imposes constraints on all animal categories (represented in LSU), while the nitrogen management requirement affects only specific crops, namely nitrogen-fixing crops.

a more significant impact. Additionally, the exogenous approach does not consider endogenous conversion choice, within the model which limits its applicability for policy impact simulations involving various types of subsidies (e.g. different types of environmentally related subsidies relevant to the CAP and F2F strategy) and their interactions.

Overall, both the endogenous and exogenous approaches may have limitations in accurately capturing farmers' conversion decisions. The two approaches represent different ways of modeling the organic conversion decision. While the former assumes farm conversion solely based on profitability, the latter relies on exogenously introduced non-monetary and monetary drivers. An approach that combines both non-monetary and monetary factors in an endogenous manner appears more promising. Such an approach would require linking unobserved costs and benefits associated with non-monetary drivers to observed costs and benefits (profits). However, deriving these unobserved costs and benefits presents a significant theoretical and empirical challenges when integrating the two approaches (Esposti, 2022; Kuminoff & Wossink, 2010).

While we have implemented the organic conversion selection in an individual farm model, it is important to note that this issue is relevant to other modeling methods as well. For instance, when modeling the organic target with a partial equilibrium model, it becomes necessary to introduce appropriate supply shocks. This process involves implicit assumptions about the share of different activities that will switch to organic production, along with the magnitude of yield and cost changes for each activity. Essentially, this assumption indirectly represents the farm selection process in an individual farm model. In essence, the selection approach used in an individual farm model explicitly determines which types of farms are more likely to convert to organic production. However, this is not an additional assumption compared to more aggregated models; instead, it offers greater transparency. Therefore, modelling organic targets in aggregated models may benefit from integration with individual farm models to enhance the accuracy of organic conversion modeling.

The findings of this paper have also some policy implications. The simulations show that a considerable share of farms experience a positive income change when converting to organic production (including in the exogenous approach). This result aligns with the findings of Kerselaers et al. (2007) for Belgium, who estimate a sizable positive 'economic conversion potential'[33] compared to the conventional production system. These findings indirectly suggest the presence of non-monetary factors that may constrain farms from converting. Therefore, in the context of the F2F strategy's objective of promoting organic production, it may be necessary for the policy mix to address non-monetary factors (e.g., training, networking, and market access) in addition to providing monetary incentives. This approach could enhance the F2F strategy's effectiveness in achieving its goal of reaching 25% organic area in the EU.

The paper's findings suggest that the F2F organic target could have significant implications for food security. Simulations indicate a potential substantial decrease in the production of major crop and livestock products within the EU. To fully assess its impact on global food security – including the overall supply of agricultural commodities, market impacts, and access to food for vulnerable consumers – conducting further analysis using global market models is essential. This becomes particularly important in the current global context marked by food inflation and the ongoing war in Ukraine (European Commission, 2023).

When drawing conclusions from our findings, it is necessary to recognize the assumptions inherent in our model. First, our simulation results are conditional on the assumption that the organic price premiums over conventional products remain unchanged from the current (pre-target) level. However, an increased supply of organic products could potentially lead to a decrease in the price premiums, potentially impacting farm income more adversely than simulations suggest. Second, our model assumes a fixed farm structure, meaning that farms' production specialization and size remain unchanged following conversion to organic production. In reality, converted farms may make more significant adjustments in production structure and scale than model accounts for. A third potential caveat is that our analysis does not include market price feedback effects. The substantial production decrease simulated for the F2F organic target is expected to raise market prices, impacting farm income. Consequently, our model may understate income increases in the endogenous approach and overstates income decreases in the exogenous approach. Fourth, the exogenous approach in our study only considers factors affecting farm organic conversion that were observed in FADN. However, as literature suggests, there are several other drivers not available in the FADN that may impact organic conversion decisions, such as farmers' knowledge and skills about organic production methods, access to organic markets, or organic

[33] They define 'economic conversion potential' as 'the potential difference in individual farm income obtained under the current conventional production mode and an estimated income under organic production mode'.

certification costs. These factors would need to be incorporated into future analyses when data become available. Finally, our analysis focuses solely on the economic impacts of the organic targets. Future research needs to extend the analysis to include environmental impacts. This would allow for a more comprehensive investigation of the trade-offs between economic and environmental effects in the transition of the EU farming sector towards greater adoption of organic production. Addressing these limitations and conducting further research will enhance the robustness of our results and provide a more complete understanding of the EU-wide impacts of organic targets set in the F2F strategy.

DISCLAIMER

The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

REFERENCES

Acs, S., Berentsen, P. B. M., & Huirne, R. B. M. (2007). Conversion to organic arable farming in The Netherlands: A dynamic linear programming analysis. *Agricultural Systems*, *94*(2), 405–415. https://doi.org/10.1016/j.agsy.2006.11.002

Acs, S., Berentsen, P., Huirne, R., & van Asseldonk, M. (2009). Effect of yield and price risk on conversion from conventional to organic farming. *Australian Journal of Agricultural and Resource Economics*, *53*(3), 393–411. https://doi.org/10.1111/j.1467-8489.2009.00458.x

Alvarez, R. (2021). Comparing Productivity of Organic and Conventional Farming Systems : A Quantitative Review. *Archives of Agronomy and Soil Science*, *00*(00), 1–12. https://doi.org/10.1080/03650340.2021.1946040

Baker, B. P., Green, T. A., & Loker, A. J. (2020). Biological control and integrated pest management in organic and conventional systems. *Biological Control*, *140*(August 2019), 104095. https://doi.org/10.1016/j.biocontrol.2019.104095

Barbieri, P., Pellerin, S., & Nesme, T. (2017). Comparing crop rotations between organic and conventional farming. *Nature Scientific Reports*, *June*, 1–11. https://doi.org/10.1038/s41598-017-14271-6

Barbieri, P., Pellerin, S., Seufert, V., & Nesme, T. (2019). Changes in crop rotations would impact food production in an organically farmed world. *Nature Sustainability*, *2*(5), 378–385. https://doi.org/10.1038/s41893-019-0259-5

Barreiro Hurle, J., Bogonos, M., Himics, M., Hristov, J., Dominguez Perez, I. Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., Elleby, C., Barreiro-Hurle, J., Bogonos, M., Himics, M., Hristov, J., Pérez-Domiguez, I., Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., & Elleby, C. (2021). Modelling environmental and climate ambition in the agricultural sector with the CAPRI model. In *JRC Technical Report*. https://doi.org/10.2760/98160

Basnet, S. K., Manevska-Tasevska, G., & Surry, Y. (2018). Explaining the process for conversion to organic dairy farming in Sweden: An alternative modelling approach. *German Journal of Agricultural Economics*, *67*(1), 14–30.

Bonfiglio, A., Abitabile, C., & Henke, R. (2022). A choice model-based analysis of diversification in organic and conventional farms. *Bio-Based and Applied Economics*, *11*(2), 131–146. https://doi.org/10.36253/bae-12206

Bravo-monroy, L., Potts, S. G., & Tzanopoulos, J. (2016). *Drivers influencing farmer decisions for adopting organic or conventional coffee management practices*. *58*, 49–61. https://doi.org/10.1016/j.foodpol.2015.11.003

Bremmer, J., Gonzalez-Martinez, A., Jongeneel, R., Huiting, H., Stokkers, R., & Ruijs, M. (2021). *Impact assessment of EC 2030 Green Deal Targets for sustainable crop production* (Issues 2021–150). Wageningen Economic Research. https://doi.org/10.18174/558517

Burton, M., Rigby, D., & Young, T. (1999). Analysis of the determinants of adoption of organic horticultural techniques in the UK. *Journal of Agricultural Economics*, *50*(1), 47–63. https://doi.org/10.1111/j.1477-9552.1999.tb00794.x

Buysse, J., Van Huylenbroeck, G., & Lauwers, L. (2007). Normative, positive and econometric mathematical programming as tools for incorporation of multifunctionality in agricultural policy modelling. *Agriculture, Ecosystems and Environment*, *120*(1), 70–81. https://doi.org/10.1016/j.agee.2006.03.035

Canavari, M., Gori, F., Righi, S., & Sciences, F. (2022). Factors fostering and hindering farmers ' intention to adopt organic agriculture in the Pesaro-Urbino province (Italy). *AIMS Agriculture and Food*, *7*(March), 108–129. https://doi.org/10.3934/agrfood.2022008

Castellazzi, M. S., Wood, G. A., Burgess, P. J., Morris, J., Conrad, K. F., & Perry, J. N. (2008). A systematic representation of crop rotations. *Agricultural Systems*, *97*(1–2), 26–33. https://doi.org/10.1016/j.agsy.2007.10.006

Chatzimichael, K., Genius, M., & Tzouvelekas, V. (2014). *Informational cascades and technology adoption : Evidence from Greek and German organic growers*. *49*, 186–195. https://doi.org/10.1016/j.foodpol.2014.08.001

Chmelíková, L., Schmid, H., Anke, S., & Hülsbergen, K. J. (2021). Nitrogen-use efficiency of organic and conventional arable and dairy farming systems in Germany. *Nutrient Cycling in Agroecosystems*, *119*(3), 337–354. https://doi.org/10.1007/s10705-021-10126-9

Chmielinski, P., Pawlowska, A., Bocian, M., & Osuch, D. (2019). The land is what matters: factors driving family farms to organic production in Poland. *British Food Journal*, *121*(6), 1354–1367. https://doi.org/10.1108/BFJ-05-2018-0338

Ciaian, P., Maria, E. G., Gomez y Paloma, S., Heckelei, T., Sckokai, P., Elouhichi, K., Thomas, A., & Vard, T. (2013). Farm level modelling of CAP: a methodological overview. In S. Langrell (Ed.), *JRC Scientific and Policy Reports*. Publications Office of the European Union. http://publications.jrc.ec.europa.eu/repository/handle/JRC79969

Darnhofer, I., Schneeberger, W., & Freyer, B. (2005). Converting or not converting to organic farming in Austria: Farmer types and their rationale. *Agriculture and Human Values*, *22*(1), 39–52. https://doi.org/10.1007/s10460-004-7229-9

De Ponti, T., Rijk, B., & Van Ittersum, M. K. (2012). The crop yield gap between organic and conventional agriculture. *Agricultural Systems*, *108*, 1–9. https://doi.org/10.1016/j.agsy.2011.12.004

Djokoto, J. G., Owusu, V., Awunyo-vitor, D., Djokoto, J. G., Owusu, V., & Awunyo-vitor, D. (2016). Adoption of organic agriculture : Evidence from cocoa farming in Ghana Adoption of organic agriculture : Evidence from cocoa farming in Ghana. *Cogent Food & Agriculture*, *52*. https://doi.org/10.1080/23311932.2016.1242181

Dury, J., Schaller, N., Garcia, F., Bergez, A. R., & Eric, J. (2012). Models to support cropping plan and crop rotation decisions . A review. *Agronomy for Sustainable Development*. https://doi.org/10.1007/s13593-011-0037-x

Esposti, R. (2022). *The co-evolution of policy support and farmers behaviour. An investigation on Italian agriculture over the 2008-2019 period*. *11*, 231–264. https://doi.org/10.36253/bae-12912

European Commission. (2008). *Regulation (EC) No 889/2008*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32008R0889

European Commission. (2018a). *Impact assessment accompanying the proposal for Regulations under COM(2018)392, COM(2018)393 and COM(2018)394*.

European Commission. (2018b). *Regulation (EU) 2018/848 of the European Parliament and of the Council of 30 May 2018 on organic production and labelling of organic products*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32018R0848

European Commission. (2019). *Communication on the European Green Deal (COM/2019/640 final)*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2019%3A640%3AFIN

European Commission. (2020). *COM/2020/381 final: A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020DC0381

European Commission. (2021). *Communication on an action plan for the development of organic production COM(2021) 141 final/2*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021DC0141R%2801%29

European Commission. (2023). *Drivers of Food Security. Commission Staff Working Document, SWD(2023) 4 final. Brussels*.

Fairweather, J. R. (1999). Understanding how farmers choose between organic and conventional production: Results from New Zealand and policy implications. *Agriculture and Human Values*, *16*(1), 51–63. https://doi.org/10.1023/A:1007522819471

Flaten, O., & Lien, G. (2009). Organic dairy farming in Norway under the 100% organically produced feed requirement. *Livestock Science*, *126*(1), 28–37. https://doi.org/10.1016/j.livsci.2009.05.014

Gaudaré, U., Pellerin, S., Benoit, M., Durand, G., Dumont, B., Barbieri, P., & Nesme, T. (2021). Comparing productivity and feed-use efficiency between organic and conventional livestock animals. *Environmental Research Letters*, *16*(2). https://doi.org/10.1088/1748-9326/abd65e

Genius, M., Pantzios, C. J., & Tzouvelekas, V. (2006). Information acquisition and adoption of organic farming practices. *Journal of Agricultural and Resource Economics*, *31*(1), 93–113. https://doi.org/10.22004/ag.econ.10150

Hattam, C. E., & Holloway, G. J. (2005). Adoption of certified organic production: Evidence from Mexico. *International Sci-Entific Conference on Organic Agriculture.*, 1–5.

Hermansen, J. E., Strudsholm, K., & Horsted, K. (2004). *Integration of organic animal production into land use with special reference to swine and poultry*. *90*, 11–26. https://doi.org/10.1016/j.livprodsci.2004.07.009

Jones, P., & Richard Crane. (2014). *England and Wales under organic agriculture : how much food could be produced ?* (Issue January 2009).

Kallas, Z., Serra, T., Gil, J. M., Kallas, Z., Serra, T., & Gil, J. M. (2009). *Farmer ' s objectives as determinant factors of organic farming adoption Farmer ' s objectives as determinant factors of organic farming adoption*. 1–19.

Kerselaers, E., De Cock, L., Lauwers, L., & Van Huylenbroeck, G. (2007). Modelling farm-level economic potential for conversion to organic farming. *Agricultural Systems*, *94*(3), 671–682. https://doi.org/10.1016/j.agsy.2007.02.007

Kremmydas, D., Athanasiadis, I. N., & Rozakis, S. (2018). A review of Agent Based Modeling for agricultural policy evaluation. *Agricultural Systems*, *164*(April), 95–106. https://doi.org/10.1016/j.agsy.2018.03.010

Kremmydas, D., Petsakos, A., Ciaian, P., Baldoni, E., & Tillie, P. (2022). *The EU-Wide Individual Farm Model for Common Agricultural Policy Analysis (IFM-CAP v.2)*. https://doi.org/10.2760/248136

Kuminoff, N. V., & Wossink, A. (2010). Why isn't more us farmland organic? *Journal of Agricultural Economics*, *61*(2), 240–258. https://doi.org/10.1111/j.1477-9552.2009.00235.x

Küstermann, B., Christen, O., & Hülsbergen, K. J. (2010). Modelling nitrogen cycles of farming systems as basis of site- and farm-specific nitrogen management. *Agriculture, Ecosystems and Environment*, *135*(1–2), 70–80. https://doi.org/10.1016/j.agee.2009.08.014

Lampkin, N., Measures, M., & Padel, S. (Susanne) (Eds.). (2017). *2017 Organic farm management handbook* (11th ed.). The Organic Research Centre, Hamstead Marshall, Newbury.

Läpple, D., & Rensburg, T. Van. (2011). Adoption of organic farming : Are there differences between early and late adoption ? *Ecological Economics*, *70*(7), 1406–1414. https://doi.org/10.1016/j.ecolecon.2011.03.002

Lee, J., Necpálová, M., & Six, J. (2020). Biophysical potential of organic cropping practices as a sustainable alternative in Switzerland. *Agricultural Systems*, *181*(April 2019). https://doi.org/10.1016/j.agsy.2020.102822

Lin, H. C., Huber, J. A., Gerl, G., & Hülsbergen, K. J. (2016). Nitrogen balances and nitrogen-use efficiency of different organic and conventional farming systems. *Nutrient Cycling in Agroecosystems*, *105*(1), 1–23. https://doi.org/10.1007/s10705-016-9770-5

Lohr, L., & Salomonsson, L. (2000). Conversion subsidies for organic production: Results from Sweden and lessons for the United States. *Agricultural Economics*, *22*(2), 133–146. https://doi.org/10.1016/S0169-5150(99)00045-6

Louhichi, K., Ciaian, P., Espinosa, M., Colen, L., Perni, A., & Paloma, S. G. y. (2017). Does the crop diversification measure impact EU farmers' decisions? An assessment using an Individual Farm Model for CAP Analysis (IFM-CAP). *Land Use Policy*, *66*(September 2016), 250–264. https://doi.org/10.1016/j.landusepol.2017.04.010

Louhichi, K., Ciaian, P., Espinosa, M., Perni, A., & Gomez y Paloma, S. (2018). Economic impacts of CAP greening: application of an EU-wide individual farm model for CAP analysis (IFM-CAP). *European Review of Agricultural Economics*, *45*(2), 205–238. https://doi.org/10.1093/erae/jbx029

Malá, Z., & Malý, M. (2013). The determinants of adopting organic farming practices: A case study in the Czech Republic. *Agricultural Economics (Czech Republic)*, *59*(1), 19–28. https://doi.org/10.17221/10/2012-agricecon

Meemken, E. M., & Qaim, M. (2018). Organic Agriculture, Food Security, and the Environment. *Annual Review of Resource Economics*, *10*, 39–63. https://doi.org/10.1146/annurev-resource-100517-023252

Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K. H., Smith, P., Klocke, P., Leiber, F., Stolze, M., & Niggli, U. (2017). Strategies for feeding the world more sustainably with organic agriculture. *Nature Communications*, *8*(1), 1–13. https://doi.org/10.1038/s41467-017-01410-w

Offermann, F., & Nieberg, H. (2000). The profitability of organic farming in Europe. *OECD Workshop, Organic Agriculture: Sustainability, Markets and Policies*, *November*, 141–151.

Parra López, C., & Calatrava Requena, J. (2005). Factors related to the adoption of organic farming in Spanish olive orchards. *Spanish Journal of Agricultural Research*, *3*(1), 5. https://doi.org/10.5424/sjar/2005031-119

Petsakos, A., Ciaian, P., Espinosa, M., Perni, A., & Kremmydas, D. (2022). Farm-level impacts of the CAP post-2020 reform : A scenario-based analysis. *Applied Economic Perspectives and Policy*, *February*, 1–21. https://doi.org/10.1002/aepp.13257

Reganold, J. P., & Wachter, J. M. (2016). Organic agriculture in the twenty-first century. *Nature Plants*, *2*(February), 15221. https://doi.org/10.1038/nplants.2015.221

Reimer, M., Möller, K., & Hartmann, T. E. (2020). Meta-analysis of nutrient budgets in organic farms across Europe. *Organic Agriculture*, *10*, 65–77. https://doi.org/10.1007/s13165-020-00300-8

Richardson, G. P. (2011). Reflections on the foundations of system dynamics. *System Dynamics Review*, *27*(3), 219–243. https://doi.org/https://doi.org/10.1002/sdr.462

Rozman, Č., Pažek, K., Kljajić, M., Bavec, M., Turk, J., Bavec, F., Kofjač, D., & Škraba, A. (2013). The dynamic simulation of organic farming development scenarios - A case study in Slovenia. *Computers and Electronics in Agriculture*, *96*, 163–172. https://doi.org/10.1016/j.compag.2013.05.005

Sapbamrer, R. (2021). *A Systematic Review of Factors Influencing Farmers ' Adoption of Organic Farming*.

Serebrennikov, D., Thorne, F., & Kallas, Z. (2020). *Factors Influencing Adoption of Sustainable Farming Practices in Europe: A Systemic Review of Empirical Literature*. 1–23.

Seufert, V., & Ramankutty, N. (2017). Many shades of gray—the context-dependent performance of organic agriculture. *Science Advances*, *3*(3). https://doi.org/10.1126/sciadv.1602638

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Shmueli, G. (2010). *To Explain or to Predict ? 25*(3), 289–310. https://doi.org/10.1214/10-STS330

Smith, L. G., Jones, P. J., Kirk, G. J. D., Pearce, B. D., & Williams, A. G. (2018). Modelling the production impacts of a widespread conversion to organic agriculture in England and Wales. *Land Use Policy*, *76*(May), 391–404. https://doi.org/10.1016/j.landusepol.2018.02.035

Sossidou, E. N., Bosco, A. D., Castellini, C., & Grashorn, M. A. (2015). Effects of pasture management on poultry welfare and meat quality in organic poultry production systems. *World's Poultry Science Journal*, *71*(2), 375–384. https://doi.org/10.1017/S0043933915000379

Thomas, A. (2003). A dynamic model of on-farm integrated nitrogen management. *European Review of Agricultural Economics*, *30*(4), 439–460. https://doi.org/10.1093/erae/30.4.439

Timsina, J. (2018). Can organic sources of nutrients increase crop yields to meet global food demand? *Agronomy*, *8*(10), 1–20. https://doi.org/10.3390/agronomy8100214

Watson C.A., Atkinson, D., Gosling, P., Jackson, L. R., & Rayns, F. W. (2002). Managing soil fertility in organic farming systems. *Soil Use and Management*, *18*(3), 239–247. https://doi.org/10.1079/sum2002131

Willock, J., Deary, I. J., Edwards-Jones, G., Gibson, G. J., McGregor, M. J., Sutherland, A., Dent, J. B., Morgan, O., & Grieve, R. (1999). The role of attitudes and objectives in farmer decision making: Business and environmentally-oriented behaviour in Scotland. *Journal of Agricultural Economics*, *50*(2), 286–303. https://doi.org/10.1111/j.1477-9552.1999.tb00814.x

Xu, Q., Huet, S., Poix, C., Boisdon, I., & Deffuant, G. (2018). Why do farmers not convert to organic farming? Modeling conversion to organic farming as a major change. *Natural Resource Modeling*, *31*(3). https://doi.org/10.1111/nrm.12171

Yu, C. H., Yoo, J. C., & Yao, S. B. (2014). Farmers' willingness to switch to organic agriculture: A non-parametric analysis. *Agricultural Economics (Czech Republic)*, *60*(6), 273–278. https://doi.org/10.17221/82/2013-agricecon

APPENDIX

Table A5. Estimated median percentage difference in the expected crop prices between organic and conventional farming in the EU.

	Central Europe North	Central Europe South	Northern Europe	Southern Europe	UK & Ireland
Wheat	+60%	+45%	+20%	+6%	+72%
Maize	+59%	+39%	+35%	+8%	+35%
Other cereals	+48%	+26%	+11%	+5%	+57%
Oilseeds	+31%	+27%	+13%	+8%	+20%
Sugar beet	+2%	+100%	+51%	+51%	+51%
Vegetables	+56%	+114%	+30%	+19%	+98%
Fruits	+39%	+34%	+37%	+11%	+13%
Other permanent crops	+30%	+49%	+8%	+20%	+16%
Fodder crops	+24%	+5%	+5%	+1%	+5%

Source: own econometric estimations.
Note: - Of the 463 organic price coefficients estimated at FADN region level, 68% are statistically significant at 90% confidence level.
- Central Europe North: Belgium, Luxemburg, Netherlands, Germany, Poland.
- Central Europe South: Austria, Czech Republic, France, Hungary, Slovakia, Romania.
- Northern Europe: Sweden, Finland, Estonia, Lithuania, Latvia, Denmark.
- Southern Europe: Bulgaria, Croatia, Cyprus, Greece, Italy, Malta, Portugal, Spain, Slovenia.

Table A6. Estimated median percentage difference in the expected crop yields between organic and conventional farming in the EU.

	Central Europe North	Central Europe South	Northern Europe	Southern Europe	UK & Ireland
Wheat	-44%	-34%	-41%	-12%	-56%
Maize	-32%	-22%	-20%	-5%	-20%
Other cereals	-43%	-34%	-32%	-16%	-45%
Oilseeds	-57%	-32%	-42%	-11%	-35%
Vegetables	-42%	-44%	-41%	-11%	-76%
Sugar beet	-2%	-22%	-12%	-12%	-12%
Fruits	-51%	-57%	-36%	-22%	-64%
Other permanent crops	-9%	-21%	-5%	-12%	-4%
Fodder crops	-16%	-5%	-10%	-4%	-9%

Source: own econometric estimations.
Note: - Of the 550 organic yield coefficients estimated at FADN region level, 77% are statistically significant at 90% confidence level.

Table A7. Ranges of percentage differences in estimations variable crop production costs between organic and conventional farms by farm specialization and region in the EU.

	Seeds/ha		Fertilizers/ha		Crop protection/ha		Other costs/ha	
	Max	Min	Max	Min	Max	Min	Max	Min
Per Farm Specialization								
Specialist COP (15)	-4%	+18%	-91%	-31%	-88%	-18%	-24%	+57%
Specialist other field crops (16)	-15%	+78%	-71%	-17%	-99%	-13%	-26%	+9%
Specialist horticulture (20)	-25%	-2%	-15%	-4%	-29%	+2%	-7%	+82%
Specialist wine (35)	-30%	+3%	-19%	+25%	-21%	-13%	+1%	+16%
Specialist orchards - fruits (36)	-24%	+31%	-47%	-14%	-41%	-19%	-24%	+8%
Specialist olives (37)	-3%	-3%	-7%	-7%	-19%	-19%	+2%	+2%
Permanent crops combined (38)	-11%	+5%	-31%	-8%	-13%	-12%	-37%	+12%
Specialist milk (45)	-10%	+13%	-52%	-11%	-54%	-12%	-5%	+35%
Specialist sheep and goats (48)	-9%	+22%	-81%	-16%	-33%	+2%	-10%	+21%
Specialist cattle (49)	-14%	+42%	-60%	-5%	-50%	-3%	-10%	-2%
Specialist granivores (50)	-32%	+5%	-39%	-20%	-67%	+18%	-17%	+98%
Mixed crops (60)	-19%	-1%	-45%	-17%	-40%	-18%	-46%	+4%
Mixed livestock (70)	-8%	+2%	-46%	-18%	-52%	-21%	-56%	+39%
Mixed crops and livestock (80)	-10%	+5%	-80%	-16%	-70%	-16%	-13%	+6%
Per Region								
Central Europe North	-32%	+5%	-49%	+25%	-52%	-13%	-17%	+57%
Central Europe South	-17%	+31%	-63%	-4%	-67%	-12%	-46%	+82%
Northern Europe	-25%	+19%	-52%	-11%	-54%	+2%	-56%	0%
Southern Europe	-30%	+9%	-41%	-3%	-41%	+18%	-9%	+98%
UK & Ireland	-24%	+78%	-91%	-15%	-99%	-22%	-24%	+35%

Source: own econometric estimations.
Note: - Estimations performed by region, type of farming, and cost item. Given the numerous cost combinations estimated and to facilitate result visualization, the table presents minimum and maximum median values for each cost group.
- Of the 1,748 organic coefficients estimated, 55% are statistically significant at 90% confidence level.

Table A8. Estimated median percentage difference in the expected livestock price between organic and conventional farming in the EU.

	Central Europe North	Central Europe South	Northern Europe	Southern Europe	UK & Ireland
Beef meat	+5%	+7%	+15%	+4%	+4%
Dairy milk for sale	+26%	+12%	+8%	+4%	+22%
Eggs/laying hens	+44%	+7%	+16%	+32%	+25%
Pork meat	+93%	+29%	+113%	+78%	+78%
Poultry meat	+45%	+45%	+45%	+45%	+45%
Sheep/goats milk for sale	+4%	+8%	+4%	+1%	+4%
Sheep/goats meat for fattening	+29%	+29%	+29%	+29%	+29%

Source: own econometric estimations.
Note: - For milk, 65% of the 60 estimated coefficients for prices are significant at 90% confidence level. For other livestock activities, approximately 52% of the estimated coefficients for prices were significant at 90% confidence level.

Table A9. Estimated median percentage difference in the expected livestock yields between organic and conventional farming in the EU

	Central Europe North	Central Europe South	Northern Europe	Southern Europe	UK & Ireland
Beef meat	-26%	-29%	-15%	-10%	-18%
Dairy milk for feeding	-9%	-15%	-6%	-10%	-10%
Dairy milk for sale	-20%	-18%	-10%	-8%	-14%
Eggs/laying hens	-0.1%	-7%	-10%	-7%	-6%
Pork meat	-3%	-18%	-32%	-18%	-18%
Poultry meat	-10%	-10%	-10%	-10%	-10%
Sheep/goats milk for feeding	-14%	-14%	-14%	-14%	-14%
Sheep/goats milk for sale	-14%	-14%	-14%	-14%	-14%
Sheep/goats meat for fattening	-10%	-10%	-10%	-10%	-10%
Female calves	-1%	-1%	-1%	-1%	-1%
Male calves	-1%	-1%	-1%	-1%	-1%

Source: own econometric estimations, except poultry meat (Gaudaré et al., 2021).
Note: - For milk, 65% of the 60 estimated coefficients yields are significant at 90% confidence level. For other livestock activities, approximately 32% of the estimated coefficients for yields were significant at 90% confidence level.

Table A10. Thresholds of livestock units per hectare provided in the EU organic regulation 2018/848.

Animal activity	Regulation Threshold (LSU per ha)	Land usage coefficient (Ha per LSU)
Dairy cows	2	0.5
Other cows	2.5	0.4
Breeding heifers	2.5	0.4
Cull dairy cows	2	0.5
Calves for fattening	5	0.2
Ewes	13.3	0.075188
Pigs for fattening	14	0.071429
Breeding sows	6.5	0.153846
Laying hens	230	0.004348
Table chickens	580	0.001724

Source: EU organic regulation 2018/848 and own calculations (last column).

Table A7. Covariates used in the prediction of the likelihood to convert.

Name	Type	Description	Class frequency/Summary statistics	
			Mean	Std. Dev.
REGION	Class	FADN region dummies	10,20,30,…,862	
TF14	Class	Dummies for the 14 FADN classes of type of farming	15(0.168), 16(0.105), 20(0.055), 35(0.051), 36(0.049), 37(0.015), 38(0.013), 45(0.173), 48(0.050), 49(0.086), 50(0.051), 60(0.033), 70(0.026), 80(0.118)	
ACTIVITIES	Numeric	Share of the total agricultural area by production activity. Additionally, the share of cereals is interacted with all other activities. In total 24 activities	0.27	0.44
LIVESTOCK	Class	Dummy for the presence/absence of livestock activities	0.58	0.49
MAX SHARE CROP DETAILED	Numeric	Maximum share of the major crop according to FADN activities	0.59	0.24

Name	Type	Description	Class frequency/Summary statistics	
			Mean	Std. Dev.
MAX SHARE CROP AGGREGATE	Numeric	Maximum share of the major crop according to IFM-CAP activities	0.71	0.21
SHANNON	Numeric	Shannon index of crop biodiversity	0.98	0.57
SHARE UAA OWNED	Numeric	Share of owned Utilized Agricultural Area	0.53	0.38
REGIONAL LAND RENT	Numeric	Regional average rental price of agricultural land per hectare	202.99	192.05
UAA	Numeric	Total Utilized Agricultural Area	101.62	283.92
SIZ6	Class	Classes of economic size	1(0.046), 2(0.173), 3(0.178), 4(0.193), 5(0.321), 6(0.087)	
TYPOWN	Class	Type of ownership of the farm	1(0.809), 2(0.114), 3(0.072), 4(0.003)	
ALTITUDE	Class	Altitude class of the holding	1(0.654), 2(0.230), 3(0.091), 4(0.023)	
ANC3	Class	Classes of Areas with Natural Constraints	1(0.482), 2(0.367), 3(0.150)	
TOTAL AWU HA	Numeric	Total Annual Working Units per hectare	2.95	8.35
SHARE UNPAID AWU	Numeric	Share of AWU of family workers	0.80	0.30
LU/HA	Numeric	Livestock Density	8.46	769.03
IRRSYS	Class	Type of irrigation system	0(0.792), 1(0.047), 2(0.060), 3(0.087), 4(0.011)	
FIXED ASSETS/HA	Numeric	Fixed assets per hectare in EUR	28,930.85	1,634,160.85
MFP	Numeric	Multifactor productivity measured as total output value divided total input costs	1.26	0.82
DECOUPLED/ HA	Numeric	Decoupled payments per hectare	269.17	1,298.88
COUPLED/HA	Numeric	Coupled payments per hectare	103.65	1,712.24
ENVIRONMENT/HA	Numeric	Environmental payments per hectare	60.71	3,695.92
LFA/HA	Numeric	Payments for Least Favoured Areas per hectare	37.94	186.54
OTHER/HA	Numeric	Other RDP payments per hectare	32.69	4,927.54
INVESTMENTS/HA	Numeric	Payments for investments per hectare	86.77	9,779.52
ORGANIC WHEAT YIELD RATIO	Numeric	Ratio between the yield of wheat for organic and for conventional farms in the FADN region	0.62	0.35
ORGANIC MAIZE YIELD RATIO	Numeric	Ratio between the yield of maize for organic and for conventional farms in the FADN region	0.61	0.39
ORGANIC MILK YIELD RATIO	Numeric	Ratio between the yield of milk for organic and for conventional farms in the FADN region	0.72	0.36
REGIONAL SHARE ORGANIC	Numeric	Share of organic farms in the region	0.10	0.09
FERTILIZERS/HA	Numeric	Expenditure per hectare in fertilizers	352.58	5,285.69
PESTICIDES/HA	Numeric	Expenditure per hectare in pesticides	232.45	1,490.94
RELATIVE FERTILIZERS/HA	Numeric	Expenditure per hectare in fertilizers relative to the expenditure of farms of the same organic status, TF14 and region	1.13	4.56
RELATIVE PESTICIDES/HA	Numeric	Expenditure per hectare in pesticides relative to the expenditure of farms of the same organic status, TF14 and region	1.10	3.13

Note: - for more information about FADN classes, please refer to the FADN farm return.
- for more information about the choice of indicators, please refer to Supplementary material Part D.
- for class variables, except REGION, the code of the classes is presented together with its relative frequency in parenthesis.

Table A8. Comparisons of the prediction accuracy metric of estimated models in the exogenous approach.

	LP	LP + SSA	LOGIT	LOGIT + SSA	PROBIT	PROBIT + SSA	RANDOM FOREST	Maximum prediction accuracy	Selected model
Belgium	0.8096	0.8053	0.9014	0.8017	0.8709	0.8066	0.9411	0.9411	RANDOM FOREST
Cyprus	0.8102	0.8148	0.8497	0.8443	0.8504	0.8435	0.8993	0.8993	RANDOM FOREST
Czechia	0.8563	0.8556	0.9424	0.9213	0.8191	0.9082	0.9653	0.9653	RANDOM FOREST
Germany	0.9273	0.9275	0.9301	0.9282	0.9293	0.9291	0.9725	0.9725	RANDOM FOREST
Greece	0.7228	0.7224	0.7543	0.7449	0.6187	0.5984	0.914	0.914	RANDOM FOREST
Spain	0.7597	0.7583	0.7683	0.7664	0.7691	0.7676	0.928	0.928	RANDOM FOREST
Estonia	0.8305	0.828	0.8029	0.9354	0.7705	0.7399	0.9653	0.9653	RANDOM FOREST
France	0.7067	0.7054	0.7253	0.5933	0.7241	0.7225	0.9251	0.9251	RANDOM FOREST
Croatia	0.8499	0.849	0.8526	0.8462	0.8482	0.8416	0.9139	0.9139	RANDOM FOREST
Hungary	0.7498	0.7434	0.7922	0.7607	0.6312	0.7714	0.8781	0.8781	RANDOM FOREST
Ireland	0.8366	0.839	0.8831	0.9843	0.8523	0.9841	0.9526	0.9843	LOGIT + SSA
Lithuania	0.9676	0.9679	0.9762	0.9743	0.9511	0.9697	0.9801	0.9801	RANDOM FOREST
Luxemburg	0.9389	0.9404	0.9905	0.9816	0.8846	0.9783	0.9802	0.9905	LOGIT
Latvia	0.8983	0.8967	0.8848	0.9361	0.9212	0.9322	0.9835	0.9835	RANDOM FOREST
Italy	0.8032	0.8017	0.7232	0.8036	0.7173	0.8019	0.8972	0.8972	RANDOM FOREST
Netherland	0.7476	0.755	0.7993	0.778	0.7951	0.7728	0.9507	0.9507	RANDOM FOREST
Austria	0.9007	0.9001	0.9006	0.9134	0.9003	0.907	0.9472	0.9472	RANDOM FOREST
Poland	0.8662	0.8655	0.9377	0.9353	0.6075	0.9293	0.9692	0.9692	RANDOM FOREST
Portugal	0.7636	0.7622	0.7776	0.7748	0.5243	0.7627	0.9411	0.9411	RANDOM FOREST
Romania	0.7314	0.7284	0.5263	0.7617	0.6627	0.7576	0.9022	0.9022	RANDOM FOREST
Finland	0.9186	0.9154	0.8801	0.9288	0.872	0.9248	0.9801	0.9801	RANDOM FOREST
Sweden	0.804	0.8021	0.7745	0.7417	0.8374	0.852	0.9561	0.9561	RANDOM FOREST
Slovakia	0.8053	0.796	0.845	0.836	0.835	0.5953	0.8997	0.8997	RANDOM FOREST
Slovenia	0.9162	0.9172	0.9456	0.9439	0.917	0.9375	0.9636	0.9636	RANDOM FOREST
Bulgaria	0.7483	0.7512	0.6083	0.6291	0.6631	0.5099	0.8783	0.8783	RANDOM FOREST
Denmark	0.9668	0.9668	0.9775	0.9759	0.9766	0.9747	0.984	0.984	RANDOM FOREST
EU	0.7288	-	0.573	-	0.5449	-	0.9367	0.9367	RANDOM FOREST

Table A9. The distribution of selected farms for conversion in the exogenous and endogenous approaches in the EU and MS organic targets in the EU by farm specialization and economic farm size (% of farms by farm specialization and size).

	Targets set at EU level		Targets set at MS level	
	Endogenous	Exogenous	Endogenous	Exogenous
Farm specialization				
Specialist Cereals, Oilseed, Protein crops (15)	17%	11%	16%	10%
Specialist other field crops (16)	5%	3%	7%	4%
Specialist horticulture (20)	20%	10%	19%	6%
Specialist wine (35)	0%	10%	0%	8%
Specialist orchards - fruits (36)	10%	12%	11%	6%
Specialist olives (37)	2%	6%	3%	2%
Permanent crops combined (38)	1%	6%	3%	10%
Specialist milk (45)	4%	9%	3%	10%
Specialist sheep and goats (48)	0%	8%	1%	10%
Specialist cattle (49)	2%	1%	2%	1%
Specialist granivores (50)	7%	7%	6%	6%
Mixed crops (60)	2%	1%	2%	2%
Mixed livestock (70)	12%	9%	12%	13%
Mixed crops and livestock (80)	17%	9%	16%	11%
Total	100%	100%	100%	100%
Economic farm size				
Small farms	63%	59%	62%	64%
Medium sized farms	22%	28%	24%	23%
Large farms	15%	13%	15%	13%
Total	100%	100%	100%	100%

SUPPLEMENTARY MATERIAL

Part A: Literature Review on drivers and impacts of organic conversion

Regarding the literature relevant to the methodological challenges of modeling organic production in an individual farm model, we recognize two main strands of analysis. The first strand deals with the drivers of conversion to organic farming. Its findings are relevant to designing the approach to model farm conversion from conventional to the organic production system. The second strand compares the organic farm performance and organic farm management practices with the conventional ones. The findings from this strand of literature are relevant for the parametrization of converted organic farms in terms of yields, price, input costs, and management practices differences from conventional farms.

6.1 Drivers of conversion to organic farming

The economic literature has primarily applied empirical analyses to identify the main drivers of organic farming conversion; theoretical literature is minimally used or not widely applied. The main reasons explaining this choice are (i) the complexity of modeling theoretically the process of adoption and diffusion of organic farming due to significant differences in the types of farming technologies applied across different farm types and regions, and (ii) the difficulties in accounting for less quantifiable drivers critical in explaining farmers' conversion decision, such as believes and attitudes towards the environment (Serebrennikov et al., 2020; Willock et al., 1999).

In order to study the likelihood of conversion to organic farming, the empirical literature has heavily relied on the use of probability models (Basnet et al., 2018; Burton et al., 1999; Chatzimichael et al., 2014; Chmielinski et al., 2019; Djokoto et al., 2016; Genius et al., 2006; Hattam & Holloway, 2005; Läpple & Rensburg, 2011; Lohr & Salomonsson, 2000; Malá & Malý, 2013; Parra López & Calatrava Requena, 2005; Serebrennikov et al., 2020). These models use a set of covariates to determine the conditional probability of adopting organic farming. They are typically used to investigate the causal effect of these covariates on the probability of conversion.

There are a wide variety of available probability models applied to estimate drivers of organic farm conversion, such as the linear probability model, nonlinear probability models, such as logit and probit, and machine-learning approaches (e.g., decision trees and their applications)[34]. For investigating the likelihood of converting to organic farming, non-linear probability models have been the most widely used empirical tools (Serebrennikov et al., 2020).

An essential aspect of many studies on the adoption of organic farming is that they have often relied on tailored surveys with a relatively narrow geographical scope (Bravo-monroy et al., 2016; Burton et al., 1999; Darnhofer et al., 2005; Fairweather, 1999; Hattam & Holloway, 2005; Kallas et al., 2009; Lohr & Salomonsson, 2000; Parra López & Calatrava Requena, 2005; Yu et al., 2014). This limited scope is likely because the drivers of adoption are highly site-specific and specific to the agricultural farming system and agricultural technology considered, as well as linked to farmers' perceptions and attitudes that may also have a local dimension (Sapbamrer, 2021; Serebrennikov et al., 2020; Willock et al., 1999).

The findings from this literature suggest that although profit maximization (costs and benefits) impacts farmers' decision to convert to organic farming, they are not necessarily the sole or primary drivers. Instead, some key factors determining the adoption of organic farming are farm characteristics – such as farm size, production specialization, age of farmer –, access to organic buyers/markets, and farmer beliefs and attitudes towards the environment. Overall, the main implication of the literature findings is that the conversion modeling cannot rely solely on profit maximization assumption, i.e., by considering only the costs and benefits of organic production and its difference from conventional farming. Instead, it also needs to consider other non-profit maximization factors affecting farmers' behavior.

6.2 Performance and management practices of organic farming

There is abundant literature analyzing the differences between organic and conventional production systems. Many studies often use detailed micro datasets to analyze the performance difference empirically (e.g., yields, profitability) between organic and conventional farms (Brenes-Muñoz et al., 2016; Froehlich et al., 2018; Gillespie & Nehring, 2013; Kuminoff & Wossink, 2010; Kuosmanen et al., 2021; Tiedemann & Latacz-Lohmann, 2013; Uematsu & Mishra, 2012; Würriehausen et al., 2015; Yu et al., 2014). Another relatively large body of literature relies on case studies (i.e., using a small sample size) to identify differences between organic and conventional systems. Some focus on management practices

[34] These include bagging, random forest, and boosting (James et al., 2013).

(Bilsborrow et al., 2013; Dobbs & Smolik, 1997; Greer et al., 2008; Krause & Machek, 2018; Shah et al., 2017; White et al., 2019), and others on environmental aspects (Chmelíková et al., 2021; Hoffman et al., 2018; Meier et al., 2015; Perego et al., 2019; Reimer et al., 2020). Given the abundance of the literature, some other studies use meta-analysis techniques to quantify the differences between organic and conventional agriculture. Several aspects have been examined, like yields (De Ponti et al., 2012; Seufert et al., 2012), crop rotations (Barbieri et al., 2017), livestock management (Gaudaré et al., 2021), productivity (Alvarez, 2021), environmental impacts (Mondelaers et al., 2009; Tuomisto et al., 2012) and nutrient budgets (Reimer et al., 2020), are examined.

Overall, the literature findings indicate that organic farms show lower performance in obtained crop yields, although results are highly heterogeneous across studies. Similar findings hold for livestock productivity, although the gap seems to be lower than in the case of crop yields. Organic products are usually found to receive price premia compared to conventional products. The findings regarding profitability are less conclusive, and organic farms are often found to show similar profitability levels as conventional farms implying that price premia of organic products may offset higher costs and lower yields of organic production (Alvarez, 2021; De Ponti et al., 2012; Offermann & Nieberg, 2000; Seufert et al., 2012). A significant difference between organic and conventional farming is in the applied management practices. Studies find that organic farms usually apply more crop rotations with longer duration, higher crop diversity, and evener crop species distribution (Barbieri et al., 2017). Also, livestock management is based on more farm-produced feed, a lower proportion of concentrate, and lower feed-use efficiency (Gaudaré et al., 2021).

Part A: References

Alvarez, R. (2021). Comparing Productivity of Organic and Conventional Farming Systems : A Quantitative Review. *Archives of Agronomy and Soil Science*, *00*(00), 1–12. https://doi.org/10.1080/03650340.2021.1946040

Barbieri, P., Pellerin, S., & Nesme, T. (2017). Comparing crop rotations between organic and conventional farming. *Nature Scientific Reports*, *June*, 1–11. https://doi.org/10.1038/s41598-017-14271-6

Basnet, S. K., Manevska-Tasevska, G., & Surry, Y. (2018). Explaining the process for conversion to organic dairy farming in Sweden: An alternative modelling approach. *German Journal of Agricultural Economics*, *67*(1), 14–30.

Bilsborrow, P., Cooper, J., Tétard-Jones, C., Średnicka-Tober, D., Barański, M., Eyre, M., Schmidt, C., Shotton, P., Volakakis, N., Cakmak, I., Ozturk, L., Leifert, C., & Wilcockson, S. (2013). The effect of organic and conventional management on the yield and quality of wheat grown in a long-term field trial. *European Journal of Agronomy*, *51*, 71–80. https://doi.org/10.1016/j.eja.2013.06.003

Bravo-monroy, L., Potts, S. G., & Tzanopoulos, J. (2016). *Drivers influencing farmer decisions for adopting organic or conventional coffee management practices*. *58*, 49–61. https://doi.org/10.1016/j.foodpol.2015.11.003

Brenes-Muñoz, T., Lakner, S., & Brümmer, B. (2016). What influences the growth of organic farms? Evidence from a panel of organic farms in Germany. *German Journal of Agricultural Economics*, *65*(1), 1–15.

Burton, M., Rigby, D., & Young, T. (1999). Analysis of the determinants of adoption of organic horticultural techniques in the UK. *Journal of Agricultural Economics*, *50*(1), 47–63. https://doi.org/10.1111/j.1477-9552.1999.tb00794.x

Chatzimichael, K., Genius, M., & Tzouvelekas, V. (2014). *Informational cascades and technology adoption: Evidence from Greek and German organic growers*. *49*, 186–195. https://doi.org/10.1016/j.foodpol.2014.08.001

Chmelíková, L., Schmid, H., Anke, S., & Hülsbergen, K. J. (2021). Nitrogen-use efficiency of organic and conventional arable and dairy farming systems in Germany. *Nutrient Cycling in Agroecosystems*, *119*(3), 337–354. https://doi.org/10.1007/s10705-021-10126-9

Chmielinski, P., Pawlowska, A., Bocian, M., & Osuch, D. (2019). The land is what matters: factors driving family farms to organic production in Poland. *British Food Journal*, *121*(6), 1354–1367. https://doi.org/10.1108/BFJ-05-2018-0338

Darnhofer, I., Schneeberger, W., & Freyer, B. (2005). Converting or not converting to organic farming in Austria: Farmer types and their rationale. *Agriculture and Human Values*, *22*(1), 39–52. https://doi.org/10.1007/s10460-004-7229-9

De Ponti, T., Rijk, B., & Van Ittersum, M. K. (2012). The crop yield gap between organic and conventional agriculture. *Agricultural Systems*, *108*, 1–9. https://doi.org/10.1016/j.agsy.2011.12.004

Djokoto, J. G., Owusu, V., Awunyo-vitor, D., Djokoto, J. G., Owusu, V., & Awunyo-vitor, D. (2016). Adoption of organic agriculture : Evidence from cocoa farming in Ghana Adoption of organic agriculture : Evidence from cocoa farming in Ghana. *Cogent Food & Agri-*

culture, *52*. https://doi.org/10.1080/23311932.2016.1242181

Dobbs, T. L., & Smolik, J. D. (1997). Productivity and Profitability of Conventional and Alternative Farming Systems: A Long-Term On-Farm Paired Comparison. *Journal of Sustainable Agriculture*, *9*(1), 63–79. https://doi.org/10.1300/J064v09n01_06

Fairweather, J. R. (1999). Understanding how farmers choose between organic and conventional production: Results from New Zealand and policy implications. *Agriculture and Human Values*, *16*(1), 51–63. https://doi.org/10.1023/A:1007522819471

Froehlich, A. G., Melo, A. S. S. A., & Sampaio, B. (2018). Comparing the Profitability of Organic and Conventional Production in Family Farming: Empirical Evidence From Brazil. *Ecological Economics*, *150*(May), 307–314. https://doi.org/10.1016/j.ecolecon.2018.04.022

Gaudaré, U., Pellerin, S., Benoit, M., Durand, G., Dumont, B., Barbieri, P., & Nesme, T. (2021). Comparing productivity and feed-use efficiency between organic and conventional livestock animals. *Environmental Research Letters*, *16*(2). https://doi.org/10.1088/1748-9326/abd65e

Genius, M., Pantzios, C. J., & Tzouvelekas, V. (2006). Information acquisition and adoption of organic farming practices. *Journal of Agricultural and Resource Economics*, *31*(1), 93–113. https://doi.org/10.22004/ag.econ.10150

Gillespie, J., & Nehring, R. (2013). Comparing economic performance of organic and conventional U.S. beef farms using matching samples. *Australian Journal of Agricultural and Resource Economics*, *57*(2), 178–192. https://doi.org/10.1111/j.1467-8489.2012.00610.x

Greer, G., Kaye-blake, W., Zellman, E., & Parsonson-Ensor, C. (2008). Comparison of the Financial Performance of Organic and conventional farms. *Journal of Organic Systems*, *3*(2), 18–28.

Hattam, C. E., & Holloway, G. J. (2005). Adoption of certified organic production: Evidence from Mexico. *International Sci-Entific Conference on Organic Agriculture.*, 1–5.

Hoffman, E., Cavigelli, M. A., Camargo, G., Ryan, M., Ackroyd, V. J., Richard, T. L., & Mirsky, S. (2018). Energy use and greenhouse gas emissions in organic and conventional grain crop production: Accounting for nutrient inflows. *Agricultural Systems*, *162*(February), 89–96. https://doi.org/10.1016/j.agsy.2018.01.021

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). An Introduction to Statistical Learning with Applications in R. Springer text in Statistics, Series Editors: Casella, G., Fienberg, S., and Olkin, I., Springer New York Heidelberg Dordrecht London, ISSN 1431-875, ISBN 978-1-4614-7137-0, DOI: 10.1007/978-1-4614-7138-7.

Kallas, Z., Serra, T., Gil, J. M., Kallas, Z., Serra, T., & Gil, J. M. (2009). *Farmer ' s objectives as determinant factors of organic farming adoption Farmer's objectives as determinant factors of organic farming adoption*. 1–19.

Krause, J., & Machek, O. (2018). A comparative analysis of organic and conventional farmers in the czech republic. *Agricultural Economics (Czech Republic)*, *64*(1), 1–8. https://doi.org/10.17221/161/2016-AGRICECON

Kuminoff, N. V., & Wossink, A. (2010). Why isn't more us farmland organic? *Journal of Agricultural Economics*, *61*(2), 240–258. https://doi.org/10.1111/j.1477-9552.2009.00235.x

Kuosmanen, N., Yli-heikkilä, M., Väre, M., & Kuosmanen, T. (2021). *Productive performance of organic crop farms in Finland*.

Läpple, D., & Rensburg, T. Van. (2011). Adoption of organic farming : Are there differences between early and late adoption ? *Ecological Economics*, *70*(7), 1406–1414. https://doi.org/10.1016/j.ecolecon.2011.03.002

Lohr, L., & Salomonsson, L. (2000). Conversion subsidies for organic production: Results from Sweden and lessons for the United States. *Agricultural Economics*, *22*(2), 133–146. https://doi.org/10.1016/S0169-5150(99)00045-6

Malá, Z., & Malý, M. (2013). The determinants of adopting organic farming practices: A case study in the Czech Republic. *Agricultural Economics (Czech Republic)*, *59*(1), 19–28. https://doi.org/10.17221/10/2012-agricecon

Meier, M. S., Stoessel, F., Jungbluth, N., Juraske, R., Schader, C., & Stolze, M. (2015). Environmental impacts of organic and conventional agricultural products - Are the differences captured by life cycle assessment ? *Journal of Environmental Management*, *149*, 193–208. https://doi.org/10.1016/j.jenvman.2014.10.006

Mondelaers, K., Aertsens, J., & van Huylenbroeck, G. (2009). A meta-analysis of the differences in environmental impacts between organic and conventional farming. *British Food Journal*, *111*(10), 1098–1119. https://doi.org/10.1108/00070700910992925

Offermann, F., & Nieberg, H. (2000). The profitability of organic farming in Europe. *OECD Workshop, Organic Agriculture: Sustainability, Markets and Policies*, *November*, 141–151.

Parra López, C., & Calatrava Requena, J. (2005). Factors related to the adoption of organic farming in

Spanish olive orchards. *Spanish Journal of Agricultural Research*, *3*(1), 5. https://doi.org/10.5424/sjar/2005031-119

Perego, A., Rocca, A., Cattivelli, V., Tabaglio, V., Fiorini, A., Barbieri, S., Schillaci, C., Chiodini, M. E., Brenna, S., & Acutis, M. (2019). Agro-environmental aspects of conservation agriculture compared to conventional systems: A 3-year experience on 20 farms in the Po valley (Northern Italy). *Agricultural Systems*, *168*(November 2018), 73–87. https://doi.org/10.1016/j.agsy.2018.10.008

Reimer, M., Möller, K., & Hartmann, T. E. (2020). Meta-analysis of nutrient budgets in organic farms across Europe. *Organic Agriculture*, *10*, 65–77. https://doi.org/10.1007/s13165-020-00300-8

Sapbamrer, R. (2021). *A Systematic Review of Factors Influencing Farmers ' Adoption of Organic Farming*.

Serebrennikov, D., Thorne, F., & Kallas, Z. (2020). *Factors Influencing Adoption of Sustainable Farming Practices in Europe : A Systemic Review of Empirical Literature*. 1–23.

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Shah, A., Askegaard, M., Rasmussen, I. A., Jimenez, E. M. C., & Olesen, J. E. (2017). Productivity of organic and conventional arable cropping systems in long-term experiments in Denmark. *European Journal of Agronomy*, *90*(October 2016), 12–22. https://doi.org/10.1016/j.eja.2017.07.001

Tiedemann, T., & Latacz-Lohmann, U. (2013). Production Risk and Technical Efficiency in Organic and Conventional Agriculture - The Case of Arable Farms in Germany. *Journal of Agricultural Economics*, *64*(1), 73–96. https://doi.org/10.1111/j.1477-9552.2012.00364.x

Tuomisto, H. L., Hodge, I. D., Riordan, P., & Macdonald, D. W. (2012). Does organic farming reduce environmental impacts? - A meta-analysis of European research. *Journal of Environmental Management*, *112*(834), 309–320. https://doi.org/10.1016/j.jenvman.2012.08.018

Uematsu, H., & Mishra, A. K. (2012). Organic farmers or conventional farmers: Where's the money? *Ecological Economics*, *78*, 55–62. https://doi.org/10.1016/j.ecolecon.2012.03.013

White, K. E., Cavigelli, M. A., Conklin, A. E., & Rasmann, C. (2019). Economic performance of long-term organic and conventional crop rotations in the mid-atlantic. *Agronomy Journal*, *111*(3), 1358–1370. https://doi.org/10.2134/agronj2018.09.0604

Willock, J., Deary, I. J., Edwards-Jones, G., Gibson, G. J., McGregor, M. J., Sutherland, A., Dent, J. B., Morgan, O., & Grieve, R. (1999). The role of attitudes and objectives in farmer decision making: Business and environmentally-oriented behaviour in Scotland. *Journal of Agricultural Economics*, *50*(2), 286–303. https://doi.org/10.1111/j.1477-9552.1999.tb00814.x

Würriehausen, N., Ihle, R., & Lakner, S. (2015). Price relationships between qualitatively differentiated agricultural products: Organic and conventional wheat in Germany. *Agricultural Economics (United Kingdom)*, *46*(2), 195–209. https://doi.org/10.1111/agec.12151

Yu, C. H., Yoo, J. C., & Yao, S. B. (2014). Farmers' willingness to switch to organic agriculture: A non-parametric analysis. *Agricultural Economics (Czech Republic)*, *60*(6), 273–278. https://doi.org/10.17221/82/2013-agricecon

Part B: Econometric estimations

Summary statistics

Summary statistics of costs, prices, and yields by cost category product and by organic status are provided in Table B.1. The statistics presented in Table B.1 refer to the FADN farms for the period 2007-2016. The distribution of farms across MS and by organic status is presented in Table B.2.

Table B.1. Summary statistics of costs, prices and yields.

Variable	Conventional		Fully organic		Partly organic		In conversion	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Cost (EUR/ha)								
Fertilizers	443	4,770	221	1,754	621	2,170	378	3,044
Other	1,553	17,676	414	6,955	1,043	8,812	704	10,211
Protection products	279	1,900	228	1,278	482	1,534	284	1,131
Seeds and seedlings	1,727	24,629	382	9,156	982	6,775	305	2,074
Price (EUR/ton)								
Cereals	169	72	214	131	185	115	166	95
Fruits	783	5,739	967	1,934	1,045	1,699	988	1,573
Grass	77	656	73	254	67	79	58	57
Maize	170	240	262	336	186	125	165	171
Milk	369	3,147	365	474	317	213	371	2,204
Nonfruit perm. crops	934	6,212	877	3,620	1,130	2,110	93	67
Oilseeds	404	1,448	1,141	3,585	428	590	482	493
Sugarbeet	37	30	63	29	40	34	37	12
Vegetables	1,143	24,632	8,780	144,521	5,406	219,841	828	975
Wheat	170	52	254	309	185	72	181	127
Yield								
Cereals (ton/ha)	5.4	21.5	3.2	2.2	3.9	2.3	4.2	2.3
Fruits (ton/ha)	14.8	57.6	7.8	11.2	7.3	9.7	10.9	12.6
Grass (ton/ha)	13.0	26.7	8.3	16.5	7.5	7.9	4.7	3.8
Maize (q/ha)	82.2	123.6	68.8	33.7	64.3	33.3	70.1	32.7
Milk (kg/cow)	5,958.7	69,761.0	5,501.9	6,837.8	4,762.3	2,160.2	5,704.7	2,139.5
Non-fruit perm. crops (ton/ha)	71.3	5,700.9	218.5	15,060.8	23.4	389.1	8.5	9.1
Oilseeds (ton/ha)	2.9	3.7	1.7	1.5	2.2	1.0	2.5	1.8
Sugarbeet (ton/ha)	66.8	23.8	62.3	20.5	58.7	22.2	76.2	20.8
Vegetables (ton/ha)	109.7	972.8	60.3	442.7	64.9	171.3	35.4	119.0
Wheat (q/ha)	55.6	56.3	34.2	15.7	38.9	18.5	42.4	19.6

Table B.2. Distribution of farms across MS and by organic status (Number of represented farms).

Country	Conventional	Fully organic	Partly organic	In conversion
Belgium	11,504	467	96	11
Bulgaria	20,669	270	336	143
Cyprus	4,224	67	146	1
Czechia	11,737	1,613	422	3
Denmark	17,049	1,053	45	16
Germany	81,812	4,344	325	233
Greece	37,207	1,367	1,986	14
Spain	80,163	2,823	1,987	71
Estonia	4,792	760	449	98
France	70,304	2,261	1,432	253
Croatia	4,577	181	113	64
Hungary	19,372	173	110	41
Ireland	10,013	130	17	2
Italy	101,440	5,509	628	99
Lithuania	9,740	810	508	19
Luxemburg	4,311	116	18	10
Latvia	7,912	1,776	205	69
Malta	4,557	17	7	1
Netherlands	14,048	746	201	15
Austria	15,895	4,644	124	81
Poland	115,356	2,946	1,057	44
Portugal	20,508	672	721	7
Romania	41,001	460	2,341	32
Finland	7,692	990	52	13
Sweden	8,161	1,788	435	8
Slovakia	4,701	357	286	6
Slovenia	7,689	1,327	107	16
United Kingdom	25,934	1,436	508	4

Prices and yields

A log-linear econometric specification has been used to estimate the percentage difference in the expected value of yields and prices of a selected number of crop and livestock activities. This modeling approach is very convenient when comparing performance based on indicators that take non-zero and positive values. The model is represented as follows:

$$\ln y_{it} = \beta_1 + \beta_2 ORG_{it} + \boldsymbol{\beta}'_3\mathbf{X}_{it} + \varepsilon_{it} \quad (1)$$

where y_{it} is the natural logarithm of the performance indicator considered (yield or price) for farm i at time t, ORG_{it} is an indicator variable that takes the value 1 if the farm is fully organic at time t and zero otherwise, $\mathbf{X}_{it}$ is a matrix that contains a set of explanatory variable, and ε_{it} is the error term of the equation; β_1, β_2 and $\boldsymbol{\beta}_3$ are parameters to be estimated. In the yield gap analysis the list of variables contained $\mathbf{X}_{it}$ include organic status of the farm, year dummies, farm specialization, farm size, altitude of the farm, presence of natural constraints, the share of irrigated land. For livestock activities, we include

The percentage differences in expected value of the performance indicator between organic and conventional farms can be obtained from the estimate of parameter To see how, equation (1) can be written as follows:

$$\widehat{\ln y_{it}} = \begin{cases} \hat{\beta}_1 + \hat{\boldsymbol{\beta}}'_3\mathbf{X}_{it} & \text{if } ORG_{it} = 0 \\ (\hat{\beta}_1 + \hat{\beta}_2) + \hat{\boldsymbol{\beta}}'_3\mathbf{X}_{it} & \text{if } ORG_{it} = 1 \end{cases} \quad (2)$$

where $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\boldsymbol{\beta}}_3$ are the estimated parameters and $\widehat{\ln y_{it}}$ is the expected value of the logarithm of the performance indicator. The difference between the logarithm of performance indicator between organic ($ORG_{it} = 0$) and conventional farms ($ORG_{it} = 1$) can be written as:

$$\ln \widehat{y_{it}^{ORG=1}} - \ln \widehat{y_{it}^{ORG=0}} = \ln \frac{\widehat{y_{it}^{ORG=1}}}{\widehat{y_{it}^{ORG=0}}} = \hat{\beta}_2 \quad (3)$$

The logarithmic difference of equation (3) is only an approximation to the percentage difference in expected values between the organic and conventional farms. For an exact calculation of this percentage difference, the following transformation can be used (Hill et al., 2011):

$$\frac{\widehat{y_{it}^{ORG=1}}}{\widehat{y_{it}^{ORG=0}}} - 1 = \frac{\widehat{y_{it}^{ORG=1}} - \widehat{y_{it}^{ORG=0}}}{\widehat{y_{it}^{ORG=0}}} = (e^{\hat{\beta}_2} - 1) \quad (4)$$

Equation (4) is a non-linear function of the coefficient estimate $\hat{\beta}_2$ and it has been used as percentage difference in yields and prices between organic and conventional farms.

Unit costs of crop production

In contrast with prices and yield estimations, for unit costs we use a linear estimation model. This is a more appropriate approach than the log-linear one because several organic farms are associated with zero expenditure on some of the cost categories considered.

The estimation has been conducted for the four types of variable cost categories k (k=1,…,4) used in the model. These categories are seeds, fertilizers, crop protection, and other crop specific costs, all expressed on a per-hectare basis. The model is represented as follows:

$$c_{k,it} = \beta_1 + \beta_2 ORG_{it} + \boldsymbol{\beta}'_3\mathbf{X}_{it} + \varepsilon_{it} \quad (5)$$

where $c_{k,it}$ is the cost per hectare for input category k for farm i at time t, ORG_{it} is an indicator variable that takes value 1 if the farm is a fully organic at time t and zero otherwise, $\mathbf{X}_{it}$ is a matrix that contains a set of explanatory variables, and ε_{it} is the error term of the equation; β_1, β_2 and $\boldsymbol{\beta}_3$ are parameters to be estimated. The list of variables contained in $\mathbf{X}_{it}$ includes the organic status of the farm, year dummies, altitude class, areas with natural constraints, output value per hectare, share of unpaid labor in total labor, assets value per hectare, share of irrigated land, size in terms of hectares and livestock units.

The percentage differences in expected value of the unit costs per hectare between organic and conventional farms can be obtained in a different way with respect to the methodology described in equation (4) The starting point is given by the following equation:

$$\hat{c}_{k,it} = \begin{cases} \hat{\beta}_1 + \hat{\boldsymbol{\beta}}_3'\mathbf{X}_{it} & \text{if } \mathrm{ORG}_{it} = 0 \\ \left(\hat{\beta}_1 + \hat{\beta}_2\right) + \hat{\boldsymbol{\beta}}_3'\mathbf{X}_{it} & \text{if } \mathrm{ORG}_{it} = 1 \end{cases} \tag{6}$$

where $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\boldsymbol{\beta}}_3$ are the estimated parameters and $\hat{c}_{k,it}$ is the expected value of the unit cost per hectare for input category k. The percentage difference between organic (ORG_{it} = 1) and conventional farms (ORG_{it} = 0) for this unit cost can be then obtained as follows:

$$\frac{\hat{c}_{k,it}^{ORG=1} - \hat{c}_{k,it}^{ORG=0}}{\hat{c}_{k,it}^{ORG=0}} = \frac{\hat{\beta}_2}{\hat{c}_{k,it}^{ORG=0}} = \frac{\hat{\beta}_2}{\hat{\beta}_1 + \hat{\boldsymbol{\beta}}_3'\bar{\mathbf{X}}_{it}} \tag{7}$$

Where $\bar{\mathbf{X}}_{it}$ is a vector made of the averages of the variables contained in $\mathbf{X}_{it}$.

Mapping of econometric estimation categories to IFM-CAP categories

Table B.3. Mapping of FADN crop groups with crops and feed in IFM-CAP used in estimations

Product	FADN	IFM-CAP crop	IFM-CAP feed
Cereals	All cereals excluding rice (KCER)	Rye (RYEM), Barley (BARL), Oats (OATS), Other cereals for the production of grain (OCER), Rice (PARI)	Distillers Dried Grains with Solubles (DDGS)
Fruits	Fruits and berry orchards and citrus orchards (KFRU)	Apples and pears (APPL), Citrus fruits (CITR), Peaches and nectarines (PEAC), Berries (BERR), Nuts (NUTS), Other fruits (OFRU)	
Maize	Grain maize (CMZ)	MAIZ	
Non-fruit permanent crops	Olive groves + Vines+ permanent crop under glass + nurseries + Other permanent crops + Growth of young plantation (KOPC)	Table wine (TWIN), Table grapes (TAGR), Table olives (TABO), Olive oil (OLIV)	
Oilseeds	Rapes (CRAPE)+ Sunflower (CSNFL) + Soya (CSOYA) + Linseed (CLINSED) + Other oilseeds (CCRPOILOTH)	Other oil (OOIL), rapeseed (RAPE), Sunflower (SUNF), Soya (SOYA), Pulses (PULS), Other industrial crops (OIND)	Soya cake (SOYC), Rapeseed cake (RAPC), Sunflower cake (SUNC), Rapeseed oil (RAPO), Soya oil (SOYO), Sunflower oil (SUNO)
Vegetables	Fresh vegetables melons and strawberry open field (CVEGOF) + Fresh vegetables melons and strawberry market gardening (CVEGMG) + Fresh vegetables melons and strawberry under glass (CVEGUG)	Vegetables marketing garden (VGMG), Vegetables open field (VGOF), Vegetables under glass (VGUG), Potatoes (POTA)	
Wheat	Common wheat (CWHTC)	Soft wheat (SWHE), Durum wheat (DWHE)	
Grass	Grasses (KGRA)	Other crops (OCRO), Maize for fodder (MAIF), Fodder root crops (ROOF), Other fodder crops (OFAR)	
Sugar beet	Sugar beet (CSUGBT)	Sugar beet (SUGB)	

Table B.4. Mapping of region groups used in estimations and NUTS0.

PESETA Group (Econometric Estimation)	NUTS0 code
Central Europe North	BE,LU, NL, DE, PL
Central Europe South	AT, CZ, FR, HU, SK, RO
Northern Europe	SE, FI, EE, LT, LV, DK
Southern Europe	BG, HR, CY, EL, IT, MT, PT, SI, ES
UK & Ireland	IR

Part B: References

Hill, R.C. and Griffiths, W.E. and Lim, G.C. (2010). Principles of Econometrics, 4th Edition, John Wiley & Sons, Incorporated, ISBN 9781118136966.

Part C: Behavioral constraints

Crop rotations

From an agronomic point of view, in order to substitute for no reliance on chemical fertilizers and plant protection, organic farming requires crop rotations (Reganold & Wachter, 2016; Baker et al., 2020). Indeed, Barbieri et al. (2017), based on meta-analysis, found that on average at the global scale, organic rotations last for 4.5 ± 1.7 years, which is 15% more than their conventional counterparts, and include 48% more crop categories. Below, we describe how we use this finding to elicit values for the flexibility constraints of the crop rotations in the IFM-CAP model.

First, we argue that the observed share of crop acreage[35] is related to the duration of the crop rotation and the frequency that a crop appears, as follows:

1. For a given crop duration, the share of crop acreage is proportional to the frequency that the crop appears in the rotation (the less times the crop appears, the lower the acreage share).
2. For a given frequency that a crop appears in the rotation, the crop acreage is inversely proportional to the duration of the rotation (the more years the rotation cycle, the less the acreage share).

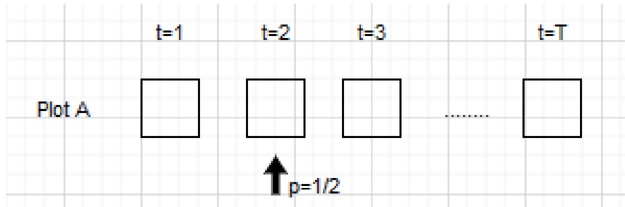

Figure C.2. The probability to find a crop in a 2-year fixed rotation that alternates with another crop.

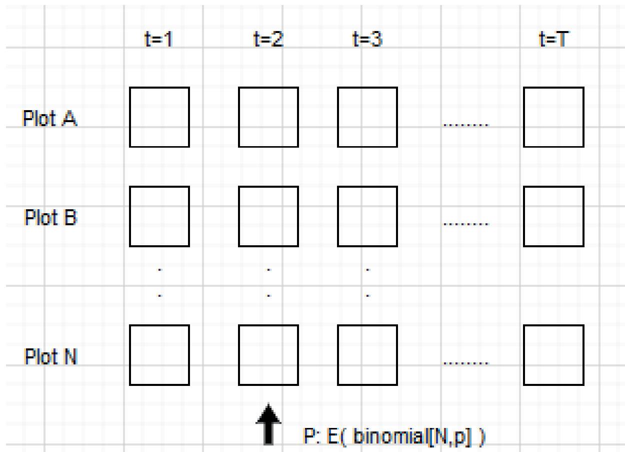

Figure C.3. Schematic of a farm with many plots and the relation of the crop acreage and the rotation frequency and length.

In order to establish the above arguments, we start from a farm that has a single 1-ha plot and follows a 2-year rotation where a crop appears once every two years. The probability of finding this crop in a random year will be 1/2, as in Figure C.2.

When we consider a farm that has more than one plot, we can deduce the relation between crop rotation and expected share of crop acreage by means of a binomial distribution[36]. For a specific year, the binomial's independent experiment is checking a plot for a crop and the 'success' event is finding this crop. As shown above, the probability of success for a single plot is p=1/2. Thus, for n independent experiments (i.e. n plots), as shown in Figure C.3, the expected number of successes equals to [p]*[n], where p=1/2. The expected share of the central crop to the total utilized agricultural area, assuming 1-ha plots, equals to [p]*[n]/[n]=[p]=1/2.

[35] We need to define the following related concepts, as used by Dury et al. (2012): *Crop acreage*, refers to the area on a farming land normally devoted to one or a group of crops every year (e.g. x hectares of wheat, y hectares of winter barley). IFM-CAP models crop acreage. *Crop allocation*, is the assignment of a particular crop to each plot in a given piece of land. IFM-CAP does not model in plot level, so crop allocation is not relevant. *Crop rotation* is defined as the practice of growing a sequence of plant species on the same land. It is characterized by a cycle period. Again, IFM-CAP does not contain explicit plot level information and thus crop rotation, as defined here, cannot be represented.

[36] The binomial distribution with parameters n and p is the discrete probability distribution of the number of successes in a sequence of n independent experiments, each asking a yes–no question, and each with its own Boolean-valued outcome: success (with probability p) or failure (with probability q = 1 − p).

Table C.1. Characteristics of different crop rotations.

Duration of rotation (D)	Frequency of a crop (f_c)	Frequency to Duration	Share of acreage (p_c)
3	1	1/3	0.33
	2	2/3	0.66
4	2	2/4	0.50
	3	3/4	0.75
5	2	2/5	0.40
	3	3/5	0.60
	4	4/5	0.80
6	2	2/6	0.33
	3	3/6	0.50
	4	4/6	0.66
	5	5/6	0.83
7	2	2/7	0.28
	3	3/7	0.42
	4	4/7	0.57
	5	5/7	0.71

We can generalize this finding for the case of fixed rotation lengths. The expected share of crop acreage will equal to

$$p_c = \frac{f_c}{D}$$

Where, p_c the expected share of crop acreage of crop c, f_c the number of appearances of the crop (frequency) and D the length (duration) of the rotation. In Table C.1 we show the share of acreages for different combinations of crop duration and crop frequency.

As mentioned above, organic farms have longer and more diversified rotations (Barbieri et al., 2017). We interpret "longer and more diversified" rotation as rotations that have longer duration and with crops that are less frequently in the rotation. According to the argumentation already presented, both mean reduced acreage shares of crops, when the farm converts. However, there is a lower limit on the reduction of the acreage, related to the crop appearing at least one in the rotation

The FADN data also supports the connection of "longer and more diversified" rotation to the crop acreage. In Table C.3, we show the differences between the mean acreage shares between the organic and conventional FADN farms (and the corresponding 95% confidence interval). The cash crops in organic farms have a lower acreage share than in the conventional ones.

We model the extensification of the rotation as a reduction on the current share of a crop. More specifically, we will introduce the following flexibility constraint to the farms that convert.

Table C.2. Expected share of acreage for a crop that appears once in the rotation.

Duration of rotation (D)	Frequency of a crop (f_c)	Share of acreage (p_c)
3	1	0.33
4	1	0.25
5	1	0.20
6	1	0.16
7	1	0.14
8	1	0.12

$$S_{f,c}^{org} \leq (1 + r_{f,c}) \cdot S_{f,c}^{conv} \quad \forall f, c$$

where $S_{f,c}^{org}$ is the share of crop c in farm f when converted to organic, $S_{f,c}^{conv}$ is the observed share of crop c in farm f when it is conventional and $r_{f,c}$ is a crop and farm-specific coefficient of share reduction related to the "longer and more diversified" rotation of a converted farm.

For estimating, $r_{f,c}$ we consider that the crops with an area share at 20% or smaller of the total UAA, are already cultivated extensively (20% correspond to a rotation of once every five year,[37] see Table C.2). Thus, a farm that converts to organic does not need to change the relative acreage allocation of those crops. Only farms that have for some crops a share greater than 20% will need to reduce the area of these crops.

Thus, for a farm that belong to farm type TF (we use the notation of $TF(f)$; i.e. the TF of f) , $r_{f,c}$ equals to:

$$r_{f,c} = \begin{cases} \dfrac{diff_{c,TF(f)}}{share_{c,TF(f)}} & if\ S_{f,c}^{conv} > 20\% \\ 0 & if\ S_{f,c}^{conv} \leq 20\% \end{cases}$$

where, $diff_{c,TF}$ is the difference between the mean acreage shares between the organic and conventional FADN farms of the Farm Type (TF) that the farm belongs (as in Table C.3; for non-significant differences, we set $diff_{c,TF}$ to zero); $share_{c,TF}$ is the average share of crop c in the conventional farms of the TF farm type (as in Table C.4).

In Table C.5, we give the for each farm type. For farm types where we did not see statistically significant differences, we set $r = 0$. Since $r_{f,c}$ is farm specific, in Table C.6 we give the percentage of farms that $r_{f,c} > 0$, so that the reader knows the impact of this constraint.

[37] This is in line with findings of Barbieri et al. (2017).

Table C.3. Difference between means of acreage shares; organic and conventional farms.

	Soft Wheat	Durum Wheat	Barley	Grain Maize	Fodder Maize	Rape seed	Sugar Beet	Sun flower	Potatoes
Specialist COP (15)	-11.3%***	+9.8%**	+2.2%^{ns}	-10.1%***	-1.1%^{ns}	-4.9%^{ns}	-5.5%^{ns}	-4.7%^{ns}	-0.4%^{ns}
Specialist other field crops (16)	-10.0%***	-2.5%^{ns}	-3.3%*	-9.7%***	-6.2%^{ns}	-0.9%^{ns}	-7.1%***	-8.7%***	-7.4%***
Specialist horticulture (20)	-11.0%*	na	-2.9%^{ns}	-24.5%*	na	na	na	-16.0%**	-5.4%**
Specialist wine (35)	-4.0%^{ns}	-4.8%^{ns}	-4.0%*	-10.7%*	-9.4%^{ns}	+15.8%^{ns}	na	na	-0.5%^{ns}
Specialist orchards - fruits (36)	-7.2%*	-14.6%***	-5.1%^{ns}	-5.3%^{ns}	-7.5%^{ns}	na	na	-6.0%^{ns}	-0.1%^{ns}
Specialist olives (37)	-1.0%^{ns}	+9.8%^{ns}	+6.6%^{ns}	na	na	na	na	na	+0.7%^{ns}
Permanent crops combined (38)	+2.6%^{ns}	-10.6%*	-1.6%^{ns}	-3.1%^{ns}	na	na	na	+13.5%^{ns}	-1.8%*
Specialist milk (45)	-5.0%***	+2.9%^{ns}	-3.8%***	-10.5%***	-13.9%***	-4.3%***	-3.5%^{ns}	-9.3%**	-1.2%***
Specialist sheep and goats (48)	-5.3%***	-5.6%**	-7.0%***	-10.1%**	-10.2%***	na	na	na	-2.0%***
Specialist cattle (49)	-5.7%***	-4.5%^{ns}	-4.3%***	-10.5%***	-16.8%***	-2.7%***	na	-8.2%***	-1.5%***
Specialist granivores (50)	-7.6%**	-0.4%^{ns}	-2.7%^{ns}	-14.7%**	-10.1%^{ns}	-6.8%*	na	+8.8%^{ns}	-4.0%^{ns}
Mixed crops (60)	-8.9%***	+0.9%^{ns}	-3.4%^{ns}	-14.7%***	na	na	na	-7.4%^{ns}	-6.2%***
Mixed livestock (70)	-6.0%***	+5.3%^{ns}	-7.1%***	-19.3%***	-11.4%^{ns}	na	na	-8.3%^{ns}	-2.2%***
Mixed crops and livestock (80)	-7.7%***	+2.0%^{ns}	-3.9%***	-11.4%***	-3.4%^{ns}	-8.5%***	-4.9%*	-14.1%***	-2.9%***

Notes: - The significance of the mean difference is based on a two-sided Welch's t-test.
- Regarding the significance levels in the superscript: (ns) means a non-significant value; (*),(**) and (***) are 95%, 99% and 99.9% significance levels.
- na means that there was not enough number of observations to get a mean difference.

Table C.4. Average shares of certain crops in conventional farms.

	Soft Wheat	Durum Wheat	Barley	Grain Maize	Fodder Maize	Rape seed	Sugar Beet	Sun flower	Potatoes
Specialist COP (15)	35.7%	36.1%	20.9%	29.4%	10.0%	22.0%	10.0%	26.0%	1.8%
Specialist other field crops (16)	29.3%	28.9%	18.3%	22.7%	21.8%	16.8%	18.4%	19.0%	21.9%
Specialist horticulture (20)	29.8%	0.0%	29.2%	32.7%	0.0%	0.0%	0.0%	21.8%	16.6%
Specialist wine (35)	20.5%	26.1%	17.8%	21.3%	20.9%	14.6%	0.0%	0.0%	3.8%
Specialist orchards - fruits (36)	19.4%	28.3%	19.2%	19.9%	18.0%	0.0%	0.0%	14.0%	4.3%
Specialist olives (37)	15.3%	27.4%	23.9%	0.0%	0.0%	0.0%	0.0%	0.0%	1.2%
Permanent crops combined (38)	22.5%	29.4%	19.4%	18.2%	0.0%	0.0%	0.0%	15.7%	3.2%
Specialist milk (45)	13.8%	15.0%	11.9%	17.6%	23.6%	9.8%	8.9%	12.6%	2.4%
Specialist sheep and goats (48)	13.7%	17.4%	18.7%	19.7%	15.8%	0.0%	0.0%	0.0%	2.6%
Specialist cattle (49)	12.8%	17.0%	11.6%	14.4%	24.0%	9.0%	0.0%	11.6%	2.2%
Specialist granivores (50)	30.0%	32.5%	27.1%	35.3%	31.8%	17.4%	0.0%	24.5%	10.4%
Mixed crops (60)	26.0%	31.6%	23.0%	26.9%	0.0%	0.0%	0.0%	23.3%	14.3%
Mixed livestock (70)	18.2%	17.7%	16.2%	24.5%	20.0%	0.0%	0.0%	13.7%	4.1%
Mixed crops and livestock (80)	23.6%	22.4%	16.8%	23.6%	12.6%	16.2%	11.8%	18.9%	6.4%

Nitrogen management

Nitrogen management is different between organic and conventional farms. In the conventional methods, inorganic/mineral fertilizers compensate for the soil nutrients removed through production. In organic farm management inorganic fertilizers are prohibited, and thus, soil fertility is maintained partially with adding organic fertilizers (mainly manure) and with crop rotation schemes, mainly green manure and nitrogen fixation from leguminous crops (Chmelíková et al., 2021; Lin et al., 2016; Reganold & Wachter, 2016). Chongtham et al. (2017) using a structured interview survey, found that the majority arable farmers used perennial clover and grass crops as green manure (referred as 'ley') in their rotation. The ley crops were undersown in annual cereal crops and remained for at least one more year during which they were cut regularly to

Table C.5. . Reduction of share of crops when a conventional farm converts to organic ($r_{TF,c}$).

	Soft Wheat	Durum Wheat	Barley	Grain Maize	Fodder Maize	Rape seed	Sugar Beet	Sun flower	Potatoes
Specialist COP (15)	-31.8%	27.2%		-34.5%					
Specialist other field crops (16)	-34.1%		-17.9%	-42.8%			-38.6%	-46.0%	-33.6%
Specialist horticulture (20)	-36.9%			-75.0%				-73.2%	-32.5%
Specialist wine (35)			-22.2%	-50.2%					
Specialist orchards - fruits (36)	-37.3%	-51.4%							
Specialist olives (37)									
Permanent crops combined (38)		-36.0%							-57.6%
Specialist milk (45)	-36.0%		-31.8%	-59.5%	-59.1%	-43.8%		-74.1%	-48.9%
Specialist sheep and goats (48)	-38.8%	-32.0%	-37.5%	-51.4%	-64.4%				-75.6%
Specialist cattle (49)	-44.1%		-36.9%	-72.7%	-70.2%	-29.9%		-71.2%	-66.2%
Specialist granivores (50)	-25.2%			-41.6%		-38.9%			
Mixed crops (60)	-34.4%			-54.7%					-43.0%
Mixed livestock (70)	-32.9%		-43.8%	-79.0%					-53.9%
Mixed crops and livestock (80)	-32.8%		-23.2%	-48.1%		-52.3%	-41.8%	-74.3%	-45.3%

Notes: - For empty cells, no reduction is applied, since the differences between organic and conventional farms were not significant.

Table C.6. Percentage of farms with $r_{TF,c} > 0$.

Soft Wheat	Durum Wheat	Barley	Grain Maize	Fodder Maize	Rape seed	Sugar Beet	Sun flower	Potatoes
59.0%	25.9%	15.6%	49.2%	28.5%	8.0%	17.1%	8.8%	15.6%

control weeds, and in some cases to sell hay or silage to neighboring farms. For dairy farmers, they report that ley was two or three years of ley followed by two years of cereals. This was a common scheme for beef and sheep farmers too. The same finding is present in Watson C.A. et al. (2002). He says that in mixed systems, the rotations are most commonly based on ley/arable rotations, where fertility is built during the ley phase, in which grazing and fodder production provide an economic return. Finally, Barbieri et al. (2017) finds through meta-analysis that at the global scale, organic rotations have fewer cereals and more temporary fodders. In addition, they find that organic rotations have 2.8 times more temporary fodder crops (such as alfalfa, clover, clover-grass, Italian ryegrass, etc.) than conventional systems, which generally occupy land for an entire year. Finally, for livestock systems, the use of permanent grassland (pastures and meadow) is also common (Watson C.A. et al., 2002).

Modeling the farm's nitrogen management is quite complex and requires information that is not available in FADN (Küstermann et al., 2010; Thomas, 2003). For this, we will not explicitly model the underlying mechanism of plot-level nutrient management. Instead, we will focus on the increase of the share of nitrogen fixing crops through a data driven approach.

The first step is to focus on the crops that relate to the nitrogen management decision of the farm. For IFM-CAP, these activities are:

1. Soya (code: SOYA)
2. PULS that is the aggregation of the following three FADN activities: 'Peas, field beans and sweet lupines', 'Lentils, chickpeas and vetches' and 'Other protein crops'.
3. OFAR that is the aggregation of the following FADN activities: 'Temporary grass', 'Green maize' and 'Leguminous plants'.
4. FALL that is the fallow land.
5. PGRA that is the permanent grassland activity, corresponding to pasture and meadows that exist in the same plot for at least 5 years.

When we compare the share of land devoted to these five activities between organic and conventional farms, we see statistically significant differences.

Table C.7. Difference of acreage share for nitrogen management related crops between organic and conventional farms.

	Conventional Mean	Organic Mean	% Difference Organic-Conventional
Specialist COP (15)	13.6%	35.0%	+21.4%***
Specialist other field crops (16)	21.9%	49.5%	+27.5%***
Specialist horticulture (20)	30.1%	29.9%	-0.20%ns
Specialist wine (35)	58.1%	79.2%	+21.1%***
Specialist orchards - fruits (36)	62.4%	74.7%	+12.3%***
Specialist olives (37)	46.3%	63.3%	+16.9%***
Permanent crops combined (38)	50.0%	59.4%	+9.30%ns
Specialist milk (45)	64.5%	85.2%	+20.7%***
Specialist sheep and goats (48)	79.3%	87.3%	+8.0%%***
Specialist cattle (49)	74.3%	92.1%	+17.8%***
Specialist granivores (50)	23.6%	58.2%	+34.6%***
Mixed crops (60)	26.8%	46.7%	+19.9%***
Mixed livestock (70)	38.9%	75.5%	+36.6%***
Mixed crops and livestock (80)	30.2%	61.4%	+31.2%***

Notes: - The significance of the mean difference is based on a two-sided Welch's t-test.
- Regarding the significance levels in the superscript: (ns) means a non-significant value; (*),(**) and (***) are 95%, 99% and 99.9% significance levels.

Thus, we model the change in nitrogen management by means of flexibility constraint that is active in the case that the farm converts:

$$\sum_{c\in N}\left(S_{f,c}^{org}\right) \geq (1+n_f)\cdot\sum_{c\in N}\left(S_{f,c}^{conv}\right) \quad \forall f$$

where, N is the set of nitrogen fixing crops of the model (PULS, OFAR, SOYA,PGRA and FALL), $S_{f,c}^{org}$ and $S_{f,c}^{conv}$ are the shares of crop c in farm f when in the organic and conventional status respectively, and n_f is a farm specific coefficient related to the type of farming that the farm belongs. We calculate it as follow.

$$n_f = \frac{diff_{TF(f)}}{share_{TF(f)}}$$

where $diff_{TF(f)}$ is the last column of Table C.5 and $share_{TF(f)}$ is the second column.

Part C: References

Barbieri, P., Pellerin, S., & Nesme, T. (2017). Comparing crop rotations between organic and conventional farming. *Nature Scientific Reports*, *June*, 1–11. https://doi.org/10.1038/s41598-017-14271-6

Chmelíková, L., Schmid, H., Anke, S., & Hülsbergen, K. J. (2021). Nitrogen-use efficiency of organic and conventional arable and dairy farming systems in Germany. *Nutrient Cycling in Agroecosystems*, *119*(3), 337–354. https://doi.org/10.1007/s10705-021-10126-9

Chongtham, I. R., Bergkvist, G., Watson, C. A., Sandström, E., Bengtsson, J., & Öborn, I. (2017). Factors influencing crop rotation strategies on organic farms with different time periods since conversion to organic production. *Biological Agriculture and Horticulture*, *33*(1), 14–27. https://doi.org/10.1080/01448765.2016.1174884

Dury, J., Schaller, N., Garcia, F., Bergez, A. R., & Eric, J. (2012). Models to support cropping plan and crop rotation decisions . A review. *Agronomy for Sustainable Development*. https://doi.org/10.1007/s13593-011-0037-x

Küstermann, B., Christen, O., & Hülsbergen, K. J. (2010). Modelling nitrogen cycles of farming systems as basis of site- and farm-specific nitrogen management. *Agriculture, Ecosystems and Environment*, *135*(1–2), 70–80. https://doi.org/10.1016/j.agee.2009.08.014

Lin, H. C., Huber, J. A., Gerl, G., & Hülsbergen, K. J. (2016). Nitrogen balances and nitrogen-use efficiency of different organic and conventional farming systems. *Nutrient Cycling in Agroecosystems*, *105*(1), 1–23. https://doi.org/10.1007/s10705-016-9770-5

Reganold, J. P., & Wachter, J. M. (2016). Organic agriculture in the twenty-first century. *Nature Plants*, *2*(February), 15221. https://doi.org/10.1038/nplants.2015.221

Thomas, A. (2003). A dynamic model of on-farm integrated nitrogen management. *European Review of*

Agricultural Economics, *30*(4), 439–460. https://doi.org/10.1093/erae/30.4.439
Watson C.A., Atkinson, D., Gosling, P., Jackson, L. R., & Rayns, F. W. (2002). Managing soil fertility in organic farming systems. *Soil Use and Management*, *18*(3), 239–247. https://doi.org/10.1079/sum2002131

Part D: Estimating conversion probabilities in the exogenous approach

The proposed exogenous approach is based on estimation of the likelihood to convert to organic farming of individual farms. Our main assumption is that the likelihood of conversion depends on the similarity of conventional farms with respect to organic ones: conventional farms that are more similar to organic ones are more likely to convert to organic farming. This assumption is consistent with the idea that farms that are already similar to exiting organic farms would need to make smaller adjustments to transition to organic production methods and at the same time capitalize on output price premiums and CAP organic support.

Unlike exercises typical of the literature on adoption of organic farming (Bravo-Monroy et al., 2016; Yu et al., 2014; Kallas et al., 2009; Parra López and Calatrava Requena, 2005; Darnhofer et al., 2005; Hattam and Holloway, 2005; Lohr and Salomonsson, 2000; Fairweather, 1999; Burton et al., 1999), this is a prediction exercise[38]. Our aim is to assign a probability of conversion to FADN farms and our focus is on all farms included in the base year of IFM-CAP (i.e., for farms in FADN in 2017). Therefore, the scope of our exercise is much broader than typical case-studies that analyze the drivers of conversion to organic farming. Here, we aim to cover different EU regions and types of farms in terms of size and specialization.

The economic literature has primarily applied empirical approaches to analyze drivers of organic conversion; theoretical models are usually not applied due to the complexity of drivers affecting organic farming decisions (Serebrennikov et al., 2020; Willock et al., 1999). Furthermore, applying theoretical models is complicated by the heterogeneity of farming systems across the whole EU. Therefore, an empirical predictive approach based on econometric estimations of the likelihood of adopting organic farming seems to be more appropriate in our context.

Regarding the estimation framework, we rely on the use of probability models. We compare the performance of multiple probability models and select the best performing one. We apply seven different prediction models to estimate the probability of conversion to organic farming: (i) the linear probability model (LP), (ii) the linear probability model with a stepwise selection algorithm (LP + SSA),[39] (iii) the logit model (LOGIT), (iv) the logit model using the covariates of model LP + SSA (LOGIT + SSA), (v) the probit model (PROBIT), (vi) the probit model using the covariates of model LP + SSA (PROBIT + SSA), and (vii) the random forest algorithm (RANDOM FOREST). The latter one is a tree-based classification/regression tool able to handle large numbers of regressors, robust to overfitting, and that does not require distribution assumptions (Biau and D'Elia, 2011; James et al., 2013). For further details on tree-based methods and on the random forest algorithm, please refer to James et al. (2013).

The model selection criterion is solely based on the ability of the models to predict the status of the current FADN farms correctly. In other words, the in-sample prediction accuracy[40] is the performance metric used to compare models and select the most performant one out of the seven considered. The performance metric of each model is calculated as the (non-weighted) average of the share of correct in-sample predictions of the conventional farms (0s) and the organic ones (1s). For example, a model that correctly predicts 90% of the conventional farms and 80% of the organic ones has a performance metric of 85%. Using a non-weighted average implies assigning equal importance to the predictive ability of the farms' conventional and organic status.

The dependent variable used in all models is binary taking value of 1 if the farm is organic and 0 if the farm is conventional (non-organic). Each model is fed with covariates chosen based on literature review and that relate to different monetary and non-monetary related factors such as the structural characteristics of the farm, the geographical location, the types of farm activities, the amount of subsidies received, the presence of organic farming in the region of activity, the performance of organic farms in the region relative to conventional ones, regional land prices, costs, and revenue information. The list of covariates used in the estimations is presented in Table D.1.

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[38] See Shmueli (2010) for a comparison between predictive and explanatory models.

[39] A stepwise selection algorithm based on the AIC criterion (implemented in R with the function *step* (R Foundation for Statistical Computing, 2022) is applied to the full specification of the LP model. This selection algorithm reduces the number of covariates used in the estimation phase and, possibly, increases the accuracy (goodness of fit) of the predictions. This reduced equation is then used to re-estimate the linear, logit, and probit models.

[40] Out-sample accuracy is also evaluated with FADN data between 2014 and 2016 used as a test set and FADN data for the year 2017.

The covariates in Table D.1 have been constructed using available FADN data to capture the structural characteristics of the farm, production specialization, the characteristics of the geographical location in which it operates, the type of farm activities, crop biodiversity index, yield gaps, labor use, the amount of subsidies received, the presence of organic farming in the region of activity, the performance of organic farms in the region relative to conventional ones, regional land prices and input expenditure. The choice of these variables was guided by findings from previous empirical literature suggesting that structural features of the farm such as size, specialization, livestock density, ownership, family contribution to farm activities, and geographical location (Genius et al., 2006; Canavari et al., 2008; Peter Silas, 2008; Koesling et al., 2008; Khaledi et al. 2010; Läpple, 2010; Kaufmann, 2011; Malá and Malý, 2013; Haris et al., 2018; Serebrennikov et al., 2020; Sapbamrer, 2021), production choices (Anderson et al., 2005; Kisaka-Lwayo, 2007; Malá and Malý, 2013; Knowler and Bradshaw, 2007; Métouolé Méda et al., 2018), subsidies (Genius et al., 2003; Läpple, 2010; Malá and Malý, 2013; Chmielinski et al., 2019; Yanakittkul and Aungvaravong, 2020), presence of organic farming in the region (Läpple, 2010; Läpple and Rensburg, 2011; Saoke, 2011; Sriwichailamphan and Sucharidtham, 2014; Haris et al., 2018), land ownership and assets (Kaufmann et al., 2011; Chmielinski et al., 2018), farm performance indicators (Parra López and Calatrava Requena, 2005; Malá and Malý, 2013; Lu and Cheng, 2019; Liu et al., 2019) as well as other non-monetary drivers (e.g., believes and attitudes towards health and the environment) (Egri, 1999; Canavari et al., 2008; Koesling et al., 2008; Läpple, 2010; Läpple and Rensburg, 2011; Mzoughi, 2011; Wollni and Andersson, 2014; Haris et al., 2018; Nguyen et al., 2020) may impact farmers' decision to convert to organic farming.

Estimations and comparisons of the performance of the seven considered models are carried out for each MS and the EU.[41] The in-sample predicted organic conversion probabilities obtained with the best performing model are then used in IFM-CAP. That is, IFM-CAP farms (in each MS or at the EU level, depending on the type of simulated policy target)[42] ranked according to their likelihood of being organic, and those with the highest probability are selected to convert. This implies that the selection of farms that convert to organic production in the exogenous approach are not necessarily those that gain the most in terms of profit-maximizing behaviour but those estimated to be most likely converting, determined by various monetary and non-monetary related factors. This is in contrast to the endogenous approach, where the sole driver is profit maximization behavior, i.e., the utility gain from the conversion.

Performance results and model selection

Table D.2 presents the performance metric of the seven models and the best performing model for MS and EU level estimations. The prediction accuracy varies between 0.51 and 0.99, with most models across MS and EU having an accuracy greater than 0.8. For the majority of MS, as well as for the EU as a whole[43], the random forest algorithm outperformed the other six models in terms of prediction accuracy. Exceptions are Luxemburg and Ireland, for which the Logit model and the Logit model with stepwise selection algorithm have shown a higher prediction accuracy, respectively. The prediction accuracy for the selected model is greater than 0.88 across MS and EU.

Table D.3 presents a more detailed performance metric for the best performing model by indicating the in-sample confusion matrices which includes the percentages of correct and incorrect predictions generated by the selected models, together with the number of observations for the conventional and organic status. The in-sample confusion matrix shows the share of correct predictions both for the conventional status (the 0-s) and for the organic status (the 1-s), as well as the share of the incorrect predictions (i.e., 0- for organic and 1- for conventional). As shown in Table D.3, the prediction performance of the selected model is relatively high. For the MS-based models, the share of correct predictions varies between 85% and 99% for the non-organic farms and between 84% and 99% for the organic ones. For the EU, the random forest algorithm also performs pretty well, with a prediction accuracy of approximately 94% for both organic and non-organic farms.

Part D: References

Anderson, J., Jolly, D., Green, R. (2005). Determinants of farmer adoption of organic production methods

[41] The models are estimated using 2014-2017 data. A data cleaning procedure is applied before estimation. Data for Italy, Denmark, and Bulgaria prior 2016 have been removed due to the very low number of organic farms compared to 2017.

[42] The estimated MS conversion probabilities are more appropriate when modeling the policy target on the share of organic land that needs to be converted at the MS level. In contrast, the EU level conversion probabilities are more appropriate when modeling the policy target set at the EU level.

[43] Due to its computation complexity, the stepwise selection algorithm is not performed with the full EU sample.

Table D.1. Covariates used in the prediction of the likelihood to convert in the exogenous approach.

Name	Type	Category	Description
REGION	Class	NM	FADN region dummies
TF14	Class	NM	Dummies for the 14 FADN classes of type of farming
ACTIVITIES	Numeric	NM	Share of the total agricultural area by production activity. Additionally, the share of cereals is interacted with all other activities. In total 24 activities
LIVESTOCK	Class	NM	Dummy for the presence/absence of livestock activities
MAX SHARE CROP DETAILED	Numeric	NM	Maximum share of the major crop according to FADN activities
MAX SHARE CROP AGGREGATE	Numeric	NM	Maximum share of the major crop according to IFM-CAP activities
SHANNON	Numeric	NM	Shannon index of crop biodiversity
SHARE UAA OWNED	Numeric	NM	Share of owned Utilized Agricultural Area
REGIONAL LAND RENT	Numeric	M	Regional average rental price of agricultural land per hectare
UAA	Numeric	NM	Total Utilized Agricultural Area
SIZ6	Class	NM	Classes of economic size
TYPOWN	Class	NM	Type of ownership of the farm
ALTITUDE	Class	NM	Altitude class of the holding
ANC3	Class	NM	Classes of Areas with Natural Constraints
TOTAL AWU HA	Numeric	NM	Total Annual Working Units per hectare
SHARE UNPAID AWU	Numeric	NM	Share of AWU of family workers
LU/HA	Numeric	NM	Livestock Density
IRRSYS	Class	NM	Type of irrigation system
FIXED ASSETS/HA	Numeric	M	Fixed assets per hectare in EUR
MFP	Numeric	M	Multifactor productivity measured as total output value divided total input costs
DECOUPLED/ HA	Numeric	M	Decoupled payments per hectare
COUPLED/HA	Numeric	M	Coupled payments per hectare
ENVIRONMENT/HA	Numeric	M	Environmental payments per hectare
LFA/HA	Numeric	M	Payments for Least Favored Areas per hectare
OTHER/HA	Numeric	M	Other RDP payments per hectare
INVESTMENTS/HA	Numeric	M	Payments for investments per hectare
ORGANIC WHEAT YIELD RATIO	Numeric	NM	Ratio between the yield of wheat for organic and for conventional farms in the FADN region
ORGANIC MAIZE YIELD RATIO	Numeric	NM	Ratio between the yield of maize for organic and for conventional farms in the FADN region
ORGANIC MILK YIELD RATIO	Numeric	NM	Ratio between the yield of milk for organic and for conventional farms in the FADN region
REGIONAL SHARE ORGANIC	Numeric	NM	Share of organic farms in the region
FERTILIZERS/HA	Numeric	M	Expenditure per hectare in fertilizers
PESTICIDES/HA	Numeric	M	Expenditure per hectare in pesticides
RELATIVE FERTILIZERS/HA	Numeric	M	Expenditure per hectare in fertilizers relative to the expenditure of farms of the same organic status, TF14 and region
RELATIVE PESTICIDES/HA	Numeric	M	Expenditure per hectare in pesticides relative to the expenditure of farms of the same organic status, TF14 and region

Notes: M: monetary variable; NM: non-monetary variable

in the fresh-market produce sector in California: A logistic regression analysis. In 2005Western Agricultural Economics Association Annual Meeting.

Biau, O., and D'Elia, A. (2012). Euro area GDP forecasting using large survey datasets. A random forest approach. Euroindicators working papers, ISSN 1977-3331, EQP 2011/02, Publications Office of the European Union, 2012.

Bravo-Monroy, L., Potts, S. G., and Tzanopoulos, J. (2016). Drivers influencing farmer decisions for adopting organic or conventional coffee management practices, *Food Policy*, 58: 49-61.

Burton, M., Rigby, D., and Young, T. (1999). Analysis of the Determinants of Adoption of Organic Horticultural Techniques in the UK, *Journal of Agricultural Economics*, 50(1): 47-63.

Table D.2. Comparisons of the prediction accuracy metric of estimated models.

	LP	LP + SSA	LOGIT	LOGIT + SSA	PROBIT	PROBIT + SSA	RANDOM FOREST	Maximum prediction accuracy	Selected model
Belgium	0.8096	0.8053	0.9014	0.8017	0.8709	0.8066	0.9411	0.9411	RANDOM FOREST
Cyprus	0.8102	0.8148	0.8497	0.8443	0.8504	0.8435	0.8993	0.8993	RANDOM FOREST
Czechia	0.8563	0.8556	0.9424	0.9213	0.8191	0.9082	0.9653	0.9653	RANDOM FOREST
Germany	0.9273	0.9275	0.9301	0.9282	0.9293	0.9291	0.9725	0.9725	RANDOM FOREST
Greece	0.7228	0.7224	0.7543	0.7449	0.6187	0.5984	0.914	0.914	RANDOM FOREST
Spain	0.7597	0.7583	0.7683	0.7664	0.7691	0.7676	0.928	0.928	RANDOM FOREST
Estonia	0.8305	0.828	0.8029	0.9354	0.7705	0.7399	0.9653	0.9653	RANDOM FOREST
France	0.7067	0.7054	0.7253	0.5933	0.7241	0.7225	0.9251	0.9251	RANDOM FOREST
Croatia	0.8499	0.849	0.8526	0.8462	0.8482	0.8416	0.9139	0.9139	RANDOM FOREST
Hungary	0.7498	0.7434	0.7922	0.7607	0.6312	0.7714	0.8781	0.8781	RANDOM FOREST
Ireland	0.8366	0.839	0.8831	0.9843	0.8523	0.9841	0.9526	0.9843	LOGIT + SSA
Lithuania	0.9676	0.9679	0.9762	0.9743	0.9511	0.9697	0.9801	0.9801	RANDOM FOREST
Luxemburg	0.9389	0.9404	0.9905	0.9816	0.8846	0.9783	0.9802	0.9905	LOGIT
Latvia	0.8983	0.8967	0.8848	0.9361	0.9212	0.9322	0.9835	0.9835	RANDOM FOREST
Italy	0.8032	0.8017	0.7232	0.8036	0.7173	0.8019	0.8972	0.8972	RANDOM FOREST
Netherland	0.7476	0.755	0.7993	0.778	0.7951	0.7728	0.9507	0.9507	RANDOM FOREST
Austria	0.9007	0.9001	0.9006	0.9134	0.9003	0.907	0.9472	0.9472	RANDOM FOREST
Poland	0.8662	0.8655	0.9377	0.9353	0.6075	0.9293	0.9692	0.9692	RANDOM FOREST
Portugal	0.7636	0.7622	0.7776	0.7748	0.5243	0.7627	0.9411	0.9411	RANDOM FOREST
Romania	0.7314	0.7284	0.5263	0.7617	0.6627	0.7576	0.9022	0.9022	RANDOM FOREST
Finland	0.9186	0.9154	0.8801	0.9288	0.872	0.9248	0.9801	0.9801	RANDOM FOREST
Sweden	0.804	0.8021	0.7745	0.7417	0.8374	0.852	0.9561	0.9561	RANDOM FOREST
Slovakia	0.8053	0.796	0.845	0.836	0.835	0.5953	0.8997	0.8997	RANDOM FOREST
Slovenia	0.9162	0.9172	0.9456	0.9439	0.917	0.9375	0.9636	0.9636	RANDOM FOREST
Bulgaria	0.7483	0.7512	0.6083	0.6291	0.6631	0.5099	0.8783	0.8783	RANDOM FOREST
Denmark	0.9668	0.9668	0.9775	0.9759	0.9766	0.9747	0.984	0.984	RANDOM FOREST
EU	0.7288	-	0.573	-	0.5449	-	0.9367	0.9367	RANDOM FOREST

Canavari, M., Cantore, N., Lombardi, D. (2008). Factors explaining farmers' behaviors and intentions about agricultural methods of production. Organic vs. conventional comparison. In Proceedings of the 16th IFOAM OrganicWorld Congress, Modena, Italy, 16–20 June 2008.

Chmielinski, P., Pawlowska, A., Bocian, M., Osuch, D. (2019). The land is what matters: factors driving family farms to organic production in Poland. *British Food Journal*, vol. 121, No. 6, pp. 1354-1367.

Darnhofer, I., Schneeberger, W., and Freyer, B. (2005). Converting or not converting to organic farming in Austria: Farmer types and their rationale, *Agriculture and Human Values*, 22: 39-52, doi: 10.1007/s10460-004-7229-9.

Egri, C.P. (1999). Attitudes, backgrounds and information preferences of Canadian organic and conventional farmers: Implications for organic farming advocacy and extension. *Journal of Sustainable Agriculture*, 13, 45-72.

Fairweather, J. R. (1999). Understanding how farmers choose between organic and conventional production: Results from New Zealand and policy implications, *Agriculture and Human Value*, 16: 51-63.

Geius, M., Pantzios, C., Tzouvelekas, V (2006). Information acquisition and adoption of organic farming practices from farm operations in Crete, Greece. *Journal of Agricultural and Resource Economics*, 31, 93-113.

Haris, N.B.M., Garrod, G., Gkartzios, M., Proctor, A. (2018). The Decision to Adopt Organic Practices in Malaysia: A Mix-method Approach. In Proceedings of the 92 Annual Conference, Coventry, UK, 16–18 April 2018

Hattam, C. E., and Holloway, G. J. (2005). Adoption of Certified Organic Production: Evidence from Mexico. Paper at: Researching Sustainable Systems - Inter-

Table D.3. Confusion matrices of the selected models by MS and for the EU as a whole.

	Belgium			Hungary			Portugal	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.948	0.052	C	0.904	0.096	C	0.954	0.046
O	0.066	0.934	O	0.148	0.852	O	0.071	0.929
	Cyprus			Ireland			Romania	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.852	0.148	C	0.984	0.016	C	0.937	0.063
O	0.054	0.946	O	0.015	0.985	O	0.132	0.868
	Czechia			Lithuania			Finland	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.978	0.022	C	0.986	0.014	C	0.98	0.02
O	0.047	0.953	O	0.026	0.974	O	0.02	0.98
	Germany			Luxemburg			Sweden	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.978	0.022	C	0.994	0.006	C	0.959	0.041
O	0.033	0.967	O	0.013	0.987	O	0.047	0.953
	Greece			Latvia			Slovakia	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.898	0.102	C	0.989	0.011	C	0.944	0.056
O	0.07	0.93	O	0.022	0.978	O	0.144	0.856
	Spain			Italy			Slovenia	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.92	0.08	C	0.917	0.083	C	0.976	0.024
O	0.064	0.936	O	0.122	0.878	O	0.049	0.951
	Estonia			Netherlands			Bulgaria	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.947	0.053	C	0.958	0.042	C	0.909	0.091
O	0.016	0.984	O	0.056	0.944	O	0.153	0.847
	France			Austria			Denmark	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.938	0.062	C	0.941	0.059	C	0.982	0.018
O	0.088	0.912	O	0.047	0.953	O	0.014	0.986
	Croatia			Poland			EU	
	$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$		$\bar{C}$	$\bar{O}$
C	0.909	0.091	C	0.971	0.029	C	0.938	0.062
O	0.081	0.919	O	0.032	0.968	O	0.064	0.936

Notes: C: conventional; O: organic; : predicted conventional; : predicted organic.

national Scientific Conference on Organic Agriculture, Adelaide, Australia, September 21-23, 2005.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). An Introduction to Statistical Learning with Applications in R. Springer text in Statistics, Series Editors: Casella, G., Fienberg, S., and Olkin, I., Springer New York Heidelberg Dordrecht London, ISSN 1431-875, ISBN 978-1-4614-7137-0, DOI: 10.1007/978-1-4614-7138-7.

Kallas, Z., Serra, T., and Gil, J. M. (2009). Farmers' objectives as determinant factors of organic farming adoption. Paper prepared for presentation at the 113th EAAE Seminar "A resilient European food industry and food chain in a challenging world", Chania, Crete, Greece, date as in: September 3 - 6, 2009.

Kaufmann, P., Zemeckis, R., Skulskis, V., Kairyte, E., Stagl, S. (2011). The Diffusion of Organic Farming in Lithuania. Journal of Sustainable Agriculture, 35, 522-549.

Khaledi, M., Weseen, S., Sawyer, E., Ferguson, S., Gray, R. (2010). Factors influencing partial and complete adoption of organic farming practices in Saskatchewan, Canada. *Canadian Journal of Agricultural Economics*, 58, 37-56.

Kisaka-Lwayo, M. (2007). A discriminant analysis of factors associated with the adoption of certified organic farming by smallholder farmers in Kwazulu-Natal, South Africa. In Proceedings of the 2007 Second International Conference, Accra, Ghana, 20-22, August 2007.

Knowler, D., and Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, 32, 25-48.

Koesling, M., Flaten, O., Lien, G. (2008). Factors influencing the conversion to organic farming in Norway. *International Journal of Agricultural Resources, Governance and Ecology*, 7, 78-95.

Läpple, D. (2010). Adoption and abandonment of organic farming: An empirical investigation of the Irish drystock sector. *Journal of Agricultural Economics*, 61, 697-714.

Läpple, D., and van Rensburg, T. (2011). Adoption of organic farming: Are there differences between early and late adopters? *Ecological Economics*, 70, 1406-1414.

Liu, X., Pattanaik, N., Nelson, M., Ibrahim, M. (2019). The choice to go organic: Evidence from small US farms. *Agricultural Sciences*, Vol. 10, No. 12, 1566-1580.

Lohr, L., and Salomonsson, L. (2000). Conversion subsidies for organic productions: results from Sweden and lessons from the United States, *Agricultural Economics*, 22, 133-146.

Lu, C.F., and Cheng, C.Y. (2019). Impacts of spatial clusters on certified organic farming in Taiwan. *Sustainability*, 11, 2637.

Malá, Z., and Malý, M. (2013). The determinants of adopting organic farming practices: A case study in the

Czech Republic. *Agricultural Economics - Czech*, 59, 19-28.

Métouolé Méda, Y.J., Egyir, I., Zahonogo, P., Jatoe, J., Atewamba, C. (2018). Institutional factors and farmers' adoption of conventional, organic and genetically modified cotton in Burkina Faso. *International Journal of Agricultural Sustainability*, 16, 40-53.

Mzoughi, N. (2011). Farmers adoption of integrated crop protection and organic farming: Do moral and social concern matter? *Ecological Economics*, 70, 1536-1545.

Nguyen, T.P.L., Nguyen, T.T., Doan, X., Tran, M.L., Tran N.M., Nguyen, T. D. (2020). A dataset of factors influencing intensions for organic farming in Vietnam. *Data in Brief*, Vol. 33, 106605.

Parra López, C., and Caltrava Requena, J. (2005). Factors related to the adoption of organic farming in Spanish olive orchards, *Spanish Journal of Agricultural Research*, 3(1), 5-16.

Peter Silas, M. (2008). Factors affecting adoption of organic farming by maize farmers in MERU South district. Master's Thesis, Kenyatta University, Kenyatta, Kenya, 2008.

Saoke, L.A. (2011). Organic Farming in the Kibera Slum in Nairobi, Kenya. Master's Thesis, Wageningen University, Wageningen, The Netherlands, 2011.

Sapbamrer, R., and Thammachai, A. (2021). A Systematic Review of Factors Influencing Farmers' Adoption of Organic Farming. *Sustainability*, 13, 3842.

Serebrennikov, D., Thorne, F., & Kallas, Z. (2020). *Factors Influencing Adoption of Sustainable Farming Practices in Europe: A Systemic Review of Empirical Literature*. 1–23.

Sriwichailamphan, T., and Sucharidtham, T. (2014). Factors affecting adoption of vegetable growing using organic system: A case study of Royal Project Foundation, Thailand. *International Journal of Economics & Management Science*, 3, 1000179.

Willock, J., Deary, I. J., Edwards-Jones, G., Gibson, G. J., McGregor, M. J., Sutherland, A., Dent, J. B., Morgan, O., & Grieve, R. (1999). The role of attitudes and objectives in farmer decision making: Business and environmentally-oriented behaviour in Scotland. *Journal of Agricultural Economics*, *50*(2), 286-303. https://doi.org/10.1111/j.1477-9552.1999.tb00814.x

Wollni, M., and Anderson, C. (2014). Spatial patterns of organic agriculture adoption: Evidence from Honduras. *Ecological Economics*, 97, 120-128.

Yanakittkul, P., and Aungvaravong, C. (2020). A model of farmers intentions towards organic farming: A case study on rice farming in Thailand. *Heliyon*, vol. 6, issue 1, e3039.

Yu, C. H., Yoo, J. C., and Yao, S. B. (2014). Farmers' willingness to switch to organic agriculture: A non-parametric analysis, *Agric. Econ. - Czech*, 60 (6): 273-278.