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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]

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

subject to:

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

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

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

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, $\mathrm{E}[gm_i]$ 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:

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

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, $C_i = \sum_k c_{i,k}$, 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, $C_i = \sum_{m \in Feed} p_m \zeta_{i,m}$, 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):

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

where:

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

for crops,

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

for animals,

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

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).

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

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

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

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

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[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%

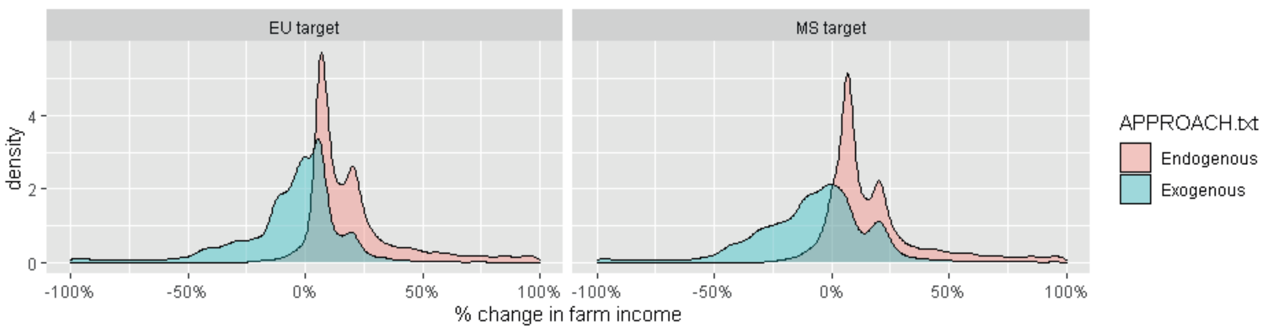

Figure 1. Probability density of the farm income change of converted farms in the EU in the MS and EU organic targets (% change to the baseline).

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.

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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, non-linear 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

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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:

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

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:

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

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:

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

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):

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

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:

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

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:

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

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:

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

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

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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).

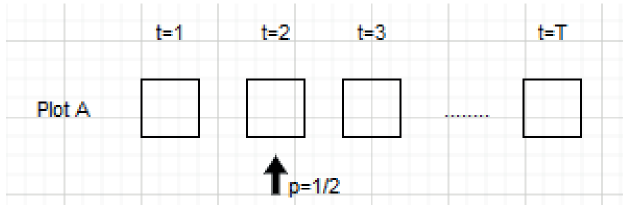

Figure C.2. The probability to find a crop in a 2-year fixed rotation that alternates with another crop.

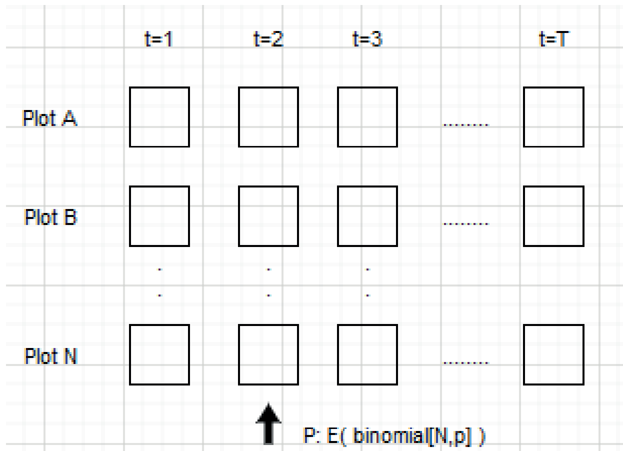

Figure C.3. Schematic of a farm with many plots and the relation of the crop acreage and the rotation frequency and length.

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

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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.

[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

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[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

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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

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

Belgium			Hungary			Portugal		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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		
	$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$		$\overline{C}$	$\overline{O}$
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.

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A systematic literature review on the rural-urban economic well-being gap in Europe

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Abstract. A large amount of policy support is spent to foster the development of rural areas in Europe. However, empirical evidence on the well-being differential between rural and urban areas in Europe is scant and incomplete. The present study develops a systematic literature review on this topic, bridging a gap in research as a systematic analysis on the subject has not been developed as far as we know. It uses the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method. The review focuses on definitions of rural-urban most used in the literature, main dimensions of well-being that are analyzed, nature of the data and, finally, evidence that emerged regarding the differences in the various dimensions of well-being between rural and urban populations. The analysis confirms that available evidence is controversial and provides advice on how to develop new and better empirical analyses on this topic.

Keywords: well-being, rural areas, PRISMA, income gap, Europe.
JEL Codes: I31, I32, O18.

1. INTRODUCTION

European countries use large amounts of public resources to support the development of rural areas, particularly through the European Union (EU) rural development policy. The reasons for supporting rural areas, which tend to be in disadvantaged conditions (Shucksmith et al., 2006), are many and vary from improving their competitiveness, creating jobs outside the agriculture industry (new businesses, development of tourism related activities etc.), development of access and connections between cities and rural areas, development of basic infrastructure in villages, particularly in new EU member states.

Our analysis refers to the issue of the economic disadvantage of households living in rural areas. Very often, rural areas are less developed and characterized by smaller incomes and greater employment, educational and administrative problems than non-rural ones (Bock et al., 2015; Shucksmith et al., 2006, 2009; Sørensen, 2014). Furthermore, rural areas and small towns are more Eurosceptic than larger cities (Dijkstra et al., 2020). All these aspects make the gap between rural and non-rural areas very important for policy makers.

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This paper investigates on this topic by means of a systematic literature review (SLR) focusing on Europe, filling a gap, as no similar analyses have been developed to the best of our knowledge. The study first aims at answering whether a well-being gap exists between rural and urban areas in Europe, focusing on the economic aspect of well-being. This also calls for answering the following additional questions: is there sufficiently robust and comparable empirical evidence to answer the research question? Are there any spaces to improve the analyses on this issue especially in terms of data and methodologies?

The results of this analysis allow to explore the complexity of the topic at stake, the large array of data, dimensions and methodologies used, and to provide a synthesis of the main empirical results.

As a consequence, the analysis paves the way for future research activities that could be developed on this relevant but somehow neglected issue.

The paper is structured as it follows. Next session describes the key concepts used in the analysis while section 3 describes the data and research methodology. Session 4 presents the results of the analysis while session 5 the discussion of them. Finally, session 6 concludes by providing a general judgment on what emerged from this analysis, its limits, and possible future developments.

2. KEY CONCEPTS USED IN THE ANALYSIS

2.1 Well-being definition

The concept of well-being is used very often, but there is no commonly agreed definition of what it is. In fact, the terms "well-being", "welfare", "quality of life", "happiness" and "life satisfaction" are often used interchangeably (OECD, 2013; Schnorr-Baecker, 2021). The OECD (2011a) argues that it concerns the satisfaction of various human needs, some of which are essential, and the ability to pursue one's goals, thrive and feel satisfied with one's own life. For this reason, well-being is a complex phenomenon and requires a multidimensional analysis approach (OECD, 2011a, 2020a; Schnorr-Baecker, 2021).

OECD (2011a, 2011b, 2020b) identifies three pillars and eleven dimensions to describe and measure the various components of people's well-being:

- Material living conditions (or economic well-being), which determine people's possibilities of consumption and their control over resources;
- Quality of life, which is defined as the set of non-monetary attributes of individuals that determines their life opportunities, and has a specific value in different cultures and contexts;
- The sustainability of the socio-economic and natural systems in which people live and work, essential for well-being to last over time.

The eleven dimensions are defined, as follows (OECD, 2011a, 2011b, 2020a):

- Material living conditions: i) Income and Wealth; ii) Jobs and Earnings; and iii) Housing;
- Quality of life: i) Health Status; ii) Work and Life Balance; iii) Education and Skills; iv) Civic Engagement and Governance; v) Social Connections; vi) Environmental Quality; vii) Personal Security; and viii) Subjective Well-Being.

This review focuses on papers including the economic dimension of well-being. Economic well-being refers to the material living conditions that determine people's consumption possibilities and their command over resources. This includes the ability of individuals to be able to consistently meet basic needs, such as food, housing, healthcare, transportation, education as well as the ability to make choices that contribute to security, satisfaction and personal fulfilment (OECD, 2011a, 2013, 2020a). Income and wealth enable individuals to meet their basic needs and thus help achieve overall economic well-being (OECD, 2011a, 2011b, 2013, 2020c).

Both the availability of jobs and the resulting earnings are relevant to an individual's well-being. Indeed, they offer people the opportunity to fulfill their ambitions, develop their skills and feel useful in the society in which they live (OECD, 2011). Societies with high levels of employment are also more politically stable, and healthier. Finally, having a home is at the apex of human material needs. Housing is the most important component of the expenses of many families and is fundamental for people's ability to meet some basic needs. Furthermore, any poor housing conditions can affect people's health, both mental and physical (OECD, 2011).

Very often looking at national averages can lead to wrong or distorted conclusions because they often mask large differences in how different parts of the population are doing. For this reason, the distribution of current well-being should be analyzed into three different types of gap (OECD, 2020b):

- Gaps between population groups;
- Gaps between those who are at very distant points of the distribution in each dimension;
- Deprivation (i.e., the share of the population that falls below a certain threshold, such as a minimum level of income, education or health).

Among possible comparisons between different population groups, the one based on the distinction between urban and rural areas can lead to interesting results. In fact, there are various aspects of well-being which are evaluated considering the rural-urban dichotomy and which provide different results. Obviously, analyses of this kind require an objective and consistent definitions of "urban" and "rural", usually in terms of settlement size or population density. There are different definitions in each country, reflecting different social constructions of what is rural and urban in that country or geographic area (Shucksmith et al., 2009).

The empirical evidence available on this issue is controversial also because different definitions of urban-rural, dimensions of well-being, evaluation methods and data sets have been used. Indeed, recent analyses in Europe show very different results for alternative European countries because of the different social and economic conditions existing in member states. For instance, rural areas are significantly poorer in some countries while in others the situation is balanced, or poverty is mainly a non-rural problem (Bernard, 2019; Shucksmith et al., 2009).

2.2 History of the European Urban-Rural issue

The distinction between city and countryside, urban and rural, has long been rooted in European civilization. The etymological roots of the terms "urban" and "rural" extend at least as far as the classical Latin words urbs (city) and rus (open space) (Woods & Heley, 2017). Usually, the city or urbs has always been the object, with the rural always being the "other", the non-urban, the open space beyond the city and the precise boundary between rural and urban, therefore, has always been open to interpretation and controversy (Woods & Heley, 2017).

The history of the concept of urban-rural relations is one in which theoretical research and practical policy development are closely intertwined and difficult to separate. Following Copus (2011) it is convenient to divide it into two main phases. The first started in the mid-1950s and died out in the 1980s (Phase 1: Growth Poles, Cumulative Causation and National Policies). The second one started in the late 90s and still continues (Phase 2: The ESDP, SPESP, ESPON, INTEREG, the Territorial Agenda, RURBAN and City Regions). For a detailed explanation of the two historical phases, see Copus (2011).

In recent years the relationship between urban and rural areas has become a recurring theme in discussions on European rural policy. In very general terms it is seen as a promising component of a more territorial approach to meeting the development needs of lagging rural areas. This, of course, is not a new idea, but dates back to the 1950s and 1960s. However, in recent decades the reality and the connections between these two areas have become much more complex (Copus, 2011).

Rural areas have undergone profound economic and social changes since the first agricultural policies aimed at modernization and land management. As a result, rurality can no longer be defined solely in terms of agricultural activities and associated lifestyles. Indeed, since the publication of the key document on L'avenir du monde rural ("The future of rural society") in 1988, the European Commission has clearly identified, for the first time, the need for a territorial rural policy that goes beyond the agriculture and included local development and environmental concerns as key elements (European Commission, 1988).

The determination of rurality, being at the core of a relevant policy debate for almost 60 years (Mantino, 2021), depends on several factors (Féret et al., 2020): 1) the global contexts (i.e. the characteristics of the socio-economic systems of which rurality is a part); 2) the discourse and the political objectives pursued; 3) the social representations of the different categories of stakeholders. In Europe, each country has developed its own definition of rurality, often as a response to a particular political, administrative and wider territorial context, and in some cases as a result of national classifications of other factors (such as population, accessibility). Approaches and definitions are rarely similar between countries (Bontron, 1996; Depraz, 2007; Shucksmith et al., 2009).

Given the complexity of the topic, six approaches can be found in the literature to define the criteria of rural: the administrative approach, the morphological approach (population density), the locational approach, the functional approach, the landscape approach, and the combined approach (combination of at least two of the other approaches) (Féret et al., 2020; Mantino, 2021). Furthermore, it is important to realize that the rural areas can be located inside a functional urban area (FUA), outside but close to a FUA or in a remote area (OECD, 2020c). For all these reasons, the debates on "rural" and "rurality" definition are an issue that still needs attention in both research programs and policies.

3. DATA AND RESEARCH METHODOLOGY

This paper uses the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), which is characterized by a rigorous and objective selection procedure that allows to increase the reliability of the final output. The approach is based on a statement that helps authors to improve reporting of the systematic review and meta-analysis (Liberati et al., 2009). The PRISMA statement consists of a checklist of 27 items divided into 7 sections / topics and a four-step flow chart.

The review uses the three most important platforms for researching scientific literature database: Scopus; Web of Science core collections (WoS); Science Direct (SD). These are easily accessible and have easy-to-use search tools (Gebre et al., 2021; Li et al., 2018). More research databases and additional methods were used to be able to adequately identify all the literature related to the topic of interest (Bramer et al., 2016). Indeed, a single database is not considered sufficient to retrieve all references for a systematic review (Bramer et al., 2017).

To try to intercept most of the existing works on the research topic, the PRISMA prospectus allows authors the possibility of adding papers from sources other than the identified databases. Therefore, we have added 15 additional articles that are considered important to address the research questions.

After identifying the goal of the search, keyword detection and eligibility criteria setting follows. The keywords chosen were: ((“income” OR “well-being” OR “welfare”) AND (“urban” OR “non-rural”) AND (“rural” OR “non-urban”) AND (“difference*” OR “gap*” OR “inequalit*”) AND (“europe” OR “eu”)). These keywords allowed for a thorough investigation and, at the same time, were relevant to the research question. Regarding the eligibility criteria only publications in English were considered and editorials and letters were excluded. Also, some sub-categories were excluded because they were deemed inconsistent in principle with the topic of our interest (i.e., medical analysis).

Studies were selected from the three databases by searching for keywords in abstracts, keywords, and titles of the research articles. After eliminating the duplicate articles, the studies were first selected by analyzing the title and abstract and subsequently reading the entire text of the remaining articles.

The search yielded a total of 158 articles, of which 143 from the three electronic databases used in this SLR and 15 added by the authors because considered important and particularly focused on the research topic, but they were not intercepted in the three databases used. By eliminating duplicates, the number of articles was reduced to 147. We then went through the articles, analysing their titles and abstracts, and excluded further 86 records, reducing the total of articles to 60.

Subsequently, after reading each single article, the eligibility criteria were applied, and another 20 studies were eliminated. Therefore, 40 articles were included in the review and formed the basis for the remaining of the analysis. In this phase, as suggested by the PRISMA guidelines, the description of the study selection process was reported (Figure 1).

The quality assessment procedure is one of the steps in this SLR process differentiating it from other types of reviews (Bimbo et al., 2017; Littell, 2006; Ma & Chen, 2020). Quality assessment of papers included in a SLR is necessary to assess the relevance of the studies to answer the research question and therefore to establish the strength and credibility of the SLR’s findings and conclusions (Yang et al., 2021). Quality assessment consists in assigning a score to each paper included in the SLR, based on pre-defined criteria. The literature quality assessment was not easy to perform given the high heterogeneity of the methodological approaches, and the lack of standardized quality assessment tools for studies belonging to the social science field. Therefore, conventional measures of study quality were not appropriate in our case.

So, similarly to Bimbo et al. (2017), Cox et al. (2015), Mirra et al., (2021) and Sulaiman et al. (2021) an ad hoc quality assessment tool was developed using the Instrument Critical Appraisal Checklist provided by Joanna Briggs Institute (2017) as a reference document. Additionally, based on the authors’ expertise, some studies characteristics considered important were included in the assessment of study quality. Eventually six criteria were identified (Table A1 in the Appendix).

The first criterion considered whether the analysis performed was qualitative or quantitative in nature. The adequacy of the sample size used was the second criterion considered. The third criterion was if there was a well-defined research question. The remaining three criteria were whether the outcomes were measured in a valid and reliable way, whether there was a clear definition of the rural-urban concept and whether well-being differences between rural and urban areas were addressed directly or just mentioned.

The studies identified were rated as low, medium, or high quality, based upon a combination of the scores assigned to each of the six criteria (Bimbo et al., 2017; Cox et al., 2015; Mirra et al., 2021). The more papers classified as “high quality” are present, the stronger and more robust the results and conclusions of the SLR will be.

A study was considered as “high quality” when showing “high” rating on four or more criteria; “medium quality,” with three “high” or two “high” and two “medium”. Finally, we classified the study as “low quality” in case of zero, one or two high rating (excluded the case of two high and two medium). Equal weighting was given to each criterion (Bimbo et al., 2017; Cox et al., 2015). The results of the quality assessment are reported in Table 1.

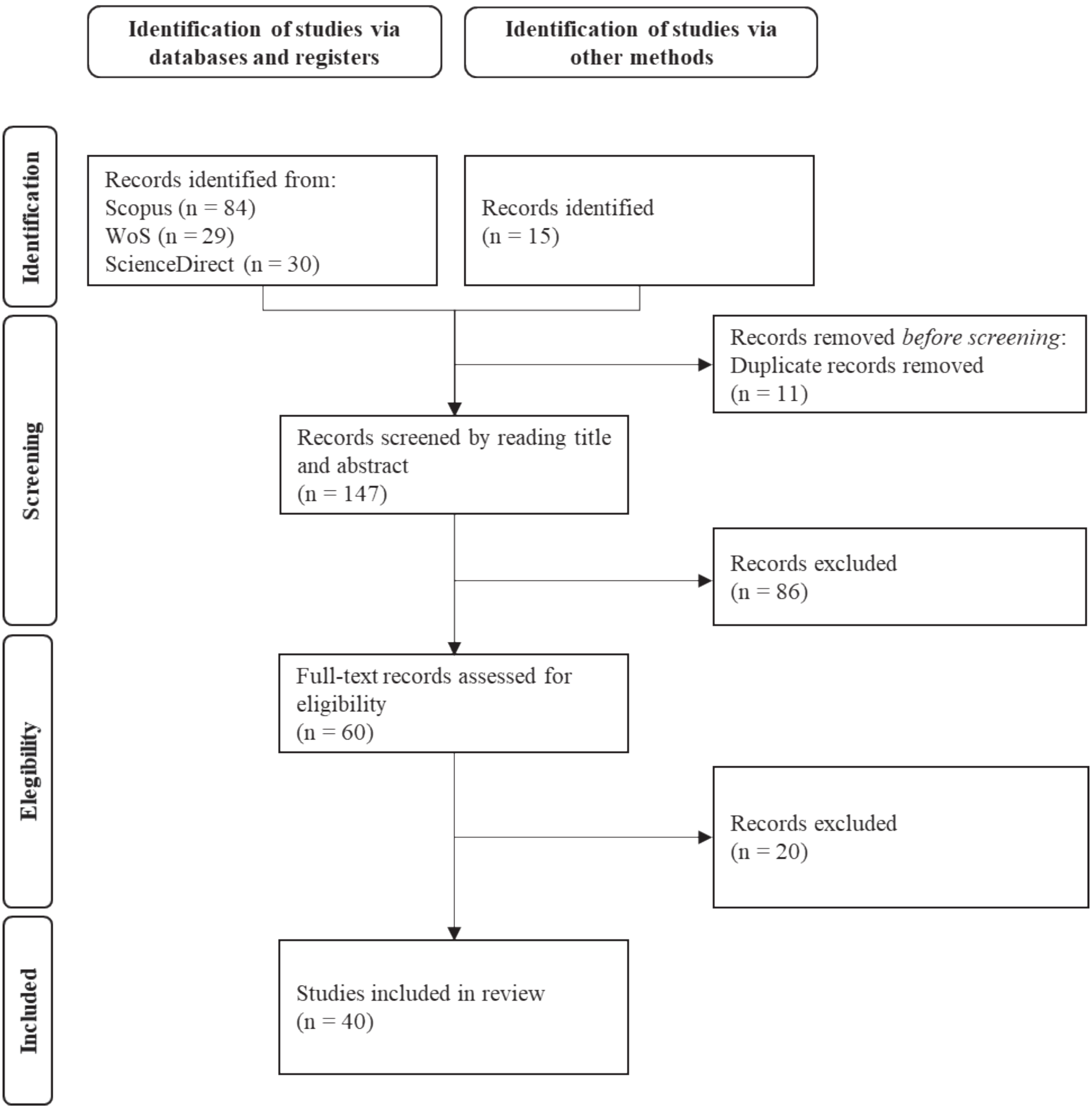

Figure 1. Articles selection process. Source: Own elaborations.

4. RESULTS OF THE ANALYSIS

The 40 publications are distributed over time as represented in the figure below. There is a growing trend from 2000 to today (Figure 2). First, the definitions of rural-urban used in the articles were identified and classified. The next step was to frame which dimensions of well-being were analyzed in the selected studies.

This means evaluating how many articles study income, education, subjective well-being, etc., following the eleven economic dimensions presented by the OECD (2011c). All the research objectives pursued in the selected literature were also analyzed, as well as the nature of the data (macro or micro approach, cross-sectional, panel, time series) and the methodologies adopted to achieve the expected results.

Table 1. Quality assessment.

Author and year	What it was the methodology researchers used in this study?	Was Sample size adequate?	Was there a well-defined question?	Were the outcomes measured in a valid and reliable way?	Was there a clear definition of rural and urban?	Well-being differences between rural and urban areas addressed directly or just mentioned?	Overall rating
Schnorr-Baecker S. (2021)	Quantitative	yes	yes	Yes	yes	yes	High
Slettebak M.H. (2021)	Quantitative	yes	yes	Yes	yes	yes	High
Ayala et al. (2021)	Quantitative	yes	yes	Yes	yes	yes	High
Novák et al. (2020)	Qualitative	yes	yes	No	yes	no	Medium
Piras S. (2020)	Quantitative	no	yes	Yes	no	no	Medium
Cipane K. and Sloka B. (2020)	Quantitative	yes	yes	Yes	no	yes	High
Wochner T. and Holzhausen A. (2019)	Quantitative	yes	yes	Yes	yes	yes	High
Viganóa et al. (2019)	Quantitative	yes	yes	Yes	yes	yes	High
Bernard J. (2019)	Quantitative	yes	yes	Yes	yes	yes	High
Grzega U. (2019)	Quantitative	yes	yes	No	no	no	Medium
Sloka et al. (2019)	Quantitative	yes	yes	Yes	no	no	High
Tobiasz-Adamczyk B. and Zawisza K. (2017)	Quantitative	yes	yes	Yes	yes	yes	High
Bruder E. and Unal H. (2017)	Quantitative	yes	yes	No	yes	yes	High
Mattioli G. (2017)	Quantitative	yes	yes	Yes	yes	no	High
Zarnekow N. and Henning C.H.C.A. (2016)	Quantitative	yes	yes	Yes	yes	yes	High
Binelli C. and Loveless M. (2016)	Quantitative	yes	yes	Yes	yes	yes	High
Bock et al. (2015)	Qualitative	yes	yes	No	no	yes	High
Alexandri et al. (2015)	Quantitative	n/a	yes	No	no	yes	Medium
Chivu et al. (2015)	Quantitative	yes	yes	No	no	no	Medium
Zwiers M. and Koster F. (2015)	Quantitative	yes	yes	Yes	yes	yes	High
Weziak-Bialowolska D. (2014)	Quantitative	yes	yes	Yes	yes	no	High
Sørensen J.F.L. (2014)	Quantitative	yes	yes	Yes	yes	yes	High
Marcotullio et al. (2014)	Quantitative	yes	yes	Yes	yes	no	High
Stanef M.R. (2012)	Qualitative	yes	yes	No	yes	yes	High
Sørensen J.F.L. (2012)	Quantitative	yes	yes	Yes	yes	yes	High
Lengsfeld J.H.B. (2011)	Quantitative	yes	yes	Yes	yes	no	High
Vicente M.R. and López A.J. (2011)	Quantitative	yes	yes	Yes	yes	no	High
Rodríguez-Pose A. and Tselios V. (2010)	Quantitative	yes	yes	Yes	yes	no	High
Shucksmith et al. (2009)	Quantitative	yes	yes	Yes	yes	yes	High
Rodríguez-Pose A. and Tselios V. (2009)	Quantitative	yes	yes	Yes	no	no	High
Macours K. And Swinnen J. F. M. (2008)	Qualitative	yes	yes	Yes	no	yes	High
Bertolini et al. (2008)	Qualitative	yes	no	No	yes	no	Low
Havard et al. (2008)	Quantitative	yes	yes	Yes	yes	no	High
Nummela et al. (2008)	Quantitative	yes	yes	Yes	yes	yes	High
Van Hooijdonk et al. (2007)	Quantitative	yes	yes	Yes	yes	no	High
Shucksmith et al. (2006)	Quantitative	yes	yes	Yes	yes	yes	High
Hoggart K. andCheng S. (2006)	Quantitative	yes	yes	Yes	yes	no	High
O'Brien E. (2005)	Qualitative	no	yes	No	no	no	Low
Gerdtham U. and Johannesson M. (2001)	Quantitative	yes	yes	Yes	yes	no	High
Rietveld P. and Ouwersloot H. (1989)	Quantitative	yes	yes	Yes	yes	yes	High

Source: Own elaborations.

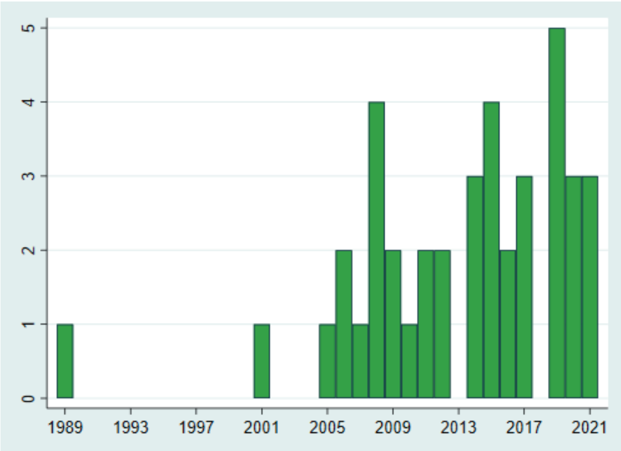

Figure 2. Number of publications per year. Source: Own elaborations.

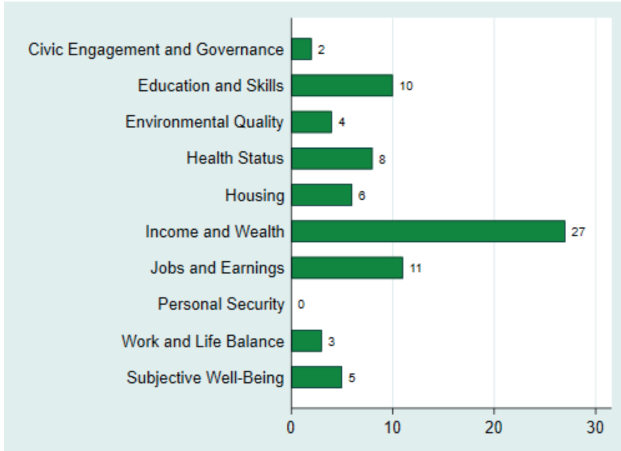

Figure 3. Number of publications per topic. Source: Own elaborations.

Finally, for each dimension of well-being, the main results in terms of differences in well-being (or individual dimensions of it) between rural and urban areas were summarized and compared.

To resume the structure of the results of our work, for each study included in the review, the dimensions that were analyzed, classified, and compared are the following:

- Definition of the rural/urban concept;
- Main dimensions of well-being observed (i.e. income, education, work-life balance, etc.);
- Aims of the research;
- Nature of the data (macro/micro, cross-sectional, panel or time series) and applied methodologies;
- Main findings related to differences in the various dimensions of rural and urban areas well-being.

As regards the definition of rural and urban, the most widespread typology in the works examined is based on the concept of population density. In fact, 22 out of 40 studies use definitions of rural and urban based on population density, 8 use other definitions and 10 do not provide any definition at all.

In 5 of the 8 studies that use other ways of defining rural and urban, the population density represents only one dimension of the definition, while in 3 studies the interviewee subjectively indicates and classifies the area in which he/she lives as rural or urban. It should be noted that of the 30 studies that provide a definition of rural and urban, 12 use simple rural-urban dummies while 18 use categorical variables, which can range from 3 to 8 categories (i.e. rural, sub-rural, sub-urban, urban, etc).

As for the dimensions of well-being (Figure 3), the most studied are income and wealth (27), job and earnings (11), education and skills (10), health status (8) and housing (6). 27 papers analyse income, of which only 8 study the job and employment as well as income, with only 5 publications dealing also with housing.

Civic Engagement and Governance and Social Connections are discussed jointly. Aims of the studies are very different both for the dimension of well-being investigated and for the centrality and importance of differences between rural and urban. Some studies investigate the relationship between a dimension of well-being and its determinants, including the rural or urban residence, or how one dimension of well-being affects the total. In these studies, the dimension of well-being is central, while the variable defining the rural-urban areas is only one of the determinants.

Therefore, the real main objective of these works is not so much to observe a difference in well-being, or in its dimensions, between rural and urban areas. Obviously, there are also studies in which the difference between rural and urban is the central aim.

Regarding the characteristics and nature of the data used, of the 40 studies reviewed in this SLR, 63% use microdata. Indeed, 26 studies use micro data, 4 macro data, 5 both micro and macro data and 5 do not use quantitative analyses. Regarding the temporal nature of the data, of the 35 quantitative studies, 27 studies use cross-sectional data, 6 use panel data and 2 use time series.

The review showed that there are both studies based on individual data (individual households) and on regional data. Obviously, this difference must be taken into account when comparing the results of the different types of analyses. In 23 papers the level of analysis is NUTS0 (Country or group of countries), in two papers is NUTS1 and NUTS2 together, in 15 papers NUTS3 or more detailed territorial levels. In studies with less spatial detail, the tendency is to perform analyses on individual/household data and compare rural and non-rural individuals/households within the country. As the territorial detail of the analysis tends to increase, the greater the tendency to compare rural areas with non-rural ones (regions, provinces, etc.) without using individual/household data.

From a methodological point of view, it emerged that among the studies mainly focusing on the gap between rural and urban, the comparison of the averages between the two groups through descriptive statistics and / or hypothesis tests (e.g., t-test, χ^2-test) are the most popular methods (14 papers).

Only few studies combine the comparison of the means with the comparison of the medians. In papers where the rural-urban differential is not the central topic, but only one of the many determinants of well-being or of a specific dimension, linear and more frequently non-linear regression models are used, such as logit, ordered logit or probit. Pearson's correlation is frequently used as a preliminary analysis (11 papers).

Regarding methodologies, it is important to underline that in various works the authors calculate and use indices and coefficients of various kinds, in relation to the objective pursued. These include the Gini Coefficients, the Lorenz Curve, the General Psychological Wellbeing Index, the Multidimensional Poverty Index and the Theil Index. Next section reports and summarises the main results of the different studies divided by dimension of well-being.

5. DISCUSSION

This section discusses the main results looking at the eleven[1] dimensions of well-being already described in sections 2 and 4. In this approach, rural and non-rural areas have been treated as homogeneous withnin each of the two. However, this is an obvious oversimplification, as there are significant differences within these areas given that the degree of rurality of the different geographical realities also varies. This has been decided based on a compromise between the complexity of the classification of rural/non-rural areas and the aggregation of the results of 40 papers. In the following subsections we try to contextualize the results considering the geographical context in which the analysed works were carried out. Even knowing that the comparison between different geographical areas, in different periods, has its limits, an attempt has been made to create a synthetic discussion of the 40 papers that is as homogeneous and coherent as possible.

[1] Civic Engagement and Governance and Social Connections are discussed jointly.

5.1 Income and wealth

In general, in Europe, the analyzed studies have highlighted a lower income situation in rural areas than in urban areas (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). What has been observed in recent years in Europe is a convergence between the two groups, characterized by a notable growth in rural areas and a less sudden growth in urban areas (Grzega, 2019; Wochner & Holzhausen, 2019). Furthermore, income differences between urban and rural areas change according to the wealth of the country of reference. In fact, urban-rural income differences are mild in the richest countries and most progressively marked in countries with a lower average income (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). Therefore, there is evidence that the income gap of rural areas compared to urban ones decreases as the country's average income increases.

Income differences between urban and rural areas in poorer countries may be less extreme than expected when considering domestic self-supply of food. Indeed, growing food and raising animals is a very common activity in rural areas of low-income countries, which helps to mitigate the existing income gap. Therefore, urban-rural differences in the poorest countries are lower than what one would expect observing the only monetary income differences (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). Furthermore, as reported by Stanef (2012), the growing importance of extra-agricultural revenue in rural families is reducing the income gap between rural and urban areas. The income differences between the two groups concern and reflect the structure of consumer expenses. Indeed, rural families spend relatively more on goods and services that satisfy their primary needs and less on those that satisfy secondary needs (Alexandri et al., 2015; Grzega, 2019).

Obviously, there are several exceptions to this rule. Indeed, in some studies lower income levels characterise urban areas while higher income levels are found in the rural areas (Rietveld & Ouwersloot, 1989; Zwiers & Koster, 2015). These results seem to indicate that high-income individuals, considering rural areas as places characterized by a better quality of life, leave urban areas and settle in more rural areas (Viganó et al., 2019; Zwiers & Koster, 2015). Sørensen (2014) found a positive correlation between income and satisfaction with life and that the inhabitants of rural areas have greater satisfaction with life than the inhabitants of the cities. As regards rural-urban perceived income differences, it was found that high-income urban residents are less likely to perceive large income differences than high-income rural residents, while there is no urban / rural difference for individuals with low income (Binelli & Loveless, 2016).

The concept of ownership also falls within the definition of Income and Wealth provided by the OECD (2011c). In Germany, car ownership is greater in rural areas, where it is essential for travel as the access to public transport services is lower (Mattioli, 2017; Schnorr-Baecker, 2021).

Regarding poverty, similar poverty reduction is occurring over time in Europe in rural and urban areas. However, there continues to be more poverty in rural areas (Macours & Swinnen, 2008; Piras, 2020). The concept of poverty seems to partly follow the logic of income analysed above. In fact, in countries with the lowest average income, the worst situation regarding poverty is observed in sparsely populated areas, while a better situation occurs in densely populated areas. In richer countries, on the other hand, poverty is relatively higher in densely populated areas than in rural areas (Weziak-Bialowolska, 2014).

Regarding poverty in Europe, the theme of the universal increase in poverty and deprivation levels as a problem of rural areas alone has been defined as wrong (Bernard, 2019). Indeed, as noted, rural-urban poverty disparities not only vary in magnitude, but, in some countries, disparities are completely reversed in favor of rural areas. According to Bernard (2019), the increase in poverty in rural areas can be observed in countries with a lower population density in rural areas (reduced accessibility to opportunities for local people), in countries with a higher percentage of farmers (especially those who work on very small farms), in post-socialist transition countries and in countries with generally lower levels of economic development and reduced living standards. As mentioned above, poverty tends in some cases to become more and more an urban phenomenon. Between 1996 and 2002 the poverty rate increased in large cities and decreased in small towns and rural areas (Bertolini et al., 2008).

However, in a cross-section perspective, rural districts still have the highest percentage of poor people. Furthermore, according to Bertolini et al. (2008), poverty rates drop further and significantly in rural areas when corrected for the fact that many rural families dwell in property homes and do not pay rents. Further work that goes in the same direction is that proposed by Rietveld & Ouwersloot (1989) in the Netherlands, according to which urban poverty has become a more serious and more widespread phenomenon than rural poverty.

According to Bruder & Unal, 2017, deprivation rates are related to the average equivalent income of the country. Thus, deprivation is not only an indicator of ownership of goods and equipment but also of the level of income and poverty of households. As for the works on deprivation in Europe, some evidence suggests a lower level in rural than in urban areas (Ayala et al., 2021). In the paper of Havard et al. (2008), relating to the metropolitan area of Strasbourg in France, the peripheral and sparsely populated areas (rural municipalities) that create a peri-urban ring around Strasbourg are characterized by low deprivation. On the contrary, socio-economic deprivation is accentuated as we approach Strasbourg and reaches its maximum in the center of the metropolitan area.

5.2 Housing

Housing is one of the key dimensions of an individual's material location and quality of life, in both rural and urban Europe (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). Housing problems are more severe in poorer European countries, in the sense that dwelling sizes, housing conditions and facilities are much worse, although levels of housing satisfaction do not differ significantly. The lack of space, the size of dwellings and the scarcity of affordable housing, including the high cost of renting or owning, are more common in urban areas, especially in richer countries (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009). In contrast, poor physical condition and lack of amenities (e.g., damp, rot and lack of indoor sanitation) are more common problems in rural areas, especially in poorer countries (Bertolini et al., 2008; Bock et al., 2015; Shucksmith et al., 2006, 2009). Overall, there is almost no difference between urban and rural areas in housing satisfaction levels (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009). Regarding the financial burden of housing costs, it seems to be no significant difference between urban and rural areas (Cipane & Sloka, 2020).

5.3 Jobs and earnings

In richer countries, unemployment in urban areas is higher than in rural areas, while in lower-income countries, where unemployment is higher, it is more of a rural phenomenon (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). The contention that rural areas have shared the shift to a service-based economy is not confirmed across enlarged Europe, except in the richest countries where most rural respondents work in white-collar and managerial occupations. Indeed, even if agriculture plays a declining role, it still has a significant weight in rural employment in Europe (Bertolini et al., 2008; Stanef, 2012). In EU countries with medium / low GDP, the rural employment structure has a high level of blue-collar workers, presumably in industrial employment, which is substantially higher than in the urban areas of these countries (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). It may be that the rural context of unemployment in these countries is more of deindustrialization than of peasant transition. Interestingly, women in rural areas feel less stressed at work than men, while the opposite is true in urban areas (Alexandri et al., 2015; Bock et al., 2015; Chivu et al., 2015; Grzega, 2019; Rodríguez-Pose & Tselios, 2009; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Sloka et al., 2019; Stanef, 2012). Viganó et al. (2019), reported that being a worker in rural areas has a negative impact on well-being, while positive in urban areas; on the contrary, being office worker in rural areas has a positive impact on well-being and a negative impact in urban areas. This could be explained by considering the corresponding type of tasks for blue-collar and white-collar workers in the two areas. A worker in a rural area gets a low wage compared to hard work, while a worker in the city gets a higher wage. On the other hand, being a white-collar employee in a rural setting could mean running a business in the agricultural sector, while a white-collar employee in the city could be someone with a high corporate position, a high level of stress and a low level of well-being. Sørensen (2014) found a negative correlation between unemployment and life satisfaction and that rural dwellers have higher life satisfaction than urban dwellers. Also in this case, there are several works with different results. For example, according to the paper by Zarnekow & Henning (2016), the determinants of quality of life, including employment, do not differ according to the degree of urbanisation of the respondent's home region, or unemployment is lower in urban areas than in rural areas. (Schnorr-Baecker, 2021).

The subject less studied in the literature is labor market. The results of Slettebak (2021) show that the effect of EU11 migrant workers on natives' income inequality is significant in rural municipalities, but weaker and not statistically significant in urban areas. This, according to the author, could be due to small and less diverse labor markets in rural areas. While natives in urban areas may have different ways of adapting to changes in competition, such as changing jobs or employment, their rural counterparts may have fewer opportunities.

Finally, as regards rural-urban differences in women's wages, it appears that wage payments for similar jobs, for people with equivalent human capital endowments, differ very little between rural and urban areas (Hoggart & Cheng, 2006).

5.4 Health status

With regard to health status, it is useful to distinguish between access to health services and the actual state of health (self-assessed health, incidence of morbidity and/or mortality, etc.). Regarding the former, urban areas generally have more infrastructure and access to health services tends to be easier for urban dwellers. However, Viganó et al. (2019) claim that in Italy there are no differences for Health Indicator in any of the 4 areas (rural, semi-rural, semi-urban, urban), probably because the Italian national health system is quite widespread in the country. Comparing these results with those of Weziak-Bialowolska (2014) at the European aggregate level, this absence of differences between the two groups is probably due to the fact that the richer a country is in terms of health, the smaller the differences between rural and urban areas; the poorer a country is in terms of health, the greater the differences between areas with different levels of degree of urbanisation.

According to the work of Sørensen (2014), both at the aggregate level of European Union and at the level of three macro groups according to the GDP of the countries, self-reported health is positively and strongly correlated with life satisfaction. Also, rural dwellers have higher life satisfaction than urban dwellers. Indeed, the countryside landscape in rural areas plays an important role in promoting health because it has been affirmed that the great advantages of the rural context is the direct link with nature (Novak et al., 2020). According to Novak et al. (2020) the countryside can serve mental well-being by restoring attention, inducing positive thoughts and emotions, and reducing people's stress levels. The countryside responds to the needs of promoting physical health by being a perfect place for outdoor activities. Sport as a direct influencer of physical and mental health promotion is strongly linked to local communities and rural citizens who are attentive to their physical and mental health. Finally, the countryside can foster the induction of social well-being when it promotes social integration, when it provides support and social security, and when it strengthens social engagement and participation (Novak et al., 2020). These results can be read in the light of another aspect that reinforces the idea that health in rural areas is better than in urban areas: the risk of morbidity and mortality is higher among urban dwellers compared to rural dwellers. According to van Hooijdonk et al. (2007), urban and highly industrialized areas tend to be characterized by a worse natural environment, which could have direct and indirect effects on human health. Greater air or noise pollution can have a direct effect on respiratory and hearing diseases, just as the absence of green areas could cause a drastic reduction in outdoor physical activities. These features of densely populated areas can indirectly generate higher mortality and hospitalization rates in urban areas (van Hooijdonk et al., 2007).

Other aspects, related to the age of individuals, can influence the self-reported state of health. Indeed, in the work of Tobiasz-Adamczyk & Zawisza (2017) on a sample of elderly Polish people, several predictors of self-rated health in urban and rural residents were found, such as loneliness and networking and social participation. A relationship between loneliness and poor health self-assessment was observed only in rural residents. In urban residents, social networking and social participation significantly predicted positive self-reported health.

Another study that confirms the positive and significant relationship between social capital, self-assessed health and urban area is that of Nummela et al. (2008). According to the authors, in fact, only in the urban area with high social capital a good health self-assessment was found. As with the other dimensions of well-being observed so far, there is no lack of contradictory results for health status. Indeed, the determinants of quality of life, including health status, proposed by Zarnekow & Henning (2016) do not differ with respect to the region of origin of the respondents.

5.5 Work and life balance

In recent years, the issue of work-life balance has emerged as a prominent topic in sociology. The ability to reconcile work and family life, working hours and other time constraints are the most studied issues in this area. The results show that average weekly working hours are increasing for clusters in poorer countries but are also consistently higher in rural areas than in cities. (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009).

Problems of reconciliation between work and private life are, however, widespread both in urban and rural areas and in rich and poor countries (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009). In relation to pressures at work, however, being too tired from housework is the most surprising aspect cited by respondents, regardless of where they live (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009).

Some gender differences emerge in work-life balance in rural but not urban areas (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009). More clearly, women with partners and children in rural areas of richer countries have fewer problems than men in achieving a satisfactory work-life balance. Moreover, work-life balance problems are widespread in both urban and rural areas, and no support was found for the idea that work-life balance is more satisfactory in rural areas (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009).

5.6 Education and Skills

Access to education improves people's employment prospects, as well as developing their skills in many other ways, and its inherent benefits (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009). Indeed, satisfaction with life increases with education (Sørensen, 2014). There are notable differences both between groups of countries and between rural and urban regions across Europe. Education levels of people living in urban areas are higher across Europe than in rural areas (Bock et al., 2015; Rodríguez-Pose & Tselios, 2011; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009; Weziak-Bialowolska, 2014). Indeed, in rural areas more people have only primary education and fewer have a university degree (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009). This could be related to the nature of jobs and labor markets in urban areas, which attract more skilled and educated people. Consistent with this, Slettebak (2021), argues that labor migrants have a greater impact on the employment status of locals and lead to greater competition in rural areas than in urban ones, since the level of general education is much lower in rural areas.

The issue linked to distance from schools is also interesting. In France, for example, the distance from primary schools for rural municipalities increased from 1980 to 1998, due to a strategy of grouping schools when the number of pupils became too small, while the average distance from secondary schools decreased (Bertolini et al., 2008). At the gender level, the differences are small, although in rural areas of the poorest countries, education levels are generally lower among women (Bock et al., 2015; Schnorr-Baecker, 2021; Shucksmith et al., 2006, 2009).

The use of the Internet, a potential indicator of a more general computer literacy, is higher in urban areas. This is true across the EU, although urban-rural differences are greater in poorer countries (Schnorr-Baecker, 2021; Shucksmith et al., 2006). Regarding the digital divide, there does not seem to be a rural-urban divide (Vicente & López, 2011) given that the degree of urbanization is clearly not one of the main criteria that determines the digital divide (understood by the authors as digital inequality and it is defined as disparity in the quantity of Internet usage), but education, age, and main vocational activity do indeed mark digital boundaries in many of the observed countries (Lengsfeld, 2011).

In summary, education levels are generally higher in richer European countries and in urban areas. Of course, there are exceptions. Indeed, according to the results obtained by Weziak-Bialowolska (2014) in Luxembourg and the United Kingdom, the least educated are people from densely populated areas, while in Malta and Germany there is hardly any difference. Moreover, and surprisingly, education levels in middle-income countries are lower than in low-income countries, mostly former Soviet countries, in both urban and rural areas. This may reflect a greater emphasis on secondary education in these countries in the past in order to reduce inequality (Bock et al., 2015; Shucksmith et al., 2009).

Furthermore, in the study by Viganó et al. (2019), education does not reach statistically significant levels in any of the 4 areas (rural, semi-rural, semi-urban, urban) as a determinant of individual well-being.

5.7 Civic engagement and governance and social connections

The human being is a social creature, therefore the frequency with contacts with others and the quality of their personal relationships are crucial determinants of well-being (OECD, 2011c). Activities are more satisfying when shared with others. Additionally, social networks can provide material and emotional support in times of need, as well as provide access to jobs and other opportunities. The nature of social interactions also has broader implications beyond the immediate social circle, affecting levels of trust within the community, which is an important driver of other outcomes, including democratic participation, crime, and health (OECD, 2011c). Participation in society and community life, for example through the expression of the political voice, is essential for individual well-being and allows people to develop a sense of belonging and trust in others (OECD, 2011c).

Considering the foregoing, the development of social capital is considered primarily significant where inadequate financial means are available for further economic and labor market growth. However, if social capital is exploited to pursue the objectives of small groups, it can also weaken social harmony and compromise economic performance. Social capital seems to be more prevalent in rural areas than in urban areas (Stanef, 2012): emotional networks (i.e., the commonality of mutual trust) are in many cases anchored to local social life, which also influences the interaction between businesses and / or the labor market.

Furthermore, the social network seems to positively affect the subjective well-being of rural elderly people, as opposed to loneliness which instead negatively impacts both rural and urban elderly (Tobiasz-Adamczyk & Zawisza, 2017). Other works in this topic present different results. Indeed, according to Sørensen (2012), no evidence of increased social and institutional trust has been found in rural areas of Denmark. The data did not confirm the provisional hypothesis of greater institutional trust in rural areas. At the same time, unpaid voluntary work in associations was found to be higher in rural areas.

5.8 Environmental quality

Contact with nature has benefits for people, often related to health. While the urban population has to look for pieces of nature in their neighborhood, the rural population lives their life in a much more direct contact with nature (Maller et al., 2005). Rural areas appear to enjoy better environmental quality than cities, positively affecting the mental and physical health of those who live there (Novak et al., 2020). As for other environmental aspects, such as land use, obviously this is a problem mainly related to urban areas (Schnorr-Baecker, 2021). Regarding waste management in Germany, (Schnorr-Baecker, 2021) does not obtain an obvious difference related to the degree of urbanization of the area. The following is an intriguing and somewhat unexpected result discovered by Marcotullio et al. (2014): European cities produce less CO2-equivalent emissions per capita than non-urban areas. Direct CO2-eq emissions per capita are lower in urban areas than in non-urban areas in all sub-regions analyzed (Eastern, Western, Northern, Southern, and entire Europe), most likely because urban areas are more carbon-efficient than non-urban areas. Eastern Europe is an outlier, with fairly similar values. This could be due to increased greenhouse gas emissions from heavy industries and/or energy production.

5.9 Personal security

No studies relating to personal security in Europe have emerged from this SLR.

5.10 Subjective well-being

The last key component of quality of life examined from an urban-rural perspective is people's level of subjective well-being, optimism, and happiness. The findings in the literature on subjective well-being in Europe do not seem to support the assertion that quality of life, indicated by the degree of life satisfaction and happiness, is higher in rural areas (Bock et al., 2015; Shucksmith et al., 2006, 2009). Life satisfaction and happiness are higher in richer countries, as expected, but urban-rural differences are modest or zero, and while the EU-12 significantly favours rural areas, the balance is marginally in favor of urban areas elsewhere (Bock et al., 2015; Shucksmith et al., 2006, 2009). Indeed, levels of optimism and happiness, in both rich and poor countries, are significantly higher in urban areas (Bock et al., 2015; Gerdtham & Johannesson, 2001; Shucksmith et al., 2006, 2009). Most interestingly, subjective measures of happiness and life satisfaction do not seem to reflect urban-rural differences in the objective quality of life in poorer countries. Such differences in subjective well-being appear to be quite small compared to large differences in some of the objective material indicators. The study conducted in Poland on the elderly component of the population by Tobiasz-Adamczyk & Zawisza (2017) is very interesting. Indeed, the social network influences subjective well-being in rural dwellers. Furthermore, poor appraisal of subjective well-being in old age increases with larger levels of loneliness and a rising number of chronic diseases in both urban and rural settings.

In conclusion, living in rural or urban areas does not appear to have statistically significant effects on subjective quality of life (Bock et al., 2015; Shucksmith et al., 2006, 2009).

6. CONCLUSIONS

The literature does not provide precise and robust answers on the existence of a well-being differential between rural and urban areas. Very often the results achieved by different studies do not agree with each other even referring to the same geographical area. Moreover, the definition of what can be called rural (and also which are the differences within the rural category) and what is urban varies between different studies.

However, what emerges from this analysis is that, considering various dimensions of well-being, a gap between rural and urban in Europe seems to exist in favor of the urban one. However, this difference tends to be minimal or even to some extent reversed in those countries with high income, while the rural-urban gap tends to widen as the country's income decreases. However, it should be noted that a growing gap exists between rural and urban areas in terms of provision of services of general interest and infrastructure (schools, mobility, health services, broadband connections) and that this is also present in countries with high income levels (European Commission, 2022). For example, the rationale behind the Italian Strategy for Inner Areas is based on findings that rural areas in Italy have greater difficulties in accessing services (including health services) than urban areas (DPCoe, 2020; UVAL, 2014). An example of a more articulated analysis is provided by Viganó et al. (2019) paper included in this SLR. Unfortunately, part of the studies reviewed in this SLR do not adequately capture the multidimensional nature of the gaps. This is mainly due to the different definitions of rurality used in the surveyed literature. For this reason, this SLR may not provide a complete picture of the real well-being gaps between rural and urban areas, suggesting that further research is still needed looking at well-being from a multi-dimensional perspective.

Despite this, the conducted SLR has provided some useful results. First, it identified the most widespread rural-urban definitions. The important finding in this regard is that the non-homogeneous definition of rural and urban in this SLR makes it difficult to compare the results of the analyses considered in this SLR. However, most of them use population density to differentiate between rural and urban areas. Second, it also explored the databases that were used to run well-being analyses by identifying the pros and cons of each. Some of the dimensions of well-being referring to quality of life are still not sufficiently considered in literature, such as Personal Security, Work-Life Balance, Civic Engagement and Governance & Social Connections. This constrains the possibility to expand the analysis to all dimensions of well-being.

At a methodological level, some of these studies seem more appropriate than others to formally verify the existence of the gap considered. However, all the methodologies require an appropriate database, based mainly on individual-household data due to the need to verify the existing heterogeneity of the conditions existing within the two samples. This issue has been addressed with not too sophisticated methodologies, probably due to the lack of data or expertise. Furthermore, many studies investigate the impact of the rural-urban component on one or more dimensions of well-being and do not explicitly assess the existence of a difference in well-being between the two groups.

Microeconomic and cross-sectional data were used in most of the studies. We believe that panel analyses would be more appropriate for analyzing the existence of differences in well-being between rural and urban, also allowing to observe how they change over time.

Finally, most of the studies refer to one or a limited number of countries, thus not providing complete results at European level on the rural-urban well-being gap. This limitation affects the possibility of drawing more general conclusions on well-being differences.

The study is not without limitations. Indeed, our SLR focuses on Europe alone. Furthermore, from a methodological point of view, the evaluation of the quality of the studies included in this work used an ad hoc protocol based on the Instrument Critical Appraisal Checklist provided by Joanna Briggs Institute (2017) due to the lack of standardized quality assessment tools for social science studies. We are aware that such limitations could affect the replicability of this SLR and make it difficult to update the study.

The limited number of analyses on the subject developed in Europe and the heterogeneity observed between Member States suggest the need to develop additional and methodologically sound empirical assessments on the issue at the whole European level.

In the end, the results of this SLR provide a useful basis in terms of the type and nature of databases to be used, methodologies and definition of rural and urban that can be used as a starting point for the development of new empirical analyses at the European level.

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APPENDIX

Table A1. Criteria of the quality assessment used in this review.

Criteria assessed	Quality rating		
	Low	Medium	High
What it was the methodology researchers used in this study?	Qualitative	n/a	Quantitative
Was Sample size adequate?	no	n/a	yes
Was there a well-defined question?	no	n/a	yes
Were the outcomes measured in a valid and reliable way?	No, it is not validated and/ or it is not an objectively quantifiable measure	n/a	Yes, it is a validated and/ or objectively quantifiable measure
Was there a clear definition of rural and urban?	no	n/a	yes
Well-being differences between rural and urban areas addressed directly or just mentioned?	no	n/a	yes
Overall rating	No, one or two high rating (excluded the case of two high and two medium)	Three high ratings or two high rating and two medium	Four or more high ratings

Source: Own elaborations.

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The forest-based bioeconomy in Latvia: economic and environmental importance

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Abstract. The bioeconomy is considered a means to achieving a climate-neutral economy as aimed for in the EU Green Deal. For Latvia, the forest-based bioeconomy has the potential to contribute to this aim. An operational definition of the forest-based bioeconomy is needed to calculate its size. This research aims to provide such a definition and to determine the contribution of the forest-based bioeconomy to GDP, employment, and greenhouse gas emissions. The direct and indirect contribution of the forest-based bioeconomy to economic indicators and climate change is identified using an input-output model. The results of the model show that the forest-based bioeconomy contributes 6.4% to GDP and 6.6% to total employment in Latvia. The contribution to greenhouse gas emissions is 4.9%. Furthermore, if CO_2 sequestration is included, the forest-based bioeconomy becomes climate neutral.

Keywords: forestry, input-output model, value added, employment, greenhouse gas emissions.
JEL Codes: C67, E01, Q23.

1. INTRODUCTION

A strong bioeconomy is a priority in recent EU policies, such as the Green Deal and the Bioeconomy Strategy, that strive towards a greener and more resource-efficient economy in the long run (EC, 2012, 2010, n.d.b). The bioeconomy comprises those parts of the economy that use renewable biological resources from the land and sea – such as crops, forests, fish, animals, and microorganisms - to produce food, materials, and energy (EC, n.d.a). Major societal challenges such as climate change call for a sustainability transition away from a fossil-based society toward a bioeconomy, in which energy and manufacturing processes are based on sustainable biological resources (Ronzon et al., 2015; Siebert et al., 2018). In this way, the bioeconomy contributes to the goals of the Green Deal to transform the EU into a modern, resource-efficient, and competitive economy, by reducing the emissions of greenhouse gases, and by decoupling economic growth from resource use (EC, n.d.b). Moreover, by promoting circular and sustainable production systems, the bioeconomy has the potential to contribute to all dimensions and objectives of the European Green Deal (EC, 2020).

This focus on the potential of the bioeconomy in EU policy narratives, makes it essential to monitor the bioeconomy and to understand its driving forces. An important step in this is to measure the contribution of the bioeconomy and its dimensions to the total economy of countries. There are ongoing efforts to measure this contribution. However, Bracco et al. (2018) point out that these efforts focus mainly on the economic importance of the bioeconomy in terms of value added and employment, whereas environmental aspects such as climate change mitigation are often ignored. An exception is Lazorcakova et al. (2022) who used input-output analysis to quantify economic as well as environmental indicators to measure the bioeconomy in the Visegrad countries. Despite studies on the economic importance of the bioeconomy, for many countries and subsectors of the bioeconomy, this information is limited or still missing (Wesseler & von Braun, 2017). This is especially true for the forest-based bioeconomy, which encompasses the entire forest value chain, from the management and use of natural resources to the delivery of products and services (Ladu et al., 2020). Lovrić, Lovrić, and Mavsar (2020) observed a high centralization of forest-based bioeconomy research in a few countries and organizations from North-Western Europe, while the Baltic countries and the countries in Central-Eastern Europe are not adequately represented. Current research contributes to closing this knowledge gap by measuring the forest-based bioeconomy (FBB) in Latvia. The focus on the forestry sector is especially relevant for Latvia, where the forest area covers more than 50% of the total territory.

This paper aims to determine the economic and environmental contribution of the FBB to the total performance of the economy in Latvia. However, measuring the FBB is not trivial, as there is no unique definition nor set of indicators, no uniform methodology for the assessment of the bioeconomy, and limited data available, especially for partially biobased sectors (Ronzon et al. 2017; FAO, 2018). FAO (2018) summarized the methodologies that can be used to assess the bioeconomy. These methodologies include the value-added/GDP approach, the input-output model, social accounting matrix multiplier models, computable general equilibrium (CGE) models, partial equilibrium models and the use of various disaggregated or composite indices. Two of these methods dominate the quantification of the bioeconomy: the value added/GDP approach and input-output (IO) models. In the value added/GDP approach, biobased shares of various products are estimated by experts and then sectorial statistics are adjusted according to these shares (Ronzon et al. 2017; Piotrowski, Carus, and Carrez, 2018). Input-output models build on the concept of biomass flows, namely, that individual industries produce biological resources or use inputs from primary biomass producing sectors, and this determines their contribution to the bioeconomy (Grealis and O'Donoghue, 2015; NordBio, 2017). The IO model has advantages over the value added/GDP approach because it automatically includes value added of all industries, and therefore GDP (sum of value added). Moreover, the IO model includes links between multiple producers and products and allows the integration of economic as well as environmental indicators (Gaftea, 2013).

In addition to traditional economic indicators (i.e., share in GDP and total employment), this research uses environmental indicators that are connected to climate change. Besides total greenhouse gas (GHG) emissions of carbon dioxide (CO_2), methane (CH_4) and nitrous dioxide (N_2O) and fluorinated gases (HFC, PFC, SF_6, NF_3) (see Appendix A), we also include a separate measure of CO_2 emissions as the main greenhouse gas. Furthermore, CO_2 is not only emitted, but also sequestered in forests and harvested wood products. Latvia's forestry sector has the potential to contribute greatly to this. Therefore, our research objective is to determine the economic and environmental contribution of the forest-based bioeconomy in Latvia.

To achieve this objective, the following approach is taken. Section 2 provides a review of the characteristics of the forest-based bioeconomy in Latvia. The framework of the IO model to measure the contribution of the forest-based bioeconomy to GDP, employment, and greenhouse gas emissions, the data used in the IO model and 3 scenarios are described in Section 3. In Section 4, we assess alternative approaches to measure Latvia's forest-based bioeconomy by using different combinations of inputs. The paper concludes with a discussion of the IO model results in Section 5.

2. THE FOREST-BASED BIOECONOMY IN LATVIA

Latvia is one of the Baltic countries situated between Lithuania and Estonia. It is a country rich in forest resources. In terms of forest area per capita, Latvia ranks 4th in the EU (behind Finland, Sweden, and Slovenia), followed by Estonia (Latvian Bioeconomy Strategy 2030, 2018). Forests occupy on average 33% of the land area in the EU, while in Latvia this is 52%, in Estonia 50%, and in Lithuania 33%. According to the Latvian State Forest Service (2019), the area of forest land was 3.35 million ha in 2018, of which forests occupied 3.04 million ha (91%), the rest being swamps and forest infrastructure. State-managed forests covered 1.49 million ha (49%), while 1.55 million ha (51%) were managed by local government and private forest owners in 2018.

Compared to 1923, when forest land had a share of 23% of the total area, the forest area in Latvia has more than doubled (Baders et al., 2019). The increase in forest area is expected to continue as a result of purposeful afforestation, as well as through the continued natural growth of forests on abandoned agricultural and non-agricultural lands. Additionally, forest biomass is increasing due to sustainable forest management in recent decades (Lazdiņš et al. 2019). In 2015, for example, the gross annual increase in biomass was 16.9 million m^3, while 10.6 million m^3 was harvested (see Appendix B for details).

Latvia's forests are mostly made up of conifers (53%), but a significant part is also occupied by other species such as birch (30%), white alder (7%) and aspen (7%) (Latvian State Forest Service, 2019). These species are common in all Baltic countries.

In Latvia we see that in 2015 24.27% of the domestically produced forestry products (CPA code A02) are used in the production of wood products (CPA code C16) being the largest user after the production of forestry products itself (39.30%). Moreover, 14.29% is exported. Although only 21.69% of domestically produced wood products are used by the domestic production of furniture (CPA code C31/C32), most are exported: 65.36%, it is the main variable input for the latter (24.21%). Therefore, we see that the production of these three products is vertically linked. However, each of them is also important on its own.

We define the forest-based bioeconomy (FBB) as the direct (i.e. the production of forestry, wood and furniture products) and indirect production (i.e. the production of inputs needed in the direct production, e.g. the production of machinery to process wood) needed to enable the final demand of forestry, wood and furniture products. So, we have three 'sub-complexes'. Final demand in IO models consists of consumer demand, demand by the public sector (i.e., public institutions), investment demand, and exports.

Table 1 shows the importance of the forest sector in Latvia and the other Baltic countries. The forest sector in Latvia had a share of 4.8% of GDP in 2017, exports amounted to EUR 2.2 billion, or 20.0% of all exports, and employed 46,000 people (5.3% of total employment). These numbers deviate from those previously mentioned because of a different year (2017 instead of 2015). There are 7,000 enterprises in the forest sector, representing 3.8% of the total number of enterprises in Latvia (ZM, 2019). These companies are often the main pillar of support for rural economies.

An important role played by forests is that they sequester CO_2. Forest land and harvested wood products are net sinks of CO_2. In 2015, they sequestered 3.8 million tons of CO_2 (Table 2), which represents a share of 60.6% in total CO_2 sequestration in Latvia. The rest is sequestered by living biomass in other types of land (Skrebele et al., 2020). The amount of sequestered CO_2 by forest land and wood products represents 35% of the 10.8 million tons of total greenhouse gas emissions in Latvia.

However, it should be noted that nearly a third of forests in Latvia have exceeded their economic maturity age (depending on dominant tree species - 41 - 121 years). The ability of these forests to sequester carbon is lower than that of young and premature forests (Latvian State Forest Research Institute Silava, 2017), where young forests sequester less than premature forests. The afforestation implemented over previous decades is expected to sequester increasing CO_2 emissions after 2030 (Lazdiņš et al., 2019). Old-growth forests serve especially the EU Biodiversity strategy 2030 goals. However, there are many risks/shortcomings in that, for example, appearance of invasive species (Zute, 2022) and, as mentioned, the intensity of carbon sequestration is lower than that of young forests that grow more

Table 1. Economic indicators (in % of total) for the forest sector in the Baltic countries, 2017.

Country	Employment	Exports	GDP
Estonia	5.3	11.9	4.3
Latvia	5.3	20.0	4.8
Lithuania	4.8	9.9	4.0

Source: Author`s calculations based on Eurostat (2020b); Eurostat (2021a); Eurostat (2021b).

Table 2. Net GHG emissions by forest land and harvested wood products, 2015.

Source	Size	Net GHG emissions in kiloton CO_2 equivalent*
Forest land	3.561 million ha	-1,995**
Harvested wood products	10.626 million m^3	-1,850

*See Appendix B for composition.
**includes sequestration by living biomass and emissions by dead woods, litter, organic soils, and wildfires and controlled burning on forest land. The negative signs represent the net sequestering of GHG emissions.
Source: Skrebele et al. (2020) and CSB (2020).

rapidly, removing much more CO_2 from the atmosphere. A forest management that avoids large emissions from the loss of old trees while rapidly removing CO_2 from the atmosphere through young forest growth can provide both storage and sequestration benefits. In addition, well-managed forests produce wood products that store carbon long after the trees are harvested. These products provide an added benefit when they are used in place of more energy-intensive ones that require more fossil fuel emissions, such as several building materials (McKinley et al., 2011).

3. MATERIALS AND METHODS

3.1 Input-Output framework

Section 2 discussed the forest-based bioeconomy (FBB) and its three sub-complexes. Next, we quantify the economic and environmental performance of the FBB using an input-output framework that allows the disentanglement of the three sub-complexes. The input-output (IO) model was developed by Leontief in the late 1930s to analyse the economy as a whole and to study the interdependence among the different industries in an economy, since the output of one industry can serve as an input for another industry directly and indirectly (Miller and Blair, 2009). Therefore, a change in the final demand for the products of one industry affects the whole economy via direct and indirect linkages (Sink, 2010). Cingiz et al. (2021) analysed the value added of the bioeconomy in 28 EU member states using an IO model. The input-output model is suitable to track biomass inputs and to determine the contribution of different industries to the FBB and, consequently, the FBB's contribution to the total economy. The IO model is linear as it assumes fixed ratios between inputs and outputs (i.e., IO coefficients) and, therefore, is applicable to determine the direct and indirect size of the FBB.

The standard IO model calculates the vector of product-level output of the industries that is linked to the final demand of products and is given by the following (Miller and Blair, 2009):

$$x = (I - A)^{-1} f \tag{1}$$

where x is the vector of total output at basic prices, I is the unity (identity) matrix, A is the matrix of IO coefficients (the square technical coefficient matrix), f is the vector of final demand of, for example, forest-based products at basic prices (see Appendix C). IO coefficients give the fixed ratio between the amount of input i used for the production of output j.

However, we adjust the model to (e.g. Momigliano & Siniscalco, 1982; Pasinetti, 1973):

$$B = (I - A)^{-1} \hat{f} \tag{2}$$

Hence, we take the diagonal matrix of ($\hat{f}$) and, instead of the vector x, we get the matrix B that shows in each column the production needed in each industry of the economy to make the final demand of each industry's product possible. Consequently, the elements in column k (vector x_k) show the production in each industry needed to produce the final demand of products produced by industry k. In this way, we disentangle the three sub-complexes of the FBB.

Assuming a fixed ratio between economic indicators (i.e., value added and employment) and environmental indicators (i.e., CO_2 and GHG emissions) with output we get:

$$z_{kl} = \hat{b}_l x_k \tag{3}$$

where z_{kl} is value added (l=1); employment (l=2); emissions of CO_2 (l=3) and GHG emissions (l=4) for the sub-complex k of the FBB, $\hat{b}_l$ is the diagonal matrix of the fixed ratio of indicator l and the output, and x_k is column k of matrix B.

3.2 Data description

According to OECD (2019), Input-Output (IO) tables describe the sales and purchase relationships of goods and services (i.e. commodities) between producers and consumers within an economy. The table shows the inter-industry linkages, final demand, and value added created. Therefore, an IO table is a numerical overview of an economy. Commodities are defined as industry outputs, for example, the product produced by agriculture (*industry-by-industry* table), or as products, for example, milk (*product-by-product* table) (OECD, 2019). An IO table only includes commodities that have a monetary value, external effects (i.e. non-priced by-products as emissions) or leaves and small branches without economic value are excluded.

This research uses the product-by-product IO table of 2015 for Latvia. There are two versions of this table, one where imports constitute a separate row, implying that intermediate demands are commodities domestically produced and used. The second version is where intermediate demands include imports. Given that we are especially interested in domestic production, we decided to use the first table. The original table contains data for 63 goods and services (i.e., products i). However, some rows or columns showing intermediate demands are empty, that is why they are added to other related products. This results in a table containing 60 goods and services. The IO table is developed every five years by the Central Statistics Bureau (CSB) of Latvia. Data are compiled according to the European Union Statistical Classification of Products by Activity (CPA) and are expressed in basic prices (million euros). Industry-by-industry IO tables are not provided by CSB. IO tables for Latvia are also provided by OECD but, due to the high level of aggregation, they are not applicable for our purpose.

To assess the economic and environmental importance of the FBB for Latvia, the following indicators are selected: value added, employment, carbon dioxide (CO_2) emissions (excluding CO_2 emissions from biomass combustion) and greenhouse gas (GHG) emissions. Value added at basic prices data (see Appendix C) are used from the IO table, employment data are used from the EU labour force survey of Eurostat (2020b), and emissions data are obtained from the air emissions accounts of Eurostat (2020a). All data used are from 2015 due to availability of the IO table. Table 3 gives the value added, employment and CO_2 and GHG emissions that are directly linked to the production of 'products of forestry, logging and related services' (CPA code A02, product i=2), 'wood and products of wood and cork, except furniture; articles of straw and plaiting materials' (CPA code C16, i=16) and 'furniture and other manufacturing such as jewellery, musical instruments, household tools, entertainment articles and other miscellaneous goods that are not covered in other parts of the classification' (aggregate CPA codes C31 and C32, i=31). In the rest of the paper, we indicate these three product categories as forest products (A02), wood (C16), and furniture (C31/32) products. Note that these data are not for the FBB as a whole because they do not include interdependencies with other sectors of the economy.

The table shows that the production of the three product categories directly contributes 5% to GDP and 5.8% to total employment in Latvia. The contribution to CO_2 emissions is 3.3% and to greenhouse gas emissions 2.6%, excluding CO_2 sequestration. 85% of GHG emitted by FBP is CO_2 (i.e. CO_2 234,009 ton/ GHG 276,656 ton).

4. SCENARIOS AND RESULTS

4.1 Scenarios

We defined the FBB as the direct and indirect production linked to the final demand for forestry products (A02), wood products (C16), and furniture (C31/32). We show the results of the FBB as a whole, but also its decomposition in the three sub-complexes linked to the final demand of the three products mentioned. Notice that the calculations imply that if forestry products (A02) are used in the production of wood products (C16) that production, value added, employment and emissions are linked to the sub-complex wood products (C16) and not to the sub-complex forestry products (A02).

4.2 Results

Table 4 shows the size of the FBB and its sub-complexes using 4 indicators. For all four indicators, the sub-complex wood products (C16) is the largest and the sub-complex furniture (C31/32) is the smallest. The overall share in GDP is 6.44%. However, if we include the value added created in the direct production of forestry

Table 3. Value added, employment, and emissions directly related to the production of Forestry (A02), Wood (C16), and Furniture (C31/32) products in Latvia, 2015.

	Value added		Employment		CO_2 emissions		GHG emissions	
	million Euros	% of GDP	thousand persons	% of total	ton	% of total	ton	% of total
Forestry products (A02)*	356	1.7	18.60	2.2	122,642	1.7	128,945	1.2
Wood products (C16)	546	2.6	23.50	2.7	100,586	1.4	136,785	1.3
Furniture (C31/32)	139	0.7	7.30	0.9	10,781	0.2	10,926	0.1
Total (A02+C16+C31/32)	1,041	5.0	49.4	5.8	234,009	3.3	276,656	2.6
Rest of the economy	20,204	95.0	809.6	94.2	6,882,766	96.7	10,501,761	97.4
Total	21,245	100	859	100	7,116,775	100	10,778,417	100

Note: GHG emissions include CO_2, N_2O in CO_2 equivalent, CH_4 in CO_2 equivalent, HFC in CO_2 equivalent, PFC in CO_2 equivalent, SF_6 in CO_2 equivalent, NF_3 in CO_2 equivalent.
* A02, C16 and C31/32 are CPA codes.
Source: Authors' calculations based on CSB (2016), Eurostat (2020a and 2020b).

Table 4. First four rows: Value added, employment, CO_2 and GHG emissions linked to the final demand of Forestry products (A02), Wood products (C16) and Furniture (C30/31) in Latvia, 2015. Next four rows (i.e. Rest): Value added, employment, CO_2 and GHG emissions of Forestry products (A02), Wood products (C16) and Furniture (C30/31) that are linked to the final demand of other products in Latvia, 2015.

Products	Value Added		Employment		CO_2 emissions		GHG emissions	
	million EUR	% of GDP	thousand persons	% of the total economy	ton	% of total	CO_2 equivalent ton	% of total
Linked to final demand of:								
Forestry products A02	211.8	1.00	10.1	1.18	72,854.5	1.02	77,109.9	0.72
Wood products C16	953.0	4.49	37.1	4.31	350,815.8	4.93	402,382.1	3.75
Furniture C30/31	202.8	0.95	9.4	1.09	45,389.6	0.64	49,657.0	0.46
Total	1,367.6	6.44	56.5	6.58	469,059.9	6.59	529,149.0	4.93
Rest								
Forestry products A02	46.6	0.22	2.4	0.28	16,046.4	0.23	16,871.2	0.16
Wood products C16	34.2	0.06	1.5	0.17	6,296.9	0.09	8,563.0	0.08
Furniture C30/31	13.7	0.16	0.7	0.08	1,056.7	0.01	1,070.9	0.01
Total Rest	94.5	0.44	4.6	0.53	23,400.0	0.33	26,505.1	0.25
Total + Total Rest	1,462.1	6.88	61.1	7.12	492,459.9	6.92	555,654.1	5.17

Source: Authors' calculations.

(A02), wood (C16) and furniture (C31/32) products that are used as intermediate inputs in the production of the final demand for other products we get a share of 6.88%. We see a similar increase for the other three indicators. This illustrates that forestry products (A02) are important in the production of wood products (C16) which, in turn, are important for the production of furniture (C31/32).

5. DISCUSSION AND CONCLUSIONS

We measured the FBB contribution to Latvia's economy using share in GDP, employment and CO_2 and GHG emissions. We did this using an IO model that incorporates the direct and indirect use of intermediate inputs in the production needed to enable the final demand of forestry (A02), wood (C16) and furniture (C31/32) products.

These linkages appear to be important, especially forestry products (A02) form an important input in the production of wood products (C16) which, in turn, are important for the production of furniture (C31/32). These linkages determine our definition of the FBB. For another country another definition could apply depending on the linkages present. For example, in other countries like Finland the paper industry, which is not present in Latvia, could be part of the FBB. The FBB had in 2015 a share of 6.44% in GDP and if we include also the value added created with the production of forestry (A02), wood (C16) and furniture (C31/32) products that are used as intermediate inputs for the production of final demand of non-FBB products, the share equals 6.88%. Similar percentages apply for employment (6.58% and 7.12%) and CO_2 (6.59% and 6.92%). The share of the FBB in total GHG emissions is somewhat lower (4.93% and 5.17%). The outcomes for the FBB are higher than the sum of the value added, employment, CO_2 and GHG emissions created with the production of forestry (A02), wood (C16) and furniture (C31/32) products, since it includes the indirect use of other products in the production of these products. To our knowledge, this is the first research that takes these linkages into account for the FBB of Latvia.

The contribution to the emissions of CO_2 and GHG excludes CO_2 sequestration. Forest land and harvested wood products sequester an estimated 3.8 million tons of GHG emissions. This is 35.2% of total GHG emissions in Latvia in 2015. GHG sequestration has increased in recent years due to the expansion of forest land and the annual growth of forest biomass. The EU Green Deal states that the EU has to become climate neutral by 2050. This requires that EU member states reduce net greenhouse gas emissions to zero. Our results show that Latvia already achieves this goal set by the EU if we take into account GHG sequestration. Furthermore, there is a great potential for further sequestration of GHGs from forest biomass. At the moment, sequestration is not included in the EU emissions trading system, including it would provide opportunities for the Latvian economy.

Besides the assumed fixed shares between inputs and outputs (i.e., IO coefficients), other drawbacks of IO models are the absence of a link between income creation and spending, and the assumption of a perfectly elastic supply of factor inputs (i.e., labour and capital) (Guerra & Sancho, 2014; Acemoglu & Azar, 2020). These drawbacks are not relevant in this research, as we use the IO model for descriptive purposes. Moreover, the IO model that we use can be applied to any country by using national or regional data sets, statistics of employment, value added, and emissions. In this way, the FBB becomes country-specific and can form a benchmark and information source for policy formulation to achieve the goals of the Green Deal because it enables monitoring the bioeconomy and understanding its driving forces.

We used the Eurostat IO table of 2015 to analyse the importance of the forest-based bioeconomy due to the lack of data in recent years. Notably, outcomes can differ between years. Ideally, we would have information for more years that would enable us to detect and analyse the development of the forest-based bioeconomy over time. A general drawback of the use of the Eurostat IO table is the high level of aggregation, preferable we would like to have more detail on the products produced in the forest-based bioeconomy. This is especially relevant in case we, for example, would like to formulate product related policies or obtain regional detail. A more specific caveat of the use of the IO table of 2015 is that in the light of the Green Deal and the Russian invasion of Ukraine, it is expected that Latvia will try to increase the use of forest-based biomass for energy production. This potential increase of the FBB cannot be investigated with the present model. Despite these drawbacks, this paper gives a first attempt to derive the size of the FBB in Latvia using not only economic but also environmental indicators and by including direct and indirect linkages in the economy.

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APPENDIX A
CO_2 AND GHG EMISSIONS

Information from the national inventory reported to the United Nations Framework Convention on Climate Change (UNFCCC) and the Convention on Long-range Transboundary Air Pollution, as well as data from the Central Statistical Bureau (CSB), is used for the calculation of CO_2 emissions.

The GHG emission indicator measures the total national emissions of the so-called 'Kyoto basket' of greenhouse gases, including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and the so-called F-gases (hydrofluorocarbons, perfluorocarbons, nitrogen trifluoride (NF_3) and sulphur hexafluoride (SF_6)). For each gas' individual global warming potential (GWP), they are integrated into a single indicator expressed in units of CO_2 equivalents.

Emissions data are submitted annually by the EU Member States as part of the reporting under the UNFCCC (UNFCCC, 2008).

APPENDIX B
SEQUESTRATION

Table B.1. Forest land, gross annual increment, potential harvest, and harvested wood products in Latvia, 2015-2018.

Year	Forest land, 1,000 ha	Gross annual increment, 1,000 m^3	Potential harvest, 1,000 m^3	Harvested wood products, 1,000 m^3
2015	3,561	23,637.10	16,927.00	10,626.50
2016	3,561	25,166.92	17,276.44	10,555.81
2017	3,576	26,312.66	17,235.59	11,443.42
2018	3,585	26,480.09	17,584.81	12,861.65

Source: Latvian State Forest Service (2019), Skrebele et al. (2020), and CSB (2020).

Table B.2. Net GHG emissions by forest land and harvested wood products, 2015-2018 (thousand ton CO_2 equivalents).

Source	2015	2016	2017	2018
Forest land	-1,995.01	-3,179.63	-4,905.08	-3,213.87
Harvested wood products	-1,850.36	-2,129.34	-2,251.33	-2,064.57
Total	-3,845.46	-5,308.97	-7,156.41	-5,278.44

Source: Skrebele et al. (2020).

APPENDIX C
PRICES

The World Bank (World Bank, 2020) provides the following price definitions:

- **The basic price** is the amount receivable by the producer, exclusive of taxes payable on products, and inclusive of subsidies receivable on products. The equivalent for imported products is the c.i.f. (cost, insurance, and freight) value, that is, the value at the border of the importing country.
- **The producer price** is the amount receivable by the producer inclusive of taxes on products except deductible value added tax and exclusive of subsidies on products. The equivalent for imported products is the c.i.f. value plus any import duties or other taxes on imports (minus any subsidies on imports).
  Producer prices = Basic prices + taxes on products (excluding VAT) - subsidies on products
- **The purchaser price** is the amount payable by the purchaser. This includes trade margins realized by wholesalers and retailers (by definition, their output) as well as transport margins (that is, any transport charges paid separately by the purchaser) and non-deductible VAT.
  Purchaser prices = Producer prices + trade and transport margins + non-deductible VAT

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The impact of COVID-19 on household income and participation in the agri-food value chain: Evidence from Ethiopia

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Abstract. The effects of COVID-19 have been highly heterogeneous, crucially depending on household livelihoods. In the context of households reliant on agri-food systems, the extent of these effects significantly depends on their position within the value chain. An assessment of the COVID-19 effects along the agri-food value chain and the identification of pivotal factors influencing these outcomes are key for designing appropriate responses and targeting the population most in need should a crisis akin to COVID-19 emerge in the future. Using a longitudinal dataset from Ethiopia, composed of a pre-COVID baseline and six follow-up phone-based surveys, this paper estimates the COVID-19-induced change in household income and job participation, tracing its evolution throughout seven months after the pandemic onset. Applying both longitudinal and cross-sectional econometric models, we show that the COVID-19 shock reduced both employment and income, with increasingly negative impacts over time. Despite initial resilience in the face of restrictive measures, farming eventually emerged as the most affected segment within the agri-food value chain over the medium term. Access to formal institutions such as insurance and credit services, formal contractual arrangements, and secured land ownership title played a key role in mitigating the likelihood of income loss.

Keywords: COVID-19, food value chain, labor market, income loss, Ethiopia.
JEL Codes: I15, O12, Q12.

1. INTRODUCTION

The COVID-19 pandemic caused unprecedented disruptions in many value chains at domestic as well as global levels (Moosavi et al., 2022), including the bioeconomy and specifically the agri-food value chains (AFVCs) (Devereux et al., 2020), although significant heterogenous effects were reported[1]. Although some segments of AFVC such as farming have

[1] For instance, in the short run the bioeconomy – i.e. the economic activities that depend on the use of biological resources, including agriculture and food processing – showed a level of resil-

been initially less affected by restriction decisions, downstream segments such as food services, restaurants, and retail as well as midstream segments such as processing, logistics, and transportation, have been impacted since the onset of the crisis[2]. The general conclusion of early studies is that the COVID-19 impact is differentiated across different segments of the AFVC as well as within each segment (Diao et al., 2020; Tamru et al., 2020; Tesfaye et al., 2020).

The pandemic and the related restrictions implemented by governments raised many challenges to individuals and households participating in the AFVC. The ability to absorb, adapt, and even transform the way a livelihood is gained by individuals and households – in short, their resilience to the COVID-19 shock – has been often limited by many factors such as access to technology, financial services, or social safety nets[3]. Indeed, many agents had limited options to cope with the COVID-19 shock, resulting in income reduction or job loss and eventually increasing poverty and food insecurity. Assessing COVID-19 impacts across AFVC segments and identifying the main factors that determined those impacts on AFVC participants and their options to adapt to the "new normal" is then crucial for designing appropriate responses and targeting the groups most in need should a shock similar to COVID-19 occur again in the future.

Using Ethiopia as a case study, this study aims at: (i) assessing which segments of the AFVC have been most affected by the pandemic, in terms of labor participation and income loss; and (ii) identifying which factors at the household level have mostly influenced the impact of COVID-19 on income, and specifically on farm income. Ethiopia has been selected for several reasons. Its economy is mainly based on agriculture, which accounts for 34% of GDP (World Bank, 2021), 80% of the population depends on agriculture (Njeru et al., 2016), and smallholder farming accounts for 95% of agricultural production (Tigre and Heshmati, 2022). However, new commercial and gig economy clusters are emerging in the country, as is the case of intensive vegetable cultivation in the central Rift Valley (Minten et al., 2020). These new activities challenge small farmers' and small enterprises' participation in the AFVC, which are compounding with already existing structural constraints such as low access to credit and extension, weak labor market, and high transaction costs (Croppenstedt et al., 2003; Bryan et al., 2009; Asfaw et al., 2011; Harvest SA, 2012). In such a situation, the COVID-19 shock could push smallholder farmers and small and medium enterprises out of the market.

The first case of COVID-19 in the country was reported on March 13^{th,} 2020[4]. In the same month, the federal government implemented a set of containment measures, such as school closure, physical distancing, and restrictions on gathering and transportation (Baye, 2020). In April, a five-month state of emergency was declared, though economic activities continued to operate. Although farmers could keep working, they faced many challenges. With borders shut, imported inputs were more difficult to find and their price increased (Hirvonen et al., 2021b, 2021c, and 2021d). Moreover, restrictions on movement made it almost impossible for farmers to reach the markets. This eventually led to a drop in agri-food sales, particularly of some vegetables such as tomatoes, papaya, and watermelon (Molla, 2020). The travel restrictions also doubled transport costs, with a further domino effect on production, raising the farmgate and retail prices of some products, such as tomatoes (Hirvonen et al. 2021b). Additionally, since many farmers could not store their goods – particularly perishable produce – they were forced to accept the low prices set by buyers (Ababulgu et al., 2022). Hired labor was also affected. Many rural workers returned to their homes and the reduced labor supply pushed up the costs of labor (Agajie, 2020). Effects were driven also by the fear of contagion. People associated raw vegetables with infection, reducing their purchases (Hirvonen et al., 2021a; Tamru et al., 2020). This determined a significant reduction in local market sales as well as exports (Ababulgu et al., 2022).

Although anecdotal evidence exists on the impacts of COVID-19 on AFVC participation and income, rigorous empirical studies based on household-level survey data are few. Josephson et al. (2021) used the World Bank phone-based surveys of Ethiopia, Malawi, Nigeria, and Uganda to document the socioeconomic impacts of the pandemic. They found that 77% of households across the four countries experienced an income loss in the immediate aftermath of the pandemic. However, the authors were not able to measure how much of the loss

ience relatively higher than the overall economy in Europe. However, this result was mainly driven by the technology-intensive sectors of the bioeconomy, such as biochemistry and bioelectricity, which partially offset the negative impact on the more traditional sectors of biomass processing, namely agriculture and food processing (Lasarte-López et al., 2023).

[2] Indeed, it was initially expected that farming experienced less direct effects, except where hired labor was important, although interlinkages with the other segments of the chain may have caused income losses and production disruption (Swinnen, 2020).

[3] For instance, Cesaro et al. (2022) found that financial liquidity and repairment of equipment and machinery were the difficulties most reported by farmers in Italy in the short run.

[4] For details, see https://www.afro.who.int/news/first-case-covid-19-confirmed-ethiopia.

can be directly determined by the pandemic, given the descriptive nature of their analysis. According to this study, Ethiopian households are significantly less likely to experience an income loss compared to those from the other three countries.

More recently, the same dataset has been used by Rudin-Rush et al. (2022) to document trends in food security over the twelve months after the onset of the COVID-19 pandemic. This study reports a sharp increase in food insecurity in the aftermath of the pandemic, with a subsequent gradual decline. Furthermore, rural households were more negatively affected than urban households in terms of food security.

IFPRI conducted a series of monthly phone-based surveys between May and August 2020 (i.e., up to five months after the pandemic onset) interviewing nearly 600 households in Addis Ababa (Hirvonen et al., 2021a). More than half of respondents reported a fall in income relative to their average pre-pandemic income at the same time of the year (Hirvonen et al., 2020), with the proportion of affected households increasing from May to July (Hirvonen et al., 2021a). Poorer households more likely reported income losses, with a significant worsening of household food security and nutritional status. Income loss and unemployment were identified as the most common shocks experienced by the respondents (Abate et al., 2020; de Brauw et al., 2020; Hirvonen et al., 2020). Despite income loss, Zhang et al. (2022) found that the population in Addis Ababa was not affected on average in terms of food security. However, the situation in other regions of the country was much different, especially in rural areas and among vulnerable individuals and households (Abay et al., 2023, Zhang et al., 2022).

Hirvonen et al. (2021b) relied on a large value chain survey administered by IFPRI in February 2020 and follow-up phone interviews collected in May 2020 to analyze the disruption of the vegetable value chain from the main producing areas in the Central Rift Valley to Addis Ababa, including changes in prices and adjustments in the marketing activities of the participants – from farmers to wholesalers and retailers. They found that nearly 60% of the smallholders and more than 60% of the investors reported less income than usual. They also found that the pandemic in Ethiopia disrupted trade not only between neighboring countries but also among subnational geographies, thus determining high volatility in agricultural prices (Hirvonen et al., 2021b). However, they found that the changes in wholesale and retail marketing margins were relatively low, suggesting a resilient response of the domestic food value chains during the pandemic in Ethiopia.

Although these studies provided important early estimates of the effects of the pandemic on relevant indicators of welfare, they present some limitations. Some of them are based on a non-representative sample. The study of Hirvonen et al. (2021d) focuses on the vegetable value chain only, while Hirvonen et al. (2021b) focus only on households living in Addis Ababa. Most of the existing studies focus only on one or a few points in time, failing to capture the evolving impact of COVID-19 over time. Other studies look at the impact on employment, such as Khamis et al. (2021), but they do not specifically disaggregate the analysis across AFVC segments. Our study aims to address these limitations contributing to estimating the magnitude of AFVC disruption caused by the COVID-19 pandemic in Ethiopia over a relatively longer time (seven months from the pandemic onset) and looking specifically at differentiated impacts on various AFVC segments. It also helps to identify the main factors that contributed to offset the negative consequences of COVID-19 shock and to keep adequate levels of income for AFVC participants. Although the data present some limitations in terms of representativeness (cf. Section 2), we think the findings emerging from this study are relevant not only because they provide a better understanding of the COVID-19 impact in Ethiopia, but also because they can contribute to a better management of COVID-19-like crises should they emerge in the future.

The paper is organized as follows. The next section describes the data used. Section 3 presents some descriptive statistics, with specific reference to employment and income. Section 4 describes the empirical strategy adopted. Section 5 presents and discusses the results of the analysis. Section 6 concludes.

2. DATA

The analysis uses a seven-rounds longitudinal dataset, which includes a baseline pre-pandemic face-to-face survey and six follow-up phone surveys. Pre-COVID data come from the 2018/19 Ethiopia Socioeconomic Survey (ESS), which is part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). It covers all regions of the country and is representative at national, urban/rural, and regional levels. The other six rounds of data are part of the World Banks's COVID-19 High-Frequency Phone Survey of Households (HFPSH) 2020. This phone-based survey is a 15-minute questionnaire administered to a subsample of the ESS 2018/19 households from April to mid-October (Figure 1). The World Bank team interviewed the same households in each round, leading to a

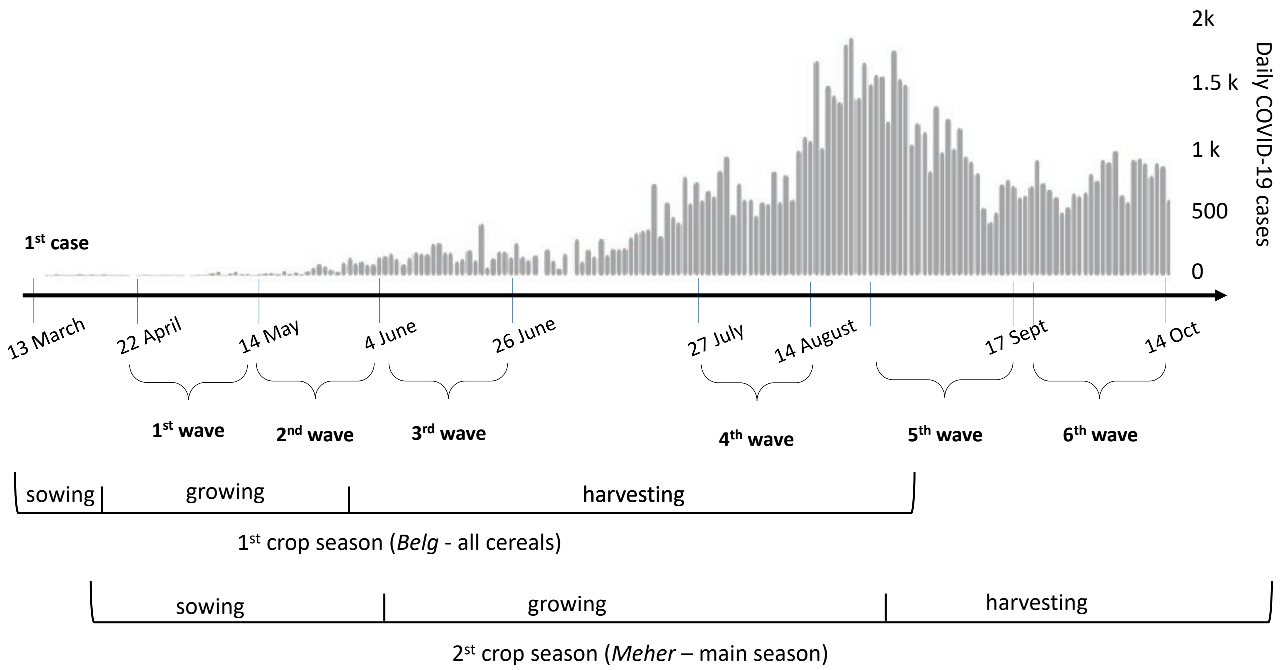

Figure 1. Timeline with daily COVID-19 cases, surveys date, and crop seasons in Ethiopia. Source: data on COVID-19 daily cases retrieved from https://covid19.who.int/region/afro/country/et; information on crop seasons retrieved from https://www.prepdata.org/stories/ethiopia-climate-and-agriculture; date of COVID-19 HFPSH data collection retrieved from https://microdata.worldbank.org/index.php/catalog/3716.

balanced dataset of 2,347 households[5]. To obtain unbiased estimates, sampling weights at the household level have been constructed by the World Bank team following Himelein (2014), thus having a sample that is representative at the national and urban/rural levels.

A major problem with the HFPSH surveys is that phone penetration in rural Ethiopia is still low, with only 40% of rural households having access to a phone. Therefore, data are representative only of those households that have access to phones in urban areas (90% of all urban households) and better-off rural households that have access to mobile phones (Wieser et al., 2020). However, these rural households are systematically different from the majority of rural households (Ambel et al., 2020a). Additionally, only one member per household – typically the household head or the spouse – has been interviewed, but household heads could systematically differ from the rest of the population, undermining the representativeness of the sample at the individual level[6].

A key methodological concern is that factors other than the COVID-19 crisis could drive the evolution of outcomes over time. Specifically, month-to-month seasonality could represent an issue. In principle, it can be controlled by including month fixed effects. However, this could not be done due to the different time reference between the baseline and phone surveys, especially for the employment variable. While the pre-COVID survey considers the employment activities over the preceding twelve months, including both planting and harvesting seasons, questions on employment in the phone surveys consider only the week before the interview. There could be then an underestimation of the farming-related employment rate. Luckily, the phone survey covers the sowing and the harvesting periods of the two main crop seasons (Figure 1)[7]. Therefore, although it is not possible to fully rule problems of seasonality out, it is likely that it does not significantly affect our estimates.

Seasonality can also bias the analysis because of its impact on farm income. There are two rainy seasons over the year: the small rainy season (*belg*), which occurs between March and May, and the main rainy season

[5] Each COVID-19 HFPSH survey has a slightly different number of observations, ranging from 2,704 to 3,249 households. In order to have a balanced panel we reduced the sample to 2,347 observations. For more information on sampling design please visit https://microdata.worldbank.org/index.php/catalog/3716.

[6] Further discussion about this issue is presented in section 4.3.

[7] Only sugarcane and taro are neither planted nor harvested in the period under analysis. Source: http://www.fao.org/agriculture/seed/cropcalendar/welcome.do;jsessionid=62FFB1AC3CB6FA74244A91586E5E1758.

(*meher*), which takes place between June and September[8] (Hirvonen et al., 2016). Around 90% of the total crop production is done during the *meher* season (Taffesse et al., 2013). Farmers usually run out of stock between July and September, which can result in increasing household food insecurity (Dercon and Krishnan, 2000; Hirvonen et al., 2016; Gilbert et al., 2017; Sibhatu and Qaim, 2017; Roba et al., 2019). However, seasonality-induced food shortage is quite homogeneous across farmers, and it is captured by a variable that controls for the aggregate time trend (cf. Section 4.3).

Another factor to consider in the analysis is the desert locusts' outbreak, i.e. the most destructive migratory pests in the world (Cressman et al., 2016; Lazar et al., 2016), that swarmed from Yemen to the Horn of Africa in the summer of 2019. In the fourth round of phone surveys[9], 45% of farmers self-reported that they experienced desert locusts on their farm, and 41% of households experienced locusts in their *kebele*[10]. Desert locusts have negative consequences on income because they destroy the crops and the fodder for livestock. Additionally, labor time is required to spray the chemicals on the area under cultivation.

3. DESCRIPTIVE STATISTICS

3.1. Employment

The first round of the phone-based survey asked if the individual did any work in the seven days before the interview, if the individual was working before the COVID-19 outbreak, and if the current work is the same as before the pandemic. For the other rounds of data, the questions were the same, but using as reference time the previous call. As shown in Figure 2, the employment rate experienced a significant reduction in the aftermath of the COVID-19 outbreak. Overall employment dropped by 11 percentage points. However, labor activities recovered quickly over the next months, exceeding the employment rate before COVID-19 (Ambel et al., 2020b), driven by own farming activity.

The dynamics of labor mobility are somehow different within the various AFVC segments[11] (Table 1).

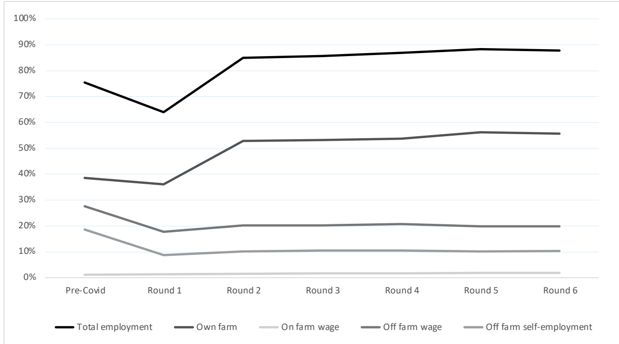

Figure 2. Evolution of employment in Ethiopia, 2018/19 – mid October 2020. Source: Own elaboration from ESS 2018/2019 and HFPSH 2020. Note: Sampling weights applied.

The upstream segment was quite stable, with 83% of people remaining in the same segment of employment and 12% moving towards non-AFVC activities after seven months. In the case of midstream activities, only 26% remained in the same segment, while 39% moved towards non-AFVC activities, 23% moved to upstream activities, and the remaining 12% moved to downstream activities. Similarly, in the downstream segment, only 27% on average did not change the segment of employment, while most of the people who did it, moved to midstream activities (49%). Finally, almost two-thirds of the ones who were not originally working in AFVC activities remained outside the AFVC, while the ones who entered the AFVC split mainly between midstream (14%) and upstream (18%) activities.

Employment changes can be in part driven by seasonality. Indeed, seasonal migration in Ethiopia occurs both from rural to urban areas, used as a coping strategy during the dry season (Asefawu, 2022), and also towards northwest Ethiopia for temporary employment on large-scale agricultural farms during the rainy season (Schicker et al., 2015). However, respondents reported that the main reason for stop working is COVID-19, especially in the early phone rounds. Between April and May (round 1), more than half of individuals stated that they lost their job because of the pandemic (Figure 3). In the last rounds instead, being "temporarily absent" is the main reason to stop working. This can be indirectly associated with the pandemic since many who temporarily left their job in the city migrated to rural areas[12].

[8] This refers to the growing period of the season.

[9] Information on desert locusts is available only in rounds 4 and 6. However, in round 6 very few respondents answered the questions related to locusts, so it is not possible to produce reliable estimates.

[10] The *kebele* is the smallest administrative unit of Ethiopia, i.e. a neighbourhood or a localized and delimited group of people consisting of at least 500 families.

[11] The variable of labor participation in AFVC activities has been decomposed into three segments, namely: a) upstream (primary production, including farming, fishing, forestry and hunting), b) midstream (manufacturing of food products, including processing; wholesale and retail trade; transport; and distribution), and c) downstream (restaurants and bars).

[12] Detailed information on the number of individuals that started to work again in each round, and the reason for having stopped working

Table 1. Labor transition matrix across AFVC segments and non-AFVC, 2018/19 – mid-October 2020.

			Round 6			
		N. Obs.	Downstream	Midstream	Upstream	Non-AFVC
Pre-Covid	AFVC Downstream	145	27.5	48.5	6.2	17.8
	AFVC Midstream	184	12.4	26,0	22.9	38.8
	AFVC Upstream	517	0.6	3.6	83.3	12.1
	Non-AFVC	834	4.0	14.4	17.8	63.9

Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.
Note: Upstream: agricultural production and agricultural employment, including fisheries, forestry, and hunting; Midstream: manufacturing of food products, including processing, trade, and transport; Downstream: restaurants and bars; Non-AFVC: all other employment activities. Sampling weights applied.

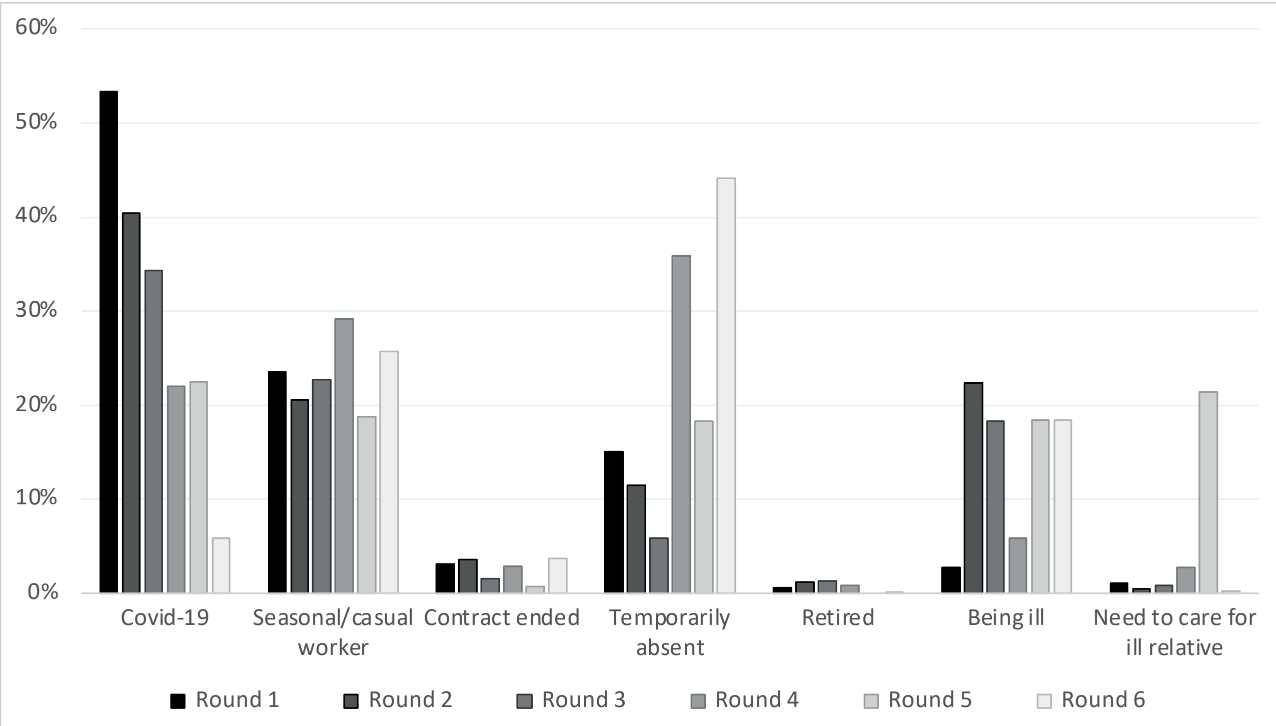

Figure 3. Reason to stop working, share on round total. Source: Own elaboration from HFPSH 2020. Note: sampling weights applied.

3.2. Income

Respondents to the phone-based survey were asked to assess the income change experienced by the household compared to the situation before the COVID-19 outbreak in the first-round interview, and compared to the previous call in the subsequent rounds. The possible answers ranged from "total loss" to "income reduction", "no change" and "income increase". The categorical nature of the question does not allow for computing accurate estimates of the magnitude of COVID-19 impact on income, limiting the analysis to the qualitative incidence of the pandemic (De Weerdt, 2008). In the case of farming income, the answer highly depends on the harvest time of cultivated crops. In fact, the bulk of crop sales occurs between December and February, though April usually records the largest sales (Hirvonen et al., 2016). Figure 4 (panel a) shows a generalized decreasing trend of the share of households that reported a reduction of income or a total loss between rounds, not only for farming income but also for other

in the previous round is reported Table A.1 in the Appendix.

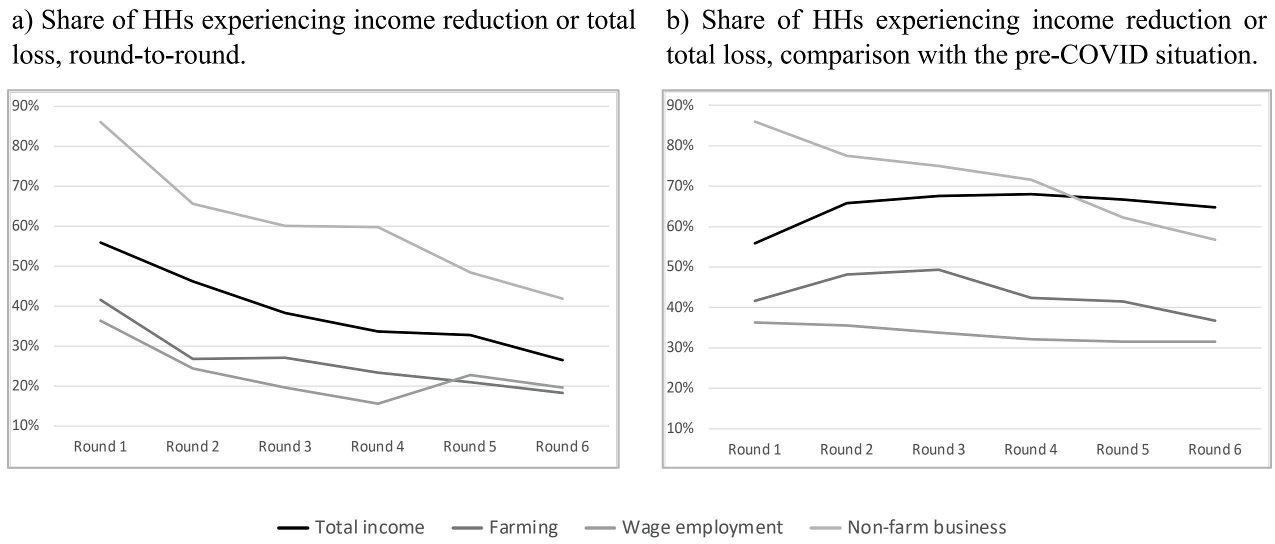

Figure 4. Share of HHs experiencing income reduction or total loss per income source category, share by income source. Source: Own elaboration from ESS 2018/2019 and HFPSH 2020. Note: Sampling weights applied.

sources of income. If we compare the income change to the situation before the COVID-19 outbreak[13] (Figure 4, panel b), the trend is different. The share of households that reported a reduction in income compared to the pre-COVID situation shrank only for non-farm business while it did not change significantly over time for other income sources. In the case of total income, the share of households experiencing a reduction/total loss even increases over time, up to 9 percentage points increase in the sixth round compared to the baseline.

Table 2 reports the descriptive statistics of the outcome variables per each round. Specifically, the employment variables show the rate of people employed in each sector, while the income variables report the share of households that experienced a reduction in income or a total loss compared to the baseline.

There are some differences between the overall baseline sample and the phone-based sub-sample (Table 3). Respondents to the HFPS sample are mainly located in urban areas, the majority of them are males, and their employment rate is higher. They are generally older, more educated, and more employed through a formal job contract. The rate of non-farm employment activities is higher compared to the baseline population. Vice versa, the rate of farm-related activities is similar and the same is true for the employment rate in the upstream segment.

Given these differences, the results of the analysis could not be generalized to the whole Ethiopian population. To check for possible problems of representativeness, we ran a robustness check using individually-adjusted weights (cf. Section 4.3).

4. EMPIRICAL STRATEGY

4.1. Outcome variables

To assess the impact[14] of COVID-19 on income and employment we estimated a household fixed effects model with a continuous treatment variable, adapting the approach implemented by Amare et al. (2020). We use two dependent variables, namely: participating in labor activities, considering any type of activity as well as specific sectors; and income change, looking at both the total income and the different income sources.

Labor activities are grouped into own-farm, on-farm wage employment, off-farm self-employment, and off-farm wage employment. We also consider employment according to segments of AFVC (i.e., downstream, midstream, and upstream activities as defined above) given the expected differentiated impact of COVID-19

[13] The change of income is computed backward up to the baseline. If, for instance, in round 2 income did not change compared to the previous round, and in round 1 it increased compared to the baseline, in round 2 it also increased compared to the baseline. The change is assumed to occur with the same amount, therefore if a household first reports an increase, and then a reduction, the net effect is null. We are aware of the arbitrariness of this methodology. For this reason, the analysis has been also conducted round by round, finding similar results, as reported in the Appendix.

[14] We use the terms "impact" and "effect" throughout the paper, but we acknowledge that we are not able to fully identify a causal mechanism with our estimation strategy due to the limitations described in Section 2.

Table 2. Descriptive statistics of employment and income outcomes.

	Round						
	Baseline	1	2	3	4	5	6
Employment: % of individuals							
Total employment	75%	64%	85%	86%	87%	88%	88%
Downstream	4%	1%	2%	2%	2%	2%	2%
Upstream	40%	37%	55%	55%	56%	58%	57%
Midstream	5%	7%	8%	8%	8%	8%	9%
Out of FVC	25%	18%	20%	21%	21%	20%	20%
Own farm	39%	36%	53%	53%	54%	56%	56%
On-farm wage	1%	1%	2%	2%	2%	2%	2%
Off-farm self-employment	28%	18%	20%	20%	21%	20%	20%
Off-farm wage employment	19%	9%	10%	10%	11%	10%	10%
Income: % of households							
Total income		56%	67%	70%	72%	72%	71%
Farming		42%	50%	51%	47%	45%	41%
Wage employment		36%	36%	34%	35%	36%	33%
Non-farm business		86%	82%	82%	76%	68%	65%

Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.
Note: Employment variables report the share of people employed in each round. Income figures show the share of households that reported income reduction or total loss compared to the baseline. Sampling weights applied.

related restrictions on different stages of the value chain (Reardon et al., 2020b, Swinnen and McDermott, 2020). For each labor activity, we computed a dummy equal to 1 if the individual operated in that activity, and zero otherwise.

We consider total income and specific income-generating activities, namely family farming, non-farm family business, wage employment of household members, and other sources of income (pension, remittances, etc.). The variables take the values -2 (total loss), -1 (income reduction), 0 (no change), and 1 (income increase).

4.2. Treatment variable

The main variable of interest is the number of confirmed cases of COVID-19 over the number of inhabitants in each region. This information has been retrieved from the Ethiopia COVID-19 Monitoring Platform[15] and weekly governmental bulletins[16]. This variable captures the evolution and the spread of the virus across the country. The variable has been transformed using the inverse hyperbolic sine (IHS) transformation, to account for zero cases in the first post-COVID survey. Regression results can be interpreted as the log transformation (Johnson, 1949; Burbidge et al., 1988).

This variable presents some limitations. Firstly, the ratio of confirmed cases over the number of tests would do a better job than using the number of the total population in each region, but unfortunately, data on testing disaggregated at the regional level are not available. Secondly, the number of confirmed cases probably underestimates the real infection level due to the limited testing capacity of the country[17]. Although the testing capacity is presumably unequal across regions, as access to basic health care in Ethiopia is highly unequal (Woldemichael et al., 2019; Alene et al., 2021), the use of fixed effects estimator (cf. Section 4.3) should partially mitigate the issue, controlling for differences across regions that do not vary over time.

Thirdly, the number of confirmed cases does not adequately proxy the treatment variable, i.e. the variation in terms of access to the market and restrictions imposed by the government, which in turn affect labor participation and income. However, we can assume that as the number of confirmed cases increases in a region, both the restrictions imposed by the government and the individually self-imposed restrictions would increase. Indeed, data confirm that the economic and health effects of the pandemic covary in Ethiopia. When using daily data retrieved from the Oxford COVID-19 Government Response Tracker (OxCGRT), the correlation between the COVID-19 cases and the stringency index is positive and significant[18]. Although there could be a time lag between the implementation of the restrictions and the effect in terms of COVID-19 cases, this lag is shorter (7 to 14 days depending on the restriction type and stringency as well as on the rate of infection of the specific COVID-19 variant) than the period analyzed in each round (i.e., one month). Therefore, the average effect of the restrictions over a month should be captured by the number of confirmed cases. It is also important to consider the heterogeneity of the response across the regions. Indeed, although measures were coordinated at the national level, each regional state in Ethiopia tailored policy implementation to the local situation through its own Public Health Emergency Opera-

[15] Available at this link: https://www.covid19.et/covid-19/.
[16] See https://www.ephi.gov.et/.

[17] The virus spread unheavenly across regions. In particular, the Addis Ababa region reported the highest proportion of cases per million population, followed by Harar and Dir Dawa. Factors that can explain this heterogeneity are a different testing capacity, driven by better infrastructure, especially in the capital and in other urban areas, population density, and degree of internal and international connectivity.
[18] Similar results were found in other countries. For instance, Amare et al. (2021) in Nigeria found that the variables of COVID-19 cases and government restrictions produced the same results, confirming that the two variables can proxy each other.

Table 3. Comparison of individual characteristics between the baseline sample and phone-based subsample.

Variable	Baseline population	Phone-based sub-sample	Student's t significance
Rural	0.72	0.64	***
	(0.45)	(0.48)	
Sex: 1=female	0.51	0.27	***
	(0.50)	(0.45)	
Employed in any activity	0.75	0.85	***
	(0.43)	(0.35)	
Age	30.69	38.33	***
	(16.38)	(13.76)	
Not engaged in Education, Employment or Training	0.10	0.11	
	(0.30)	(0.31)	
Literacy rate	0.55	0.63	***
	(0.50)	(0.48)	
Formal job contract	0.04	0.10	***
	(0.19)	(0.30)	
Years of education	3.70	4.75	***
	(4.32)	(5.12)	
Agricultural wage work	0.01	0.01	
	(0.09)	(0.09)	
Non-farm self-employment	0.10	0.15	
	(0.29)	(0.36)	
Non-farm wage work	0.12	0.22	***
	(0.32)	(0.42)	
Own farm work	0.63	0.63	***
	(0.48)	(0.48)	
Upstream of AFVC	0.63	0.64	
	(0.48)	(0.48)	
Midstream of AFVC	0.03	0.04	***
	(0.16)	(0.20)	
Downstream of AFVC	0.01	0.01	**
	(0.10)	(0.12)	
N. of observations	19,910	2,347	

Note: the first column includes all individuals at the baseline. The second column includes only individuals from the baseline who were tracked in the phone-based surveys. Sampling weights applied. Standard deviation in parenthesis. Children below 11 years old dropped from the sample. Mean difference is computed through a linear regression, where the independent variable is a dummy equal to one if the individual belongs to the phone subsample. *** p<0.01, ** p<0.05, * p<0.1.

tions Centre (PHEOC)[19]. This calls for using regionally disaggregated variables.

Fourthly, the number of confirmed cases does not capture spillover effects that may occur across regions. Indeed, each region is treated as an independent entity assuming that each of them does not have interactions with the rest of the country and no aggregate impacts occurred. This assumption does not hold when two or more regions have strong economic relationships. For instance, this may happen when a food value chain crosses over regional boundaries – e.g. a food item is produced in a region and consumed in another – or workers commute between different regions. In these cases, should one region be affected differently than others, this effect would affect not only that specific region, but also other geographically closer or economically linked regions. However, as regions in Ethiopia are quite large and people are mostly working in the local economy (e.g. high share of family farmers), the spillover effect should be limited. Additionally, the Ethiopian political system based on ethnic federalism, where the regions have been identified based on "settlement patterns, identity, languages" (Article 46.2 of the Ethiopian Constitution), makes it easier to conceptualize regions as separate economies. Evidence indeed shows that labor mobility and internal migration in Ethiopia are limited (Bundervoet, 2018) because migration across regional boundaries often creates social tensions and violence (Breines, 2020; Fessha and Dessalegn, 2020).

4.3. Model specification

The base model is the following:

$$y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1(Cases_r * Time_t) + \varepsilon_{hrt} \quad (1)$$

where y_{hrt} is the outcome variable – either labor or income – defined for each household h in region r and round t; α_{hr} captures household fixed effects, allowing controlling for unobserved time-invariant heterogeneity among households; $Cases_r$ is the number of confirmed COVID-19 cases per million population in each region; $Time_t$ is a dummy variable representing the time of observation, equal to 1 for the post-COVID round and 0 for the pre-COVID round, whose coefficient captures the aggregate time trend in the labor market and income composition; the interaction term between time and the number of cases captures the differential impact of COVID-19 on labor participation and income change across regions due to different exposure to the virus; ε_{hrt} is the error term.

Considering that the virus spread unevenly across regions over time, we need to control for this. Regions that experienced the virus earlier are indeed more likely to report more cases than the other regions. A first specification of the base model introduces the variable Day_{1r},

[19] Source: https://www.acceleratehss.org/wp-content/uploads/2022/03/Covid-Collaborative-Ethiopia-Case-Study.pdf

which reports the number of days that occurred from the first COVID-19 case at the national level to the first COVID-19 case registered in the region:

$$y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1(Cases_r * Time_t) + \beta_2(Day_{1r} * Time_t) + \varepsilon_{hrt} \quad (2)$$

To differentiate the impact of the isolated interactions and the impact of the combined spatial and temporal variabilities, we consider also a specification that includes the triple interaction between the time dummy, the number of confirmed cases per million inhabitants, and the variable as follows:

$$y_{hrt} = \alpha_{hr} + \beta_0 Time_t + \beta_1(Cases_r * Time_t) + \beta_2(Day_{1r} * Time_t) + \beta_3(Cases_r * Day_{1r} * Time_t) + \varepsilon_{hrt} \quad (3)$$

As an additional specification, we include in (3) some control variables available in the phone-based post-COVID surveys, which are not captured by the fixed effects. These variables are the presence of another member in the household who lost a job in the aftermath of the pandemic, and if the household received any assistance since the outbreak of the pandemic.

The analysis has been conducted for each post-COVID round, comparing it with the baseline. In this way, it is possible to observe the evolution of the response to the crisis over time. We expect that regions more affected by the pandemic will report a higher reduction in labor participation and income and that the effect will increase the pandemic deepening over time[20].

We used a linear probability model with household fixed effects. The advantage of this model compared to a logit or conditional logit model with fixed effects is the inclusion of all observations. In fact, the logit model with fixed effects drops the units that show no variability in the dependent variable (Beck, 2018), drastically reducing the number of observations in case of small variability. In our data, this would result in an 80% reduction of the sample size.

All analyses have been carried out using the balanced sample. However, given the existence of significant attrition rates, we replicated the analysis also using the unbalanced sample, finding consistent results (cf. Figures A.2 and A.3 in the Appendix).

An important issue that could have affected our estimates is the desert locust outbreak experienced by some regions of the country in the period of analysis, which might have harsh consequences on production[21]. For this reason, it is important to consider this shock on farming employment and income. The HFPH surveys report information on desert locust outbreak only in the 4th wave. We retrieved GIS data on desert locusts from the FAO Locusts Hub[22] and merged it with the households' location. Given that the household coordinates refer to the dwelling, and not to the parcel, and they are slightly modified for privacy reasons, we created a buffer of 3 km around the household centroid to account for these factors (on average the parcel is 1.7 km distant from the dwelling). Regarding the location of locusts, we considered the area surveyed, which is 580 hectares on average. Figure 5 reports the location of households (in purple) and where the desert locusts have been observed (in green) over the year 2020.

Although GIS data are quite accurate and reliable, many data gaps undermine the quality of the information and might represent a limitation of our analysis. Firstly, household coordinates have been slightly modified for privacy reasons and this might determine some measurement bias. Secondly, only the distance of the parcel is available, not the direction: it is not possible to know exactly where it is located. Thirdly, the information provided for locusts does not account for the locust swarm movements over time, excluding areas outside sampled locations. For these reasons, self-reported information could be more reliable to measure the effect of these pests on farm crops. Therefore, we report estimates of the impact of locust outbreak using GIS data as well as self-reported data (cf. Section 5.1).

The second part of the analysis aims at identifying the main determinants influencing changes in income in the presence of COVID-19. In doing this, we use a probability model with regressors in time t (pre-COVID) and the dependent variable in time $t + 1$ (post-COVID). In this way, we can estimate which attributes that were in place in normal conditions are more likely to affect the outcome during the pandemic. The probability that the outcome variable takes a certain value is given by

$$Prob(y_{h,t+1} = j) = \mathbf{x}^{T}_{h,t}\boldsymbol{\beta}\mathbf{c} + u_{h,t+1} \quad (4)$$

where h is the household, $\mathbf{x}$ is a column vector of observable variables, namely the attributes and factors in time t, $u_{h,t+1}$ is the error term, and j takes the value 1 if the

[20] We also estimated the impact of COVID-19 from wave to wave, comparing the outcome with the previous interview and results still hold (cf. Figure A.1 in the Appendix).

[21] The desert locust outbreak appeared in Ethiopia in second half of 2019. By January 2020, the outbreak was already significantly affecting the country, peaking around mid 2020 around the harvesting time of the first crop season (*belg*) when most cereals were ready to be harvested (see Figure 1). According to FAO, the outbreak was the worst in 25 years in the country.

[22] https://locust-hub-hqfao.hub.arcgis.com/.

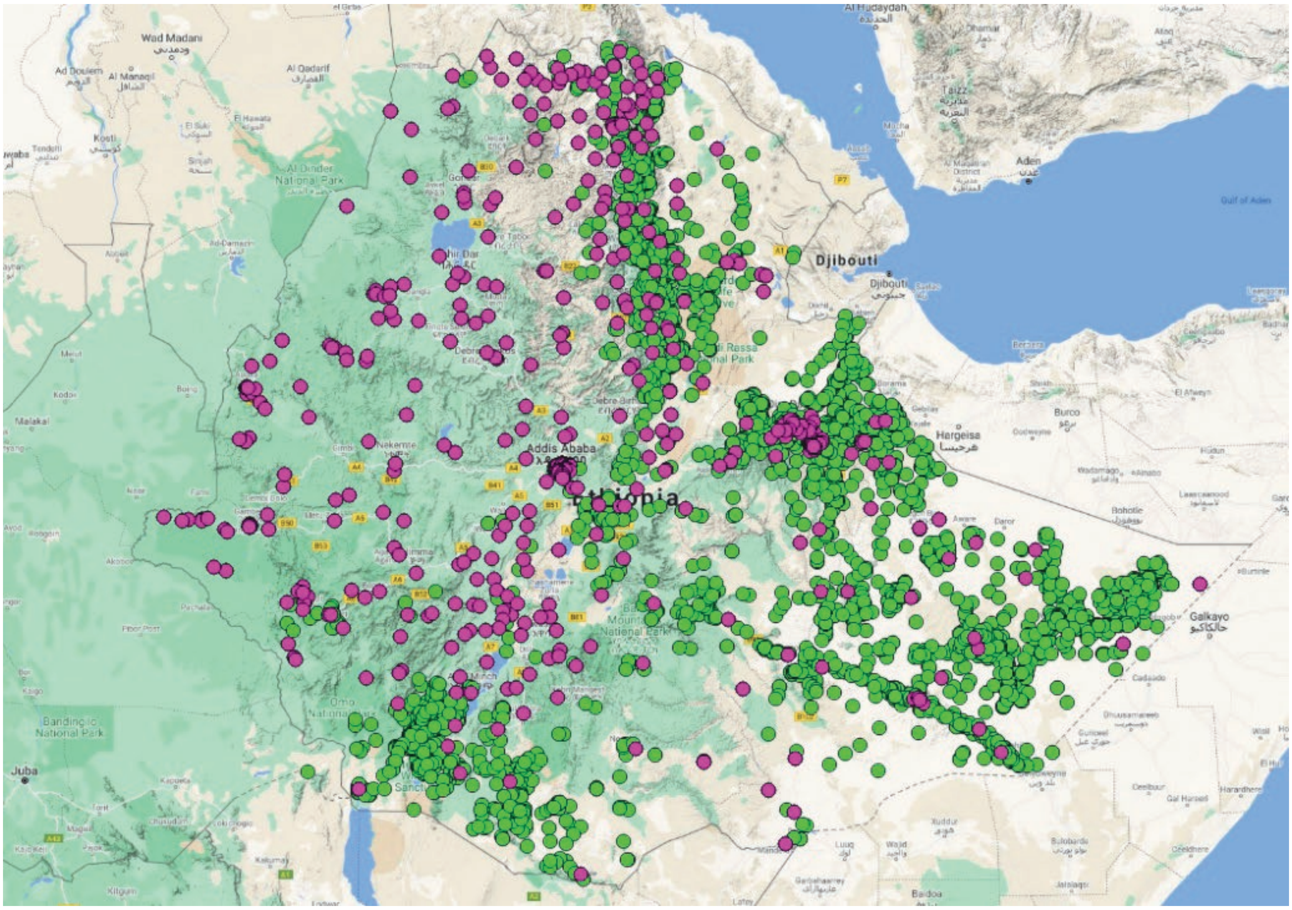

Figure 5. Map of households' location (purple circles) and locust swarm sites (green circles), 2020. Source: own elaboration using data from FAO Locusts Hub and ESS 2018/2019.

outcome is dichotomous, or multiple values if it is categorical. The regressors include household characteristics, level of infrastructure and variables at the community level, economic-related variables, and agricultural-related variables when considering farm income.

The dependent variable is the change in income at the household level. We decided to not consider the employment status because there could be problems of endogeneity because of omitted variable bias. This could occur mainly by external factors, for which information is not provided in the survey. An example could be the loss of job due to the employing company shut-down. In addition to econometric issues, as the job loss mainly depends on factors beyond household or individual control, investigating the household-related determinants of the loss of employment due to the COVID-19 crisis would make little sense.

The estimation has been conducted using a maximum likelihood estimator. We used the ordered probit model to account for the categorical nature of the dependent variable. However, given that the response rate for total loss and income increase was very low, we also created a dummy equal to 1 if income did not change or increase, and 0 otherwise. In this case, we used a probit model.

5. RESULTS

5.1. Impact of COVID-19 cases

The impact on employment

Table 4 reports the impact on employment at round 1 as resulting from the different model specifications[23],

[23] Table 4 reports the estimation for round 1 as an example. Then we provide a visual estimation of our model results (e.g. Figure 5) that makes easier understanding the evolution of the relevant outcomes over the analyzed period. The estimates of each model are available upon request to the authors.

Table 4. Regression results over different models, employment – round 1.

Dependent variable: individual employed in any activity					
Variable	(1)	(2)	(3)	(4)	(5)
Time	-0.0684***	-0.0758***	-0.0657***	-0.0658***	-0.0709***
	(0.0137)	(0.0127)	(0.0185)	(0.0193)	(0.0196)
Cases*Time	-0.0438***	-0.0353***	-0.0362***	-0.0361***	-0.0360***
	(0.00866)	(0.00577)	(0.00607)	(0.00651)	(0.00654)
Days*Time			-0.000395	-0.000386	-0.000364
			(0.000505)	(0.000644)	(0.000640)
Cases*Days*Time				-9.72e-06	-1.53e-06
				(0.000383)	(0.000383)
Constant	0.746***	0.746***	0.746***	0.746***	0.746***
	(0.0163)	(0.00507)	(0.00507)	(0.00507)	(0.00507)
Controls	No	No	No	No	Yes
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	4,694	4,694	4,694	4,694	4,694
R-squared	0.042	0.071	0.082	0.107	0.116
Number of pid		2,347	2,347	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1. Data refers to the 1st wave.

starting from model (1), which is a simple OLS over the pooled sample, to model (5), which includes all the variables and their interaction terms, the individual/household fixed effects, and the controls. We consider the last model as the best suited model for the analysis. In fact, from the theoretical viewpoint, the within estimator of the fixed effects model is robust to many types of omitted variable bias[24]. Furthermore, the inclusion of all regressors in model 5 allows controlling for more variables and provides insights on the role of such controls in determining the outcome variables. This also leads to higher adjusted R-square statistics as shown in Table 4.

As expected, our variable of interest, i.e. the interaction term Cases*Time, has a negative sign and is statistically significant, meaning that COVID-19 negatively impacted employment, while the other interaction terms are not statistically significant.

Figure 6 reports the coefficient of the interaction term between the time trend and the COVID-19 cases for each round, firstly considering any labor activities and then looking at specific sectors or segments of the AFVC. These results show how COVID-19 negatively impacted employment activities in Ethiopia. They also show that the severity of the impact increased over time.

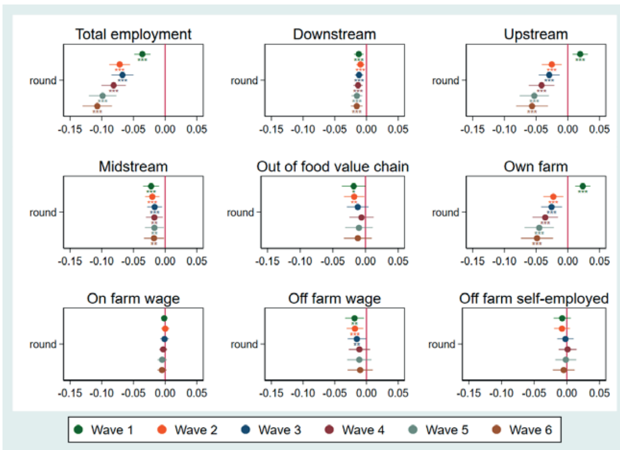

Figure 6. Impact of COVID-19 cases on employment over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if the individual is employed. Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Decomposing the impact along the AFVC, we can see that upstream activities are the most affected. Although this segment had initially been relatively less affected, it shows increasingly negative impacts in subsequent rounds. Downstream and midstream segments have

[24] However, it is more inefficient than an OLS estimator, because it reduces the variation of the independent and dependent variables used for estimation. Indeed, it is more affected by measurement errors and by omitted variables that are not constant within the household.

Table 5. Regression results over different models, income – round 1.

Dependent variable: change in total HH income					
Variable	(1)	(2)	(3)	(4)	(5)
Time	-0.567***	-0.567***	-0.544***	-0.558***	-0.549***
	(0.0274)	(0.0274)	(0.0374)	(0.0404)	(0.0412)
Cases*Time	-0.0246**	-0.0246**	-0.0266**	-0.0157	-0.0148
	(0.0112)	(0.0112)	(0.0114)	(0.0118)	(0.0119)
Days*Time			-0.000879	5.95e-05	1.58e-05
			(0.00110)	(0.00162)	(0.00161)
Cases*Days*Time				-0.000967	-0.000970
				(0.000864)	(0.000864)
Constant	0	-0	-0	-0	0
	(3.08e-10)	(0.0106)	(0.0106)	(0.0106)	(3.08e-10)
Controls	No	No	No	No	Yes
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	4,691	4,691	4,691	4,691	4,691
R-squared	0.336	0.503	0.503	0.504	0.505
Number of pid		2,347	2,347	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1. Data refers to the 1st wave.

also been negatively affected, but in this case, the impact did not significantly change over time. In the case of non-AFVC, after an initial negative impact, the coefficients became no longer significant from the third round onwards. This could mean that the COVID-19 cases no longer had an impact or that employment effects within this category offset each other. For instance, among the off-farm self-employment, construction and manufacturing reported a positive effect, while trade and restaurants, hotels, and bars showed negative coefficients.

The impact on income

Table 5 shows the results of the various models estimating the impact of COVID-19 on income change. Again, the interaction term Cases*Time is negative and most of the time statistically significant[25].

The impact of COVID-19 on income (Figure 7), takes more time to occur. Households indeed can rely on savings or other coping strategies in the short run. However, from the third round onwards total income has been negatively affected by COVID-19 cases, and, similarly to employment, the effect increases over time. Wage income and off-farm business income do not seem to have been significantly affected, while it is interesting to see the impact on farm family farming. After an initial positive effect, in the last three rounds COVID-19 cases have significantly and negatively impacted farm income. This can be explained because initially, the virus spread

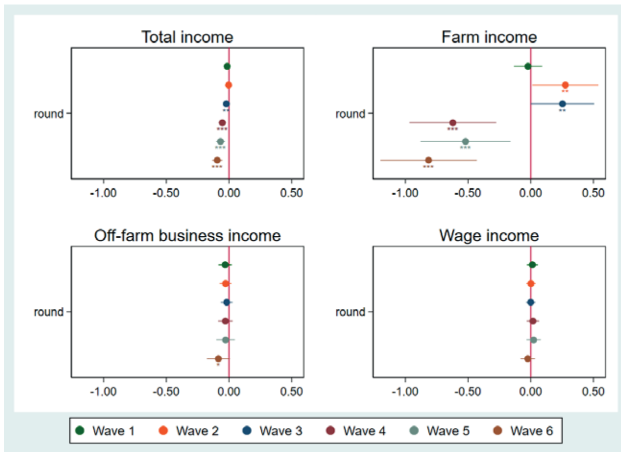

Figure 7. Impact of COVID-19 cases on income over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

[25] The coefficient loses significance when the triple interaction term is added. However, from the third round onwards it is statistically significant.

in the cities, marginally hitting farmers livelihood in rural areas. Then the virus spread across the whole country, affecting also people located in more remote areas. Additionally, if initially smallholders and subsistence farm households were more advantaged against the measures implemented by the government because they relied less on external inputs and markets, this advantage disappeared over time, due to the limited coping mechanisms they had available.

The impact of locust outbreak on farm employment and income

The inclusion of the dummy for respondents who self-reported to have experienced the desert locust shock on the farm has a significant impact on changing the coefficients associated with the number of COVID-19 cases. Results are reported in Table 6. For employment, the coefficient of the COVID-19 cases loses significance, while having locusts on the farm is positively and significantly associated with labor activities. This confirms the additional labor time required to spray the chemicals all over the land. Regarding income, compared to previous results, where the coefficient of COVID-19 cases was -0.621, the inclusion of desert locusts increases the magnitude of the coefficient to -1.103, strengthening the negative impact of COVID-19 cases on farm income. These results show that it is important to consider multiple shocks experienced by individuals and households when assessing the impact of a certain event.

When using the georeferenced data (Table 7), the locust variable loses significance for own farm labor activities. Instead, the impact of locust outbreak is significant and negative in the case of farm income. The effect of the locust dummy is larger in the 4th wave (-0.377), which corresponds to the most damaging period for crops, given the locust life cycle as well as the timing of the crop season (peak harvesting in the first crop season, cf. Figure 1). The inclusion of the locusts' data over all six waves does not significantly affect the impact of COVID-19 cases on farm income, showing only slight changes from the model not including the locust dummy estimates.

Table 6. Simultaneous impact of locusts (self-reported data) and COVID-19 on own farm employment activities and farm income change, 4th round.

	Employed in own farm activities	Farm income change
Time	0.0489	5.242***
	(0.504)	(1.893)
Cases*Time	0.0216	-1.103***
	(0.0938)	(0.372)
Days*Time	-0.0237**	-0.0998***
	(0.0115)	(0.0350)
Days*Time*Cases	0.00333*	0.0194***
	(0.00200)	(0.00671)
Locusts on the farm	0.134*	-0.0244
	(0.0685)	(0.110)
Constant	0.542***	-0
	(0.00927)	(0.0111)
Controls	yes	yes
FE	yes	yes
Observations	2,961	2,639
R-squared	0.088	0.309
Number of pid1	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1. Data refers to the 4th wave.

5.2. Determinants of income change

In this section, the results of the regressions aimed to identify the main determinants of income change are presented. Regressors have been grouped into three categories: household characteristics, infrastructures, and economic-related variables. As dependent variables, we considered the change in total and farm incomes. For illustrative reasons, this section reports only the results of the models using a dichotomous dependent variable. The estimates of the ordered probit model are reported in the Appendix (Tables A.4 and A.5).

Total income change

Figure 8 reports the estimated coefficients of household characteristics over the six rounds. The only significant variable here is the level of education of the household head. A higher level of education is positively associated with a higher probability of not experiencing an income reduction/total loss. Living in rural areas shows a positive and significant coefficient only in the first round, consistent with previous analyses that show that rural areas were initially less affected.

Economic-related variables (Figure 9) show some interesting patterns. Having a formal job contract is associated with a higher probability of income increase or unchanged income level. A similar relationship can be found with having a bank account and formal insurance, although the magnitude and the level of significance are lower than in the case of a formal contract. These results

Table 7. Simultaneous impact of locusts (GIS data) and COVID-19 on farm income change.

	wave 1	wave 2	wave 3	wave 4	wave 5	wave 6
Time	-0.377***	-0.981***	-1.163***	2.829***	3.007***	5.228***
	(0.0627)	(0.269)	(0.363)	(0.895)	(1.141)	(1.273)
Cases*Time	-0.0217	0.277**	0.254**	-0.620***	-0.519***	-0.815***
	(0.0564)	(0.134)	(0.129)	(0.174)	(0.182)	(0.196)
Days*Time	0.00110	0.0131**	0.0189**	-0.0531***	-0.0581**	-0.103***
	(0.00267)	(0.00638)	(0.00858)	(0.0169)	(0.0250)	(0.0273)
Cases*Days*Time	-0.00175	-0.00621**	-0.00654**	0.0104***	0.00923**	0.0153***
	(0.00185)	(0.00281)	(0.00272)	(0.00310)	(0.00365)	(0.00393)
Locust dummy	-0.307***	-0.350***	-0.0973	-0.377***	0.0327	-0.00324
	(0.104)	(0.129)	(0.156)	(0.144)	(0.245)	(0.213)
Constant	0.00328	0.00398	0.00131	0.00455	-0.000442	4.29e-05
	(0.0114)	(0.0126)	(0.0111)	(0.0131)	(0.0163)	(0.0139)
Controls	yes	yes	yes	yes	yes	yes
FE	yes	yes	yes	yes	yes	yes
Observations	3,025	2,882	2,850	2,853	2,844	2,843
R-squared	0.386	0.415	0.384	0.225	0.102	0.099
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Note: Dependent variable: categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Estimates are computed using a linear probability model with household fixed effects. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1.

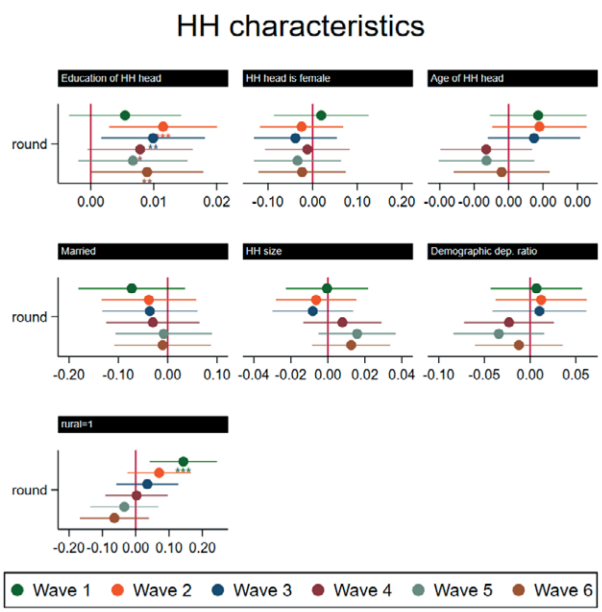

Figure 8. Effects of households' characteristics on total income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

show that access to formal institutions is a winning strategy to contrast the negative consequences caused by the crisis. Per capita household income reports a positive relationship, meaning that as per capita income increases the probability of not experiencing an income reduction increases. Richer households are then expected to suffer less from the crisis. However, the magnitude of the coefficient is quite small, suggesting that the differential effect between poorer and richer households is limited.

Regarding infrastructure variables, none of them has a substantial effect on total income (Figure 10). Being distant to the urban center, to the main road, or to the markets seems to be slightly positively associated, sometimes in a significant way, with the probability of income increase or unchanged. However, the coefficient is lower than 1%.

Farm income change

The same variables considered in the previous section show partly different patterns when considering farm income. Looking at the household characteristics (Figure 11), the education of the household head no longer seems to play a relevant role, while the household size and the age of the household head are associated with a higher probability of income reduction, although the effect is statistically significant only in a few rounds.

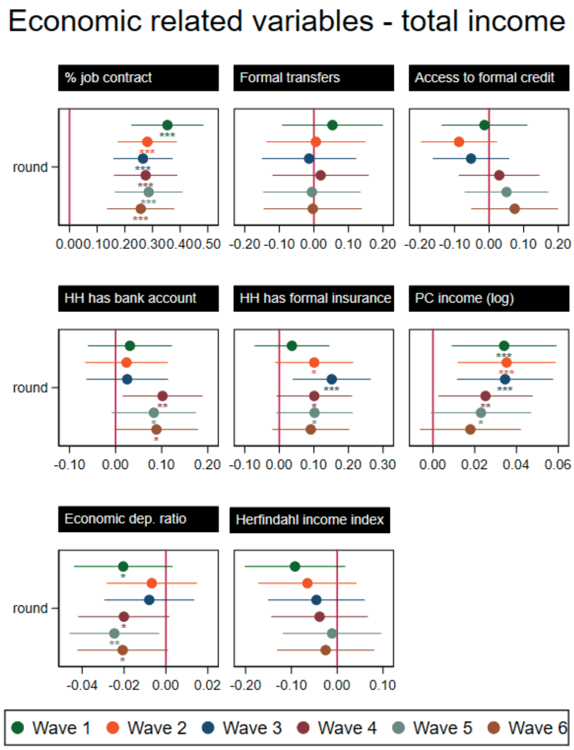

Figure 9. Effects of economic-related variables on total income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

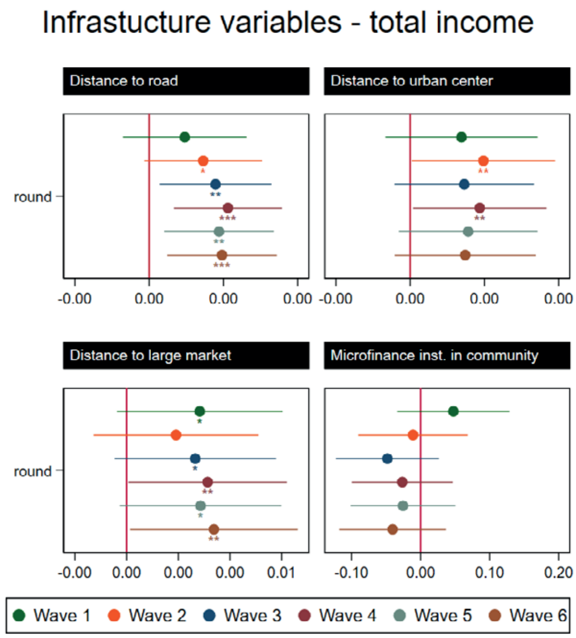

Figure 10. Effects of infrastructure variables on total income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Even in the case of farm income (Figure 12), distance does not show significant effects, except for distance to a large market, where it seems that the more distant the household the higher the probability of farm income unchanged or increased. This result may look counterintuitive. A possible explanation could be that more (economically) isolated households had already put in place some strategies to account for the distance from large markets, so they were more advantaged relatively to those farmers who were used to relying on markets. Additionally, given the travel restrictions, domestic food value chains could have reshaped to adapt to the new situation, shortening their lengths. In this way, people in remote areas relied more on locally produced agricultural products instead of going to the main urban market.

The role of microfinance institutions in the community is interesting. Indeed, differently from total income, here it shows a positive coefficient, and in the last rounds the effect is also statistically significant. This means that this type of institution matters in times of crisis.

As in the total income case, having a bank account and formal insurance rise the probability of farm income increase (Figure 13). Having a formal job contract does not show a statistically significant effect on agricultural income. This makes sense given that most households in Ethiopia run family farms and do not participate in the formal labor market.

Regarding the agricultural-related variables (Figure 14), results seem to suggest that farmers with larger areas of land have a higher probability of success compared to smallholders, as shown also by the marginal effects of land size on the probability that farm income did not decrease (Figure A.4 in the Appendix). This result is in contrast to findings from other studies conducted in different contexts. Cesaro et al. (2022), for example, found that medium-large farms in Italy expressed greater concern about the negative consequences of COVID-19 in the short term than small farms. Having a land ownership title or holding the right to use it played an important role in cushioning the negative COVID-19 impact. Households that use fertilizers and those that have agricultural machinery, although they initially experienced a positive or insignificant effect, were subsequently nega-

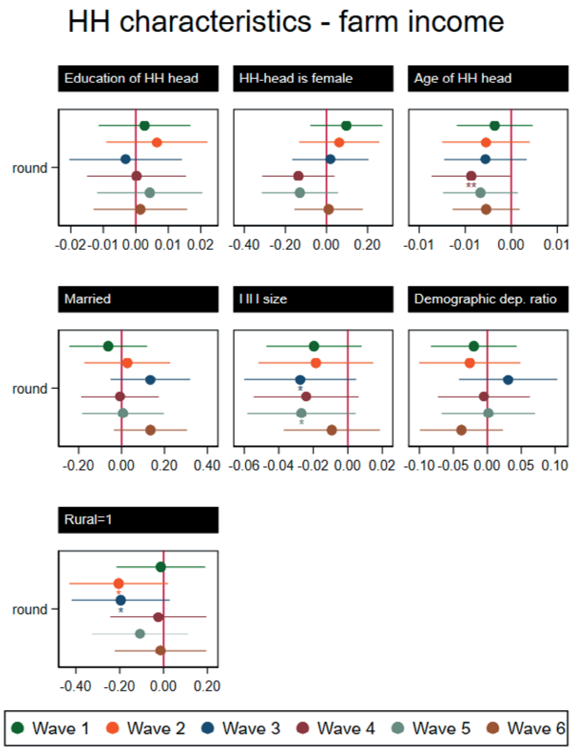

Figure 11. Effects of households' characteristics on farm income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

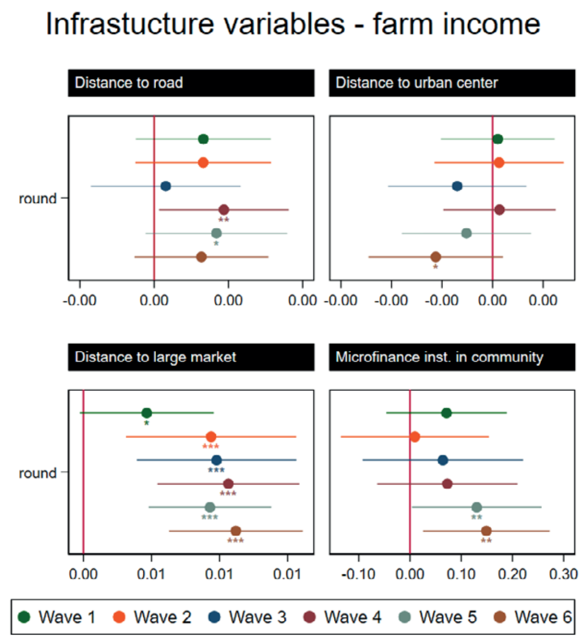

Figure 12. Effects of infrastructure variables on farm income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

tively affected. This result can be the consequence of the mobility and trade restrictions, which decreased inputs availability and increased their prices. A less diversified crop mix was detrimental to farm income increase in early rounds, as shown by the coefficient of the Herfindahl index of crop[26].

5.3. Robustness Checks

Placebo test

To test the validity of the treatment variable used in the analysis, we ran a placebo test, imputing the COVID-19 shock in the prior wave of the ESS, collected in 2015/2016, and considering as baseline the 2012/2014 ESS survey. If the variable of the number of COVID-19 cases correctly captures the impact of the COVID-19 shock, we should not find any significant effect, given that at that time the shock did not occur.

Table 8 reports the results of the test, applied for the change of total income at the household level and total employment at the individual level. The variable is valid when applied to the model of household income, where none of the coefficients related to COVID-19 is significant. Instead, when running the same model on total employment, the coefficient of the interaction between time and COVID-19 cases is significant (column 1). However, the sign is positive, in contrast to the predicted effect that the shock should have. A possible explanation is that the variable of COVID-19 cases is in a way correlated with regional characteristics. For instance, we know that COVID-19 has affected some economic sectors more than others and, if a region is specialized in one sector, this correlation will be significant. If the employment rate was expanding between 2014 and 2016 in that specific sector, the correlation would be positive.

[26] The Herfindahl index is a measure of crop concentration. It is computed as the sum of square of the proportion of individual crop groups in a portfolio. The index decreases with an increase in diversification. It ranges from 0 (complete diversification) to 1 (complete specialization) (Singh et al., 2018).

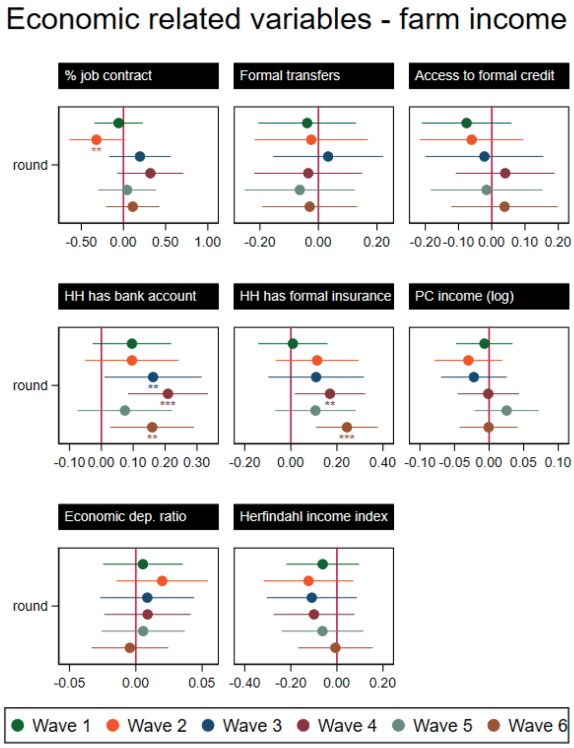

Figure 13. Effects of economic-related variables on farm income change over time. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

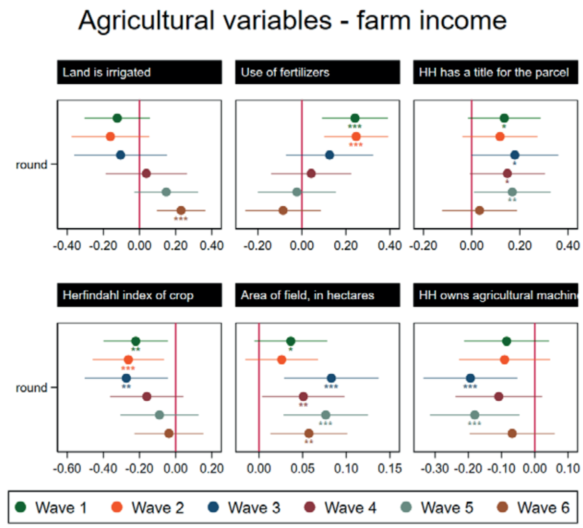

Figure 14. Effects of agricultural-related variables on farm income change over time.cSource: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Introducing regional income (column 2)[27] indeed makes the interaction term not significant.

Inverse probability weights

To address the problem of representativeness of the individual sample, we created individual-level adjusted weights using the inverse probability based on the ESS 2018/2019, and we compared the outcomes using these weights following Khamis et al. (2021)[28]. We ran a logit regression to estimate the probability of being in the HFPS subsample over a set of variables at the individual level, weighted by the household weights of ESS 2019. Variables include age, gender, years of completed education, living in rural areas, income quintile, being employed, working in own farm activities, and being not engaged in education, employment or training (NEET). Children below 12 years old have been excluded. The inverse of the estimated probability is the adjusted weight. This procedure gives greater weight to observations that appeared in the HFPS sample. Figure 15 reports the coefficients estimated with original weights vis-à-vis the adjusted ones. The correlation of the estimates using the two methods is very high, i.e. 98%. This result suggests that the labor market outcomes of the subsample of individuals are generally consistent with the outcomes of the whole working population.

6. CONCLUSIONS

The analysis showed that COVID-19 negatively impacted both household employment and income, the more so the longer the time length from the pandemic

[27] Regional income can capture the level of economic development of the region, which is in turn correlated with other factors, including the economic sector.

[28] Khamis et al. (2021) relied on the World Bank's Global Monitoring Database. Although they found similar results when applying the corrected weights compared to the original ones, they had a limited set of variables available to use for reweighting the estimates, undermining the effectiveness of the weights created. In our case, instead, we can consider more variables, increasing the ability to effectively adjust for the differences between the individuals in the subsample and the rest of the population.

Table 8. Placebo test on ESS 2012/2014 and ESS 2015/2016.

Variables	Total income change	Total employment	
		(1)	(2)
Time	0.0852	-0.294***	-0.363**
	(0.154)	(0.0850)	(0.169)
Time*cases	0.0136	0.0258**	0.0419
	(0.0204)	(0.0113)	(0.0365)
Time*days	0.00274	0.00153	0.00192
	(0.00538)	(0.00295)	(0.00311)
Time*days*cases	-0.000364	-0.000233	-0.000312
	(0.000701)	(0.000386)	(0.000431)
Cases*regional income			-4.31e-07
			(9.34e-07)
Constant	-0.00491	0.601***	0.601***
	(0.0109)	(0.00583)	(0.00584)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Observations	9,760	21,289	21,289
Number of pid	4,887	11,368	11,368
R-squared	0.023	0.050	0.050

Note: Dependent variables: categorical variable of income change, ranging from -2 (total loss) to 1 (increase) (1st column), and dummy equal to 1 if the individual is employed (2nd column). Income change is computed by comparing the amount of household income earned in each round. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

onset. Upstream activities, and specifically own farming, are the most affected segment of the AFVC. Indeed, despite an initial positive effect, the impact then became negative and increased in magnitude over time. This finding is partly in line with previous studies published in the immediate aftermath of the pandemic (Bundervoet and Finn, 2020; Reardon et al., 2020a) that show that farming was the less affected sector. However, tracking the impact over time allowed gaining a more complete understanding of the evolution of the effect, with farming increasingly severely affected by the disruption of the food value chain. The initial resilience capacity of the Ethiopian food marketing systems, as reported by Hirvonen et al. (2021b) for the vegetable value chain does not seem to persist over time. This highlights the importance of monitoring the evolution of the impact of the shock over time. Indeed, considering only the initial effect could give an incomplete and misleading understanding of the actual situation.

We also showed that the most vulnerable farmers have been hit hardest. Small farming households are more exposed to the negative consequences of the crisis. There is the need then to target specifically this group of AFVC actors, especially in situations of crisis. To do this, AFVC participants need to have access to specific tools that allow them to cope with the shock. Access to formal institutions, such as formal insurance, bank account, formal contract, and land title are all positively associated with a higher probability of income increase. The national government should then increase its effort in providing improved opportunities to access financial services as well as formal institutions.

Last but not least, multiple shocks dramatically worsen the picture. This is the case of the desert locust outbreak, that compounded with an already difficult situation created by COVID-19. Therefore, policymakers should consider the effects of simultaneous shocks when designing policy responses to the crisis.

From our data, it is not possible to identify how the above impacts may affect other important dimensions of well-being such as food security. Abay et al. (2023) found that household food insecurity increased by 11.7 percentage points. The authors did not assess the relationship between a reduction in employment/income and food security. However, there is evidence from other studies that a reduction in employment and income may or may not affect food security. Especially when subjective estimates of income change are used, the relationship is not straightforward. In Hirvonen et al. (2021a), for example, self-reported income shocks did not appear to be associated with changes in the Household Dietary Diversity Score (HDDS). Furthermore, other mechanisms may be in place that can influence food security, depending on the type of household considered, its integration into the food value chain, and the participation in safety net programs[29]. Additional analysis of the mechanisms and close monitoring of the effects of the crisis are then required to respond with appropriate policies as other crises arise.

The main limitations of this work are related to the type of data available, which reduces the internal and external validities of the findings (Abate et al., 2023). Indeed, the fact that data are collected through phone interviews limits the representativeness of the sample, especially considering the low phone penetration in the rural areas of the country. The COVID-19 cases variable is not fully able to capture the infection rate and the economic downturn caused by the policy interventions in the country. Additionally, measurement error could be widespread in self-reported data. This is particularly relevant

[29] Abay et al. (2023), in the same study cited above, showed that participation in the Productive Safety Net Program (SNP) offsets virtually almost all of the COVID-19 induced food insecurity increase (11.7 percentage points): the likelihood of becoming food insecure increased by only 2.4 percentage points for PSNP households. Qualitatively similar results are reported by Maffioli et al (2023) for Myanmar.

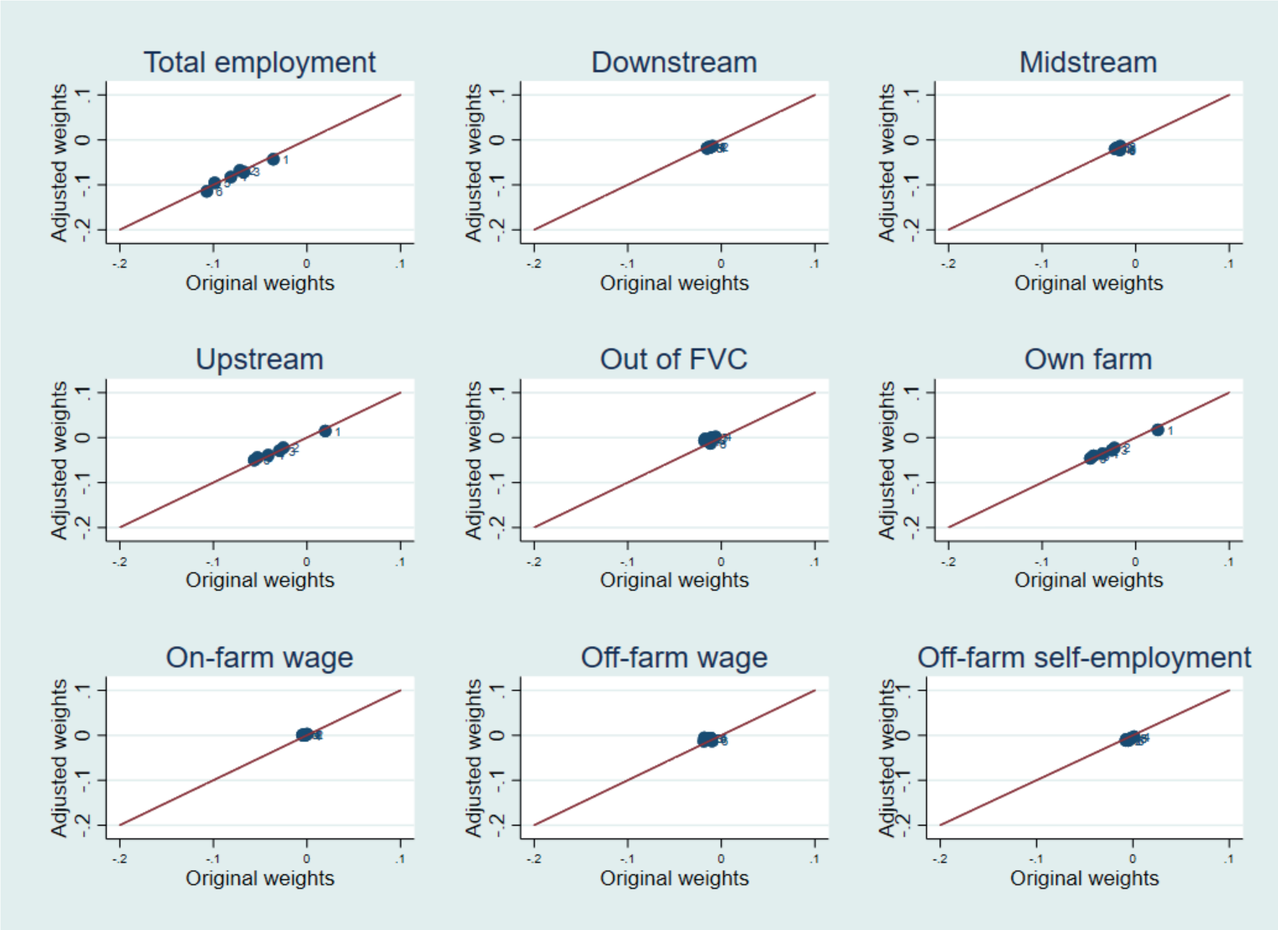

Figure 15. Comparison of weighting methods. Source: own elaboration from ESS 2018/2019 and HFPSH 2020.

for the variable of income change, which is highly subjective to respondents' perception. Income data collected through more reliable measures are then needed to avoid major measurement errors. Finally, data used in this study were not intended to specifically track AFVC participants. Household surveys based on random sampling of the whole economy are typically unable to capture a representative picture of the actors across the different segments of the value chain[30]. Vice versa, information/data retrieved through survey based on representative samples of the main AFVCs[31] coupled with cascading survey of the various AFVC segments would have been better suited to grasp a better understanding of the overall effect of the COVID-19 crisis on the Ethiopian food system.

[30] For instance, less than 100 individuals employed in the downstream segment are surveyed in each post-COVID round.

[31] Studies on specific value chains in Ethiopia have been conducted only for the dairy value chain (see Hirvonen et al., 2021c), and the vegetable value chain (Hirvonen et al., 2021d).

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APPENDIX

Figure A.1. Impact of COVID-19 cases on income change, wave by wave. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Previous call is considered the baseline. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

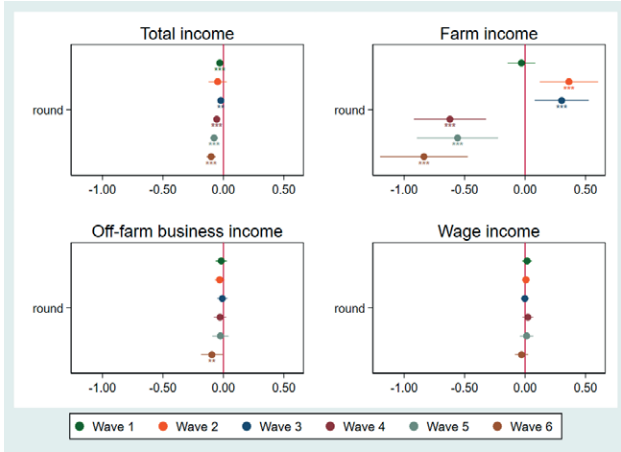

Figure A.3. Impact of COVID-19 cases on total income over time, unbalanced sample. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

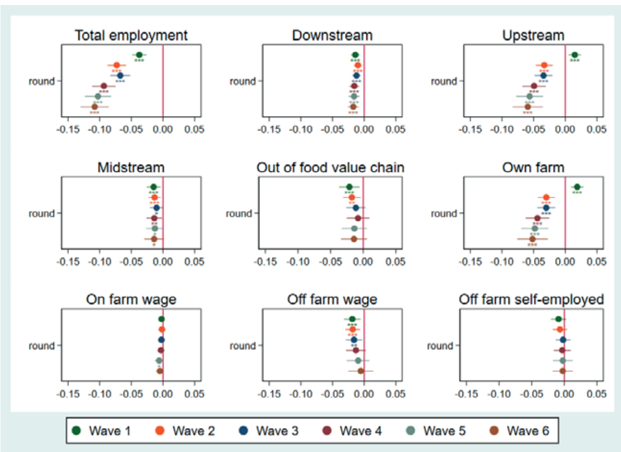

Figure A.2. Impact of COVID-19 cases on employment over time, unbalanced sample. Source: Own calculation from ESS 2018/2019 and HFPSH 2020. Note: Dependent variable = dummy equal to 1 if the individual is employed. Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

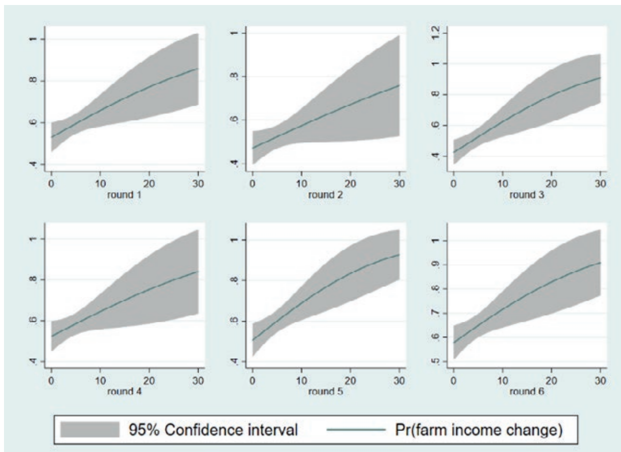

Figure A.4. Marginal effects of land size on the probability that farm income change has not decreased. Source: Own calculation from ESS 2018/2019 and HFPSH 2020.

Table A.1. Number of individuals that started to work again in each round, by reason for stop working in the previous round.

Reason for stop working	N. of individuals that started working again				
	Round 2	Round 3	Round 4	Round 5	Round 6
Seasonal/Casual worker	27	8	8	7	6
Contract ended	3	0	3	2	1
Covid-19	83	22	22	5	6
Temporarily absent	25	8	6	5	9
Retired	0	0	0	1	0
Being ill	2	8	2	1	5
Need to care for ill	1	1	1	0	0
Other	1	0	1	1	0
N/A	329	94	71	54	30
Total	471	141	114	76	57

Table A.2. Full regression estimates, total employment.

Variables	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6
Time	-0.0709***	0.313***	0.368***	0.643***	0.886***	0.961***
	(0.0196)	(0.0463)	(0.0539)	(0.0807)	(0.0975)	(0.107)
Time*Cases	-0.0360***	-0.0717***	-0.0673***	-0.0813***	-0.0987***	-0.107***
	(0.00654)	(0.00837)	(0.00879)	(0.00980)	(0.0110)	(0.0118)
Time*Days	-0.000364	-0.00707***	-0.00792***	-0.0178***	-0.0260***	-0.0296***
	(0.000640)	(0.00134)	(0.00142)	(0.00281)	(0.00377)	(0.00391)
Time*Cases*Days	-1.53e-06	0.00251***	0.00197***	0.00266***	0.00338***	0.00377***
	(0.000383)	(0.000367)	(0.000345)	(0.000434)	(0.000513)	(0.000514)
Other HH members lost job	0.0119	-0.166***	-0.0858	-0.1000	-0.233***	-0.225***
	(0.0412)	(0.0629)	(0.0663)	(0.0647)	(0.0822)	(0.0742)
HH received assistance	0.0449	0.0777	0.0571	0.0223	-0.0219	-0.000938
	(0.0358)	(0.0634)	(0.0537)	(0.0495)	(0.0480)	(0.0459)
Constant	0.746***	0.747***	0.748***	0.749***	0.752***	0.752***
	(0.00507)	(0.00840)	(0.00833)	(0.00853)	(0.00842)	(0.00863)
Observations	4,693	4,694	4,694	4,693	4,694	4,694
R-squared	0.122	0.086	0.079	0.098	0.124	0.116
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if individual is employed. Coefficients estimated using a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. 95% confidence intervals in parenthesis. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.

Table A.3. Full regression estimates, total income.

Variables	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6
Time	-0.549***	-0.599***	-0.502***	-0.237*	-0.0341	0.203
	(0.0412)	(0.0522)	(0.0685)	(0.124)	(0.160)	(0.186)
Time*Cases	-0.0148	-0.00295	-0.0216**	-0.0533***	-0.0677***	-0.0937***
	(0.0119)	(0.0102)	(0.0110)	(0.0150)	(0.0179)	(0.0206)
Time*Days	1.58e-05	-0.00265	-0.00653**	-0.0154**	-0.0162*	-0.0172*
	(0.00161)	(0.00198)	(0.00311)	(0.00670)	(0.00945)	(0.0102)
Time*Cases*Days	-0.000970	0.000198	0.000921	0.00199**	0.00188	0.00192
	(0.000864)	(0.000564)	(0.000685)	(0.000947)	(0.00119)	(0.00124)
HH received assistance	-0.0774	-0.141**	-0.201***	-0.117	-0.163**	-0.165**
	(0.0808)	(0.0549)	(0.0760)	(0.0768)	(0.0779)	(0.0787)
Other HH members lost job	-0.0758	-0.119	-0.123	-0.0720	-0.128	-0.108
	(0.0871)	(0.0839)	(0.0759)	(0.0823)	(0.0809)	(0.0802)
Constant	-0	-0	0	0	-0	0
	(0.0105)	(0.0107)	(0.0122)	(0.0137)	(0.0151)	(0.0156)
Observations	4,691	4,693	4,694	4,691	4,693	4,685
R-squared	0.505	0.568	0.540	0.472	0.408	0.363
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable: categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Estimates are computed using a linear probability model with household fixed effects. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4. Ordered probit, total income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	-0.00171**	-0.00620**	0.00730**	0.000611*	-0.00211**	-0.00595**	0.00678**	0.00129**	-0.00160	-0.00291	0.00331	0.00119
	(0.000869)	(0.00296)	(0.00348)	(0.000348)	(0.000983)	(0.00283)	(0.00319)	(0.000635)	(0.00130)	(0.00241)	(0.00273)	(0.000968)
HH head is female	-0.00176	-0.00647	0.00759	0.000643	0.0117	0.0304	-0.0358	-0.00640	0.0288	0.0446	-0.0554	-0.0181
	(0.0102)	(0.0381)	(0.0445)	(0.00384)	(0.0118)	(0.0284)	(0.0344)	(0.00587)	(0.0247)	(0.0292)	(0.0416)	(0.0123)
Age of HH head	-0.000461*	-0.00167*	0.00197*	0.000165	-0.000205	-0.000577	0.000657	0.000125	3.79e-05	6.89e-05	-7.85e-05	-2.83e-05
	(0.000276)	(0.000975)	(0.00115)	(0.000103)	(0.000323)	(0.000923)	(0.00105)	(0.000198)	(0.000429)	(0.000779)	(0.000887)	(0.000321)
HH head is married	0.00802	0.0306	-0.0355	-0.00314	0.00925	0.0275	-0.0306	-0.00615	0.0162	0.0319	-0.0347	-0.0134
	(0.00975)	(0.0393)	(0.0449)	(0.00416)	(0.0107)	(0.0337)	(0.0366)	(0.00782)	(0.0184)	(0.0370)	(0.0392)	(0.0163)
HH size	-0.000397	-0.00144	0.00169	0.000141	0.000208	0.000586	-0.000667	-0.000127	0.000337	0.000613	-0.000698	-0.000252
	(0.00206)	(0.00744)	(0.00877)	(0.000733)	(0.00242)	(0.00683)	(0.00777)	(0.00148)	(0.00344)	(0.00626)	(0.00713)	(0.00257)
Asset index	0.00193	0.00699	-0.00823	-0.000689	-0.000412	-0.00116	0.00132	0.000251	-0.00147	-0.00268	0.00305	0.00110
	(0.00164)	(0.00593)	(0.00696)	(0.000620)	(0.00180)	(0.00503)	(0.00574)	(0.00109)	(0.00267)	(0.00469)	(0.00539)	(0.00196)
HH consumption (log)	-0.00901	-0.0326	0.0384	0.00321	0.00215	0.00605	-0.00689	-0.00131	0.00419	0.00761	-0.00867	-0.00313
	(0.00662)	(0.0233)	(0.0276)	(0.00241)	(0.00756)	(0.0212)	(0.0242)	(0.00462)	(0.00975)	(0.0178)	(0.0202)	(0.00731)
% of members with job contract	-0.0635***	-0.230***	0.271***	0.0227***	-0.0634***	-0.178***	0.203***	0.0386***	-0.0686***	-0.125**	0.142**	0.0513**
	(0.0148)	(0.0494)	(0.0580)	(0.00629)	(0.0143)	(0.0367)	(0.0423)	(0.00933)	(0.0248)	(0.0522)	(0.0564)	(0.0203)
HH receives social assistance	-0.0111	-0.0470	0.0530	0.00514	0.00674	0.0174	-0.0205	-0.00370	-0.00351	-0.00662	0.00740	0.00273
	(0.0113)	(0.0549)	(0.0595)	(0.00674)	(0.0188)	(0.0443)	(0.0538)	(0.00927)	(0.0217)	(0.0423)	(0.0465)	(0.0175)
HH has formal credit	-0.00174	-0.00641	0.00751	0.000639	0.0325*	0.0662**	-0.0851**	-0.0136**	0.0414	0.0531**	-0.0723*	-0.0223**
	(0.0113)	(0.0424)	(0.0494)	(0.00428)	(0.0193)	(0.0268)	(0.0401)	(0.00610)	(0.0275)	(0.0221)	(0.0382)	(0.0111)
HH has savings	0.0289***	0.107***	-0.126***	-0.0102***	0.0163*	0.0456*	-0.0520*	-0.00989*	0.00586	0.0106	-0.0121	-0.00437
	(0.00887)	(0.0298)	(0.0354)	(0.00329)	(0.00957)	(0.0258)	(0.0297)	(0.00568)	(0.0125)	(0.0230)	(0.0262)	(0.00940)
HH has bank account	0.000199	0.000722	-0.000850	-7.10e-05	-0.000563	-0.00158	0.00180	0.000343	-0.00125	-0.00227	0.00259	0.000933
	(0.00918)	(0.0333)	(0.0392)	(0.00328)	(0.0106)	(0.0297)	(0.0338)	(0.00642)	(0.0142)	(0.0258)	(0.0294)	(0.0106)
HH has formal insurance	-0.00823	-0.0329	0.0377	0.00343	-0.0199**	-0.0726*	0.0756**	0.0169*	-0.0321***	-0.0817**	0.0793**	0.0346**
	(0.00832)	(0.0360)	(0.0403)	(0.00400)	(0.00835)	(0.0377)	(0.0364)	(0.00978)	(0.0117)	(0.0387)	(0.0328)	(0.0174)
Distance to main road	-0.000181	-0.000657	0.000774	6.47e-05	-0.000246	-0.000693	0.000790	0.000150	-0.000418*	-0.000761*	0.000867*	0.000313*
	(0.000156)	(0.000561)	(0.000660)	(5.67e-05)	(0.000176)	(0.000495)	(0.000566)	(0.000106)	(0.000227)	(0.000405)	(0.000466)	(0.000164)
Distance to urban center	-4.57e-05	-0.000166	0.000195	1.63e-05	-0.000132*	-0.000373**	0.000424**	8.06e-05*	-0.000138	-0.000250	0.000285	0.000103
	(5.15e-05)	(0.000188)	(0.000220)	(1.89e-05)	(6.85e-05)	(0.000187)	(0.000213)	(4.33e-05)	(9.06e-05)	(0.000161)	(0.000183)	(6.77e-05)
Distance to market	-0.000476	-0.00173	0.00203	0.000170	-0.000356	-0.00100	0.00114	0.000217	-0.000705	-0.00128	0.00146	0.000527
	(0.000300)	(0.00108)	(0.00127)	(0.000108)	(0.000345)	(0.000967)	(0.00111)	(0.000207)	(0.000466)	(0.000854)	(0.000972)	(0.000345)

(Continued)

Table A.4. (contd.) Ordered probit, total income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Microfinance institution	-0.00341	-0.0124	0.0145	0.00123	0.00690	0.0192	-0.0220	-0.00412	0.0149	0.0265	-0.0306	-0.0108
	(0.00761)	(0.0278)	(0.0326)	(0.00280)	(0.00866)	(0.0239)	(0.0273)	(0.00524)	(0.0118)	(0.0211)	(0.0241)	(0.00870)
Electricity	0.00876	0.0340	-0.0394	-0.00340	-0.00303	-0.00835	0.00957	0.00180	0.00114	0.00208	-0.00237	-0.000857
	(0.00800)	(0.0330)	(0.0376)	(0.00342)	(0.0105)	(0.0281)	(0.0326)	(0.00605)	(0.0140)	(0.0258)	(0.0292)	(0.0106)
Safe water	0.00339	0.0119	-0.0141	-0.00114	0.00513	0.0136	-0.0158	-0.00290	0.0197	0.0298	-0.0373	-0.0122
	(0.00953)	(0.0323)	(0.0388)	(0.00302)	(0.0112)	(0.0280)	(0.0333)	(0.00595)	(0.0156)	(0.0197)	(0.0267)	(0.00846)
Toilet	0.0258*	0.0701**	-0.0901**	-0.00581**	0.0254	0.0522**	-0.0669*	-0.0107**	0.0212	0.0307	-0.0392	-0.0127
	(0.0152)	(0.0299)	(0.0427)	(0.00249)	(0.0164)	(0.0239)	(0.0353)	(0.00505)	(0.0193)	(0.0214)	(0.0314)	(0.00919)
HH income (log)	-0.00805***	-0.0292***	0.0344***	0.00287***	-0.00995***	-0.0280***	0.0319***	0.00606***	-0.0119***	-0.0216***	0.0246***	0.00888***
	(0.00262)	(0.00819)	(0.00973)	(0.00108)	(0.00330)	(0.00805)	(0.00930)	(0.00212)	(0.00388)	(0.00653)	(0.00731)	(0.00299)
Demographic Dependency Ratio	0.000241	0.000873	-0.00103	-8.60e-05	-0.00134	-0.00376	0.00428	0.000814	-0.00581	-0.0106	0.0120	0.00434
	(0.00499)	(0.0180)	(0.0212)	(0.00178)	(0.00546)	(0.0154)	(0.0175)	(0.00335)	(0.00826)	(0.0145)	(0.0167)	(0.00609)
Economic Dependency Ratio	0.00329	0.0119	-0.0140	-0.00117	0.00224	0.00630	-0.00717	-0.00136	0.00438	0.00797	-0.00907	-0.00328
	(0.00223)	(0.00803)	(0.00946)	(0.000806)	(0.00224)	(0.00631)	(0.00714)	(0.00141)	(0.00366)	(0.00636)	(0.00728)	(0.00273)
Income diversification	0.0201*	0.0728*	-0.0857*	-0.00717*	0.0187	0.0527	-0.0600	-0.0114	0.0147	0.0268	-0.0305	-0.0110
	(0.0109)	(0.0379)	(0.0448)	(0.00407)	(0.0121)	(0.0327)	(0.0376)	(0.00723)	(0.0157)	(0.0286)	(0.0327)	(0.0116)
Rural	-0.0297**	-0.0993***	0.120**	0.00883**	-0.0331**	-0.0815***	0.0973***	0.0173***	-0.0239	-0.0402	0.0476	0.0165
	(0.0125)	(0.0382)	(0.0469)	(0.00370)	(0.0139)	(0.0275)	(0.0349)	(0.00655)	(0.0163)	(0.0258)	(0.0311)	(0.0109)
HH received assistance since COVID-19 outbreak	0.0230	0.0653	-0.0827	-0.00563*	0.0269*	0.0575**	-0.0727**	-0.0117**	0.0441*	0.0572***	-0.0779**	-0.0234**
	(0.0193)	(0.0433)	(0.0593)	(0.00335)	(0.0150)	(0.0250)	(0.0349)	(0.00513)	(0.0261)	(0.0205)	(0.0364)	(0.00975)
Observations	2,344	2,344	2,344	2,344	2,346	2,346	2,346	2,346	2,347	2,347	2,347	2,347

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4. (contd.) Ordered probit, total income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	-0.00165	-0.00310	0.00278	0.00197	-0.000920	-0.00220	0.00151	0.00161	-0.00137	-0.00329	0.00204	0.00262
	(0.00130)	(0.00249)	(0.00222)	(0.00156)	(0.00113)	(0.00273)	(0.00187)	(0.00198)	(0.00117)	(0.00280)	(0.00176)	(0.00220)
HH head is female	0.0102	0.0180	-0.0168	-0.0115	0.0228	0.0477	-0.0357	-0.0347	0.0284	0.0582	-0.0404	-0.0462
	(0.0228)	(0.0366)	(0.0358)	(0.0236)	(0.0225)	(0.0366)	(0.0311)	(0.0279)	(0.0241)	(0.0368)	(0.0297)	(0.0310)
Age of HH head	0.000673	0.00126	-0.00113	-0.000802	0.000735	0.00176*	-0.00121*	-0.00129*	0.000402	0.000965	-0.000599	-0.000768
	(0.000473)	(0.000840)	(0.000754)	(0.000554)	(0.000447)	(0.000954)	(0.000674)	(0.000721)	(0.000400)	(0.000929)	(0.000578)	(0.000749)
HH head is married	0.00689	0.0134	-0.0118	-0.00854	0.00394	0.00963	-0.00651	-0.00707	0.00505	0.0124	-0.00755	-0.00993
	(0.0202)	(0.0398)	(0.0344)	(0.0256)	(0.0180)	(0.0443)	(0.0296)	(0.0328)	(0.0182)	(0.0453)	(0.0270)	(0.0364)
HH size	-0.00296	-0.00555	0.00498	0.00353	-0.00408	-0.00975	0.00669	0.00714	-0.00219	-0.00526	0.00327	0.00419
	(0.00339)	(0.00625)	(0.00564)	(0.00399)	(0.00311)	(0.00714)	(0.00499)	(0.00523)	(0.00301)	(0.00719)	(0.00448)	(0.00571)
Asset index	-0.00126	-0.00237	0.00213	0.00151	-0.00249	-0.00595	0.00408	0.00436	-0.00228	-0.00548	0.00340	0.00436
	(0.00261)	(0.00473)	(0.00430)	(0.00304)	(0.00258)	(0.00564)	(0.00393)	(0.00429)	(0.00259)	(0.00579)	(0.00364)	(0.00474)
HH consumption (log)	0.000210	0.000394	-0.000354	-0.000250	0.00482	0.0115	-0.00792	-0.00844	0.00866	0.0208	-0.0129	-0.0165
	(0.00968)	(0.0181)	(0.0163)	(0.0115)	(0.00852)	(0.0207)	(0.0141)	(0.0151)	(0.00821)	(0.0198)	(0.0121)	(0.0159)
% of members with job contract	-0.0684***	-0.128**	0.115**	0.0815**	-0.0557**	-0.133**	0.0914**	0.0974**	-0.0518**	-0.124*	0.0772**	0.0990**
	(0.0261)	(0.0578)	(0.0491)	(0.0340)	(0.0229)	(0.0663)	(0.0439)	(0.0448)	(0.0231)	(0.0657)	(0.0393)	(0.0490)
HH receives social assistance	-0.00183	-0.00350	0.00311	0.00222	0.00179	0.00420	-0.00292	-0.00307	-0.00323	-0.00804	0.00487	0.00640
	(0.0231)	(0.0449)	(0.0395)	(0.0285)	(0.0206)	(0.0474)	(0.0333)	(0.0347)	(0.0202)	(0.0521)	(0.0309)	(0.0414)
HH has formal credit	0.0165	0.0266	-0.0260	-0.0172	0.00197	0.00462	-0.00321	-0.00339	-0.00502	-0.0127	0.00764	0.0101
	(0.0245)	(0.0322)	(0.0347)	(0.0220)	(0.0204)	(0.0465)	(0.0327)	(0.0342)	(0.0191)	(0.0517)	(0.0300)	(0.0408)
HH has savings	0.0158	0.0289	-0.0260	-0.0186	0.0216*	0.0497*	-0.0343**	-0.0370*	0.0205*	0.0473*	-0.0295*	-0.0383*
	(0.0123)	(0.0229)	(0.0202)	(0.0149)	(0.0113)	(0.0257)	(0.0174)	(0.0194)	(0.0115)	(0.0257)	(0.0157)	(0.0213)
HH has bank account	-0.0313**	-0.0570**	0.0522**	0.0360**	-0.0197	-0.0464	0.0322	0.0339	-0.0264*	-0.0618**	0.0390**	0.0492**
	(0.0156)	(0.0260)	(0.0244)	(0.0169)	(0.0128)	(0.0293)	(0.0204)	(0.0215)	(0.0135)	(0.0292)	(0.0188)	(0.0235)
HH has formal insurance	-0.0165	-0.0365	0.0299	0.0231	-0.0198**	-0.0599*	0.0360*	0.0437*	-0.00828	-0.0216	0.0127	0.0172
	(0.0128)	(0.0334)	(0.0252)	(0.0208)	(0.0100)	(0.0359)	(0.0194)	(0.0264)	(0.0139)	(0.0404)	(0.0224)	(0.0318)
Distance to main road	-0.000559**	-0.00105***	0.000940***	0.000665***	-0.000424**	-0.00101**	0.000696**	0.000742**	-0.000431**	-0.00103**	0.000641**	0.000823**
	(0.000220)	(0.000402)	(0.000359)	(0.000254)	(0.000202)	(0.000491)	(0.000320)	(0.000368)	(0.000210)	(0.000492)	(0.000297)	(0.000398)
Distance to urban center	-0.000160**	-0.000301**	0.000270**	0.000191**	-0.000158**	-0.000377**	0.000259**	0.000276**	-0.000145**	-0.000349**	0.000216**	0.000278**
	(7.91e-05)	(0.000138)	(0.000127)	(8.77e-05)	(7.36e-05)	(0.000148)	(0.000106)	(0.000114)	(7.34e-05)	(0.000152)	(9.85e-05)	(0.000125)
Distance to market	-0.000889**	-0.00167**	0.00150**	0.00106**	-0.000755*	-0.00181*	0.00124*	0.00132*	-0.000951**	-0.00228**	0.00142**	0.00182**
	(0.000451)	(0.000849)	(0.000756)	(0.000533)	(0.000396)	(0.000982)	(0.000663)	(0.000706)	(0.000415)	(0.00101)	(0.000615)	(0.000793)

(Continued)

Table A.4. (contd.) Ordered probit, total income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Microfinance institution	0.00552	0.0102	-0.00925	-0.00651	-0.00157	-0.00378	0.00259	0.00277	-0.00132	-0.00318	0.00197	0.00253
	(0.0114)	(0.0211)	(0.0191)	(0.0133)	(0.00940)	(0.0225)	(0.0154)	(0.0165)	(0.0103)	(0.0248)	(0.0153)	(0.0198)
Electricity	-0.000411	-0.000768	0.000691	0.000488	-0.00458	-0.0107	0.00743	0.00783	0.00543	0.0134	-0.00818	-0.0107
	(0.0147)	(0.0274)	(0.0246)	(0.0174)	(0.0135)	(0.0306)	(0.0218)	(0.0224)	(0.0127)	(0.0324)	(0.0193)	(0.0258)
Safe water	0.0306	0.0431**	-0.0455*	-0.0281**	0.0220	0.0421*	-0.0329*	-0.0312*	0.0215	0.0420*	-0.0297*	-0.0338*
	(0.0187)	(0.0193)	(0.0240)	(0.0135)	(0.0149)	(0.0221)	(0.0198)	(0.0170)	(0.0138)	(0.0222)	(0.0176)	(0.0181)
Toilet	0.0213	0.0315	-0.0322	-0.0205	0.0178	0.0344	-0.0266	-0.0255	0.0235	0.0435*	-0.0317	-0.0353*
	(0.0191)	(0.0215)	(0.0257)	(0.0147)	(0.0168)	(0.0249)	(0.0223)	(0.0192)	(0.0168)	(0.0227)	(0.0199)	(0.0193)
HH income (log)	-0.0104***	-0.0194***	0.0174***	0.0123***	-0.00920**	-0.0220***	0.0151***	0.0161***	-0.00762**	-0.0183**	0.0113**	0.0146**
	(0.00394)	(0.00674)	(0.00599)	(0.00452)	(0.00361)	(0.00729)	(0.00508)	(0.00570)	(0.00362)	(0.00767)	(0.00484)	(0.00635)
Demographic Dependency Ratio	-0.000787	-0.00148	0.00133	0.000938	0.00397	0.00948	-0.00651	-0.00694	-7.28e-05	-0.000175	0.000108	0.000139
	(0.00762)	(0.0142)	(0.0128)	(0.00904)	(0.00638)	(0.0160)	(0.0108)	(0.0116)	(0.00654)	(0.0157)	(0.00974)	(0.0125)
Economic Dependency Ratio	0.00640*	0.0120*	-0.0108*	-0.00762*	0.00723**	0.0173**	-0.0119**	-0.0127**	0.00598*	0.0144*	-0.00891*	-0.0114*
	(0.00383)	(0.00674)	(0.00607)	(0.00443)	(0.00336)	(0.00725)	(0.00498)	(0.00554)	(0.00340)	(0.00765)	(0.00471)	(0.00627)
Income diversification	0.0115	0.0215	-0.0193	-0.0136	0.00290	0.00693	-0.00476	-0.00507	0.00715	0.0172	-0.0107	-0.0137
	(0.0160)	(0.0302)	(0.0271)	(0.0191)	(0.0137)	(0.0329)	(0.0226)	(0.0240)	(0.0138)	(0.0332)	(0.0207)	(0.0263)
Rural	-0.0184	-0.0319	0.0298	0.0205	-0.0148	-0.0330	0.0235	0.0243	-0.00540	-0.0127	0.00797	0.0101
	(0.0158)	(0.0256)	(0.0244)	(0.0168)	(0.0137)	(0.0274)	(0.0203)	(0.0207)	(0.0137)	(0.0313)	(0.0199)	(0.0251)
HH received assistance since COVID-19 outbreak	0.00888	0.0155	-0.0145	-0.00989	0.0141	0.0304	-0.0223	-0.0222	0.0133	0.0291	-0.0193	-0.0232
	(0.0183)	(0.0291)	(0.0286)	(0.0188)	(0.0172)	(0.0309)	(0.0249)	(0.0232)	(0.0158)	(0.0297)	(0.0213)	(0.0242)
Observations	2,344	2,344	2,344	2,344	2,346	2,346	2,346	2,346	2,338	2,338	2,338	2,338

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5. Ordered probit, farm income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	-0.000162	-0.00105	0.00110	0.000115	-0.000382	-0.00382	0.00323	0.000972	2.50e-05	0.000465	-0.000373	-0.000117
	(0.000910)	(0.00591)	(0.00617)	(0.000648)	(0.000635)	(0.00646)	(0.00547)	(0.00163)	(0.000380)	(0.00702)	(0.00563)	(0.00177)
HH income (log)	-0.000180	-0.00116	0.00121	0.000127	0.00277	0.0277	-0.0234	-0.00705	0.00128	0.0238	-0.0191	-0.00601
	(0.00277)	(0.0178)	(0.0186)	(0.00194)	(0.00219)	(0.0192)	(0.0162)	(0.00528)	(0.00140)	(0.0193)	(0.0156)	(0.00513)
HH consumption (log)	0.00915	0.0590	-0.0617	-0.00646	0.00433	0.0433	-0.0366	-0.0110	0.00113	0.0211	-0.0169	-0.00531
	(0.00624)	(0.0365)	(0.0379)	(0.00503)	(0.00442)	(0.0476)	(0.0394)	(0.0127)	(0.00269)	(0.0539)	(0.0427)	(0.0138)
HH head is female	-0.00946	-0.0696	0.0702	0.00881	0.00185	0.0179	-0.0153	-0.00441	-0.00273	-0.0560	0.0433	0.0155
	(0.00817)	(0.0673)	(0.0652)	(0.0105)	(0.00863)	(0.0810)	(0.0703)	(0.0194)	(0.00465)	(0.0969)	(0.0714)	(0.0300)
Age of HH head	0.000362	0.00233	-0.00244	-0.000255	0.000440	0.00441**	-0.00373**	-0.00112*	0.000207	0.00385*	-0.00308*	-0.000970*
	(0.000303)	(0.00173)	(0.00183)	(0.000210)	(0.000312)	(0.00211)	(0.00181)	(0.000643)	(0.000206)	(0.00201)	(0.00166)	(0.000574)
HH head is married	0.00565	0.0395	-0.0405	-0.00464	0.00306	0.0319	-0.0264	-0.00861	-0.0100	-0.134	0.116	0.0283
	(0.00952)	(0.0705)	(0.0712)	(0.00891)	(0.00783)	(0.0831)	(0.0672)	(0.0238)	(0.00957)	(0.0856)	(0.0771)	(0.0174)
HH size	0.00243	0.0157	-0.0164	-0.00171	0.000526	0.00526	-0.00445	-0.00134	0.000362	0.00673	-0.00540	-0.00170
	(0.00182)	(0.0115)	(0.0119)	(0.00143)	(0.00144)	(0.0151)	(0.0127)	(0.00384)	(0.000727)	(0.0149)	(0.0119)	(0.00373)
Asset index	-0.00397	-0.0256	0.0268	0.00280	-0.00481*	-0.0481**	0.0407**	0.0122*	-0.000429	-0.00799	0.00640	0.00201
	(0.00326)	(0.0195)	(0.0201)	(0.00274)	(0.00265)	(0.0211)	(0.0175)	(0.00647)	(0.00117)	(0.0214)	(0.0171)	(0.00547)
Land is irrigated	0.0220	0.105	-0.118	-0.00901	0.0113	0.0908	-0.0827	-0.0193	-0.00132	-0.0267	0.0209	0.00703
	(0.0217)	(0.0730)	(0.0890)	(0.00614)	(0.0139)	(0.0924)	(0.0895)	(0.0170)	(0.00626)	(0.134)	(0.103)	(0.0374)
Organic fertilizer	-0.0535**	-0.221***	0.255***	0.0199**	-0.0385*	-0.216***	0.202***	0.0522***	-0.0131	-0.154**	0.129**	0.0381*
	(0.0244)	(0.0503)	(0.0644)	(0.00981)	(0.0199)	(0.0510)	(0.0505)	(0.0186)	(0.0124)	(0.0758)	(0.0644)	(0.0226)
Title of the land	-0.00855	-0.0525	0.0557	0.00526	-0.0101	-0.0892	0.0781	0.0212	-0.00894	-0.130	0.108	0.0306
	(0.0106)	(0.0627)	(0.0679)	(0.00557)	(0.00907)	(0.0642)	(0.0585)	(0.0150)	(0.00919)	(0.0847)	(0.0744)	(0.0190)
% of members with job contract	0.00606	0.0391	-0.0408	-0.00427	0.0509**	0.509***	-0.430***	-0.129**	-0.0180	-0.335	0.268	0.0843
	(0.0166)	(0.107)	(0.112)	(0.0120)	(0.0229)	(0.193)	(0.164)	(0.0547)	(0.0164)	(0.221)	(0.175)	(0.0616)
HHI_crop	0.0290**	0.187***	-0.196***	-0.0205*	0.0271**	0.271***	-0.229***	-0.0688**	0.0164	0.304***	-0.244***	-0.0767**
	(0.0134)	(0.0712)	(0.0734)	(0.0120)	(0.0126)	(0.0772)	(0.0643)	(0.0275)	(0.0121)	(0.0943)	(0.0743)	(0.0321)
Land size (hectares)	-0.00553**	-0.0357**	0.0373**	0.00390*	-0.00189	-0.0189	0.0160	0.00480	-0.00265	-0.0494**	0.0396**	0.0124**
	(0.00280)	(0.0150)	(0.0157)	(0.00234)	(0.00178)	(0.0159)	(0.0136)	(0.00413)	(0.00209)	(0.0197)	(0.0162)	(0.00562)
Income diversification	0.00666	0.0430	-0.0449	-0.00470	0.00412	0.0412	-0.0348	-0.0105	0.000694	0.0129	-0.0104	-0.00326
	(0.00966)	(0.0613)	(0.0643)	(0.00670)	(0.00738)	(0.0748)	(0.0634)	(0.0189)	(0.00445)	(0.0834)	(0.0670)	(0.0208)
Social assistance	0.00305	0.0188	-0.0199	-0.00195	-0.00407	-0.0437	0.0356	0.0122	-0.00397	-0.0938	0.0698	0.0280
	(0.0123)	(0.0724)	(0.0776)	(0.00705)	(0.00677)	(0.0753)	(0.0586)	(0.0235)	(0.00421)	(0.0890)	(0.0606)	(0.0324)
Agricultural machinery	0.00849	0.0503	-0.0535	-0.00522	0.00483	0.0461	-0.0397	-0.0112	0.0135	0.189***	-0.162***	-0.0402***
	(0.0100)	(0.0544)	(0.0595)	(0.00513)	(0.00725)	(0.0610)	(0.0543)	(0.0140)	(0.0109)	(0.0587)	(0.0558)	(0.0142)

(Continued)

Table A.5 (contd.). Ordered probit, farm income change.

Variables	Round 1				Round 2				Round 3			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Formal credit	0.0103	0.0580	-0.0626	-0.00568	0.00727	0.0626	-0.0553	-0.0146	0.00299	0.0482	-0.0398	-0.0114
	(0.0124)	(0.0605)	(0.0678)	(0.00530)	(0.00873)	(0.0663)	(0.0605)	(0.0146)	(0.00525)	(0.0726)	(0.0610)	(0.0168)
Savings	0.0155*	0.0973*	-0.103*	-0.00988*	0.00196	0.0194	-0.0164	-0.00491	0.00897	0.138**	-0.113**	-0.0342**
	(0.00934)	(0.0541)	(0.0581)	(0.00595)	(0.00568)	(0.0555)	(0.0473)	(0.0139)	(0.00719)	(0.0582)	(0.0492)	(0.0155)
Bank account	-0.00410	-0.0263	0.0274	0.00296	-0.00637	-0.0652	0.0550	0.0166	-0.00667	-0.128**	0.101**	0.0339*
	(0.00847)	(0.0554)	(0.0575)	(0.00642)	(0.00620)	(0.0604)	(0.0513)	(0.0156)	(0.00549)	(0.0631)	(0.0498)	(0.0188)
Formal insurance	0.00245	0.0153	-0.0161	-0.00162	-0.00740	-0.0878	0.0692	0.0261	-0.00384	-0.0944	0.0709	0.0273
	(0.0100)	(0.0599)	(0.0637)	(0.00627)	(0.00563)	(0.0713)	(0.0523)	(0.0250)	(0.00354)	(0.0870)	(0.0611)	(0.0292)
Distance to road	-0.000101	-0.000653	0.000683	7.14e-05	-3.87e-05	-0.000387	0.000327	9.83e-05	1.52e-05	0.000283	-0.000227	-7.13e-05
	(0.000107)	(0.000695)	(0.000730)	(7.50e-05)	(7.21e-05)	(0.000721)	(0.000616)	(0.000178)	(5.12e-05)	(0.000901)	(0.000722)	(0.000230)
Distance to urban center	1.70e-05	0.000110	-0.000115	-1.20e-05	1.04e-05	0.000104	-8.84e-05	-2.66e-05	1.17e-05	0.000218	-0.000175	-5.50e-05
	(4.00e-05)	(0.000259)	(0.000269)	(2.95e-05)	(2.94e-05)	(0.000287)	(0.000243)	(7.36e-05)	(1.87e-05)	(0.000308)	(0.000248)	(7.81e-05)
Distance to market	-0.000458	-0.00295*	0.00309*	0.000323	-0.000730**	-0.00730***	0.00617***	0.00186***	-0.000470	-0.00874***	0.00701***	0.00220***
	(0.000279)	(0.00175)	(0.00183)	(0.000220)	(0.000349)	(0.00248)	(0.00219)	(0.000701)	(0.000327)	(0.00270)	(0.00221)	(0.000822)
Microfinance institution	-0.00380	-0.0254	0.0263	0.00287	0.00304	0.0292	-0.0250	-0.00723	-0.00241	-0.0492	0.0387	0.0130
	(0.00677)	(0.0467)	(0.0482)	(0.00528)	(0.00612)	(0.0566)	(0.0487)	(0.0140)	(0.00356)	(0.0651)	(0.0506)	(0.0180)
Electricity	-0.0172*	-0.103**	0.109**	0.0111*	-0.00393	-0.0387	0.0329	0.00972	-0.00377	-0.0647	0.0524	0.0160
	(0.00981)	(0.0435)	(0.0485)	(0.00572)	(0.00540)	(0.0517)	(0.0442)	(0.0129)	(0.00393)	(0.0573)	(0.0471)	(0.0139)
Safe water	0.0379**	0.159***	-0.185***	-0.0116**	0.0224	0.152**	-0.144**	-0.0296**	0.00478	0.0723	-0.0610	-0.0161
	(0.0182)	(0.0491)	(0.0621)	(0.00542)	(0.0151)	(0.0643)	(0.0670)	(0.0127)	(0.00644)	(0.0764)	(0.0669)	(0.0157)
Toilet	0.261	0.222**	-0.468***	-0.0145**	0.105*	0.263***	-0.327***	-0.0406***	0.0178	0.168	-0.155	-0.0307
	(0.194)	(0.0929)	(0.107)	(0.00635)	(0.0599)	(0.0393)	(0.0744)	(0.0110)	(0.0339)	(0.169)	(0.180)	(0.0220)
Demographic Dependency Ratio	0.00346	0.0223	-0.0233	-0.00244	0.00151	0.0151	-0.0128	-0.00385	-0.000883	-0.0164	0.0132	0.00414
	(0.00442)	(0.0270)	(0.0284)	(0.00313)	(0.00309)	(0.0303)	(0.0257)	(0.00774)	(0.00181)	(0.0317)	(0.0255)	(0.00804)
Economic Dependency Ratio	0.000186	0.00120	-0.00125	-0.000131	-0.00155	-0.0155	0.0131	0.00395	5.26e-05	0.000978	-0.000784	-0.000247
	(0.00189)	(0.0122)	(0.0127)	(0.00133)	(0.00165)	(0.0149)	(0.0127)	(0.00387)	(0.000836)	(0.0156)	(0.0125)	(0.00396)
Rural	-0.00160	-0.0101	0.0107	0.00108	0.0117*	0.149	-0.109*	-0.0519	0.00456	0.111	-0.0820	-0.0340
	(0.0138)	(0.0855)	(0.0904)	(0.00895)	(0.00699)	(0.0973)	(0.0591)	(0.0463)	(0.00432)	(0.113)	(0.0758)	(0.0408)
HH received assistance since COVID-19 outbreak	0.0550**	0.203***	-0.245***	-0.0136**	0.0533**	0.267***	-0.278***	-0.0419***	0.00494	0.0765	-0.0641	-0.0174
	(0.0253)	(0.0534)	(0.0726)	(0.00607)	(0.0222)	(0.0529)	(0.0590)	(0.0123)	(0.00537)	(0.0617)	(0.0532)	(0.0137)
Observations	678	678	678	678	535	535	535	535	503	503	503	503

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5 (contd.). Ordered probit, farm income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Years of education	8.28e-05	0.000870	-0.000482	-0.000471	-0.000283	-0.00482	0.00156	0.00355	-1.55e-05	-0.00121	0.000287	0.000938
	(0.000613)	(0.00637)	(0.00352)	(0.00346)	(0.000432)	(0.00692)	(0.00221)	(0.00512)	(7.73e-05)	(0.00606)	(0.00144)	(0.00470)
HH income (log)	-0.00103	-0.0108	0.00599	0.00585	-0.00179	-0.0304	0.00981	0.0224	-0.000304	-0.0237	0.00563	0.0184
	(0.00169)	(0.0176)	(0.00969)	(0.00963)	(0.00154)	(0.0199)	(0.00648)	(0.0148)	(0.000317)	(0.0182)	(0.00450)	(0.0142)
HH consumption (log)	0.00504	0.0529	-0.0293	-0.0286	0.00245	0.0417	-0.0135	-0.0307	-0.000217	-0.0169	0.00401	0.0131
	(0.00379)	(0.0436)	(0.0233)	(0.0239)	(0.00272)	(0.0504)	(0.0157)	(0.0373)	(0.000579)	(0.0439)	(0.0105)	(0.0340)
HH head is female	0.00478	0.0460	-0.0273	-0.0236	0.00346	0.0531	-0.0193	-0.0372	-0.000200	-0.0161	0.00361	0.0127
	(0.0114)	(0.0979)	(0.0621)	(0.0472)	(0.00629)	(0.0835)	(0.0338)	(0.0558)	(0.000981)	(0.0817)	(0.0172)	(0.0655)
Age of HH head	0.000545	0.00572***	-0.00317***	-0.00310**	0.000275	0.00468***	-0.00151**	-0.00345**	5.44e-05	0.00424**	-0.00101**	-0.00329**
	(0.000353)	(0.00208)	(0.00114)	(0.00131)	(0.000248)	(0.00180)	(0.000627)	(0.00145)	(4.51e-05)	(0.00182)	(0.000488)	(0.00144)
HH head is married	-0.000763	-0.00791	0.00444	0.00424	-0.00312	-0.0486	0.0175	0.0342	-0.000821	-0.0560	0.0155	0.0413
	(0.00852)	(0.0882)	(0.0500)	(0.0468)	(0.00565)	(0.0818)	(0.0323)	(0.0549)	(0.00137)	(0.0773)	(0.0246)	(0.0542)
HH size	0.000591	0.00621	-0.00344	-0.00336	0.000854	0.0145	-0.00469	-0.0107	8.68e-05	0.00677	-0.00161	-0.00525
	(0.00125)	(0.0139)	(0.00766)	(0.00747)	(0.000731)	(0.0140)	(0.00444)	(0.0103)	(0.000157)	(0.0115)	(0.00275)	(0.00895)
Asset index	-0.00191	-0.0201	0.0111	0.0109	-0.000490	-0.00834	0.00269	0.00614	-3.48e-05	-0.00271	0.000644	0.00210
	(0.00172)	(0.0159)	(0.00905)	(0.00858)	(0.00118)	(0.0194)	(0.00631)	(0.0142)	(0.000239)	(0.0187)	(0.00443)	(0.0145)
Land is irrigated	-0.00461	-0.0564	0.0278	0.0332	-0.00532	-0.131*	0.0221**	0.114	-0.00148	-0.227***	-0.0240	0.252***
	(0.00788)	(0.105)	(0.0454)	(0.0671)	(0.00450)	(0.0783)	(0.00937)	(0.0787)	(0.00106)	(0.0500)	(0.0309)	(0.0763)
Organic fertilizer	-0.00700	-0.0657	0.0388	0.0340	0.000899	0.0156	-0.00490	-0.0115	0.000232	0.0186	-0.00427	-0.0145
	(0.00997)	(0.0746)	(0.0469)	(0.0376)	(0.00448)	(0.0799)	(0.0247)	(0.0597)	(0.000844)	(0.0687)	(0.0155)	(0.0541)
Title of the land	-0.0148	-0.128*	0.0779	0.0647*	-0.00704	-0.108	0.0398	0.0753	9.23e-05	0.00719	-0.00168	-0.00559
	(0.0126)	(0.0726)	(0.0500)	(0.0348)	(0.00723)	(0.0731)	(0.0307)	(0.0488)	(0.000915)	(0.0711)	(0.0164)	(0.0556)
% of members with job contract	-0.0314	-0.330*	0.183*	0.178*	-0.00580	-0.0986	0.0318	0.0726	-0.00167	-0.130	0.0309	0.101
	(0.0205)	(0.170)	(0.0965)	(0.0938)	(0.0113)	(0.182)	(0.0586)	(0.134)	(0.00250)	(0.174)	(0.0411)	(0.136)
HHI_crop	0.0164	0.172*	-0.0955*	-0.0933*	0.00462	0.0787	-0.0254	-0.0579	0.00187	0.146*	-0.0346*	-0.113*
	(0.0119)	(0.0884)	(0.0505)	(0.0500)	(0.00706)	(0.0949)	(0.0306)	(0.0712)	(0.00164)	(0.0774)	(0.0189)	(0.0618)
Land size (hectares)	-0.00138	-0.0145	0.00805	0.00786	-0.00189	-0.0321**	0.0104*	0.0237**	-0.000325	-0.0253*	0.00601	0.0196*
	(0.00131)	(0.0122)	(0.00690)	(0.00655)	(0.00166)	(0.0159)	(0.00573)	(0.0118)	(0.000283)	(0.0150)	(0.00396)	(0.0115)
Income diversification	0.00648	0.0681	-0.0378	-0.0369	-0.00144	-0.0245	0.00789	0.0180	-0.00107	-0.0833	0.0198	0.0646
	(0.00738)	(0.0748)	(0.0413)	(0.0408)	(0.00437)	(0.0703)	(0.0227)	(0.0519)	(0.00112)	(0.0689)	(0.0167)	(0.0539)
Social assistance	-0.00463	-0.0555	0.0278	0.0323	0.00467	0.0672	-0.0254	-0.0464	0.000747	0.0509	-0.0141	-0.0375
	(0.00637)	(0.0797)	(0.0352)	(0.0508)	(0.00633)	(0.0754)	(0.0324)	(0.0489)	(0.00145)	(0.0800)	(0.0255)	(0.0561)
Agricultural machinery	0.00823	0.0785	-0.0463	-0.0404	0.0127	0.173***	-0.0691**	-0.116***	0.00106	0.0728	-0.0201	-0.0538
	(0.00782)	(0.0561)	(0.0360)	(0.0279)	(0.0106)	(0.0566)	(0.0281)	(0.0387)	(0.00115)	(0.0547)	(0.0174)	(0.0388)

(Continued)

Table A.5 (contd.). Ordered probit, farm income change.

Variables	Round 4				Round 5				Round 6			
	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1	Marginal effects for -2	Marginal effects for -1	Marginal effects for 0	Marginal effects for +1
Formal credit	-0.00172	-0.0190	0.0103	0.0105	-0.000403	-0.00700	0.00222	0.00518	-0.000362	-0.0309	0.00648	0.0248
	(0.00551)	(0.0622)	(0.0329)	(0.0348)	(0.00408)	(0.0713)	(0.0223)	(0.0531)	(0.000743)	(0.0654)	(0.0121)	(0.0541)
Savings	0.0229**	0.188***	-0.108***	-0.103***	0.0130	0.177***	-0.0605**	-0.129***	0.00347	0.220***	-0.0601***	-0.163***
	(0.0117)	(0.0496)	(0.0305)	(0.0297)	(0.0103)	(0.0614)	(0.0237)	(0.0460)	(0.00272)	(0.0538)	(0.0195)	(0.0402)
Bank account	-0.0173*	-0.176***	0.0928***	0.101***	-0.00623	-0.110	0.0332	0.0828	-0.00233	-0.179***	0.0357***	0.145***
	(0.00953)	(0.0571)	(0.0322)	(0.0359)	(0.00582)	(0.0679)	(0.0208)	(0.0527)	(0.00183)	(0.0528)	(0.0134)	(0.0462)
Formal insurance	-0.00937*	-0.139**	0.0591***	0.0890*	-0.00549	-0.139**	0.0264**	0.118*	-0.00141	-0.200***	0.00292	0.198***
	(0.00516)	(0.0626)	(0.0206)	(0.0490)	(0.00428)	(0.0695)	(0.0103)	(0.0688)	(0.00101)	(0.0569)	(0.0223)	(0.0746)
Distance to road	-6.24e-05	-0.000655	0.000363	0.000355	-7.66e-05	-0.00130*	0.000421	0.000959*	-1.25e-05	-0.000975	0.000232	0.000756
	(7.13e-05)	(0.000726)	(0.000412)	(0.000384)	(6.42e-05)	(0.000783)	(0.000274)	(0.000565)	(1.37e-05)	(0.000873)	(0.000217)	(0.000676)
Distance to urban center	-2.93e-06	-3.08e-05	1.71e-05	1.67e-05	3.12e-05	0.000532*	-0.000172*	-0.000391*	3.54e-06	0.000276	-6.55e-05	-0.000214
	(2.13e-05)	(0.000224)	(0.000125)	(0.000121)	(2.65e-05)	(0.000274)	(8.90e-05)	(0.000209)	(4.90e-06)	(0.000347)	(8.51e-05)	(0.000268)
Distance to market	-0.000617*	-0.00649***	0.00359***	0.00351***	-0.000415	-0.00706***	0.00228***	0.00520***	-0.000101	-0.00785***	0.00186***	0.00609***
	(0.000322)	(0.00163)	(0.00108)	(0.000917)	(0.000302)	(0.00178)	(0.000799)	(0.00128)	(7.01e-05)	(0.00184)	(0.000671)	(0.00140)
Microfinance institution	-0.00583	-0.0674	0.0346	0.0386	-0.00912	-0.194***	0.0324**	0.170***	-0.00131	-0.119**	0.0167**	0.103**
	(0.00515)	(0.0593)	(0.0282)	(0.0362)	(0.00637)	(0.0543)	(0.0149)	(0.0593)	(0.000937)	(0.0524)	(0.00793)	(0.0504)
Electricity	-0.00352	-0.0359	0.0202	0.0192	-0.00618	-0.0924*	0.0313	0.0673*	0.000139	0.0110	-0.00259	-0.00852
	(0.00513)	(0.0503)	(0.0288)	(0.0266)	(0.00510)	(0.0549)	(0.0201)	(0.0393)	(0.000628)	(0.0502)	(0.0118)	(0.0391)
Safe water	0.0279	0.182***	-0.133**	-0.0766***	0.0120	0.140**	-0.0632*	-0.0886**	0.00222	0.133**	-0.0477	-0.0878**
	(0.0189)	(0.0623)	(0.0562)	(0.0237)	(0.00940)	(0.0616)	(0.0338)	(0.0347)	(0.00207)	(0.0659)	(0.0301)	(0.0383)
Toilet	0.00334	0.0320	-0.0189	-0.0164	0.0198	0.179**	-0.0910	-0.107**	0.00825	0.256***	-0.120**	-0.144***
	(0.0118)	(0.104)	(0.0650)	(0.0504)	(0.0176)	(0.0903)	(0.0625)	(0.0425)	(0.00726)	(0.0905)	(0.0612)	(0.0370)
Demographic Dependency Ratio	0.00179	0.0188	-0.0104	-0.0102	-0.000284	-0.00484	0.00156	0.00356	0.000374	0.0292	-0.00693	-0.0226
	(0.00279)	(0.0288)	(0.0158)	(0.0158)	(0.00192)	(0.0322)	(0.0104)	(0.0238)	(0.000450)	(0.0288)	(0.00707)	(0.0223)
Economic Dependency Ratio	-0.000513	-0.00539	0.00299	0.00292	-0.000111	-0.00188	0.000608	0.00139	0.000131	0.0102	-0.00242	-0.00790
	(0.00137)	(0.0139)	(0.00778)	(0.00754)	(0.000771)	(0.0129)	(0.00418)	(0.00953)	(0.000194)	(0.0133)	(0.00314)	(0.0104)
Rural	0.00213	0.0236	-0.0125	-0.0132	0.00105	0.0186	-0.00568	-0.0140	-0.000584	-0.0415	0.0114	0.0307
	(0.00823)	(0.0939)	(0.0479)	(0.0542)	(0.00531)	(0.0980)	(0.0283)	(0.0750)	(0.00155)	(0.0969)	(0.0297)	(0.0688)
HH received assistance since COVID-19 outbreak	-0.00148	-0.0160	0.00871	0.00880	-0.00337	-0.0622	0.0175	0.0481	0.000167	0.0127	-0.00311	-0.00975
	(0.00538)	(0.0601)	(0.0320)	(0.0334)	(0.00397)	(0.0680)	(0.0166)	(0.0553)	(0.000840)	(0.0613)	(0.0155)	(0.0467)
Observations	506	506	506	506	497	497	497	497	496	496	496	496

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

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Bioeconomy and resilience to economic shocks: insights from the COVID-19 pandemic in 2020

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Abstract. Using the latest release of employment and value added numbers in the bioeconomy sectors, we conducted an analysis on the performance of the EU bioeconomy during the COVID-19 pandemic in 2020. Our findings point to a possibly higher level of resilience of the bioeconomy sectors compared to the overall economy. While employment in the bioeconomy registered a similar (but slightly sharper) decrease to the total EU average (-1.7% vs. -1.4%), the value added fell substantially below average (-0.4% vs. -4.0%). The more contemporary biomass-processing sectors (chemicals and pharmaceuticals, as well as bioelectricity) performed better than the more traditional sectors (such as food or textiles). At the Member State level, we observe a high degree of heterogeneity in sectoral performance. By discussing these estimates alongside previous qualitative insights from the related literature, we emphasize the relevance of the bioeconomy not only for environmental sustainability but also for socioeconomic resilience.

Keywords: COVID-19 shock, bioeconomy, socioeconomic indicators, European Union, green transition, resilience.
JEL Codes: Q57, O44.

1. INTRODUCTION

The bioeconomy is composed by all those economic activities that depend on the use of biological resources. This definition includes not only all biomass-producing and processing sectors, but also related services (European Commission, 2018). The launch of the EU's Bioeconomy Strategy in 2012[1], along with its update in 2018[2], positioned the bioeconomy as both a

[1] Innovating for sustainable growth: A bioeconomy for Europe. https://op.europa.eu/en/publication-detail/-/publication/1f0d8515-8dc0-4435-ba53-9570e47dbd51
[2] A sustainable bioeconomy for Europe: Strengthening the connection between economy, society and the environment: updated bioeconomy strategy. https://op.europa.eu/en/publication-detail/-/publication/edace3e3-e189-11e8-b690-01aa75ed71a1/language-en/format-PDF/source-149755478

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key enabler and a result of transitioning to a green and fair economy in the EU. As a result, synergies have been identified with the overarching European Green Deal strategy, which aims to address climate and environmental challenges. Specifically, the Bioeconomy Strategy can help evaluate and address trade-offs between policy objectives and competing resource uses, promoting both environmental sustainability and socioeconomic gains and resilience (European Commission, 2022).

The significance of the bioeconomy in enhancing resilience to external economic shocks has gained considerable attention in both academic and policy debates, particularly in light of recent major events. In 2020, the COVID-19 pandemic strained global supply chains under stress, due to shifts in demand and labour shortages (OECD, 2020; Ozdemir et al., 2022; Galanakis et al., 2022). More recently, the Russian invasion of Ukraine led to price increases in basic resources like food and energy products (Ramanauske et al., 2022). In this context, the strategic importance of the bioeconomy has become evident in its potential to create shorter and more circular bio-based value chains, thus reducing dependence on imported basic resources (Farcas et al., 2020; Galanakis et al. 2022; European Commission, 2022). An additional step in this direction is the Council of the European Union's Conclusions on the opportunities of the bioeconomy, approved on April 25, 2023. These conclusions emphasize the potential of the bioeconomy to address challenges such as climate change, fossil fuel dependency and food security, as well as contributing to increased resilience[3].

Despite its recognized strategic importance, the literature examining the role and economic performance of the bioeconomy under the aforementioned events is still scarce and inconclusive. Some studies provided qualitative insights into the economic impact of these events on the bioeconomy (see Fritsche et al., 2021; Galanakis et al., 2022; Kulisic et al, 2021 or Woźniak & Tyczewska, 2021). An ex-ante quantitative assessment was also provided by González-Martínez et al. (2020). However, to the extent of our knowledge, an ex-post analysis on the impact of these events on the bioeconomy is still missing in the academic literature.

In June 2023, the EU-Bioeconomy Monitoring System[4] (EU-BMS, hereinafter) was updated with data on employment and value added in the bioeconomy sector for 2020. This fact opens the possibility of analysing the performance of the bioeconomy during the pandemic. Therefore, this article aims to fill the gap in the literature by using the latest release of the EU-BMS to answer the following research questions:

- What was the impact of the pandemic on the bioeconomy in the EU and its Member States?
- Did the bioeconomy sectors exhibit greater resilience compared to the overall economy and other sectors?
- Are there any drivers or common sectoral patterns explaining the performance of the bioeconomy across countries in 2020?

This short article is structured as follows. Section 2 describes the methodology to estimate jobs and value added in the EU bioeconomy. Section 3 presents and discusses the main results. Section 4 concludes.

2. DATA AND METHODOLOGY

The sectoral scope of this study comprises all biomass producing and transforming activities, namely the primary sectors and the bio-based manufacturing and electricity ones presents the selected sectors in this study and their contributions to the bioeconomy.

The indicators on employment and value added in these sectors from the EU-BMS are computed following the methodology proposed by Ronzon et al. (2018, 2020, 2022) and Lasarte-López et al. (2023a). The process involves two main steps. In the first step, data from Eurostat is collected and cleaned for sectors falling within the bioeconomy scope defined by the EU's Bioeconomy Strategy (European Commission, 2018). National Accounts data is used for primary sectors (nama_10_a64_e for employment and nama_10_a64 for value added), while Structural Business Statistics (sbs_na_ind_r2) is used for bio-based manufacturing and electricity.

In the second step, output bio-based shares are applied to those sectors considered as 'hybrid' (their output can contain biomass but also other non-bio-based materials). These shares inform about the proportion of final production by sector made of biomass. Therefore, this approach assumes that the quantity of jobs and value added from each sector allocated to the bioeconomy is proportional to its bio-based output.

The bio-based shares are initially prepared at the product level (for each item in the PRODCOM product classification). The proportion of biomass incorporated by all products is estimated using expert knowledge and scientific literature review. This information is then aggregated to determine sectoral bio-based shares at

[3] Access to the press release and related documents: https://www.consilium.europa.eu/en/press/press-releases/2023/04/25/promoting-a-more-sustainable-competitive-and-resilient-europe-and-boosting-rural-areas-council-approves-conclusions-on-the-opportunities-of-the-bioeconomy/
[4] Access to the EU- Bioeconomy Monitoring System: https://knowledge4policy.ec.europa.eu/bioeconomy/monitoring_en

Table 1. Sectoral scope and bio-based share by sector.

	Sectors	NACE codes	Aggregated bio-based share for the EU27
Primary sectors	Agriculture, forestry and fishing	A01, A02, A03	100
	Food, beverages and tobacco	C10, C11, C12	100
	Bio-based textiles	C13, C14, C15	42.0
Bio-based manufacturing and electricity	Wood products and furniture	C16, C31	72.4
	Paper	C17	99.5
	Bio-based chemicals, pharmaceuticals and rubber	C20, C21, C22	13.7
	Bio-based electricity	D3511	5.8

Own elaboration from Lasarte-López et al. (2023b).

the 2- and 4- digit levels of the NACE classification (see Ronzon et al., 2017, for details).

The latest release of the EU-BMS indicators was conducted with a different data pre-processing than previous releases. This new pre-processing incorporates additional economic information (when available) to estimate missing values. Specifically, National Accounts estimates on employment and value added by sectors are used as auxiliary variables to compute missing values in Structural Business Statistics (see Lasarte-López et al., 2023a, for details).

3. RESULTS

3.1. General trends in the EU

The EU bioeconomy provided 17.16 million jobs in 2020 (8.3% of total employment) and contributed with 664.82 billion euro value added (4.9% of total GDP). These figures reflect a decline in employment above the EU average in comparison to 2019 (-1.7% vs. -1.4%), and a slight decline in the value added with regard to GDP (-0.4% vs. -4.0%).

The decline in employment and value added are explained by differences in behaviours by sector. Figure 1 illustrates the growth rates of employment and value added and their breakdown by sector. As for employment, most sectors registered negative growth in 2020, with the primary and the traditional biomass-transforming sectors (particularly, food and textiles) explaining a large portion of the total decline. Regarding value added, the impacts are mixed; while more traditional bio-based sectors exhibited a negative impact (excluding wood and furniture manufacturing sectors), the bio-based chemicals and pharmaceuticals, plastics, and rubber sectors continued to grow in 2020.

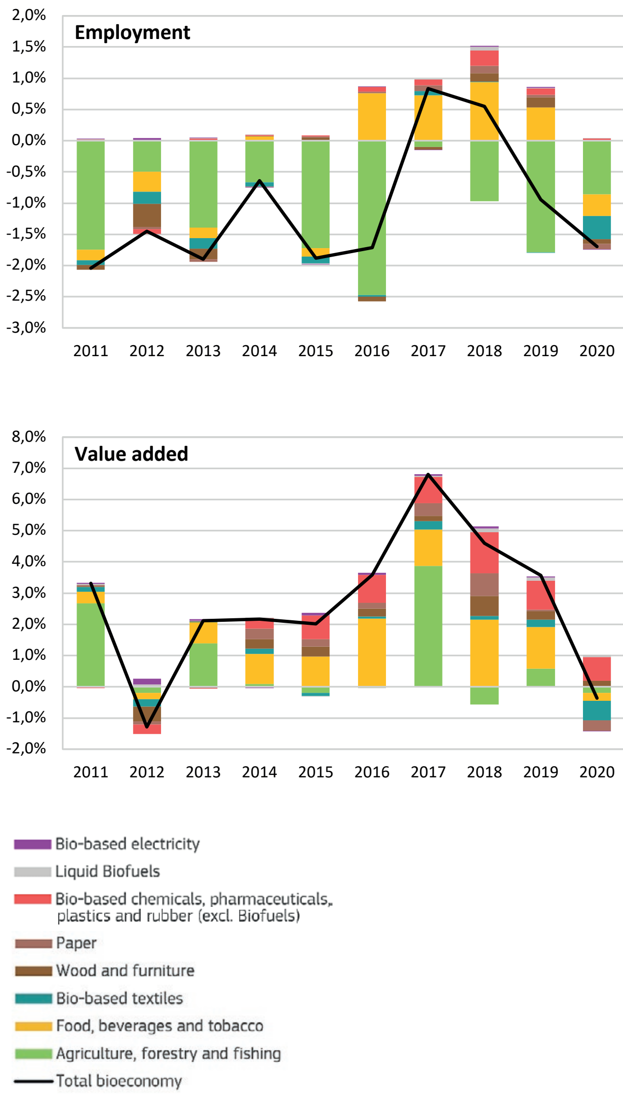

Figure 1. Growth rate of employment and value added in the EU bioeconomy, and decomposition by sector. Source: Own elaboration from Lasarte-López et al. (2023b).

3.2. Analysis by Member States

The heterogeneous behaviour is also manifested in the evolution of the bioeconomy for the 27 EU Member States (MS). Section 3.2.1 describes the employment dynamics in the bioeconomy sectors by MS, while Section 3.2.2 focuses on value added by MS.

3.2.1. Employment in the bioeconomy by MS

Table 2 shows the growth rate of employment in 2020 for the bioeconomy, the total economy, primary sectors, the bio-based manufacturing and electricity sectors, and the total manufacturing sector. Despite bio-based employment registering a slightly higher decrease than total EU employment, there were 15 MS where employment in the bioeconomy sectors overperformed that of their respective aggregated economies. This is particularly true for Finland, France, Latvia, Poland and Slovakia, where employment in the bioeconomy grew while decreasing (or remaining stable) in the overall economy. Conversely, Luxembourg and Malta registered notably better employment growth in the total economy compared to the bioeconomy.

Splitting the bioeconomy employment into agriculture and bio-based manufacturing and electricity, we see that both subsectors registered a decrease in employment in 9 MS. The consequent overall negative employment performance of the bioeconomy is aligned with the total economy (besides the already mentioned Luxembourg). Conversely, only Finland and Latvia registered growth in employment for both subsectors. In the remaining 16 MS, the two subsectors registered variations of opposite signs. In 10 cases, the overall performance of the bioeconomy was driven by the primary sector (4 decreases and 6 increases). In the other 6 cases, the bio-based manufacturing conditioned the sign of the overall bioeconomy (3 increases and 3 decreases).

Within the EU manufacturing sector, the decrease of bio-based employment in 2020 was less pronounced compared to the overall manufacturing sector. Bio-based employment outperformed total manufacturing employment in 17 MS, with 8 MS even experiencing growth in bio-based employment while the overall manufacturing sector witnessed a decrease. However, the remaining 9 MS registered greater declines in bio-based employment than the total manufacturing. Only Ireland recorded growth in both categories, although the growth rate was lower for bio-based employment.

Figure 2 decomposes the aggregate growth rate of bio-based manufacturing and electricity sectors. The figure reveals that there are no clear patterns observed across MS. However, two sectors appear to explain most of the growth in the top-performing MS: (1) wood products and furniture (Eastern and Northern countries such as Latvia, Slovakia, Estonia, Finland and Slovenia, with the exception of Spain) and (2) the manufacturing of food, beverages and tobacco (France, Denmark and, to a lesser extent, Finland and Spain). In contrast, for countries experiencing negative growth in employment, the main drivers are the food, beverages and tobacco sectors, as well as the bio-based textiles sector. Notably, Bulgaria, Portugal and Romania show a significant impact from both sectors. Food, beverages and tobacco explains most of the negative growth in Germany, Sweden, and Luxembourg, while the bio-based textiles manufacturing sector experienced particularly poor performance in Italy.

3.2.2. Value added in the bioeconomy by MS

The analysis of value added draws a slightly different picture (see Table 3). As for the EU, the value added growth of the bioeconomy outperformed that of the overall economy in 22 of the 27 MS. Within these countries, the added value of the bioeconomy grew while the total economy decreased in 12 of them; both magnitudes increased in Lithuania, Bulgaria and Denmark and decreased in the remaining 7 MS. In the other 5 MS, the bioeconomy performed worse than the total economy: in Luxembourg and Ireland by growing less than the total economy; in Finland and Romania by decreasing more. Only in Sweden value added in the bioeconomy decrease while it slightly increased in the total economy.

The growth of value added in the two main subsectors of the bioeconomy (agriculture and bio-based manufacturing and electricity) exhibited the same sign in 15 MS, with 11 of them experiencing positive growth and being negative in the other 4. In other 4 cases, the value added in primary sectors grew while it decreased in the bio-based manufacturing, resulting in all cases in a negative overall decrease of the bioeconomy, except for Spain. As for the remaining 8 MS, the bio-based manufacturing sector recorded growth in valued added while there was a decrease in agriculture. The combined effect of these trends resulted in an overall growth for the bioeconomy, except in Hungary, Portugal, and Sweden.

When comparing the evolution of value added between both bio-based and total manufacturing, the direction of value added growth for the two sectors was the same in 11 MS (7 negative and 4 positive). In 15 of the remaining 16 MS, the bio-based sector grew while the total manufacturing decreased. The only exception was Greece.

It is worth noting that, according to Table 3, countries with a more positive or less negative GDP trend tend to be positioned in the upper half of the table when ranked by the overall growth of bioeconomy sectors, particularly in terms of value added. Assuming that the decline in a country's GDP is related with the pandemic's impact (including lockdown implementation and the effectiveness of measures taken to mitigate the shock), this national

Table 2. Employment change (%) in the bioeconomy sectors and in the overall economy by MS (2020).

	Total bioeconomy	Total economy	Agriculture, forestry and fishing	Total biobased manufacturing and electricity	Total Manufacturing
LV	3.4	-2.3	0.5	6.9	-3.4
PL	2.2	0.0	4.5	-1.5	-4.0
FI	2.1	-1.9	2.2	2.1	-1.7
FR	1.8	-0.7	-0.4	3.6	-1.2
SK	1.0	-1.9	-2.6	3.9	-4.3
HU	0.8	-1.1	1.8	-0.2	-3.8
MT	0.6	2.8	2.4	-0.2	-1.1
NL	0.6	-0.5	1.5	-0.3	-0.2
AT	0.5	-1.6	1.9	-0.7	-1.3
CY	0.3	-1.1	0.8	-0.2	-0.8
IE	0.2	-2.8	-0.2	0.8	2.7
DK	0.0	-1.1	-2.9	2.1	-3.0
CZ	-0.3	-1.7	0.8	-1.0	-3.7
BE	-0.5	0.1	0.8	-1.0	-1.1
SE	-1.2	-1.3	1.0	-2.5	-1.8
HR	-1.2	-1.2	-1.3	-1.2	-1.3
EE	-1.4	-0.4	-8.6	2.2	-1.7
SI	-1.4	-0.7	-3.0	1.1	-1.9
LU	-1.5	1.7	0.0	-2.3	-1.7
BG	-1.5	-2.3	-0.2	-6.1	-4.8
EU27_2020	-1.7	-1.4	-1.6	-1.8	-2.8
PT	-2.5	-1.8	-0.4	-5.5	-3.0
IT	-2.5	-2.2	-2.5	-2.5	-2.1
EL	-2.7	-1.8	-2.9	-2.1	-0.1
ES	-2.9	-4.2	-6.5	1.3	-4.4
DE	-3.4	-0.8	-3.0	-3.5	-2.5
RO	-5.2	-2.1	-5.2	-4.8	-6.4
LT	-6.4	-1.6	-11.7	-1.5	-1.3

Note: The categories identified by each typology of arrow are defined following the same classification than Mubareka et al. (2023), where a negative performance in 2020 (below -1.0%) is flagged with a red arrow, a stable one (between -1.0% and 1.0%) is remarked with a yellow arrow, and a good performance (above 1.0%) is assigned a green arrow.
Source: Own elaboration from Lasarte-López et al. (2023b).

effect on the performance of the bioeconomy partially explains the observed heterogeneity across countries.

The dynamics of value added within the bio-based manufacturing and electricity subsectors also present a high degree of heterogeneity. Figure 3 shows the contribution by sector to the growth rate of value added. Similar to employment, two sectors play a substantial role in driving positive growth in bio-based manufacturing for the top-performing MS: (1) wood products and furniture (Latvia, Lithuania, Estonia, Slovakia, Slovenia and Luxembourg) and food, beverages and tobacco (Lithuania, Slovakia, Bulgaria and The Netherlands). Among the countries with a lower (negative) growth in value added, the food beverages and tobacco sectors were also important drivers. These countries are located in Southern and Eastern Europe, i.e., Croatia, Italy, Romania, Spain and Greece. Within them, Croatia experienced the poorest performance in these sectors, which explain most of the decline in value added within its bioeconomy. In contrast to employment, there is a generalized positive impact across countries from the bio-based chemicals and pharmaceuticals, plastics and rubber, as well as the bio-based electricity sectors.

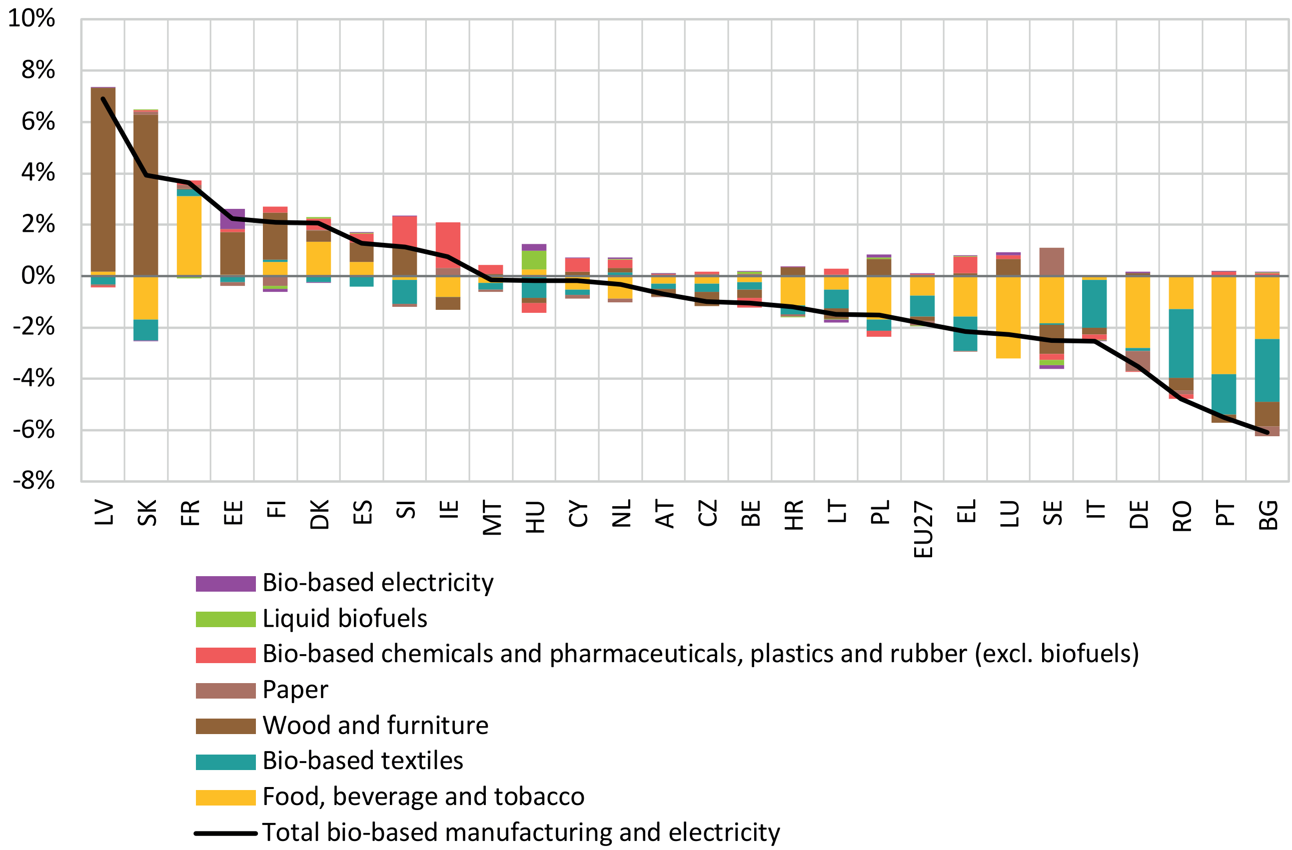

Figure 2. Decomposition of growth in employment in the bio-based manufacturing and electricity sectors (2020). Source: Own elaboration from Lasarte-López et al. (2023b).

3.3. Sectoral trends across the pandemic

The next step is to identify if there were common break in sectoral across countries due to the disruption of the pandemic. For this purpose, we conducted a paired sample t-Test to determine whether the growth of bioeconomy sectors by country in 2020 differed significantly from the average growth during the period 2014-2019, which covers the last expansionary phase of the business cycle in the EU27 before the COVID-19 shock. The results are shown in Table 4.

For the overall bioeconomy, there are no significant breaks in employment trends, which contrast, with the statistically significant negative difference observed in the total employment variation. However, for value added, we identify a statistically significant difference in the growth rate of 2020 compared to the 2014-2019 average, although this difference is of lesser magnitude than the observed for total value added.

In the two big sectors of the bioeconomy, a common break in trends is identified for both employment and value added in the bio-based manufacturing and electricity sectors, but not for Agriculture, Forestry and Fishing. The greater relative weight of employment in the primary sector in the bioeconomy can explain the absence of a statistically significant break in total employment within the bioeconomy. As for value added, the lower relative contribution of primary sectors would not offset the negative impact of bio-based industries, therefore explaining the statistically significant break in the total bioeconomy.

From a sectoral point of view, the differences in the growth rate of 2020 across countries are statistically significant for the more traditional biomass-processing sectors, namely, the manufacturing of food, beverages and tobacco, bio-based textiles and, only for employment, the paper industry.

Regarding bio-based chemicals and pharmaceuticals, plastics and rubber, we find no statistically significant differences in the growth trends of this sector across the EU countries. As spotted in Section 3.2.2, the contribution of this sector was positive for most coun-

Table 3. Value added change (%) in the bioeconomy sectors and in the overall economy by MS (2020).

	Total bioeconomy	Total economy	Agriculture, forestry and fishing	Total biobased manufacturing and electricity	Total Manufacturing
LT	↑ 14.4	↑ 1.6	↑ 15.4	↑ 13.7	↓ -1.4
MT	↑ 13.7	↓ -5.8	↑ 53.6	↑ 1.1	→ 0.7
LV	↑ 9.2	↓ -1.1	↑ 2.8	↑ 15.6	↑ 2.4
BG	↑ 6.1	→ 0.6	↑ 7.8	↑ 4.7	↓ -4.6
SI	↑ 5.2	↓ -1.9	→ 0.9	↑ 7.4	↓ -3.5
SK	↑ 4.4	→ -0.8	↑ 2.4	↑ 6.2	↓ -9.3
PL	↑ 3.8	→ -1.0	↑ 7.1	↑ 2.1	↓ -3.8
DK	↑ 3.8	→ 0.5	↑ 8.3	↑ 2.5	→ -0.9
EE	↑ 2.8	→ 0.0	↓ -14.7	↑ 12.2	↓ -3.1
LU	↑ 2.8	↑ 4.3	→ 0.0	↑ 3.9	↑ 4.6
BE	↑ 2.8	↓ -3.4	↑ 7.6	↑ 2.0	↓ -4.4
IE	↑ 1.9	↑ 5.2	↑ 7.6	→ 0.6	↑ 12.7
ES	↑ 1.1	↓ -9.7	↑ 4.4	↓ -1.5	↓ -9.4
AT	→ 0.5	↓ -3.6	↓ -1.0	→ 0.9	↓ -5.1
CZ	→ 0.3	↓ -3.6	→ 0.8	→ 0.0	↓ -9.7
NL	→ 0.3	↓ -2.1	↓ -4.2	↑ 3.4	↓ -1.6
DE	→ 0.2	↓ -1.3	↓ -4.9	↑ 1.6	↓ -6.2
EL	→ -0.2	↓ -8.7	→ 0.4	↓ -1.2	→ 0.7
EU27_2020	→ -0.4	↓ -3.5	→ -0.6	→ -0.2	↓ -5.9
CY	→ -0.5	↓ -4.2	→ 0.4	↓ -1.1	↓ -1.8
PT	→ -1.0	↓ -5.8	↓ -2.6	→ 0.0	↓ -5.5
SE	↓ -1.1	→ 0.7	↓ -3.8	→ 0.1	↓ -2.7
HU	↓ -1.2	↓ -6.0	↓ -4.3	↑ 1.9	↓ -6.6
FR	↓ -1.3	↓ -5.0	↓ -2.3	→ -0.8	↓ -12.2
FI	↓ -2.6	→ -0.5	↑ 3.6	↓ -6.7	↓ -1.8
RO	↓ -5.3	↓ -1.4	↓ -7.0	↓ -2.2	↓ -9.1
IT	↓ -5.8	↓ -6.8	↓ -2.6	↓ -7.6	↓ -9.5
HR	↓ -6.3	↓ -8.0	↓ -2.5	↓ -8.8	↓ -8.1

Note: The criteria that define the orientation of each arrow is the same as in Table 2 (see note).
Source: Own elaboration from Lasarte-López et al. (2023b).

tries in terms of value added. This is probably explained by the crucial role of the bio-based pharmaceuticals sector during the COVID-19 pandemic, which was reflected in the economic performance of this sector.

The existence of similar breaks in certain sectors suggests that the observed heterogeneity in the overall performance of the bioeconomy across MS could also be partially explained by their sectoral composition. Thus, the specialization of some countries in traditional biomass-processing sectors (particularly food and textiles) could have had a negative effect on the aggregate performance of their bioeconomies (e.g., the cases of Hungary, Italy, France or Spain).

3.4. Comparison of results with previous studies

The COVID-19 pandemic and the measures taken to contain it had strong economic consequences in most countries worldwide. In the EU MS, there were widespread falls in production and employment levels (OECD, 2020). Besides the effects of restrictions, the collapse of oil prices also hindered the development of the bio-based economy (Chulok, 2021). According to Fritsche et al. (2021) and Galanakis et al. (2022), the effects of the pandemic on the production and distribution of biomass value chains were primarily explained by changes in the demand structure by sector and labour shortages in the supply side, due to mobil-

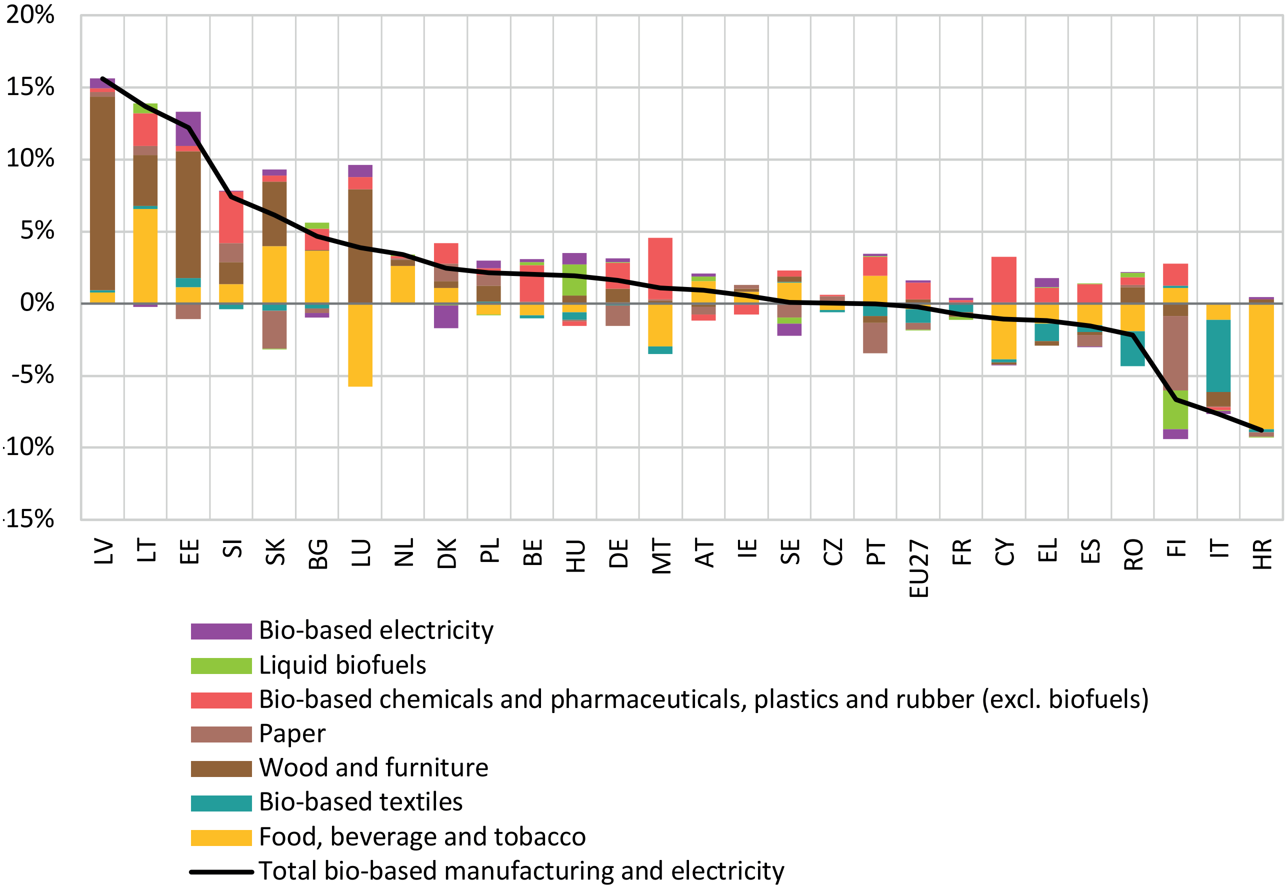

Figure 3. Decomposition of growth in value added in the bio-based manufacturing and electricity sectors (2020). Source: Own elaboration from Lasarte-López et al. (2023b).

ity restrictions. However, an expert survey conducted by Kulisic et al. (2021) revealed that biomass supply chains demonstrated overall resilience to the pandemic shock: no significant changes in the level of aggregated production were identified for the bio-based industries, and potential productivity gains were anticipated. These findings align with the results in Section 3. The decline in value added was less pronounced than that of employment within the bioeconomy, as well as in comparison to GDP.

Galanakis et al. (2022) highlight that the primary and food manufacturing sectors (NACE codes A01, A03, C10 and C11) experienced labour shortages and sharp decreases in demand from food services, which led to income decreases. González-Martinez et al. (2020) anticipated a higher resilience in the agriculture sector, and limited impacts on the agri-food sectors overall. These findings are also consistent with our own analysis, as no breaks in trends are found for the primary sectors across MS, and the decline in employment and value added in the agri-food sectors generally remained below the EU average for the total manufacturing sector.

The textiles industries (C13, C14 and C15) experienced an increase in demand for protective clothing (e.g., masks) (Galanakis et al., 2022). However, according to our analysis, this foreseeable increase did not have a positive impact on the demand of bio-based products, which is affected by the general decline of the sector. This decrease was more pronounced in those countries most affected by the pandemic in the first stage (therefore, implementing stronger restrictions). For instance, the textile sector in Italy registered an important decrease in jobs and value added.

Galanakis et al. (2022) also identified the paper, wood products and furniture industries (C16, C17 and C31) as mainly affected by changes in demand (decrease in wood demand for construction, increase in wood products for home and pallets for distribution). Based on our estimates, the net effect on employment and value added was positive, especially in the main wood-

Table 4. Mean and variance of sector growth by period, and results of the t-Test for Paired Two Sample for Means.

	Employment			Value added		
	Average growth 2014-2019 (Variance)	Change 2020 (Variance)	P-value	Average growth 2014-2019 (Variance)	Change 2020 (Variance)	P-value
Total Bioeconomy	-0.0030 (0.0003)	-0.0078 (0.0005)	0.3277	0.0384 (0.0002)	0.0179 (0.0025)	0.0335**
Agriculture, forestry and fishing	-0.0142 (0.0004)	-0.0123 (0.0013)	0.8012	0.0282 (0.0008)	0.0271 (0.0139)	0.9633
Bio-based manufacturing and electricity	0.0125 (0.0004)	-0.0049 (0.0009)	0.0231**	0.0480 (0.0003)	0.0185 (0.0032)	0.0070***
Food, beverage and tobacco	0.0157 (0.0004)	-0.0133 (0.0006)	0.0001***	0.0417 (0.0005)	0.0066 (0.0029)	0.0044***
Bio-based textiles	-0.0133 (0.0004)	-0.0635 (0.0035)	0.0004***	0.0267 (0.0009)	-0.0806 (0.0179)	0.0008***
Wood and furniture	0.0094 (0.0015)	0.0193 (0.0036)	0.5213	0.0601 (0.0010)	0.0698 (0.0313)	0.8012
Paper	0.0136 (0.0006)	-0.0060 (0.0011)	0.0189**	0.0521 (0.0009)	0.0014 (0.0147)	0.0546*
Bio-based chemicals and pharmaceuticals, plastics and rubber	0.0318 (0.0009)	0.0376 (0.0040)	0.6077	0.0736 (0.0030)	0.1059 (0.0157)	0.1528
Bio-based chemicals and pharmaceuticals, plastics and rubber (excl. biofuels)	0.0339 (0.0009)	0.0379 (0.0050)	0.7581	0.0854 (0.0129)	0.1151 (0.0174)	0.1928
Liquid biofuels	0.0457 (0.0454)	0.4952 (3.2358)	0.2420	0.1477 (0.0793)	0.5688 (3.1269)	0.2406
Bio-based electricity	0.1429 (0.0300)	0.1352 (0.0866)	0.9169	0.1324 (0.0351)	-0.1690 (2.0624)	0.3203
Total economy	0.0168 (0.0001)	-0.0120 (0.0002)	<0.0001***	0.0466 (0.0008)	-0.0251 (0.0014)	<0.0001***
Total manufacturing and electricity sectors	0.0119 (0.0001)	-0.0216 (0.0003)	≤0.0001***	0.0539 (0.0026)	-0.0368 (0.0027)	<0.0001***

Note: The null hypothesis is rejected with a significance level of 10% (*), 5% (**) or 1% (***).
Source: Own elaboration from Lasarte-López et al. (2023b).

producing economies (Nordic and Baltic countries). The increase in the price level of wood as commodity is behind this growth, which conditioned the performance of their overall bioeconomies.

The bio-based chemicals and pharmaceuticals, plastics and rubber industries sectors (C20, C21 and C22) witnessed a generalised increase in demand for products such as ethanol and alcohols (for disinfectants). An increased demand for bio-based plastics is also identified, given the higher usage of one-single use plastics products (Galanakis et al., 2022, Fritsche et al., 2021, Woźniak and Tyczewska, 2021). These facts, besides the crucial role of the pharmaceuticals sector during the pandemic, are consistent with the superior performance of these sectors in the EU and most MS in 2020.

4. CONCLUDING REMARKS

The economic consequences of the major events occurring since 2020 (the COVID-19 pandemic and, more recently, the Russian invasion of Ukraine war) underlined the potential role of the bioeconomy not only to achieve environmental sustainability but also socio-economic stability. Our results shows a higher level of resilience of the EU bioeconomy compared to the overall economy in the initial stage of the pandemic. While employment in the bioeconomy declined similarly to the EU average in 2020 (-1.7% vs -1.4%), value added fell substantially below (-0.4% vs -4.0%). As the primary sectors remained stable, this greater resilience was driven by some bio-based sectors such as chemicals, pharmaceuticals, bioelectricity and wood products, which partially offset the negative impact on more traditional biomass-processing sectors (mainly food, beverages, tobacco, and bio-based textiles).

At the MS level, the bioeconomy performance was quite heterogeneous, although a potential effect of the country overall economic performance was identified. Furthermore, the disruptions observed in traditional biomass-transforming sectors (food, textiles and paper) were generalised across countries, while bio-based chemicals and bioelectricity kept their positive growth trends in most countries. These findings suggest that the sectoral composition of the bioeconomy could also have an impact on its overall performance at the country level, negatively affecting those countries with higher specialization in the aforementioned traditional biomass-transforming sectors.

The lower relative impact of the pandemic shock on the bioeconomy provides empirical evidence for the academic literature and the policy documents supporting the need for the EU to reinforce the bio-based value chains (e.g. Farcas et al. 2020, Galanakis et al. 2022; European Commission, 2018, 2022), so as to fulfil sustainability goals while enhancing socioeconomic resilience to economic shocks and disruptions in the global value chains.

These insights are subject to some limitations, caused by the data availability. For 2021 onward, the available information is still scarce, due to long publication delays of some of the required data sources (14 months in the case of the PRODCOM survey, needed for the product-level bio-based shares; and 21 months for Structural Business Statistics, the main data source for employment and value added in the bio-based manufacturing and electricity sectors). As the year 2020 is the most recent data point available in our dataset, it is still not possible to analyse the full impact of the pandemic on the bioeconomy (i.e., including the recovery in 2021) nor of the Russian invasion of Ukraine starting in 2022. An additional limitation is that the current composition on the jobs and growth indicators for the bioeconomy only considers biomass-producing and transforming sectors. The bioeconomy services are foreseen to be integrated in the future, following the methodology from Ronzon et al. (2022b).

These limitations also pave the way for future research. The in-depth analysis of the aforementioned events in 2021 and 2022 would be useful to further support (or not) the hypothesis of a stronger resilience of at least some bioeconomy sectors to economic shocks. The integration of services into the said indicators would also provide an opportunity to analyse the performance of the tertiary sector in comparison to biomass-producing and transforming sectors, as well as their non-bio-based counterparts.

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