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Bio-based Business Models: specific and general learnings from recent good practice cases in different business sectors

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Abstract. Business models can be a perfect tool to meet the challenges in highlighting the competitiveness and sustainability potential of bio-based solutions, and facilitating primary producers to benefit from the opportunities offered by bioeconomy. In this work six concrete bio-based good practices that have succeeded in progressing from early ideas to products on the market were analysed. These examples pose new insights that can be used by a wide range of experts and stakeholders for the analysis of benefits and challenges of value chains in the bio-based economy sectors. It is concluded that the traditional Business Model Canvas needs to be extended with additional factors related to sustainability and business ecosystem. In order to establish a practical framework promoting economic viability of bio-based business cases, the importance is highlighted for adjusting the exclusive focus on Technology Readiness Levels by introducing levels reflecting business or market readiness.

Keywords: Bioeconomy, Business Modelling, Business Model Canvas, Bio-Based Industry, Business Readiness Level.
JEL Codes: O31, O32, Q01, Q14, Q16, Q20, Q50, Q55, Q56.

1. INTRODUCTION

1.1 Special role of business models in bioeconomy - dissemination of good practices

The shift towards a circular economy and bioeconomy is one of the main focuses of political initiatives aimed at replacing fossil feedstock by renewable biological sources while still achieving economic growth.[1] Awareness raising activities, highlighting the potential of bioeconomy for competitiveness and sustainability are necessary for informing the general public as well as the different policy departments and business sectors.[2] Bio-based business models, the importance of which is clearly stated in the updated Bioeconomy Strategy of the European Commission (EC),[3] can be a perfect tool to meet this challenge. According to this strategy, bioeconomy is sustainable and circular, and includes, among others, "economic and industrial sectors that use biological resources and processes to produce food, feed, bio-based products, energy and services".

One of the "pilot actions" included in the European Bioeconomy Strategy aims to better link national bioeconomy strategies and national strategic plans under the Common Agricultural Policy (CAP), in order to support inclusive bioeconomies in rural areas. It is also highlighted at this action that dissemination of good practices is among the most important tools to foster the deployment of the bioeconomy and enables primary producers to benefit from the opportunities offered by bioeconomy approaches.[3] A strong support for economic information is imperative for enhancing the convergence between bioeconomy and the CAP or other relevant agricultural policies and priorities.[4] When developing CAP strategic plans supporting the setting up of sustainable bioeconomy businesses in rural areas, particular attention has to be paid to primary producers because they play a key role in bioeconomy value chains. Countries with well-developed primary sectors have certainly many opportunities to develop downstream value chains.[5]

The bioeconomy's strength lies in its diversity, adaptability and close interactions with local and rural communities,[2] and business modelling can represent all of these aspects in a unified structure, taking into consideration the local economic and social environment where the business operates.

When talking about an innovative solution as part of the workflow in research and development (R&D) projects where companies or business oriented organizations (e.g. clusters, chambers) are involved, the first immediate question that arises on their part is whether deployment of the solution is economically viable. Further questions that arise are: What evidence underpins the real potential and economic feasibility of the technology solution? Has the technological viability been already demonstrated? Has the technology been operated on a large scale? How does the innovation fit into the business environment? No matter how eager the representatives of business-supporting organizations (e. g. clusters, farmers' associations, consultancy services, etc.) are to widely share the bioeconomy-related technologies and opportunities to their network, they are not able to make steps forward in qualitative terms without having answers to these questions above. Bearing in mind the precious trust gained from stakeholders they have been working with, representatives feeling responsible simply cannot afford to introduce these promising solutions, as long as it is not fully clear and proven that these innovations would not cause any economic disadvantage to these stakeholders. Involvement of farmers is especially essential, since this is the key to ensuring that farmers, instead of being mere biomass providers, benefit from the profit-creating value-addition that is achieved by the innovative transformation processes in bioeconomy businesses.

The study on the participation of the agricultural sector in the Bio-Based Industries Joint Undertaking (BBI JU) emphasizes that business models in the bio-based sector are worth highlighting.[6] An easy-to-understand business model is a great tool for several purposes, i.e.: awareness raising in different sectors, dissemination of bioeconomy good practices, involving primary producers. The model is expected to clearly explain the key components of a business and how they relate to each other in order to create value and a favorable balance of cost structure and revenue streams that can make the business model viable.[7]

This current work focuses on business aspects within the bioeconomy concept, which are of key importance for this industrial sector, and intends to show interlinks between these aspects and others considered essential for the successful implementation. The aim is to analyse real-life, concrete examples of 'bio-based concepts' that have succeeded in progressing from the early ideas to final products placed on the market, and assessing their business models, in order to provide learnings that can be used by experts of consultancy services and other business-supporting organizations, clusters, research organizations, legal authorities, etc., for the development of innovative companies. The results contribute to developing a common and shared perspective of different sectors involved in bioeconomy developments, with special regard to academic or R&D organizations and industrial actors implementing bio-based industrial solutions in real life.

1.2 Business Model Canvas

In very general terms, business models explain how enterprises work to deliver value to their customers. A competitive model represents a business activity that is better than the existing options or may offer more value to a discrete group of customers or may even completely replace the old way of doing things and become the standard for other entrepreneurs. Business Model Canvas (BMC) is a template framework identifying and addressing the nine most important so called building blocks of a business solution and its environment:[8, 9]

- Value proposition is the bundle of benefits that a company offers to customers. It is the concept at the heart of the model, including the product or service itself (or the combination of these), and also value factors being the reasons behind the customer's motivation to buy it.

- Key partners, Key activities, Key resources are the internal building blocks that are mostly under direct control of the Value proposition's owner, including all the operational components that make the Value proposition a reality.
- Customer relationships, Channels, Customer segments are the external building blocks, including all components related to the understanding and reaching people and companies representing the market.
- Cost structure and Revenue streams are the finance-related building blocks, describing the financial viability and feasibility of the business.

BMC is a useful tool for facilitating the entrepreneurial process by breaking down the most relevant aspects of a business solution, and helping to understand and visualize the interplay of the different components creating value. While BMC might be helpful to understand existing business models, it is also suitable to design novel innovations.[7]

The internal building blocks of BMC can be more complex for bio-based industry than other industries. In most bio-based value chains biomass raw material comes from a sector different from the one where it is utilized in a bio-based process (Figure 1). This means that bioeconomy solutions evidently involve different sectors and thus require the cooperation of various and divergent players which rarely interacted so far, such as established chemical companies and small-scale farmers.[10] Moreover, the bioeconomy concept, as all holistic innovation systems, needs to involve all groups of stakeholders according to the Quintuple Helix Approach: economic, education and political systems, civil society and natural environment.[11]

In 2017, a systematic literature review was conducted by Reim *et al.* on research articles describing bioeconomy-related forest-based business solutions.[1,12] The review assessed to which level of detail the BMC building blocks were investigated in these studies. The building block that is extensively covered in literature is the Value proposition, mainly by describing existing or potential offers related to bioeconomy. Key activities and Key resources are also well-discussed. Customer relationships block often mentions the need for reliable information to convince potential customers, however, there is not much written explicitly about Customer relationships. Channels is the BMC building block that is least addressed. Details about the cost structure can also be found in literature even though detailed calculations are currently missing. The most frequent explicitly addressed cost is related to the cost of biomass or feedstock.

1.3 Extension of BMC to meet sustainability and business ecosystem aspects

BMC is often chosen for business modelling, due to the ease of its practical application and worldwide recognition. However, applying the principles of the circular economy and bioeconomy exceeds the existing BMC components.

The potential contribution of the bioeconomy to sustainability and its social value generation (e. g. local employment, rural regeneration, energy security) are highly evident and well-described in the recent literature.[1] However, bioeconomy is not per se sustainable just because it is based on renewable resources, and sometimes it even brings about new challenges, despite the fact that it can be a way to solve sustainability problems and may contribute to the Sustainable Development Goals defined by the United Nations.[13] Besides competition with food and feed, increased use of biomass also has its effects on land use, water avail-

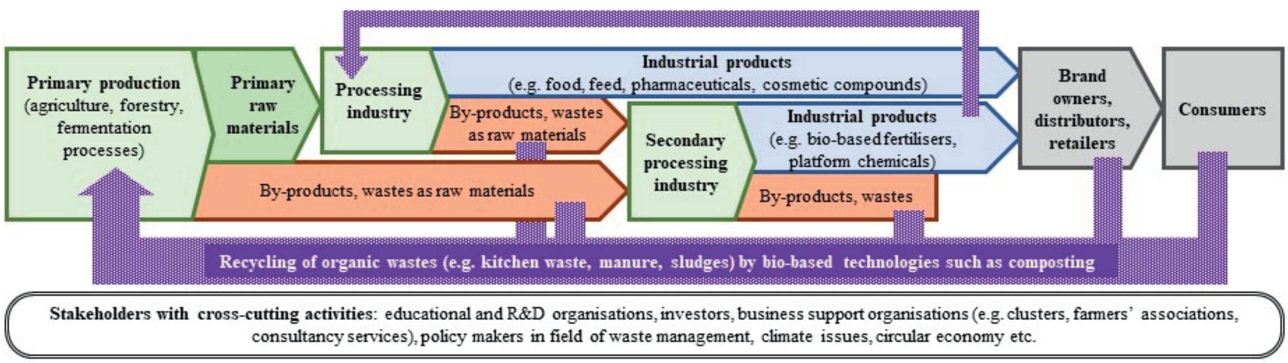

Figure 1. Bio-based value chain structure demonstrating the stakeholders involved.

ability and on other sectors. For example, forest-based industries (such as production of pulp and paper, building materials, etc.) are affected by the increased use of wood for energy conversion.[14] As already seen in the context of bioenergy, rise of the demand for bio-based products will increase the pressure on limited biomass and land resources and thus may cause several sustainability conflicts.[13] To make sustainability as one of the key concepts behind bioeconomy supply chains noticeable, sustainability-related aspects can be added as extensions to the BMC. This extension enables the BMC to indicate/demonstrate that bio-based solutions are not aimed at merely replacing fossil resources by bio-based ones, but also generating societal and ecological values and contributing to a long-term structural change.[13] Various models based on the original BMC have already been published which suggest to add further blocks to the top, side and/or bottom sections to reflect a wider perspective.[15] An example is the framework presented by Antikainen and Valkokari, which shows how to create values also in environmental and social terms, which is particularly relevant in bioeconomy businesses requiring the cooperation of various and divergent players.[16]

2. METHODOLOGY

2.1 Selection and categorisation of bio-based solutions

The starting point for the selection was a collection of nineteen bio-based solutions which were described in detail in a study in the framework of the POWER4BIO project.[17] In the first step, this collection was screened to select good practice solutions having high technological maturity (TRL8 or TRL9, the highest Technology Readiness Levels used in H2020 Framework Programme for Research and Innovation[18]) and proven business potential. Additionally, sufficient quality and quantity of the data of the solutions should be available. In this step, knowing a reliable contact person at the company owning the bio-based solution who had permission for sharing necessary and relevant information for all nine building blocks of the BMC was an important aspect. The third step was to identify different solutions to cover the four categories as defined by COWI, Bio-Based World News and Ecologic Institute:[19]

1. Final product (product that can be sold to the end consumer, without any further processing, e.g. tableware, biofuel, mushroom grown on agricultural wastes, etc.);
2. Material (product that can be used as raw material to produce bio-based final products, e.g. bio-based fibers, bio-based foam for packaging applications, hemp-based insulation material for buildings, plant-based material for clothes, etc.);
3. General building block or biopolymer (chemical monomer or polymer to produce materials, e.g. bio-based 1,4-butanediol, an industrial chemical used as a building block for the production of plastics, elastic fibers and polyurethanes);
4. Technology licensing.

The authors selected six recently developed bio-based good practice cases and described them following the BMC modelling system.

2.2 Data collection

Intensive desk and literature research were carried out to extract the valuable information from publicly available sources such as webpages of the companies, (bio)economy news portals, press releases issued by the companies, conference presentations, economical/statistical databases, scientific articles, etc. Online or telephone interviews were conducted with the owners or experts of selected solutions. One person was interviewed per company. The company experts were informed of the aim and subject of the interviews in advance, during the appointment arrangement process. A set of relevant questions was compiled before the meetings, structured by the elements of BMC, to help covering all relevant details during the interviews. For the case when a company preferred to fill in a questionnaire rather than giving an oral interview, this set of questions was sent to its representative expert. The collected data were processed and organized using BMC structure.[8] Companies have checked and endorsed the business model descriptions.

2.3 Literature review

To learn from previous experiences and take into consideration bio-based business models elaborated earlier, a literature review was made to obtain an overview about the work already performed in the field of application of bio-based industry business modelling methodologies, especially BMC. Based on this review, the cases presented in the following studies were included to develop learnings about the bio-based business models and their development, together with the good practice cases described in this paper:

- The study on the participation of the agricultural sector in the BBI JU was carried out between March and August 2019.[6] Fifteen business models from

European countries and five from non-European countries were studied.

- BE-Rural project, funded under the same H2020 call topic as POWER4BIO, delivered a report in November 2019, addressing business models for regional bioeconomies[20] which analyses four models based on BMC.
- In 2017 a one-day stakeholder workshop was organized in Lleida, Spain in the AgriMax project funded by BBI JU, to develop business models for valorisation of agricultural and food-processing waste. Farmers, agricultural cooperatives, food producers, investors and other stakeholders were invited, and BMC was used to elaborate three case studies and map existing and innovative ways to create value for the new supply chains.[15]
- In 2019 a report was prepared for the EC by COWI Group, Bio-Based World News and Ecologic Institute, in order to "provide concrete examples of 'bio-based concepts' that have succeeded in progressing from the early ideas to a final product placed on the market", to a fully commercial level, or close to that. Fifteen success stories are presented in this report.[19]

2.4 Framework for the extension of BMC to meet sustainability and business ecosystem aspects

In order to extend the traditional BMC with sustainability and business ecosystem aspects, authors used the framework offered by Antikainen and Valkokari,[16] which complements current business model tools by integrating the following additional factors: trends, drivers, stakeholder involvement (business ecosystem level), and environmental, social and business requirements and benefits (sustainability impact). A collection of examples for these additional factors was compiled based on the authors' own experiences and the work of Philp and Winickoff,[21] Biber-Freudenberger *et al.*[22] and Pavlovskaia,[23] and categorised as follows: drivers and stakeholder involvement tools; sustanability requirements; sustainability benefits.

3. RESULTS

Table 1 summarizes the good practice cases presented in this article and Figure 2 shows the locations where these cases are being operated by the owner companies. Figures 3-8 present the business models in BMC format behind the analyzed solutions numbered S1, S2, S3, S4, S5 and S6, respectively. For each solution short additional background information is presented next.

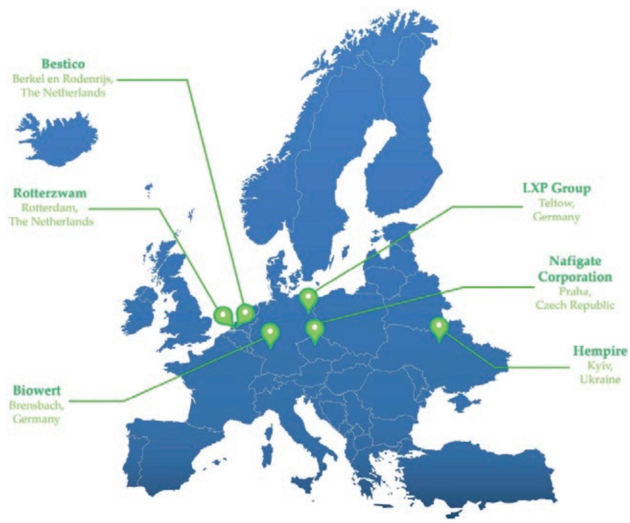

Figure 2. Locations of the companies operating the good practice cases listed in Table 1.

S1. Production of feed quality protein meal and oil with high nutritional value by the bioconversion of residual organic streams using Black Soldier Fly Larvae (Bestico, Berkel en Rodenrijs, The Netherlands)

Bestico B.V. founded in 2013 focuses on the production and sales of Black Soldier Fly (BSF) (*Hermetia illucens*) larvae and their processing to protein for animal feed (especially aquaculture feed and pet food), insect oil and fertilizer agent (Figure 3). The efforts of Bestico B.V. are supported by its mother company, Koppert Biological Systems, an internationalized firm with subsidiaries in 27 countries which is a leading provider of arthropods and microbes for biological control of agricultural pests and has developed expertise in the production of insects since 1967. The company provides a tailored, scalable solution (being at TRL8 at the time of the interview) to use biomass by-products and convert this into feed-quality protein and oil with high nutritional value. When the data collection was performed, the production rate was around 6-12 tonnes of fresh larvae per week. The growing process takes about 14 days, and within this period the larvae reduce the feedstock weight by 40-60% while half of this, i.e., 20-30% of the feedstock weight is converted into larvae biomass, depending on the nutritional profile of the feedstock.

S2. Local production of fresh oyster mushroom combined with the valorization of the coffee ground residues (Rotterzwam, Rotterdam, The Netherlands)

Rotterzwam B.V. is a private company, established in 2013. The company is dedicated to cultivation, production and sale of fresh edible mushrooms grown on cof-

Table 1. Summary of the bio-based solutions selected for this study. Product types, defined in Section 2.1, are as follows: 1: Final product, 2: Material, 3: Building block or polymer, 4: Technology licensing.

No. of solution	Name of solution	Bio-based product(s)	Product type	Company (country)	Mode of data collection
S1	Production of feed quality protein meal and oil with high nutritional value by the bioconversion of residual organic streams using Black Soldier Fly (BSF) Larvae	feed quality protein meal, oil with high nutritional value; fertiliser	1	Bestico (The Netherlands)	personal interview (08.01.2020); desk research
S2	Local production of fresh oyster mushroom combined with the valorisation of the coffee ground residues	fresh oyster mushroom and processed products	1	Rotterzwam (The Netherlands)	desk research, email discussion
S3	Natural insulation material produced using hemp hurds and own-produced limestone-based binder	insulation material based on hemp hurd	2, 4	Hempire (Ukraine)	personal interview (11.11.2019); desk research
S4	Meadow grass silage biorefinery producing grass fibre reinforced plastic composite granulates and bio-based insulation material, combined with biogas plant producing electrical energy from grass juice and food residues	grass fibre reinforced plastic granulates, natural insulation material, electrical energy from biogas, organic fertiliser	2	Biowert (Germany)	data and descriptions provided by the company in written form by filling a questionnaire; desk research
S5	Production of bio-based chemicals, high-quality natural lignin, biogas and biofuels from 2nd generation biomass by cracking technology	biochemicals, natural lignin, biogas, biofuels	3, 4	LXP Group (Germany)	personal interview (24.02.2020) and email discussion; desk research; content of slides used by the company at public presentations
S6	Production of polyhydroxyalkanoates (PHA) using waste cooking oil	polyhydroxyalkanoates (PHA)	3, 4	Nafigate Corporation (Czech Republic)	personal interview (06.12.2019), followed by email discussion; desk research

fee grounds and its application in other related products (Figure 4). Its mushroom nursery is the largest coffee ground-based mushroom farm in Europe and the company aims to develop it to be energy neutral and CO_2 negative. The cultivation units contain a modular and sustainable climate system, which is fully optimized for mushroom cultivation. These units, which are especially designed for an urban environment, can also be very well used in remote rural areas. Rotterzwam also provides services like workshops, educational activities and consultancy in the field of urban management through the radical renewal of chains. They work with local partners to find new ways to put products derived from coffee grounds and oyster mushrooms into the market, developing products such as oyster mushroom vegetarian snacks and beer.

S3. Natural insulation material produced using hemp hurds and own-produced limestone-based binder (Hempire, Ukraine)

Hempire is a company based in Ukraine and having a site in California, USA as well. The company was established to provide insulation technology based on hemp and lime (Figure 5). In the last few years, the company has been involved in more thatn 60 building construction projects and successfully developed its own lime-based binder material called “Fifth Element” which does not contain cement, sand or toxic components. The binder material is produced in the company’s own facilities, both in Ukraine and in the USA. Through extensive R&D the company has created a very light insulation material called “Hempire Mix”. This highly energy efficient material consists of three components, which are mixed on the construction sites using a special mixer: hemp hurds, water and the special proprietary binder mentioned above. Hempire Mix is applied on the walls and it can be used to insulate any wall, floor and roof inside a new or an existing building. It contains only non-toxic components and has numerous benefits: insulation acting as humidity and temperature regulator in the building; excellent thermal insulation properties resulting in significant savings on heating and cooling all year round; with vapor permeable walls there is no need to install a ventilation system; high thermal mass and thermal inertia help prevent temperature fluctuations; no rotting but protecting walls from fungus due to the regulation of humidity; excellent acoustic absorption due to high porosity; non-flammable material which repels rodents.

<table>
<tr>
<td rowspan="2"><u>Key Partnerships</u>
· raw material providers ensuring biomass feedstock of appropriate quality
· industrial and academic partners to increase TRL and to find new applications for BSF larvae products and side streams</td>
<td><u>Key Activities</u>
· feedstock reception (GMP+ grade for feed application) and strict quality control upon receipt (dry matter content, free of pesticides/insecticides)
· primary production of insects
· processing insects into concentrated protein meal, insect oil and natural fertilizer
· adapting the technology to fit into existing operations (scale-up of current process)
· continuous R&D for cost effective and higher quality production</td>
<td rowspan="2"><u>Value Proposition</u>
· tailored sustainable solutions for growing and processing insects
· scalable solution to utilise excess biomass from potato industry, beer and alcohol industry into valuable feed-quality and storable protein and oil with high nutritional value
· protein from BSF (with protein content up to 60%) suitable for farmed fish, poultry and other livestock, providing essential amino acids which are low in feeds produced from plant origin and which are easily digested by most animals
· substrate remaining after isolation of protein and oil has value as fertiliser
· automated processing secures consistent and safe products
· BSF larvae system is adaptable to a wide range of residual organic streams, making food chain more sustainable</td>
<td><u>Customer Relationships</u>
· Business to Business (B2B) and Business to Customers sales strategies
· using a sales force of 3-5 persons in Europe (France, United Kingdom, The Netherlands)</td>
<td rowspan="2"><u>Customer Segments</u>
· pet food industry
· pet food consumers
· aquaculture
· animal feed industry (farm animals)</td>
</tr>
<tr>
<td><u>Key Resources</u>
· raw material feedstock (e.g. vegetable waste coming from potato and alcohol industries) of appropriate quality (very low content of insecticides) and uniform in physical and nutritional properties affecting the time required to larvae growth
· infrastructure for feedstock storage and quality control
· facilities comprising conditioned rearing cells and equipment for feeding of the insects
· equipment to isolate protein meal and insect oil
· know-how on BSF eggs production and insects growing
· sales competences</td>
<td><u>Channels</u>
· reaching customers by company website, social media and YouTube channels
· conferences and presentations at fairs and other events
· cooperation projects</td>
</tr>
<tr>
<td colspan="2"><u>Cost Structure</u>
· CAPEX is estimated in the range between 3-5 million EUR;
· main long-term expenses: plant and equipment purchases, building and improvements, instrumentation and automation of the process;
· most important operational expenses: feedstock, energy/utilities and labour costs, with equal shares within OPEX being in the range of 3-5 million EUR/year</td>
<td colspan="3"><u>Revenue Streams</u>
· sales of dry insects for animal feed and pet food;
· estimated price of dry BSF larvae as animal feed: 1-3 EUR/kg; price of pet food: 15-40 EUR/kg (based on the retail prices in the webshop)</td>
</tr>
</table>

Figure 3. BMC of solution ‘S1’ (Bestico, The Netherlands).

Key Partnerships	Key Activities	Value Proposition	Customer Relationships	Customer Segments
· local coffee grounds providers · local industries for the development of new products: partners cooperating in the development and sales of products listed at the Value proposition (restaurants, supermarkets, breweries, bakeries etc.)	· collection of coffee grounds from companies or organizations that use at least 50 kg of coffee beans per month · cultivation, storage and packaging of oyster mushrooms · sales and marketing of fresh oyster processed products · activities related to the development of processed products and to the services provided	· valorisation of coffee residues on a local scale into the best possible uses such as food products · production of fresh oyster mushrooms · mushroom-based and coffee ground-based processed products (beer, snacks, soap, fertiliser etc.) · growkit for common people to convert their own coffee grounds into oyster mushrooms · substrate remaining after mushroom production can be used as soil improver	· direct sales to local people, restaurants and shops · attracting new customers and engaging entrepreneurs interested in mushroom growing and utilisation of coffee grounds · unique marketing strategy and communication package on valorisation of coffee ground	· strong focus on the citizens of the local municipality · local shops, restaurants and markets · local hospitality sector (food category) · green consumers or entrepreneurs, with preference for local food production, environmentally friendly products and consumption of proteins of non-animal origin and concerned about the environment
	Key Resources · coffee ground material as the main feedstock · know how on oyster mushrooms cultivation techniques on coffee grounds · cultivation container units optimized for mushroom cultivation, especially designed for an urban environment · infrastructure and adapted facilities for production of mushrooms · vehicles for the collection and transport of coffee grounds and mushrooms		**Channels** · company's own website and Facebook site · online shops · catering wholesalers offering oyster mushrooms snacks · network of local mushroom nurseries promoting the growkit · social and traditional media · online e-learning courses and seminars, presentations, workshops · factory visits	

Cost Structure	Revenue Streams
· 400 000 EUR from crowdfunding (Symbid) in 2018 to build the site; · shares of investments: 34% for breeding units (8 containers), including climate system and installation; 16% for substrate preparation area, mixer, packaging machine, office space, cold room; 7% for installation of solar panels on the entire nursery; 7% for roll out quasi franchise; 8% for R&D; 8% branding and marketing campaign; 8% accelerated sales & rollout of new products and 12% for the other costs · shares of the different costs within the OPEX structure are the following: staff costs: 33%, cost of sales: 29%, other operating costs: 34%, depreciation and financial expenses: 4%	· producers of coffee ground material pay for its collection (15 EUR/kg) · fresh oyster mushrooms sales (8,5-10 EUR/kg) · sales of processed products (beer – 9 EUR/litre; vegetarian snacks etc.) · growkit for people to convert their own coffee grounds into oyster mushrooms: 15 EUR per kit · E-learning courses and seminars on mushrooms growing (50-350 EUR per module)

Figure 4. BMC of solution 'S2' (Rotterzwam B.V., The Netherlands).

S4. Meadow grass silage biorefinery producing grass fiber reinforced plastic composite granulates and bio-based insulation material, combined with biogas plant producing electrical energy from grass juice and food residues (Biowert, Germany)

Biowert Industrie GmbH was founded in 2000 as a Swiss-German company. The first Biowert grass refinery which started its operation in 2007 is located in

<table>
<tr>
<td rowspan="2">Key Partnerships
· raw material providers: hemp growers and lime provider
· logistic partners</td>
<td>Key Activities
· feedstock transport and storage
· producing lime-based binder
· binder transport
· mixing binder, water and hemp hurds on the construction site
· close cooperation with hemp growers
· design, planning and implementation services
· technology development for more cost effective and higher quantity production</td>
<td rowspan="2">Value Proposition
· natural hemp-based insulation solutions using local ingredients for environment-friendly buildings
· building and energy cost-effective construction solution
· special lime-based binder material (free from cement, sand or toxic components) for the on-site production of insulation material
· processes to be done on the construction sites are easy-to-learn and do not require high level of skills
· wide range of services: consultation, services related to insulation, design, planning and implementation, quality control</td>
<td>Customer Relationships
· direct relationship and close cooperation with customers
· B2B and B2C sales strategies
· providing technical support
· informing the public about new buildings and construction solutions, to add more visibility to the solution</td>
<td rowspan="2">Customer Segments
· private persons, organizations, business companies, communities interested in making a hemp-based building
· consulting services: architects, designers, builders, contractors and other actors in the construction industry</td>
</tr>
<tr>
<td>Key Resources
· estate for the buildings and feedstock storage
· buildings and machinery for lime-based binder production
· high quality raw materials: hemp and lime (dust content of the hemp has to be as low as possible, it can't be mouldy or wet, hurd particles shall be 1-4 cm long)
· vehicles for feedstock and product transport and handling
· know-how and knowledge for optimization based on own experiences</td>
<td>Channels
· marketing: company's own website, Facebook site
· presentations and workshops to inform stakeholders about the company's activities and current developments
· staying in contact with former customers</td>
</tr>
<tr>
<td colspan="2">Cost Structure
· CAPEX: building and equipment for a new facility: 2 million USD in USA or Canada, while around 1 million USD in Europe or Ukraine
· OPEX: price of raw materials: hemp hurds as main feedstock (120 EUR/t) and lime; energy costs; labour costs (4 people in the binder production facility and other 4 people working at the construction site); general & administrative expenses</td>
<td colspan="3">Revenue Streams
· sale of binder material: 12 EUR per one bag, which contains 25 kg (480 EUR/t) and for a retail price of 32 USD per one bag, which contains 23 kg (1 390 USD/t) in the USA
· revenues from sale of insulation material (180 EUR/m³) and insulation services
· revenues from consultation and other services mentioned at Value Proposition</td>
</tr>
</table>

Figure 5. BMC of solution 'S3' (Hempire, Ukraine).

Brensbach, Germany. The "grass factory" system combines the biorefinery process, the multistage production of innovative bio-based materials and an affiliated anaerobic digestion facility with a CHP plant producing green electricity (Figure 6). The biorefinery is fed by meadow grass from their own permanent pastureland and arable land for crop production, and produces different innovative biomaterials: a fire safe blow-in insulation material for wall, roof and floor cavities which naturally controls the absorption and release of water vapor to ensure the ideal building environment and safe from rodents, insects and mould (AgriCell),

<table>
<tr>
<td rowspan="2"><u>Key Partnerships</u>
· raw material providers: local farmers
· partners for transporting feedstock and products
· waste material handling companies to provide organic wastes feeding the biogas plant</td>
<td><u>Key Activities</u>
· feedstock transport and storage (seasonality: meadow grass grows in spring and early summer, it can be harvested up to 4 times a year, but ensiling makes it durable, so it is available all year round)
· biorefinery process: cellulose fibres are separated from the grass using mechanical processing and then dried
· processing of the fibres into plastic based granulates or insulation material, using recycled plastic
· electricity and heat production by the biogas plant
· processing of digestate to a concentrated organic fertilizer
· keeping regular contacts with industrial customers and local farmers</td>
<td rowspan="2"><u>Value Proposition</u>
· meadow grass processed into materials by a biorefinery process and green energy by an affiliated biogas plant, using food residues, other organic wastes and grass juice, ensuring energy needs (e.g. drying of cellulose fibres)
· products: grass fibre reinforced plastic granulates, insulation material, organic fertiliser
· positive environmental impacts: reducing the use of fossil-based plastics; reducing CO_2 footprint by using grass being a natural CO_2 adsorber; energy produced from wastes; agricultural and food industrial waste reduction</td>
<td><u>Customer Relationships</u>
· sales strategy: B2B relations with industrial partners
· cooperation with local farmers</td>
<td rowspan="2"><u>Customer Segments</u>
· grass fibre reinforced plastic granulates: industrial customers in a wide range
· insulation material: construction industry
· electricity and heat: own use and local electric service provider
· organic fertiliser: local farmers
· licensing the solution to actors interested in technology implementation</td>
</tr>
<tr>
<td><u>Key Resources</u>
· suitable biomass feedstock (mainly meadow grass, harvested before the panicle is pushed and ensiled, at a dry matter content of 25-30%)
· estate for the buildings and feedstock storage
· buildings and machinery for technology processes listed under Key Activities
· know-how and optimization based on own experience, included in patents as well
· specific-skilled workforce and high-quality experts</td>
<td><u>Channels</u>
· marketing: company's own website and Facebook site
· presentations and workshops to inform stakeholders</td>
</tr>
<tr>
<td colspan="3"><u>Cost Structure</u>
· CAPEX cost estimated: 7-10 million EUR for biorefinery and 8 million EUR for biogas plant
· 18-24 months long period needed to install and optimise the technology (related costs also have to be taken into account)
· OPEX: feedstock (meadow grass: 140 EUR/tonne dry matter), energy and labour costs, general and administrative expenses
· energy costs depend on the share provided by the biogas plant</td>
<td colspan="2"><u>Revenue Streams</u>
· selling of grass fibre reinforced plastic granulates (2 500 t/year produced; price: 1,95-3,50 EUR/kg, depending on additives and final recipe)
· selling of insulation material (1 400 t/year produced; 1,38 EUR/kg)
· energy sold to the local electric service provider, (price set by feed-in tariffs; CHP plant produces 5,2 GWh/year, the energy need of the biorefinery is 2,5-3 GWh/year, thus the surplus can be sold)
· by-product of the biogas plant is a nitrogen-rich material, sold as organic fertiliser (11 000 t/year)
· indirect revenue: waste management costs are lower, as by-product of the biorefinery (e. g. grass juice wastewater, 2 000 t/year) is processed in the biogas plant</td>
</tr>
</table>

Figure 6. BMC of solution 'S4' (Biowert, Germany).

a light, dimensionally stable and temperature resistant fiber-reinforced composite material with 30 to 75% natural fibers (AgriPlast) and an organic fertilizer made from biogas digestate (AgriFer). The facility has an annual throughput of about 2 000 tonnes of dry matter (equivalent to 8 000 tonnes of grass per year at 25–30% dry matter content). Grass juice, as waste of the biorefinery process and other co-substrates (biogenic residual materials such as local food waste, 15 000 tonnes/year) are used for biogas production (1 340 000 m^3/year) in the anaerobic digestion facility.

This solution is a good example of the case being quite specific for the circular bio-based business models, when the producer and converter of the biomass are one and the same party, i.e., producer directly uses its by-product as a feedstock for a bio-based process.

S5. Production of bio-based chemicals, high-quality natural lignin, biogas and biofuels from 2nd generation biomass by cracking technology (LXP Group GmbH, Straubing, Germany)

The goal of the company, founded in 2009 is to optimize 2nd generation biomass value chains. They have developed and patented a pre-treatment technology (LX-Process) that "gently cracks" the lignin strands in 2nd generation biomasses (such as agricultural residues, forest materials, energy grasses, organic municipal solid waste, fibrous portion of digestate from biogas plants) into oligosaccharides, lignin, cellulose and other polysaccharides which are available for further processing in fermentation processes (Figure 7). Since no inhibitors are left after the cracking process, downstream fermentation does not require expensive, custom-tailored enzymes for hydrolysis. To be economically feasible, the capacity of the plant has to be at least 10 kilotonne dry matter of processed biomass per year. The LX Pre-treatment plants can serve as raw material producers for the chemical industry or the energy sector. The first industrial LX Demonstration plant is located near Straubing, Bavaria, Germany, it was inaugurated in February of 2020 and has a planned maximum capacity of 500 tonnes (dry matter) of biomass. Initially the plant processes biogas digestate and will test additional biomass types to prove that lignocellulosic biomass from agriculture, forestry and municipal waste are also suitable for the LX Technology. German-funded projects and an EU-funded project helped the development of the technical solution. The company is interested in own technology implementation (Product type 3) as well as licensing the optimized technology solution to other companies (Product type 4). The model presented on Figure 7 describes the own technology implementation activity.

S6: Production of polyhydroxyalkanoates (PHA) using waste cooking oil (NAFIGATE, Czech Republic)

NAFIGATE Corporation, a knowledge-based company founded in 2011 has developed HYDAL Biotechnology. This technology, as the first in the world on the industrial scale, uses waste cooking oil (mostly a mixture of different plant oils such as rapeseed and sunflower oil) to produce polyhydroxyalkanoates (PHA) by using a bacterial fermentation process (Figure 8). The pilot PHA production started in 2013 and the pilot of the downstream process (isolation of the polymer from microbial cells) in 2015. In 2019 the suitability of sludge palm oil was also verified by the company's research activity for PHA production.

The PHA family of biopolymers is unique to plastics from renewable resources, as it comprises the only group of polymers converted from raw materials into their final form directly by microorganisms. Polyhydroxybutyrate (PHB), a specific type of PHA is similar in its material properties to polystyrene, has a good resistance to moisture and aroma barrier properties. It has a unique position in the PHA family, as it biodegrades within a reasonable timescale in a wide range of microbiologically active environments[24] such as soils, fresh water, aerobic and anaerobic composting, wastewater treatment plants. Currently, the PHB biopolymer's application is multifaceted, it can replace toxic substances in UV filters; microplastics in e. g. cosmetic industry, healthcare products or medical applications (e.g., covering for capsules, stitching of wounds, bone implants); synthetic plastics in different applications such as bottles, disposable cups, cutlery, lamination foils etc.; and materials in the agriculture sector for the slow release of fertilizers, insecticides, pesticides or fungicides in the soil.[25] Poly-3-hydroxybutyrate (P3HB), the final desired biopolymer has a purity higher than 99% and high molecular weight. NAFIGATE uses pure P3HB powder in cosmetic products (shower milk, sunscreen, etc.) which are sold by their sales and marketing partner company established in 2015. NAFIGATE is working on broadening the use of biopolymer into the medical and agricultural sector.

In the context of the extension of traditional BMC, Table 2 shows examples for the three additional factors[16] (left column) and good practice examples identified by authors in the reviewed business cases (right column).

<table>
<tr>
<td rowspan="2"><u>Key Partnerships</u>
· raw material providers
· sales partners
· partners in waste management
· R&D partners cooperating in successful plant operation
· financial advisory service, investors</td>
<td><u>Key Activities</u>
· feedstock transport and storage
· technology steps: LX chemical pre-treatment process, precipitation of cellulose and lignin, separation / filtration of each component
· enzymatic hydrolysis
· recovery of solvent and precipitant
· technical problem solving
· product transport
· technology optimization and design for scale up</td>
<td rowspan="2"><u>Value Proposition</u>
· production of wide range of bio-based chemicals, non-toxic, sulphur-free, high-quality natural lignin, biofuels and biogas
· high feedstock flexibility: any lignocellulosic raw material can be processed (using only non-food biomass), meaning that the plant is not fixed to a single feedstock
· using the output materials from LX-Process technology, bio-processing plants can produce sugars by enzymatic hydrolysis which can be then converted through microbial fermentation processes into a multitude of valuable end products (e.g. biogas, ethanol, lactic acid, etc.)
· LX-Process leaves little inhibitors (such as furfural or formic acid) the presence of which is a principle hurdle faced in downstream bioprocessing, as they cannot not be removed economically
· simple, modular technology system
· decentralized bio-based production is possible
· circular bioeconomy approach supported by legislation on EU and national level
· GHG reduction</td>
<td><u>Customer Relationships</u>
· B2B sales strategy
· operating a large-scale pilot plant
· personal follow-up contacts with stakeholders showing interest after presentations at conferences or website visits</td>
<td rowspan="2"><u>Customer Segments</u>
· chemical industrial enterprises interested in 2nd generation bio-chemicals
· key players in development of bio-based, “drop-in” replacement of petrochemicals
· customers seeking natural lignin of unique quality
· cosmetic industry
· 3D printing market
· sectors of construction industry interested in green construction materials
· producers of biopolymers (resins, plastics) and adhesives
· bioethanol and biogas consumers</td>
</tr>
<tr>
<td><u>Key Resources</u>
· regionally available biomass feedstock (biogas digestate, agricultural and forestry residues)
· estate for the buildings and feedstock storage
· buildings and machinery for processes listed under Key Activities
· vehicles for transport and handling of feedstock and products
· specific-skilled workforce and their technical experiences</td>
<td><u>Channels</u>
· marketing: company website
· presentations and workshops to inform stakeholders
· demonstration activities performed in the large-scale pilot plant</td>
</tr>
<tr>
<td colspan="3"><u>Cost Structure</u>
· CAPEX costs highly depend on scale and integration scenario
· main OPEX items: feedstock, energy (heat / electricity)
· feedstock price: as cheap as possible, but up to 100 EUR/tonne
· simplicity of the process keeps operational costs low: low temperature, around 70°C, enabling use of residual waste heat; normal atmospheric pressure/tolerance/corrosiveness</td>
<td colspan="2"><u>Revenue Streams</u>
· sales of the materials produced by LX-Process technology
· bulk products as lignin, cellulose, sugars generate revenue with relatively good margins but can also benefit from a wide market of niche products, such as vanillin, which generate high margins but in much lower volume markets
· 6-7 years long payback time is estimated for a plant with a capacity of 25 kt dry matter processed biomass per year
· deployment of the technology is already economical from ca. 10 000 tonnes of throughput (dry matter biomass) per year</td>
</tr>
</table>

Figure 7. BMC of solution ‘S5’ (LXP Group, Germany).

<table>
<tr>
<td rowspan="2"><u>Key Partnerships</u>
· industrial feedstock providers ensuring large amount of waste cooking oil
· sales partner
· R&D partners providing laboratories and equipment needed for the production (if these resources are not owned by the producer)</td>
<td><u>Key Activities</u>
· feedstock transport to the production site
· technology steps: microbial fermentation (transforming waste cooking oil into a PHA biopolymer, stored inside the bacterial cell); isolation of polymer from microbial cells; mixing with additives for stabilization
· production of cosmetics from P3HB
· product transport
· product selling activities
· continuous technology development and optimisation</td>
<td rowspan="2"><u>Value Proposition</u>
· HYDAL biotechnology producing biodegradable PHA (polyhydroxyalkanoates) from waste cooking oils
· PHA: raw material in cosmetic or medicine industry for biodegradable microbeads, UV filter in sunscreens or bioplastics
· PHA product of the highest priority: poly-3-hydroxybutyrate (P3HB)
· production of cosmetics (e.g. peeling shower milk, sunscreen) from P3HB
· the technology does not use crops or other feedstock produced on agricultural land
· the technology contributes to reducing pollution caused by plastics and microplastics and to solving the problem of waste cooking oil utilization as well, and, at the same time requires less water and energy compared to PHB production from sugar beet, potato, wheat or corn</td>
<td><u>Customer Relationships</u>
· close cooperation with industrial customers using PHA
· B2B and B2C sales strategies
· close cooperation with sales partners</td>
<td rowspan="2"><u>Customer Segments</u>
· PHA, P3HB: industrial customers (cosmetic and medicine industry, agriculture sector)
· cosmetics: supermarket chains, wholesalers and retail customers
· licences and know-hows: market actors interested in large scale PHA production</td>
</tr>
<tr>
<td><u>Key Resources</u>
· buildings, laboratories and equipment for processes listed under Key Activities
· know-how related to the specific bacterial fermentation process, based on own experience
· high quality experts and specific-skilled workforce</td>
<td><u>Channels</u>
· webshop of NAFIGATE Cosmetics to reach retail consumers directly
· marketing: company's own website, Facebook site
· press releases, presentations and workshops to inform stakeholders</td>
</tr>
<tr>
<td colspan="3"><u>Cost Structure</u>
· technology development was financed by own investment and public funding
· relatively high CAPEX costs purchasing equipment (new facility producing PHA on industrial scale would cost around 9 million EUR, according to the company's estimation)
· OPEX: cost of waste cooking oil as main feedstock (0,6 EUR/kg); rental costs of laboratory and equipment; energy costs; service costs (including the high cost of laboratory testing services that has to be purchased to provide certificates for cosmetics); labour costs; general and administrative expenses</td>
<td colspan="2"><u>Revenue Streams</u>
· revenues from PHA, PH3B sales
· selling of cosmetics (60 EUR/litre, based on retail prices in the webshop)
· licensing of know-how</td>
</tr>
</table>

Figure 8. BMC of solution 'S6' (NAFIGATE Corporation, Czech Republic).

4. DISCUSSION

4.1 Cross-cutting analysis

Based on the internal building blocks in the business models of bio-based solutions in Table 1 and described in the reports listed in Section 2.3, the following points were identified as especially important cross-cutting elements and also as factors that are specific to the bio-based industry in several aspects:

– Biomass feedstock as a key resource, local biomass suppliers as key partners and maintaining good relationships with them as a key activity, since the constant availability of biomass and solving the related logistic issues are of key importance. For bio-based companies it is essential to have close relation with farmers by offering them reliable and convenient services, e. g. secure and regular payments irrespective of harvest time, assurance of timely transport

Table 2. Examples for additional factors to extend the traditional BMC, and good practices identified in bio-based business models for these factors.

Examples for the additional factors to extend the traditional BMC	Concrete good practice examples of bio-based business models
Additional factor: Drivers and stakeholder involvement tools	
· identifying and informing "opinion formers" in different stakeholder groups · active participation and support of regional or industrial clusters, advocacy forums and other organisations in stakeholder involvement, by action platforms to promote new technologies and innovations · knowledge exchange and development through networks and across value chains, involving learning activities, mostly on the emerging technologies · market formation involving activities that contribute to the creation of a demand for the emerging technology (e. g. taxation, procurement) · general policy instruments (e. g. long-term public strategies on industry regulations, incentives for product labelling, consumer information, industry collaboration) · public funding for early-stage research and competence building	· LXP Group: cooperation with Chemie-Cluster Bayern, a market-oriented development network of entrepreneurs and research institutions in the Bavarian chemical industry, acting as a catalyst facilitating the diffusion of innovative products into new markets[17] · Rotterzwam: cooperation with many local partners to find new ways for marketing products from coffee grounds and oyster mushrooms[17] · Wilson Bio-Chemical: partnerships increasingly strengthened through R&D into higher value applications, anticipating delivering more economic, technical, environmental and social benefits[15] · AF Biomass: strengthening the supply chain network by exploring new end-markets such as for linseed straw in the paper industry in Spain and with a new straw pelleting plant in the UK[15] · Bio-Lutions received grant from the German government for upscaling their technology[20] · NAFIGATE Corporation started its operation with low investment amount and public support (most of these funds spent on R&D activities and know-how development)[17]
Additional factor: Sustainability requirements	
· energy and materials are conserved during the production process and the form of energy and materials applied are most appropriate for the desired result · work practices (including the use of chemical substances, physical agents or technologies) that present hazards to human health or the environment are continuously reduced or eliminated · products (including their packaging) and services are designed to be safe and ecologically sound throughout their life cycle · wastes and ecologically incompatible by-products are continuously reduced, eliminated, or recycled · non-food-competitive land use · biodegradability of bio-based materials in industrial, soil, or marine environments · avoiding health and ecological risks caused by improper use of technologies · management of companies is committed to an open, participatory process of continuous evaluation and improvement, focused on the long-term economic performance	· NAFIGATE Corporation: HYDAL technology transforming waste cooking oil into high-value biomaterial polymers does not use crops or other feedstock produced on agricultural land, moreover, requires less water and energy compared to PHB production from sugar beet, potato, wheat or corn[17] · LXP Group: LX-Process can be readily adapted for large-scale 2nd generation ethanol manufacturing[17] · Biowert Industrie GmbH: 'grass refinery' solution using agricultural and food industrial wastes[17] · Bestico: BSF larvae can transform nearly any kind of organic waste into high-quality protein[17] · Wilson Bio-Chemical: downstream reprocessing of recyclables[15] · AF Biomass: growing use of biomass for energy can positively contribute to energy security, the low carbon economy and 'green' jobs[15] · Hédinn protein plant: process requiring less water and energy than comparable technologies and thus economically and environmentally beneficial[20] · Spawnfoam renewable biocomposite: By creating sustainable and biodegradable products, fossil-based products are substituted[20] · Bio-Lutions: using local resources to produce biodegradable products, based on raw material being outside of the human food chain and other value chains[20]

before new crop needs planting, access to financing opportunities within the business group to support farmers investing in e.g. storage facilities.[15]

– Logistic and quality assurance partnerships and activities, since keeping transport costs low is crucial for costs-efficiency, and so are the activities ensuring adequate biomass supply (e.g. handling seasonality and perishability, quality monitoring etc.). Volumes of resources, especially feedstocks from agricultural production can fluctuate, which represents a constraint for markets traditionally not subjected to large fluctuations in feedstock supply, like for chemical products, hence issues in logistics, storage and quality preservation should be constantly addressed.[26] Steady supply of the required seasonal feedstock, which may increase storage costs, is often reported as a weakness.[18] Challenges from seasonality are tackled by building appropriate stor-

Table 2. (Continued).

Examples for the additional factors to extend the traditional BMC	Concrete good practice examples of bio-based business models
Additional factor: Sustainability benefits	
· valorisation of biomass which would otherwise end up as waste · higher recycling rates · novel energy sources for households · increasing food production and lowering production costs · reducing greenhouse gas emissions and air pollution · decreasing the use of pesticides · generation of livelihood opportunities and income sources for farmers · health benefits due to medical applications · benefits in terms of energy provisioning and food security, for example, using waste as feedstock for insects or algae which are subsequently used as feedstock for further applications	· Rotterzwam: oyster mushrooms grown on coffee grounds, as source of proteins of non-animal origin with minimal footprint and food miles[17] · LXP Group: LX-Process reduces GHG emissions and enables 1st generation biorefineries and biogas plants to convert to 2nd generation feedstocks, thus reducing required acreage for 1st generation feedstocks[17] · Hempire: hemp-based building material reduces energy required for heating/cooling; 1 m^3 of Hempire Mix locks up 165 kg of CO_2 (negative carbon footprint)[17] · Biowert Industrie GmbH: their solution reduces CO_2 footprint by using grass as a natural CO_2 adsorber and the use of fossil-based plastics as well (and thus the consumption of fossil raw materials)[17] · Bestico: low environmental footprint of producing alternative protein sources for animal feeds by BSF larvae[17] · Wilson Bio-Chemical: biodegradable waste fraction diverted from landfill, reducing greenhouse gas emissions and freeing up land for other purposes whilst producing feedstock for renewable energy[15] · Soldebre: use of olive kernels as a low-carbon biofuel, environmental impacts are reduced such as achieving a reduction in carbon emissions by using less fossil fuel[15] · Small-scale pellet production: local pellet production reduces the dependence from fossil fuels, replaces them in households and CHP plants, etc., thus reducing overall logistics costs and emissions from fossil fuels[20] · Hédinn protein plant: more targeted fishing of cyprinids helps to reduce eutrophication which may have positive environmental impacts while supporting rural development at the same time[20] · Spawnfoam renewable biocomposite: solution facilitates defossilisation for a range of products, reduces GHG emissions and prevents the deposit of waste in landfills or in the seas[20]

age capacity and technologies converting perishable biomass to a stable feedstock (e.g. ensiling).

– Research background (laboratories as a key resource or a key partnership, research-based developments as a key activity), since bioeconomy and industrial biotechnology are highly innovative and research-intensive sectors. Continuous R&D is part of business models for more cost effective and higher quality production as well as developing new applications for products and sidestreams.

The Value proposition is versatile since it can be extended to include social and environmental values besides the economic value the business creates. For example, in bioenergy producing solutions, the local production strengthens the local economy and reduces the dependence from fossil fuels at the same time.[27] Values that are generally recognized in all the business cases reviewed in this study include: valorization of wastes or untapped feedstocks; creation of more sustainable products; mitigating dependence from fossil fuels in the case of energy-producing solutions; local value creation by using locally produced feedstock; local job and income creation.

Public and private partners from diverse sectors need to be involved in order to establish strategic collaborations for bioeconomy initiatives.[26] For example, a biorefinery evolves in a territory with an economic, political and social identity, thus, the success of such a business model depends on the ability to form partnerships and collaborate with local players: (large number of) primary producers, agricultural cooperatives, industries, educational and research organizations, local authorities.[26] Showing them the environmental, social and business benefits as part of sustainability impact that the biorefinery project can bring to their local level can greatly improve this ability, and thus the chance for a successful and profitable project implementation. Business support organisations such as development authorities and clusters acting in the field of regional development or a specific industrial sector can play a key role in this integration process.

4.2. Readiness level of value proposition

The solutions analyzed in the present study comprise a technology and its bio-based product with just enough features to be subjected to customer feedback (i.e., suitable to build a demo plant on it or to be offered to customers) and to gain experiences in connection with actual market needs, forming the basis for future developments. The level of development of these solutions more or less corresponds to the stage of the "Minimum Viable Product" (MVP), a concept from Lean Startup that stresses the impact of learning for further product development. E. Ries defined an MVP as such version of a new product which may lack some or many features that may prove essential later on but allows the development team to collect the maximum amount of validated learning about customers with the least effort.[28]

The initial MVP and the abovementioned customer feedback loops with new versions of the MVP, developed in accordance with the feedbacks to the initial MVP, are two consecutive levels of the Business Readiness Level (BRL) scale defined by R. Ramsden; this scale can be used to benchmark the current status of a business proposition, from concept to mature business fully embedded in the market[29] Although TRL scale[18] is widely used to understand the current status of a technical innovation, even TRL9 does not entail by itself that the technology is ready for market. This is because business-related aspects are not necessarily taken into account when TRL is defined for a technology, moreover, TRL classification can be subjective. As put eloquently in a report produced under the framework of Access2EIC, the official network for H2020 National Contact Points for the new European Innovation Council:[30] "TRL level as commonly used in H2020 can be used to define if a technology is ready to go to market or not, but it does not capture properly how 'ready' is the business based on such technology to go to market." That is why it is useful to adjust the focus generally being on TRLs and involve BRLs when considering a technology being part of the Value proposition, in order to measure readiness in terms of creating real customer value in an objective manner.

4.3 Customer-related building blocks: Customer segments, Channels, Customer relationships

The customer-related building blocks can be a weak point of the business cases described. These building blocks could not be described properly in several cases in the BMCs due to the lack of relevant information, not because of insufficient data provision but because the owner of the Value proposition has not mapped all the possible segments yet. Grant-based subsidies covering the innovation costs as well as not fully market-driven developments focusing on increasing the TRL of R&D results mainly aim at the optimization of technology processes and reaching the MVP but fail to pay sufficient attention to customer-related building blocks, if any.

The results of a survey conducted with the participation of 66 companies from South-East Finland in 2012[31] clearly support the importance of external building blocks in bio-based industry: they show that two of the six measures investigated, i.e., "Customer value-added" and "Supply chain collaboration" had statistically significant effects on business performance, while the other four (i.e., "Opportunities from business environment", "Business forces", "Innovations", "R&D collaboration") did not show any remarkable statistical effect on expected business performance.[31] This finding demonstrates that it is useful to start the development of the BMC at the Customer segments building block where the Value proposition can be delivered to. Once there is a clear and thorough knowledge and understanding regarding who the customers are and what problems or needs they have, it is easier to define the Value proposition which is the value that can be added to these customers' activities.

Customer relationships building block includes, among others, identifying and tracking the specific customer segments and the customers' needs. Many customers are willing to pay slightly more for environmentally friendly, natural, chemical-free, local products, which aspects are easily discernible for products of bio-based solutions. Accordingly, companies clearly need to identify these segments[12] and products need to be tailored to "bioeconomy customers" identified.

Word-of-mouth promotion by personal contacts and providing continuously updated content online via e. g. company website, social media, blogs, newsletters sent by email proved to be crucial for the bio-based industry to deliver, communicate and sell value propositions and to raise the customer awareness of a company's products and services. However, Channels is the least addressed building block in the analysed models, probably because many applications for bioeconomy have not yet reached a stage where attention to distribution channels can no longer be ignored.

4.4 Finance-related building blocks: Cost structure, Revenue streams

From the business models described in Section 3, it appears that the main drivers for the innovation development from lower TRLs to the stage where the level of technology readiness allows the introduction of an MVP are:

– financial resources available to cover several CAPEX items, which can come from different sources, i.e. external ones such as EU funds or governmental support and the profit of the business, but for the majority of solutions presented in Section 3 it has been some kind of public subsidy so far;
– the cheap biomass feedstock material ensuring lower OPEX, meaning that the low price has to include logistic costs already.

The availability of the financing needed for the main CAPEX items is a determining factor because the development and implementation of new technologies in the bioeconomy in most cases requires large upfront investments. Moreover, uncertainties inherent to bioeconomy hinder these investments,[1] that is why many initiatives in this sector are dependent on grant subsidies. For example, Clariant is investing more than 100 million EUR in a commercial-scale cellulosic ethanol production plant in Podari, Romania and this plant receives more than 40 million EUR funding[32] from the EU and BBI JU within SUNLIQUID and LIGNOFLAG projects, although this multinational large company has been successfully operating a first pilot plant since 2009 and a large-scale pre-commercial plant in Straubing, Germany since 2012.[33]

When the COWI report was launched in 2019, 13 out of the 15 technologies mentioned were at TRL9, meaning an actual system proven in operational environment,[18] or about to reach that level in the very near future.[19] Among these 13 bio-based solutions, only 3 success stories were characterized by an investment requirement below 5 million EUR, while the success of 2 companies out of these 3 was based on financial support from H2020 SME Instrument funding and European Structural and Investment Funds (ESIF). Most of the large companies involved in the study developed their bio-based product as an addition to a wider set of products, and they have thus been able to mobilize the finance internally through leveraging on profits generated elsewhere in the business. All these large companies are reported not having received public funding for the set-up of the bio-based production plants, but all of them have benefited from EU funds in the initial phase of their bio-based developments (the bio-based development included in the report and/or others) which funds have been available to support R&D phases preparing the ground for the investment in the industrial scale plant.[19]

Utmost attention should be paid to logistic costs among OPEX items, as most waste and by-product streams used as feedstock for bio-based processes are bulky, making transportation a significant cost driver.[34] The largest distance for profitable transportation of raw materials to a bio-based industrial plant depends on the density of the feedstock and the actual products produced out of it. However, based on our own development activities and also participation at relevant workshops, the highest distance from which the transport of raw materials to the bio-based industrial plant is profitable is maximum 60 km. This relatively low value means that the place of a new plant has to be very carefully planned, in consideration for the logistic aspects.

In many cases, the production of value-added products from specific agricultural wastes and by-products may not be economically feasible mainly because of the low quantities and seasonality, high transportation costs, water content of raw materials and low market price of products. In order to overcome these problems, bio-based sidestreams can be treated on-site by the same producing industry, in order to produce intermediate products that can be more easily stored than the original raw material and more economically transported to the place of further processing.[34] For example, Hédinn protein plant can be run by fisheries or fish processing companies; in this case, products are processed at the feedstock source and sold on-site to customers.[20] Another example is Melodea technology producing ‘Cellulose Nano Crystals’, which can be deployed at on-site pulp mills, where the feedstock, the necessary infrastructure and utilities are already in place.[19]

The outcome of a good practice case, even if the solution is technologically mature enough, cannot be turned into a real consumer product without marketing and public relation (PR) activities like e.g., a campaign including advertising, promoting by social media, press releases etc. The costs that have to be allocated for marketing and PR activities often exceed by a factor of several times the technology development costs. However, usually neither activities nor actors related to marketing and PR do appear in the Key activities and Key partners blocks, respectively. Furthermore, the related costs are not indicated in Cost structure, because solution owners give low priorities to sales development activities and customer segment analyses. (See also Section 4.3 for this weak point of the business models.)

As a basic principle, a long-term sustainable bioeconomy needs to be economically self-sustaining through the provision of marketable products that are independent from long-term subsidies.[13] Currently, many ongoing bioeconomy-related development activities are heavily dependent on grants and other subsidies, especially for SMEs, and they are quite far from reaching economic profitability, even if their bio-based technology is reported to be on high TRL and BRL. Generally, the income from bio-based product sales is quite low, at least during the initial stages of market introduction, especially if compared with the total development and investment costs. A typical indirect revenue resulting from the bio-based industrial processes comes from the utilization of wastes produced by other activities of the same company E. g. by-product of the Biowert biorefinery is processed in their biogas plant (S4 in Section 3 and Figure 7), and thus decreasing costs associated with the disposal of these wastes.

It is relevant to add here that waste management costs are often reduced on the side of feedstock providers, such as the olive-producing farmers selling olive stones to Cooperativa La Carrera (Spain) using this feedstock as fuel for biomass heaters.[6] This saving on the feedstock provider's side can be included in the Value proposition, as in the business model of Hédinn protein plant described in the BE-Rural project, though Value proposition is meant to be delivered for Customers, not Key partners, so this aspect is difficult to interpret by BMC. It is mentioned in the BMC of Hédinn plant that fisheries, processing industries, etc. can save on their fish waste disposal costs.[20] However, these feedstock producers are key partners in this model, so this saving can be regarded as an indirect revenue only when the protein plant is run by the feedstock producer itself, using its own wastes.

When it comes to revenues, it is often stated that the products connected to bioeconomy are not profitable as long as they have to be sold at the same price as the non-bio-based product. Higher price of bio-based products compared to fossil-based solutions causing a deficient market pull is one of the most important basic limitations to the bioeconomy development.[6] It can be difficult to justify higher market prices for bio-based products, since many of them are commodity products and end-consumers rarely care where the original raw material comes from. Moreover, even if they are conscious "bioeconomy customers", they cannot distinguish the end-product from earlier, non-bio-based products. In this regard, products need to be tailored to these customers, and this specific customer segment has to be kept in the focus, since they are willing to pay higher but competitive price if the products fulfil their special demands while achieving similar functionality.[31] Similarly to farmers, brand owners are are less involved in the development of the bio-based economy. However, they consider climate challenges, sustainable production and consumption to an increasing extent[35], and can play a key role in supporting market uptake of bio-based products and to influence consumer choices in relation to these products.[36]

With a very few exceptions, only large companies have the financial means to develop the technology, invest in the necessary infrastructure and commercialize the product exclusively through internal financing, and without putting the entire company at risk.[19] Size of the company can be a determining factor when defining internal building blocks Key resources and Key partnerships: larger companies are usually able to finance the human and financial resources to do long-term development work in-house concerning their products and processes, while SMEs' ability to extend their knowledge and competence base is significantly more limited. Smaller companies are much more dependent on external networks and the ability to create such networks,[31] which is reflected in their cost structure as well.

Bio-based solutions have to be market-driven in order to achieve market viability, become independent from external financing in the long-term and that subsidies should focus on providing a learning curve in order to establish competitive business.

5. CONCLUSIONS

Assessment of six bio-based solutions using BMC allows to present all general or sector-specific business-related aspects to interested stakeholders in an easy-to-understand way. This way of presenting provides new insights for the relevant stakeholders in the bio-based economy and facilitates mutual understanding by different bioeconomy actors which often operate in different sectors like agriculture, industry, government or R&D. Increased understanding of how bioeconomy businesses work not only facilitates SMEs and large enterprises to benefit from replicating bio-based businesses, but opportunities for other type of stakeholders increase as well:

- producers of bio-based wastes or by-products can transfer these materials to bio-based industry, thus reducing their waste management costs or even generating income;
- rural communities benefit from local industrial development, job creation and local renewable bioenergy or food production;
- investors may profit from mapping attractive investment opportunities as they can be instrumental in meeting environmental and climate challenges;
- policy makers may benefit from identifying industrial initiatives supporting their existing objectives related to sustainability and climate policies.

This study shows that many bioeconomy business models developed thus far have in common that especially the customer-related building blocks have been weakly elaborated. At the supplier end, involvement of 'rural entrepreneurs' like primary agricultural producers, forest owners, their associations and other small rural businesses is prerequisite for success of the emerging bio-based economy. As proven economic feasibility is essential for acceptance of innovative solutions, well-developed, easy-to-understand business models such as those presented in this article can serve as a helpful tool to bring the good practice cases closer to primary producers, by making these cases more comprehensible and realistic.

At the same time, BMC can serve as a useful and effective tool for enhancing the replication of existing good practice cases, even if the business model always needs to be individually tailored to each local deployment situation. For such tailoring, the business models have to be elaborated in much more detail than presented in this study.

These findings point to the usability of BMC to identify strengths and weaknesses in the business concept at early stages of business planning. Near market introduction, scaling systems such as BRL can facilitate linking technology innovation (as the main part of Value proposition) and the often under-elaborated Customer segments. BRL can be difficult to define, but it can describe the actual business potential of bio-based solutions in a more exact and objective manner, reflecting to which extent the customer may be willing to pay for the Value proposition. The introduction of a scaling system such as BRLs in the assessment of bioeconomy solutions and alignment of TRLs and BRLs can create a practical framework to direct the development of bio-based start-up companies as well as funding instruments for technology developments and business acceleration.

The traditional BMC benefits from extending with additional factors related to sustainability requirements and benefits as well as factors related to the business ecosystem such as drivers and stakeholder involvement tools. The additional factors can show how to create short-term or longer term structural values also in environmental and social terms, which is particularly relevant in bioeconomy businesses requiring the cooperation of various and divergent players.

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Food loss and waste accounting: the case of the Philippine food supply chain

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Abstract. In recent years, the interest in food loss and waste has been gaining momentum from researchers and policy-makers. Much of the attention on the matter is centered in industrialized countries, creating a knowledge gap within developing countries, among which is the Philippines. This lack of information impedes the country-level response in solving the issue, whose implications extend to food and nutrition security, productivity, and resource use. For this reason, our paper estimates the food loss and waste levels in the Philippine food supply chain of rice, corn, and banana commodities. We were first to identify the percentage accumulation of food loss and waste in each stage of the food supply chain and translated such portions into edible food volumes initially intended for human consumption. Our findings revealed that between one-seventh to one-fifth of edible rice, corn, and banana quantities are lost/wasted in their respective food supply chains. For each of the commodities analyzed, the principal activities responsible for the problem are drying, dehanding, and harvesting, respectively. Our results suggest the following for policy intervention and research: establish an agreed-upon food loss and waste definition; calibrate interventions at the level of the food supply chain; follow a supply chain system approach in reducing the problem; and determine an acceptable level of loss/waste.

Keywords: Food loss and waste, Food supply chain, Philippines.
JEL code: Q13, Q18.

1. INTRODUCTION

The widespread attention placed on losses is not of recent concern. It has been first expressed as one of FAO's organizational mandates during its establishment in 1945 (Parfitt *et al.,* 2010). The matter was highlighted again during the Seventh Session of the United Nations General Assembly in 1975 when they aimed to halve postharvest losses by 1985 (Fabi & English, 2019). Long after, the food crisis in 2007-2008 paved the renewed interest in addressing the problem (Fabi *et al.,* 2021). By 2011, the issue was better realized by releasing the first global estimate of FLW, where about one-third of the food produced for human consumption is lost or wasted (Gustavsson *et al.*, 2011). Subsequently, the international community recognized the concerning levels of food loss and waste (FLW) in the Sustainable Development Goals (SDGs) and stated its reduction goal in Target 12.3.

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The broad interest in FLW is due to its implications transcending the issue of unrealized physical food quantities. For example, the FAO (2017) reports that recovering or minimizing food outflow from the chain can increase productivity, promote food and nutrition security, and minimize negative environmental impacts. Further, there are also moral overtones surrounding the problem (Gjerris, 2020), given that 155 million people globally are acutely food insecure (FSIN & GNAFC, 2021). However, to design an effective policy intervention, there is a need to establish empirical information on the magnitude and causes of FLW generation. Moreover, at the country level, there is a need to strengthen efforts to understand the problem at a disaggregate scale, particularly on the different commodity food supply chains (FSCs).

Currently, limitations to an evidence-based policymaking process in this field exist, which also constraints the synchronized global effort to reduce FLW. For example, Xue *et al.* (2017) identified three significant biases in the literature: first, the analyses are more concentrated in industrialized countries; second, over half of the publications relied on secondary data, with some authors using outdated data; and third, studies are abundant at the retail and consumption stages.

These biases imply that information on the issue is limited in developing countries such as the Philippines. In this country, the potential benefits of FLW reduction on food security and poverty reduction are vital if we consider that 64% of the Filipino population is chronically food insecure (IPC, n.d.). Further, two of the most important FSC actors, farmers and fishermen, are consistently classified as the country's poorest groups. Moreover, in the Philippines, commodity losses from harvesting to distribution are reported to reach as high as 50% (Mopera, 2016). The FAO (2019) notes that this is a manifestation of the significant constraints actors face in performing their activities. Collectively, these imply that the recovery or prevention of food outflow from the chain has great potential in feeding and improving the livelihoods of people in the country.

Despite the potential positive impacts of FLW reduction on the Philippines' sustainable development, studies on the matter lack. Following Gustavsson *et al.* (2011), we considered FLW at the main stages of the FSC, namely the agricultural production, postharvest handling and storage, processing and packaging, distribution, and consumption. Further, we used the concept of FLW of Gustavsson *et al.* (2011) to understand loss/waste in the all stages of the rice, corn, and banana FSCs. The selected commodities are three of the most important crops in the Philippines, creating significant implications on the country's agricultural sector. Moreover, owing to the methodological elements we used in this paper, our estimations can be considered as the first national accounting of edible food reductions initially allocated for human consumption across all stages of the FSC in selected Philippine commodities. We also included the consumption stage in our FSC analysis, a level of investigation where knowledge on the problem is lacking. Finally, through an extensive review of relevant literature, we attempt to explain the causes of FLW generation to recognize the actions or decisions that lead to the problem.

As previously mentioned, we used the definition offered by Gustavsson *et al.* (2011), where food loss refers to the reduction in food quantities from the activities of agricultural production until the point prior to retail, while that of food waste is found at the retail and consumption stages. The terms are further characterized such that only edible portions and food shares for human consumption are considered FLW (Gustavsson *et al.,* 2011). We followed the interpretation offered by Gustavsson *et al.* (2011) because we adopted their methodology in estimating the magnitudes of FLW. This choice was important prior to our assessment because it was crucial to operationalize the elements characterizing the concepts.

The literature on the subject, however, articulates that there is no fixed definition and that various entities provide different interpretations depending on their objective of assessing the issue (Chaboud & Daviron, 2017; FAO, 2014). As such, publications on the matter have varying illustrations and usage of the terms (FAO, 2014; Parfitt *et al.,* 2010; Ishangulyyev *et al.,* 2019; Chaboud & Daviron, 2017; Garrone *et al.*, 2014; Papargyropoulou *et al.*, 2014; Galli *et al.,* 2019; von Massow *et al.*, 2019).

To apply the approach of Gustavsson *et al.* (2013), we conducted an extensive literature review to gather the potential variables and organized them into a matrix to facilitate the data selection and estimation of FLW. This effort was due to a lack of systematized information from official sources. It also reinforces the need for more research and information on the issue.

The paper is organized as follows: Section 2 presents the methodology we adopted for this study and the requisite dataset for the estimations, Section 3 presents and discusses the results, and Section 4 concludes.

2. METHODOLOGY AND DATA

2.1 Estimation Approaches

Gustavsson *et al.* (2013) offered two approaches to estimating FLW: the percentage accumulation of loss/waste in the FSC and the resulting volumes generated at

Table 1. Estimation guide for the percentage loss/waste accumulation in the FSC.

Agricultural Production (AP)	Postharvest Handling and Storage (PHS)	Processing and Packaging (PP)	Distribution (D)	Consumption (C)
%AP	%PHS× (1-%AP)	%PP× (1-%AP)× (1-%PHS)	%D× (1-%AP)× (1-%PHS)× (1-%PP)	%C×(1-%AP) ×(1-%PHS) ×(1-%PP) ×(1-%D)

Note: %AP, %PHS, %PP, %D, and %C=weight percentages per FSC stage.
Source: Gustavsson *et al.*, 2013.

each stage. Although the two methods show the magnitude of the problem, we opted to use both means because the elements in each estimation bring different realizations. The first one shows the percentage accumulation of FLW as food moves through each stage of the FSC. With this information, we can determine the total portion of the commodity that was lost/wasted. In comparison, the second one reflects the volumes of FLW at each stage of the chain. In other words, it translates the figures into actual food volumes that could have been utilized in the country. Indirectly, the volume estimates can also show the significance of the commodity as food for the country.

Table 1 presents the details of the first approach. To illustrate the use of this information and formula, let us start with a hypothetical agricultural production equal to 100. At this stage, the loss/waste is equal to %AP. At the postharvest handling and storage stage (PHS), the percentage of loss/waste (%PHS) is computed out of the remaining share of production at the preceding stage (1-%AP). The same approach is used in the subsequent stages.

For the calculation of the FLW volumes, we used the formulae presented in Table 2 and based our estimations on the mass flow model (Figure 1). This model presents in a diagram the domestic supply quantities and utilization elements that provide the quantity of food available for consumption.

There are three columns in Table 2. The first one lays out the stages of the FSC. The second and third columns present the formulae we followed in calculating for the FLW volume of cereal and non-cereal commodities, respectively. In each FSC stage, we followed a two-step approach in estimating its FLW volume.

The first step of the estimation process calculates the loss/waste in its entirety. These elements are denoted by the index *W* in Table 2. In other words, it relates to the first aspect of the FLW definition of Gustavsson *et al.* (2011), where it is the total reduction of food quantities in the FSC. The second step accounts for the peculiarity of FLW such that only the shares for human consumption (*HC*) and edible portion (*E*) are considered.

Using the PHS stage as an example, we first determined the volume of FLW at PHS (PHS_W) by multiplying the percentage loss/waste (%PHS) at this stage by the total production (A).

The second part of the estimation adjusts the volume of FLW (in our previous example, PHS_W) to fit the FLW definition of intention for human consumption (PHS_{HC}) and edibility (PHS_E). We adjusted the first-level estimate for cereals using allocation factors (AF) and for non-cereal items with conversion factors (CF).

The differing factor adjustments between cereal and non-cereal commodities (AF and CF) come from the nature of their utilization and mass flows model data. According to Gustavsson *et al.* (2013), a significant portion of cereal production is adopted for means other than human consumption. For this reason, we used the allocation factor to capture the share of cereals appropriated for human consumption. In contrast, for non-cereal commodities, the relevant aspect is edibility, which we estimated with the use of the conversion factors. We recognize that cereals have portions which are inedible. However, the data on rice and corn are already in their milled and grain forms, respectively, thereby rendering the use of conversion factors irrelevant.

As seen in Table 2, there are other nuances in the formulae used for different commodity types and FSC stages. For cereals, the difference comes from the specificities of the individual FSCs. In the estimation of rice, for example, we only used element “Food” (denoted by *J*) in the final three FSC stages because all rice grains deemed as food are used in milled form (Gustavsson *et al.*, 2013). For corn, we used elements “Processing” (denoted by *H*) and “Milled food” (denoted by *K*) in the last FSC stages because the commodity can be used as food both in its grain and milled forms.

On the other hand, for the last three stages of non-cereal commodities, we used “Processing” (denoted by *H*) and the sub-elements of “Food” (denoted by *J*). The sub-elements of “Food” could be in either “Fresh” (denoted by *K*) or “Processed” (denoted by *L*) forms. As previously mentioned, *H* refers to the quantities of

Table 2. Estimation guide for the volume of FLW generated at each FSC stage and by crop.

FSC Stage	Cereals	Non-cereals
Agricultural Production (AP)	$AP_W = \frac{\%AP}{1-\%AP} \times A$ $AP_{HC} = AP_W \times AF$	$AP_W = \frac{\%AP}{1-\%AP} \times A$ $AP_E = AP_W \times CF$
Postharvest Handling and Storage (PHS)	$PHS_W = \%PHS \times A$ $PHS_{HC} = PHS_W \times AF$	$PHS_W = \%PHS \times A$ $PHS_E = PHS_W \times CF$
Processing and Packaging (PP)	Rice: $PP_R = \%PP \times J$ Corn: $PP_C = \%PP \times (H + K)$	$PP_W = \%PP \times (H + L)$ $PP_E = PP_W \times CF$
Distribution (D)	Rice: $D_R = \%D \times (J - PP_R)$ Corn: $D_C = \%D \times (H + K - PP_C)$	$D_{F,W} = \%D_F \times K$ $D_{F,E} = D_{F,W} \times CF$ $D_{P,W} = \%D_P \times (H + L - PP_W)$ $D_{P,E} = D_{P,W} \times CF$ $D_{total} = D_{F,E} + D_{P,E}$
Consumption (C)	Rice: $C_R = \%C \times (J - PP_R - D_R)$ Corn: $C_C = \%C \times (H + K - PP_C - D_C)$	$C_{F,W} = \%C_F \times (K - D_{F,W})$ $C_{F,E} = C_{F,W} \times CF$ $C_{P,W} = \%C_P \times (H + L - PP_W - D_{P,W})$ $C_{P,E} = C_{P,W} \times CF$ $C_{total} = C_{F,E} + C_{P,E}$

Note: %AP, %PHS, %PP, %D, and %C=weight percentages per FSC stage, A=Production, H=Processing, J=Food, K=Fresh/milled food, L=Processed food, sub-components of Food (J) = K and L; sub-scripts: W=Total FLW, HC=Human consumption, E=Edible portion, F=Fresh food, P=Processed food, total=fresh + processed FLW.
Source: Gustavsson *et al.*, 2013.

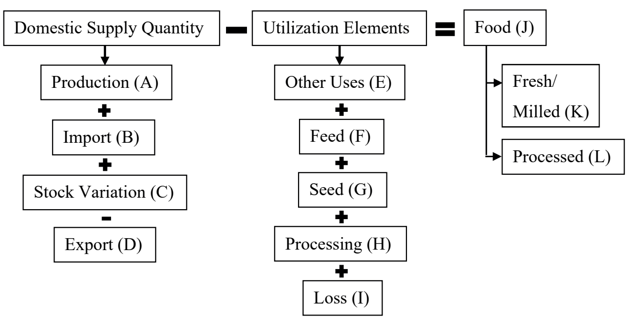

Figure 1. The mass flows model. Source: Gustavsson *et al.*, 2013.

the commodity that are used as raw material to manufacture food products, while L indicates the quantity of the commodity that is consumed in its non-fresh form. Moreover, since non-cereals can be consumed in fresh and processed forms, we separated the calculations of FLW according to its product form. This aspect was considered in the distribution and consumption stages, since the differentiation of the product materializes after the processing and packaging stage. Only after calculating the loss/waste between the two product forms (D_F and C_F for fresh; D_P, C_P for processed) we can estimate the total loss/waste generated for the distribution and consumption stages (D_{total} and C_{total}).

2.2. Data

Gustavsson *et al.* (2013) illustrated the FSC as a five-stage succession of activities, starting from production, postharvest handling and storage, processing and packaging, distribution, and consumption. To estimate the FLW generated at each stage, we first collected the weight percentages of loss/waste at each point in the FSC for all relevant commodities in the Philippines. We found this information through an extensive online search of studies, reports, and other pertinent publications of various researchers and institutions such as the United Nations Industrial Development Organization (UNIDO), Philippine Center for Postharvest Development and Mechanization (PhilMech), and Philippine Statistics Authority (PSA). We compiled all data and entered them into a matrix to analyze the information we had at hand. Upon assessing our matrix, we selected our data sources based on two grounds: data reliability and ability to reflect a relatively full picture of the FSC. It was also vital that we minimized the number of sources for commodity loss/waste weight percentages because we recognize that their methods and contexts differ.

This first stage of data gathering was the most laborious and limiting in terms of the number of commodities we can analyze for our study. Because of data availability and reliability issues and guided by the 2017 PSA publication on the food commonly consumed in the Philippines, we ultimately selected rice, corn, and banana for the study.

After establishing the food items for the study, we searched for their conversion and allocation factors using the same approach as the loss/waste weight percentages. As previously mentioned, these two factors align the initial FLW volume estimates with the definition offered by Gustavsson *et al.* (2011).

Another requirement for the calculations was the construction of the mass flows model. Primarily, it includes domestic supply and utilization elements. Concerning domestic supply, we collected information on production, import, stock variation, and export. As for the utilization elements, we gathered data on non-food uses, feed, seed, processing, and loss. Depending on the food category, we divided the food quantities into fresh and processed (non-cereals) and milled and feed (cereals). We determined the fresh food quantities for non-cereal commodities using the information on the portion of food utilized as fresh, which we also found through an online search. Finally, we identified milled food using the minimum main product recovery during the milling process.

There were two potential data sources for the mass flows model. Ultimately, we used the 2017 PSA data on Supply and Utilization Accounts because of the persistent value discrepancies in the processing parameter of FAOSTAT's Food Balance Sheet. Nonetheless, we had to adjust the PSA data to fit our methodological requirements. The first modification entailed the disaggregation of the processing data to capture the processed food quantities from the total value of the parameter, which includes non-food shares. For this, we took the prescribed proportions from PSA's measurement of the parameter. Our second adjustment was to separate the feeds and loss (or waste) into two parameters. Because there was no PSA guide to isolate the two, we took the proportions of each from FAOSTAT data and applied them to our PSA data. Lastly, we also assumed a value of one for the export parameter because PSA did not indicate the exact figure.

The mass flows model was also relevant in completing the loss/waste weight percentages for the PHS stage. According to Gustavsson *et al.* (2013), the element "loss" represents the food outflow for the said stage. For this, we took the portion of loss from the sum of production, import, and stock variation to extract the PHS weight percentage.

Of all the secondary data collected, the loss/waste weight percentages were highly influential in the FLW volume estimation. Some FSC stages have multiple activities, implying multiple loss/waste weight percentages per stage. Instead of adding the weight percentages, we calculated the FLW generated by each activity and deducted it from the succeeding activities within a stage.

Specifically for bananas, we modified its FLW volume estimation by following the data on banana loss/waste weight percentages. This meant a reorganization of the banana FSC such that distribution preceded the processing and packaging stage. As a result, we used the mass flows elements for processing (H) and food (J) in the calculation. At the processing and packaging stage, we deducted the FLW volume estimate from distribution activities. Lastly, we only used the fresh food formula for the consumption stage because of the lack of loss/waste weight percentage data for the processed food consumption of bananas.

3. RESULTS AND DISCUSSION

Our estimated total FLW, both in percentage terms and million metric tons (MT), are shown in Table 3. The largest share is generated in the banana FSC, followed by that of rice and corn. In terms of volume, rice has the highest FLW due to its role as a staple crop in the Philippines and, therefore, has the highest quantities of food in the supply chain. In comparison, corn and banana have less in terms of volume.

Presented in Figure 2 below is the total estimated FLW shares of all FSC stages of rice, corn, and banana commodities. From this figure, we can note that all stages contribute to the total FLW produced in each FSC. However, the critical stages are crop-specific. In particular, the critical loss points are processing and packaging in rice, agricultural production for corn, and distribution for bananas.

In deconstructing FLW figures, the FAO (2019) uses the term critical loss points to refer to the areas in the

Table 3. Total estimated FLW in the Philippine FSC by commodity.

Commodity	Percentage FLW	Volume FLW (million MT)
Rice	18.10	2.3
Corn	14.69	0.246
Banana	20.05	0.854

Source: authors' calculation.

FSC where food loss and waste levels are highest. Thus, directing the reduction efforts at these sites might have the most impact on food security and economic returns (FAO, 2019). In other words, by using the critical loss points as guides in policy formulation, we might recover the most food quantities and incomes we once lost from the FSC.

3.1 Rice

The literature on rice postharvest losses dictates a varied set of estimates and the extent of FSC stages covered. Some studies report a wide range of losses, such as Parfitt *et al.* (2010), who noted that rice losses in the Philippines are between 10-37%. Others state a more definite estimate, like Manalili *et al.* (2015), who claim that the average total loss incurred from harvesting up to milling is 15%. In comparison with these figures, it may seem that our total rice loss estimate of 18.10% does not deviate much from the two studies. However, because of the non-existence of a standard accounting method for FLW, our FSC coverage and estimation approach differ. In turn, this influences the results we offer from our analysis.

Deconstructing the processing and packaging stage, the critical loss point of rice, our estimates indicate that drying and milling activities are the primary sources of FLW. Of these two, drying generates the highest share at 30.67%, followed by milling at 27.19%. In volume terms, these portions respectively equate to 727,030 MT and 644,720 MT of rice loss. Confirming our results, Mopera (2016) reports that the two sub-stages of processing and packaging are the problematic areas in the rice FSC. However, she reported higher shares for the two, at 36% and 34%, respectively (Mopera, 2016).

There are several causes of drying losses. Manalili *et al.* (2015) point to low-quality equipment, improper use of machinery, and unfavorable drying conditions as the contributory causes of loss. These may indicate that drying losses are merely a result of the inappropriate adoption of machinery. Yet, there is another potential source of FLW for rice. The traditional method of sun drying, which is still prevalent in the country, can decrease grain quality and even cause the grain to crack (Mopera, 2016). Also, laying the grains on the ground creates difficulty in complete grain collection after drying (de Padua, 1999). Even though actors often express sun-drying as a low-cost production option, ultimately, they might receive a decreased income since low-quality grains command low market prices (Mopera, 2016).

In turn, improperly dried grains that enter the milling process will have a lower milling recovery (Chapungco *et al.*, 2008). This fact means that the expected quantity of milled rice was not met and lost instead. Aggravating the issue of grain recovery rate is the prevalent

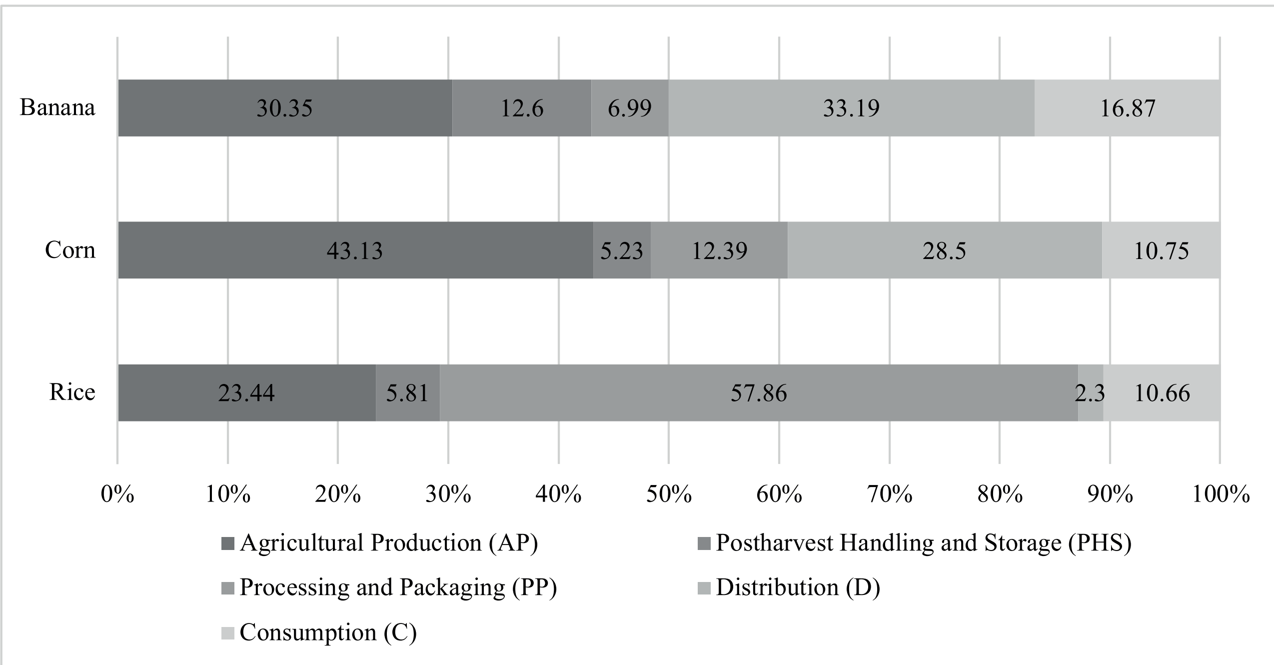

Figure 2. Total estimated FLW shares in each FSC stage by commodity. Source: authors' calculation.

use of dated milling equipment in the country (OECD, 2017). Besides loss generation, these two factors can also affect the marketability of low-quality milled rice, since Filipinos, regardless of social status, prefer to eat good quality rice (eds. Manilay and Frio, 1985 cited in Manalili *et al.*, 2015).

Although less critical than processing and packaging in the FSC of rice, the agricultural production stage also has a considerable level of loss (502,810 MT). At this stage, harvesting and threshing are the main activities and contributors to FLW generation. Respectively, the two activities contribute 11.22% and 11.79% shares of total rice loss. When translated into volume, these two activities amount to 235,100 MT and 258,440 MT of rice loss. Some reported causes for harvesting losses are the natural separation of the grain from the panicle, grain spillage, and unharvested panicles, which can be an intentional labor practice for personal gain (UNIDO, 2012). On the other hand, the accumulation of loss during rice threshing can be caused by machine inefficiency. This situation pertains to mixing grains with the chaffs or the blending of partially threshed panicles with the completed ones (UNIDO, 2012).

In contradiction with our results, a study on the perception of loss generation revealed that farmers view harvesting activity as the primary source of loss (Dela Cruz & Calica, 2016). By focusing their assessment on actors' perceptions, Dela Cruz and Calica (2016) included social and cultural practices that are usually overlooked in analyzing commodity losses. However, when they compared their results against a previous actual loss assessment as a validation measure, it revealed drying as the critical activity of loss. They offered three explanations for such difference: first, the recall of their farmer-respondents was based on the past two cropping seasons that were affected by two strong typhoons that hit the country; second, harvesters intentionally leave portions of crops for gleaners; and third, farmers might be shifting the product forms they sell (from dried grains to wet grains) (Dela Cruz & Calica, 2016).

The study of Dela Cruz and Calica (2016) is important in understanding the complexities of FLW. First, it shows us that changing the approach to analyzing the problem yields different realizations that do not negate one for the other. Second, the inclusion of the interplay of society and culture, which affects the decisions of FSC actors, might provide a profound realization behind FLW generation. For example, the intentional leaving of grains at the field for gleaners might reflect altruism or other tacit relationships and agreements in the community rather than farmer inefficiency or carelessness. Finally, the omission of performing an activity may not impact the FLW levels for a stage or an actor but will do so for the latter ones.

Our estimation for the rice consumption stage revealed that Filipino households waste 252,630 MT of rice. In 2018, the Philippine Family Income and Expenditure Survey showed that the bottom three income classes in the country spend about 58% of their income on food and about 22% of which they spent on bread and cereal (PSA, 2020). The constancy of rice in a typical Filipino diet reflects its relative importance in food expenditure. Further, since there is a consumer preference for good quality rice (eds. Manilay & Frio, 1985 cited in Manalili *et al.*, 2015), which commands a higher market price, the unrealized economic loss from a seemingly inconsequential rice wastage might be considerable.

3.2 Corn

Comparing rice with corn, the other cereal commodity in our study, we can note that the total FLW generated in the entire supply chain is a little below the estimate for rice, at 3.41 percentage points. However, when translated into volume, the corn FLW only amounts to 246,400 MT. The observable similarities in rice and corn supply chain activities might lead one to assume that the accrual of losses should be nearly level. However, the significant disparity exhibited by the two crops primarily comes from the definition we used for the study, which was captured by the allocation factor. One of our estimation guidelines was to only account for the food outflow of those quantities reserved for human consumption (Gustavsson *et al.*, 2013). As the staple crop in the country, rice production is primarily utilized as food in the country. This form of commodity use is, in turn, reflected in our findings.

On the other hand, the allocation factor we adopted for corn demonstrates the stark difference between the grains' losses. Our data indicate that only about a fifth of the commodity is used for human consumption (JBIC Institute, 2002). Even in the corn mass flows model, we found most of its quantities in the non-food utilization elements. All these imply that our FLW estimates only reflect a segment of the commodity supply chains. Consequently, it is possible that accounting for the commodity outflow in the non-food supply chains might result in greater levels of FLW.

The critical loss point for corn is agricultural production, where we estimated 117,880 MT of corn loss. When we consider the sub-stages, corn harvesting accounts for the highest loss level (21.85%), followed by shelling (16.15%). The causes of harvesting loss were unharvested corn and spillage, while that of threshing loss were incomplete shelling, accidental mixing of corn grains with the cobs, and low quality of threshing machine used (UNIDO, 2012).

In contrast with our results, Castro (2003) reports that drying contributes the highest share of corn losses (37%), followed by storage (24%) and shelling (21%). This divergence does not necessarily negate our estimates. The study where we derived the weight percentages of loss/waste for corn reported that two typhoons affected the harvest period during the cropping season of recall. Since weather patterns heavily influence agriculture, rainfall could play a vital role in the discrepancy between the critical points of this study and that of Castro (2003). The weather disturbances caused the continued deterioration of the kernels, which was evident in its discoloration, fungal growth, and mechanical damage (UNIDO, 2012).

The other critical loss point of corn is the distribution stage, where we estimated 63,040 MT worth of the commodity was lost/wasted. UNIDO (2012) reports that torn sacks (26,877 MT) and pest infestation during storage (36,165 MT) were the reasons for the FLW generation.

The reaching effect of natural calamities can be seen in the drying activity (i.e., processing and packaging stage) of corn. Although this stage is not as critical as the other two, drying contributes a 12.39% (27,410 MT) share of the total estimated corn losses. During the typhoons, the submersion of the kernels prolonged the drying time, which was aggravated by the preferred method of sun-drying, and resulted in discoloration (UNIDO, 2012).

3.3 Banana

Compared to grains, fruits are more perishable commodity items, which could be the primary reason why bananas generated the highest percentage share of losses among the three crops. Our estimated banana FLW of 20.05% might be the highest in our analysis, but literature indicates that bananas losses in the Philippines can range from 4-60% (Serrano, 2006).

As previously mentioned, the distribution stage is the critical loss point for the FSC of bananas. Two actors were operating at this stage; the consolidator and the wholesaler contributed to 12.53% (124,530 MT) and 17.24% (134,640 MT) of total FLW, respectively. These levels are due to their continued handling, sorting, and transport of bananas, as Calica *et al.* (2018) reported.

For highly perishable items such as fruits, time and distance are essential in the generation of loss/waste. The Philippines is an archipelagic country composed of over 7,000 islands, making the transportation of highly perishable goods challenging. Our study source for the banana loss/waste weight percentages reported that the bananas were transported in an uncontrolled environment for 12 hours from the area of production to the location of the trader/wholesaler (Calica *et al.*, 2018). In a country with high temperature and relative humidity, the common lack of temperature control during the succeeding stages of harvesting is conducive to the deterioration of the produce (Mopera, 2016).

Another critical loss point for bananas is agricultural production. During the production stage, there is a practice called dehanding. It is an activity where each hand of a banana bunch is removed. However, farmers disregard the bottom two hands because they are small and immature, thus, deemed unmarketable by consolidators (Calica *et al.*, 2018). This practice resulted in 29.08% or 342,346 MT of banana losses, the highest in the production stage.

Although dehanding is a common farm activity after harvesting banana bunches, the act of discarding the bottom two hands is a consequence of a market standard. Compared to the other underlying causes previously mentioned, FLW due to market standards is not the result of a decision or limitation of a single actor. It also involves actors that are beyond the stage where the standards are realized as loss/waste. In dehanding bananas, farmers follow the directive of the middlemen, who then follow the demand preferences set by consumers. To counter the FLW resulting from market standards, changes in attitude, commodity use, or expectation would involve all three actors.

Our estimate for banana waste was 16.87% of the total FLW or 67,321 MT at the consumption stage. According to Esguerra *et al.* (2017), the primary reason for fruit wastage was the consumers' forgetfulness to eat the item. Since fruits inherently have a short shelf-life, extensive delay in consumption can highly contribute to wastage. The onset of decay can happen immediately after, or even before, the point of purchase.

4. CONCLUSIONS

We used the methodology designed by Gustavsson *et al.* (2013) to estimate FLW generation in the Philippines. Our study provides the first estimates of the problem, covering the entire extent of the FSC in the country. Given the novelty of this analysis in the country, we suggest further research and relevant policy design in addressing the problem.

First, our study highlights the need for a standard and well-established FLW definition at the level of the

FSC. According to the literature, institutional objectives and motivation guide the characterization of 'loss' and 'waste' (FAO, 2014; Chaboud and Daviron, 2017; Cattaneo, *et al.*, 2021). Consequently, this stipulation gives entities some flexibility in establishing their interpretation of the terms. However, they should also consider the definitional implications on FLW measurement and policy creation. For example, by adopting the definition of Gustavsson *et al.* (2011) in our study, which only considers edible quantities intended for human consumption, our estimates only represent a fragment of the agrifood sector. We recognize that the omission of the non-food supply chains underestimates the magnitudes and restricts the achievement of a comprehensive FLW reduction policy.

Concerning policy design, the agreed-upon terminology should also not contradict the reduction efforts at the country level. In our estimations, we considered the rejected banana hands at the dehanding activity as losses in the banana FSC. Although farmers repurpose the rejected bananas as feed (Calica *et al.,* 2018), the definition of Gustavsson *et al.* (2011) prescribes the inclusion of such quantities to the FLW estimations. This situation implies that although the bananas were recovered and reused by the farmers, they will remain 'lost' because of the confines of the established definition. From a policy perspective, this might render specific reduction efforts ineffective because of the measurement guidelines followed. Therefore, the resulting estimates might undermine the accuracy of tracking policy successes or failures.

Another limitation in quantifying the extent of FLW in the Philippines is the lack of an accounting standard covering all stages of the FSC. The absence of a consistently used methodology is an obstacle in accurately identifying the critical loss points and, by extension, the achievements or failures in minimizing the problem. The country-relevant actors can refer to the growing body of literature on this topic. Of recent note is the micro-level survey developed and tested by Delgado *et al.* (2021), which covered the current gaps in the measurement of FLW—quantity and quality losses and pre-harvest losses. Moreover, their methodology also allows for results to be comparable across countries and provides a granular understanding of the problem at the producer, middleman, and processor level. Food waste, however, was not covered in their newly proposed method because of its distinct data collection and measurement requirements from food loss (Delgado *et al.,* 2021). This specificity suggests that the micro-level analysis of FLW requires a mixture of methods to capture the total amounts of food outflow from the entire chain.

Compounding the issue on the creation of an accounting standard is the intricacy of the FSC. From the illustration of Gustavsson *et al.* (2013), the FSC may seem simple. Further, our estimations may reflect a singular FSC for a commodity. In reality, one commodity has numerous supply chains, and each varies in extent and number of actors. While it is improbable to determine every existing chain in the food system, there is a need to understand the trend of commodity flow through each stage and sub-stage and analyze the FLW-influencing actions and decisions. This situation implies the need to balance the benefits and limitations of micro and macro-level analysis from a policymaking perspective.

Another consideration in analyzing FLW is detecting the drivers of its generation. Although identifying the extent of the problem is a vital part of FLW information, determining the accompanying causes of the estimated figures can lead to a deeper understanding of the issue. By extension, the availability of this information will contribute to the accurate design of FLW reduction policies.

Furthermore, the lack of relevant data that constrained our paper also challenges evidence-based policymaking. Our FLW estimates strongly depend on the availability of reliable loss/waste weight percentages and conversion and allocation factors, among other information. The Philippines shares with other countries the lack of these critical statistics from official sources, compromising the quality of the estimates. We extend the same concern with some of the elements needed in the mass flows model.

Unfortunately, the repercussions of national data deficiencies are not isolated within a country. It is also consequential on a global scale. As targets in the SDGs, the Global Food Loss Index and the Food Waste Index, which were developed and under the respective management of FAO and UNEP, rely on country-level statistics (Fabi & English, 2019). The indices will reflect the growth or decline of FLW over time. As such, Fabi *et al.* (2021) stress the need for comparable and reliable national data in light of coordinating reduction policies and worldwide monitoring of the problem. The authors also called the international community to formulate a standard definition and metadata to create synergies in data collection and policy actions (Fabi *et al.*, 2021).

Comparing our results and those from other studies shows the need to consider the conditions under which FLW estimates were calculated. Depending on the time of data collection or the relevant cropping season of recall, the presence of extreme weather events is likely to affect FLW levels. In alignment with our findings, the study of Delgado *et al.* (2021) also reported that producers of selected staple crops in Ecuador, Peru, Guatemala, Honduras, and China all indicated the lack of rainfall or other weather conditions as one of their causes of loss.

Our comparison of results also suggests that social and cultural aspects reveal a deeper insight into the causes of FLW generation. While capacities and knowledge are important in current practices, embedded social and cultural structures also affect the actions and decisions of FSC actors. Soma *et al.* (2021) also highlight this point and express that practices, particularly that of farmers, are not solely based on rational decisions. Instead, it results from the interplay of their physical assets, competencies, and viewpoints (Soma *et al.*, 2021). Thus, analyzing and incorporating the underlying causes of FLW in reduction policy design may be more beneficial to the relevant FSC actors.

Our evidence suggests that all stages of the FSC contribute to the generation of FLW in the Philippines. However, the critical loss points and the determinant factors are commodity-specific. Therefore, effective policies aimed at reducing FLW should be calibrated at the specific FSC stages. Our analysis shows that the following shortcomings pose the most significant challenge in preserving the food quantities in the FSC: technological limitations, farming practices, and market standards in the rice, corn, and banana chains, respectively. It follows that efforts targeted at these issues may significantly reduce the problem. In line with the notion set by FAO (2019), addressing these constraints may be highly consequential in improving the FLW levels in the country.

Our study also highlights a fundamental mechanism of the FSC—it is a relay of the commodity from one stage to another. In other words, the FLW incurred in the later stages may be affected by the activities performed or omitted in the prior ones (Gustavsson *et al.*, 2011). Although the critical loss points have the greatest potential in reducing FLW levels, this peculiarity also demonstrates the importance of addressing the bottlenecks in other FSC points. This consideration suggests a supply chain system approach for the containment of FLW and not a fragmented policy intervention focused on the single stages (Luo *et al.*, 2021).

In the pursuit to reduce FLW, the FAO (2019) also pointed out the possibility of establishing acceptable levels of loss/waste, which would warrant further research effort. This suggestion is rooted in the diminishing marginal returns of investments and the potential negative trade-offs with other sustainability aspects (FAO, 2019; Chaboud & Daviron, 2017). Although the FAO (2019) acknowledges the difficulty of setting such a threshold, its identification can guide policy coherence, which is important in allocating limited mitigation resources, particularly in developing countries such as the Philippines.

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The role of network characteristics of the innovation spreaders in agriculture

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Abstract. The diffusion of innovations is largely influenced by the characteristics of the network of initial adopters (or innovation spreader). We investigate how these characteristics tend to influence the adoption rate and the speed of the diffusion process of a technological innovation in agriculture. The diffusion process is simulated through an Agent Based Model that replicates real-world data. We found that the closeness and the clusterization of the networks are the variables that tend to affect the most the capability of spreading innovations among members. Our findings have direct policy implications: since innovations help advancing the economic development of the agricultural sector, promoting the emergence of networks that have desirable characteristics would enhance growth. Our analysis provides specific insights on how to plan networks with desirable characteristics for the innovation spreaders.

Keywords: Diffusion of innovations, Agent Based Model, Social network analysis.
JEL Codes: C63, O33, Q18, Q55.

1. INTRODUCTION

Improving the diffusion of innovations is a key strategy to promote the economic development. The agricultural sector, more and more oriented toward a bio-based sector (Moro et al., 2019), is very much interested by innovations (Scoppola, 2015; Viaggi, 2015), and in a constant need of them as a way to face major challenges such ensuring food security, coping with climate change, and lowering the pressure on the environment. (Li et al., 2022; Ray et al., 2022) Investigating the network characteristics underlying the adoption and diffusion of innovations among farmers is very relevant, since the benefits that would be derived from a wide use and a fast adoption of promising innovations are undoubted (e.g. Hendricks, 2018; Chavas and Nauges ,2020). The success of innovations is tightly connected to the critical mass of their potential users and to their relationships: the successful innovations are generally associated with well performing networks of adopters capable of influencing both adoption and diffusion of innovations. The literature has pointed out clearly that the characteristics of the networks matter

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for the success of innovations – i.e. a fast diffusion with a high adoption rate – (Tey and Brindal, 2012; Banerjee et al., 2013; Barbuto et al., 2019). On the contrary, relatively little emphasis, with remarkable exceptions (Esposti, 2012; Vollaro et al., 2019; De Maria and Zezza, 2020), has been devoted to the agricultural sector.

Within the diffusion process, how social networks operate is key (Valente, 1995): the set and pattern of support, the friendship, and the communication relations are important in defining the evolution and the success of innovations (Morone and Lopolito, 2010): spreading them is “a special type of communication, in that the messages are concerned with new ideas” (Rogers, 2003:5). The innovations may be novel techniques or new strategies, on which the entrepreneurs have a scarce knowledge, and little experience: knowledge, familiarity, experience, and social learning are valuable catalysts for adoption (Santeramo, 2018, 2019). In fact, sharing information and reaching a mutual understanding on the innovation tend to favour its first adoption and diffusion (Rogers, 2003).

If the importance of networks is clear, the reason behind such a relevant role is still unclear. So simply, why networks are so crucial for the diffusion of innovations?

The ssocial networks act through several channels: first, they favour the circulation of *information,* by reducing the uncertainty and facilitating a better assessment of benefits and costs for the adopters; second, the redundancy of the information that can be derived through *social reinforcement,* also named as “indirect experience” (*cfr.* Santeramo 2019), helps overcoming uncertainty; third, the *homophily* among potential adopters, strengthened by the similarity of characteristics (e.g.level of education, socioeconomic status, individual preferences), favours common meanings, the sharing of beliefs and a mutual understanding (Rogers, 2003). In agriculture the third channel is an important catalyst for consumptions habits (Santeramo et al., 2018). This work focuses on the first and the second channels. In this regard, an actor’s ability to circulate information to other actors depends on its position in the network, while its ability to be a source of social reinforcement depends on its level of clusterisation, also referred to as the density of neighborhoods, or, put differently, on how many of contacts are linked with oter members of the network (Namtirtha et al., 2021; Centola, 2010). The social network analysis (SNA), a technique devoted to study and investigate networks, uses indexes to quantify the network characteristics.

In this paper we investigate how the network characteristics (i.e. the SNA indexes to measure the position and the clusterisation level) of the initial adopter influence the diffusion of innovations in agriculture. We aim is to show which characteristics may predict the best spreaders. This outcome is informative for policy makers, innovators and practitioners interested in planning effective spreading campaigns. This study focuses on a technological innovation (mulching films), and relies on a case study derived from specialist horticultural farmers located in the Apulia region. The diffusion process for the innovative mulching films is replicated through an Agent Based Model (ABM), a powerful simulation modeling technique capable of capturing emergent phenomena with systemic characteristics stemming from the interplay of the individuals and which cannot be reduced to the system’s parts (Bonabeau, 2002). The major ABM distinctive feature is its ability to describe the system from the perspective of its constituent units (Bonabeau, 2002).

The adoption of novelties is a complex process typically involving a large body of interacting actors. Although several computational models have been developed (Bass, 1969; Kumar and Kumar, 1992; Sharma et al., 1993; Tanner, 1978), the empirical investigations on micro-level decisions are limited and challenging (Janssen, 2020). One of the problems with these models is that they can explain the observed success in the diffusion processes, but cannot predict alternative emerging paths. The ABM approach helps overcoming this limitation. Proven its ability to describe the complex dynamics of the system by some simple rules acting at micro-level, it provides enough flexibility to capture the emergent phenomena (Bonabeau, 2002). In the specific case of innovation diffusion, the ABM modeling allows us to test various hypotheses on the characteristics of the agents, which represent the autonomous decision-making entities, i.e. in our analysis we refer to the farmers. We focus on their position in the networks and on their social connections. Differently from other approaches, the ABM can be aplpied in ex-ante analyses to predict whether a certain configuration is likely to succeed or to fail.

We have calibrated the model on real-world data, acquired through a survey and by collecting secondary data. A further novelty of our analysis is the use of information that can directly replicate an existing social network. In short, we use a mixed approach which combines a case study, the SNA and a simulation, to feed the empirical model and estimate the effects of the social relations on the diffusion of the innovation.

The next section describes our integrated approach. The section 3 presents the findings of the analysis. We conclude with a discussion and reflections on policy implications to emphasize the relevance of study of this kind.

2. BACKGROUND

A major issue in the process of diffusion of innovation is represented by the interpersonal communication channels, which play a crucial role in influencing the choice of the single agents to adopt or reject the innovation (Rogers 2003). These channels provide means for communication between people, including the information transfer needed to make agents aware of the novelty (Banerjee et al., 2013), and consists of the social relations connecting them (Chavas and Nauges, 2020; Genius et al., 2014). The most suitable social relations to play the role of communication channels are represented by friendship, kinship and professional relationships (Barbuto et al., 2017; Cheboi and Mberia, 2014; Wang et al., 2020).

This paper focus on the role of the network characteristics of the initial adopter in the diffusion of an innovation in a group of farmers. To analyze this process we model a network formed by nodes, each representing a farmer (i.e. agent), and links, each representing the social relations among farmers. The spread of the innovation is assessed by analyzing three outcomes: 1) the adoption rate – i.e. the fraction of farmers adopting the innovation within a time period; 2) the diffusion speed, which depend on the time required by the diffusion process to reach its maximum number of adopters; 3) the magnitude of the diffusion, that is a combination of the two previous outcomes (see table 3 below for details on their definitions and measurement). These outcomes are influenced by the nature of the network, and more precisely by i) the position of the innovation spreaders (Kitsak et al., 2010; Zhang et al., 2016), ii) by the structure of the network, proven that diffusion can reach more people and spread more quickly in clustered networks than in random networks, since the diffusion process is improved by reinforcing signals coming from clustered links (Centola, 2010); and iii) by the socio-demographic characteristics of the farmers forming the network (Banerjee et al., 2013).

As for the agents' characteristics, previous studies have shown that factors such as age, education level, mass-media exposure, experience in the sector, size of the farm are among the most important for the adoption of innovations (Reimers and Klasen, 2013; Wang et al., 2020). Moreover, agents involved in innovation adoption process typically exhibit an intrinsic "propensity to adopt", an individual preference towards the innovation which stimulate the farmers to the adoption when the perceived quality of the innovation is sufficiently high (Delre et al. 2007, van Eck et al. 2011). In other terms, each potential adopter has a resistance to innovate, and this reluctance can be modeled as as a farmer-specific adoption threshold: the first adopters have a very low threshold for adoption whereas the later adopters have higher thresholds (i.e. a stronger resistance to the innovation) that tend to be exceeded only when many other members of the network have adopted the innovation and have reported on its goodness (Macy 1991).

We hypothesize that the spreaders who have higher chances of reaching a vast majority of farmers in the network, by mean of one- (direct) or two- or more-step (indirect) relations, are expected to achieve a large spread; conversely, the spreaders who are closest to the vast majority of farmers are expected to allow a rapid spread and to reach the maximum number of adopters. Figure 1 depicts this process by representing a simple diffusion model. It illustrates the impact that the network characteristics of the spreader have on the number of adopters and on the time required to spread the innovation.

The time unit is conceived as the period needed for the information to pass from one agent to another, that is the time for the communication to occurs. The timing of the diffusion process is broken down in three periods: at t_0 one agent is picked from the network to become the first adopter of the innovation(i.e. the spreader); at t_1 the spreader informs on the existence of the innovation its neighbors (agents connected to the spreader), which become in turn aware of this novelty; at t_2 a second-order information-passing occurs, at t_2 when the spreader's neighbors transfer the information to their neighbors in turn. In both diagrams the agents are distinguished according to the time at which they adopt the innovation. There are four types of agents, represented by different gradations of grey on a black-to-white scale, assuming that the probability that informed agents adopt the innovation is 1: i) the black circle represents the spreader who adopts the innovation at time t_0; ii) the dark-gray circles represent the adopters at t_1 (also named early adopters); iii) the light-gray circles represent the adopters at t_2 (also named late adopters); iv) the white circles represent the non-adopters. Spreaders A and B are embedded in two to different networks exhibiting different network characteristics: spreader A has four direct links to other agents; spreader B has only two direct connections. As a result, the diffusion processes are very different: in diagram 1 we found four early adopters and one late adopter, while in diagram 2 the opposite is true. Put differently, the choice of spreader A leads to a fast diffusion, with four out of five potential adopters reached in the first period, while spreader B takes more periods to reach the vast majority of potential adopters but allows to spread the innovation to more adopters.

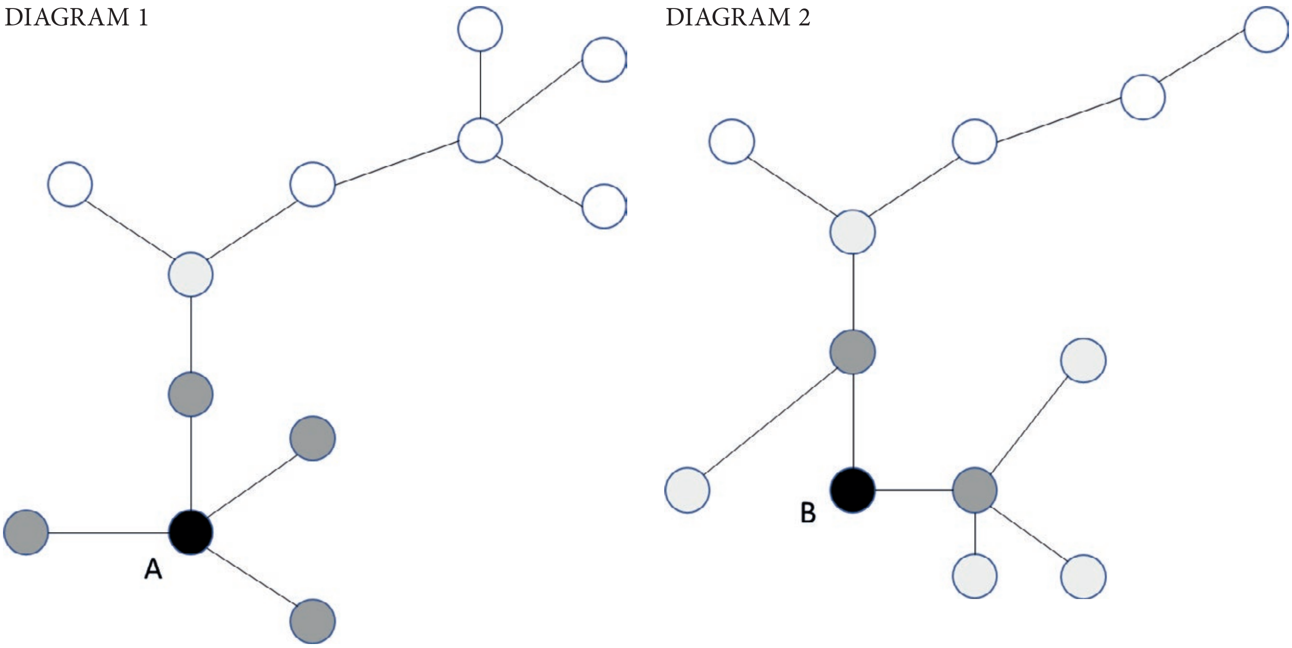

Figure 1. The impact of the network characteristics of the spreader on the size and time of diffusion. Source: own elaboration.

The most straightforward node indicator is represented by the *degree centrality* accounting for the number of connections the farmer has with other farmers (Wasserman and Faust, 1994). In our example (fig. 1), the degree of centrality of node A and B are respectively 5 and 3: the more the connection the farmer has, the higher its influence on closeby farmers, proven that a very central node can pass information to a large fraction of the network directly (with no mediators).

However, the degree of centrality is not the only source of influence. A great part of the influence that a node farmer has depends on its intermediary role in connecting other farmers. This happens when a node lies between two other nodes. The *betweenness centrality* concept has been developed to capture this characteristic: it is calculated as the sum of links connecting other nodes which pass through the original node (Borgatti et al., 2013) and is a measure of its bridge capacity.

Another measure of the centrality of a node is represented by the *closeness*. This index is expressed as the reciprocal of the farness of a given node. This latter index is the sum of the lengths of the shortest paths to every other node: the closer a node is to all the others, the higher its influence is likely to be. The index can be measured, as explained in the next section, as *average reciprocal distance* and through the *eigenvector*.

Finally, another relevant metrics related to the position of each single node is the *local clustering coefficient* which is the density (the total number of connections divided by the total number of possible connections) for the neighbourhood of the node (Borgatti et al. 2002; Newman, 2003): it measures the proportion of contacts which are linked together. A high level of local clustering generates reinforcing effects in the information passing which is an important issue in the adoption of a new behaviour or an innovation (Centola, 2010).

3. MATERIAL AND METHODS

We assess how the network characteristics of the spreaders influence the rate, the speed and the magnitude of the diffusion of the innovation in the farmers' network.

To this end we estimate the empirical model specified as follows:

$$Y_i = \beta_0 + \sum_{d=1}^{D} \beta_d X_{id} + \sum_{n=1}^{N} \beta_n X_{in} + \varepsilon_i \tag{1}$$

where Y_i represents the dependent variables capturing the diffusion process measured in terms of final fraction of adopters, speed of diffusion, and diffusion magnitude; X_{id} refers to the socio-demographics (D) of the spreaders, and X_{in} denotes their network structure (N). The variables of the model are described in Table 1.

To feed the model we adopted a mixed approach which combines case study analysis, SNA and simula-

Table 1. The variables of the model.

Name	Cod.	Kind	Description
Adoption rate	DIF	Dependent (Y_i)	The adoption rate is the proportion of farmers which adopted the innovation in consequence of the spreader operation
Speed	SPE	Dependent (Y_i)	The speed of diffusion is the complement to unity of the number of time steps employed by the spreader to reach its maximum adoption rate in relative terms respect to the slowest spreader (i.e. the one who employs the maximum steps in absolute terms)
Magnitude	MAG	Dependent (Y_i)	The magnitude of diffusion is the product of DIF and SPE
Education	EDU	Independent (X_{id})	education, it is a discrete variable varying in the range [1-5], according to the education level of the farmer (post-doc, degree, undergraduate = 1; high school =2; middle school = 3; elementary school = 4; no school = 5)
Mass-media	MAS	Independent (X_{id})	mass-media, which is a discrete variable ranging in the interval [0-3], according to the number of information channels used by the farmer among three kinds (firm web site, use of e-commerce, specialized journal subscription)
Experience	EXP	Independent (X_{id})	experience, that is a discrete assuming values in the range [1-4], according to the class of experience (< 5 years = 1; < 10 years = 2; < 20 years = 3; > 20 years = 4)
Age	AGE	Independent (X_{id})	age, it counts the age of the farmer
Size	SIZE	Independent (X_{id})	size counts the number of ectaras of the farm
Employees	EMP	Independent (X_{id})	employees represents the number of employees enrolled in the farm
Degree Centrality	DEG	Independent (X_{in})	The centrality degree of a given node is the number of nodes linked with it (Wasserman and Faust, 1994)
Betweenness	BET	Independent (X_{in})	This is a measure of the bridge capacity of a node and is expressed as the sum of links connecting other nodes which pass through the node analysed (Borgatti et al., 2013)
Closeness	CLO	Independent (X_{in})	This index is expressed as the reciprocal of the farness of a given node. This latter index is the sum of the lengths of the shortest paths to every other node. The normalized closeness, here used, is obtained dividing the closeness by the minimum possible closeness expressed as a percentage
Average Reciprocal Distance	ARD	Independent (X_{in})	This index represents a more accurate measure of closeness, including into the calculation not only the reciprocal of farness of the given node, but also the reciprocal of farness of the other nodes from the given node (Borgatti et al., 2013)
Eigenvector	EIG	Independent (X_{in})	It Is a centrality measure in which the other nodes connected to the node under analysis are weighted by how central they are. In other words, the centrality of each node is therefore determined by the centrality of the nodes it is connected to
Local Clustering Coefficient	LCC	Independent (X_{in})	The local clustering coefficient is the density (the total number of ties divided by the total number of possible ties) of the neighborhood of an actor (Borgatti et al. 2002; Newman, 2003)

tion. Figure 2 unfolds the procedure we have employed and explains how we have derived the input variables expressed in Eq. 1.

3.1 The case study

To define the boundaries of the network, we referred to the 107 specialist horticulture farmers surveyed in a previous study on the diffusion of mulching techniques (Scaringelli et al., 2016) in one of the largest horticultural areas in Italy (i.e. Province of Foggia). The sample analysed in that study covered the 2,8% of the population of farmers producing vegetables crops in that area and was representative of the local horticultural sector. The interviewed farmers were identified as potential adopters of a newer mulching technique based on biodegradable films derived from organic waste (Montoneri et al., 2011; Franzoso et al., 2015). This case study provided the socio-demographics represented by the X_{id} in the [Eq. 1] and described in Table 2.

The average level of education is 2.45: the farmers represented in the sample reached high or medium education. They use at least one information channel among web site, e-commerce, and specialized journal subscrip-

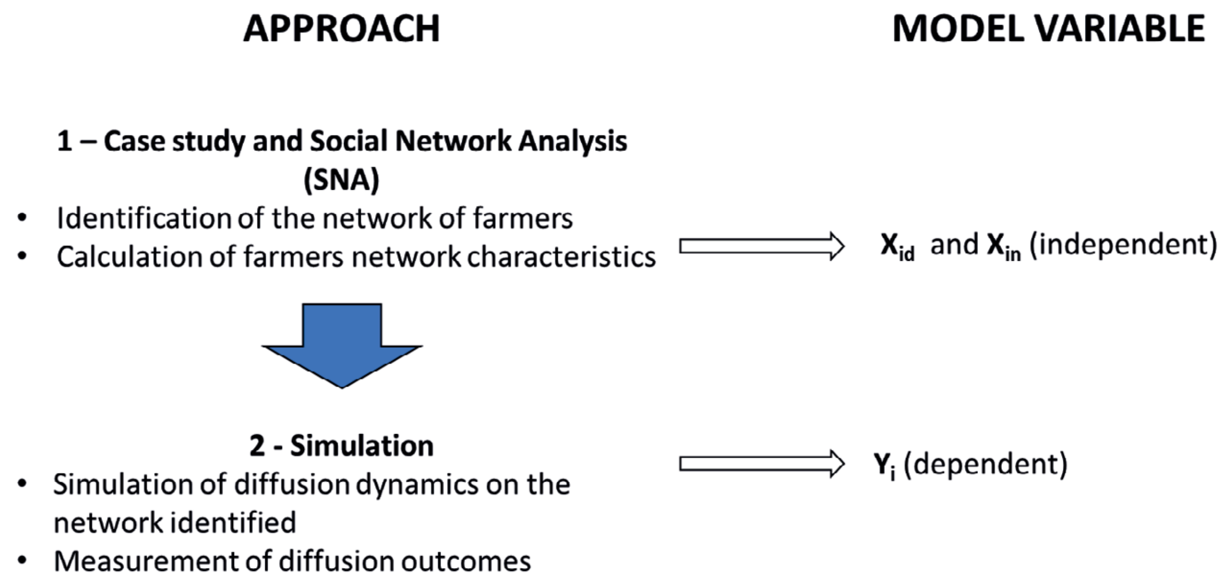

Figure 2. The integrated approach. Source: own elaboration.

tion. They have between 10 and 20 years of experience. They are, on average, 47 years old in mean, with the youngest and elder farmers being 24 and 75 years old respectively; 58% of farmers are in the 40-60 years old range (the standard deviation is 12 years). The variable with the greatest variability is the firm size: it varies between 4 and 1805 hectares, with 65% firms having less than 50 hectares. The average number of workers per firm is 13 with 80% of the sample with less than 20 employees.

Rather than having a probabilistic sample of horticulture sector, the rationale of choosing this case study was to obtain enough relational data to reproduce the complexity of a real farmer social network able to feed and calibrate the simulation model with a stylized representation of the interaction opportunities among farmers. These are based on the typical contact people have in a real-world network formed of group membership (representing, for example, co-workers), family and friend links, some connections to geographically close alters, and some ties to random alters in the population. Instead of using stochastically generated network by means of specialised software, which generates ideal network configurations (i.e. random networks or regular lattice), we adopted a participatory social network approach, a network survey technique directed at gathering data from actors well informed on the structure of network for their direct membership or for their expertise in the sector (Campbell et al., 2019; Delgadillo et al., 2020). We interviewed three experts, one agronomist with a long-time experience in local extension services and two expert farmers. These three interviewees know in depth the local context and the interactions among farmers. To ease the respondent's task and maximizing their recalling potential we employed the following investigation procedure: 1) we divided the geographical area of the case study into four quadrants and grouped the farmers belonging to each quadrant, obtaining four

Table 2. Statistics of the socio-demographics independent variables.

	Education (EDU)	Mass media (MAS)	Experience (EXP)	Age (AGE)	Firm size (SIZE)	Employees (EMP)
Mean	2.45	0.81	3.22	46.88	69.99	13.23
Min	0.00	0.00	1.00	24.00	4.00	1.00
Max	4.00	4.00	4.00	75.00	1805.00	112.00
Dev.st	0.79	1.05	1.06	11.50	176.76	15.68

Source: own elaboration on data from (Scaringelli et al., 2016).

groups; 2) for each group we asked the interviewees to recall the social links between farmers; 3) we repeated the procedure asking the interviewees to detect any intragroup links. Since the objective is to piece together the social network structure as accurately as possible, traced back friendship, kinship and professional relationships between the farmers. To this end we posed two driving questions: 1) *what are the farmers who are members of the same cooperative?*, 2) *what are the farmers who have known each other?*

In case the respondent acknowledged the existence of any relations between two farmers, each relation was further inquired by means of deeper analysis aimed at identifying also the kind of relation. For the relations acknowledged based on question 1, we asked the respondent to specify the if a professional relation existed between the two farmers connected asking the following sub-questions: i) *did they entered a professional agreement?*, ii) *do they share means or other resources?*, iii) *do they contract each other for any operation?*. For the relations acknowledged based on question 2 we also asked if the farmers connected were relatives of friends.

Of course, we did not expect that the three experts knew all the social interactions existing amongst the 107 members of the network, proven that this means to know information on 11.432 potential relations. Rather than mapping the entire web of relations, our goal was to obtain a realistic network configuration resembling the typical morphology of a real-world network. The use of the participatory social network approach allowed us to cover all the typical forms of actors' actual contact and not just random or regular ideal configurations.. Indeed, we obtained a network formed of 2152 total connections, 1595 of which are local intergroup links and 557 arelong intragroup links. To define the network characteristics of the farmer, we applied the principal social network indicators of centrality and position described in section two. These formed the second group of independent variables (X_{in}) in Eq.1.

3.2 *The simulation of diffusion process*

We simulated the diffusion outcomes within the network of farmers by means of an ABM. Although networks typically exhibit complex dynamics, we have intentionally focused on a simple model to trade-off the explanatory capacity and the clarity of interpretation of our results. It is formed of 107 agents interconnected which exactly reproduces the network described in the case study section. This web of social connections forming the network represents the interaction opportunity among agents which they use to exchange information about a technological innovation. The agents have specific attributes: (a) the preference toward the novelty; (b) the adoption threshold, as referred in the background section; (c) the level of education; (e) the spreader attribute, that is set *true* when the agent is used as spreader.

As descends from attribute (e), the model runs two types of agents: ordinary farmers and spreaders. The spreader does not have to take any decision about its behavior, proven that it is set as the first adopter at the model setup. Its unique role is to spread information on the innovation to its neighbors through the social relations interconnecting them. On the contrary, the ordinary farmers interact with the rest of the network, receiving and sending information and taking decision toward the adoption. In each time step, after having received information, each farmer recalculates its preference for the novelty on the base of its previous step preferences and the average of preferences of its neighbors weighted by a factor representing the level of homophily between the farmer and its neighbors. This average is then corrected multiplying it by a factor representing the years of education of the farmer. Then each farmer adopts (rejects) the novelty if its preference is greater or equal (lower) than its innovation threshold. This process is repeated until a specific time span is covered, and three diffusion outcomes of the spreader operation are obtained: i) the diffusion rate, that is the proportion of farmers which adopted the innovation; ii) the speed of diffusion, that is calculated as:

$$SPE_i = 1 - \frac{Steps_i^{max}}{max(Steps_i^{max})} \quad (2)$$

where SPE_i is the speed of spreader *i*, $Steps^{max}{}_i$ is the number of time steps employed by the spreader *i* to reach its maximum adoption rate; iii) the magnitude of diffusion, that is the product of the outcomes *sub* i) and ii). These outcomes represent the dependent variables (Y_i) in Eq.1 (see table 1).

The identification of the parameters of the model was based on the data available from the case study or according to the model internal logic. Specifically, at the model setup, (a) the preferences of the farmers toward the new technology was set at 0, assuming that nobody, excepting the spreader, knows the novelty; (b) the innovation threshold was calibrated using data from Scaringelli et al. (2016) which surveyed the attitude of the farmers towards the adoption of new kind of mulching films along a six-degree Likert scale (0 very adverse – 5 very favorable) (c) the level of education was set at the level of education of the respondents; (d) regarding the spreader attribute, we used each farmer as a spreader

Table 3. Statistics of the network independent variables.

	Degree Centrality (DEG)	Betweenness (BET)	Closeness (CLO)	Average Reciprocal Distance (ARD)	Eigenvector (EIG)	Local Clustering Coefficient (LCC)
Mean	20.11	62.26	0.08	45.34	0.73	54.70
Min	1.00	45.00	0.01	0.00	0.00	39.26
Max	98.00	101.67	0.26	1122.56	1.00	91.38
Dev.st	17.58	9.40	0.06	167.84	0.22	7.25

one at a time alternately across the 107 model runs. This was to find the network characteristics best predicting effective spreaders (i.e. those with high levels of outcomes). The analysis produced 107 specific combinations of spreader/farmers.

3. RESULTS

To guarantee the robustness of the simulations, each spreader/farmers combination has been replicated 100 times producing (107 x 100) 107,000 observations. Each simulation has been ran for 500 time periods, which is the time span that guarantees the convergence of the diffusion process for all spreaders and to reach a steady number of adopters. We computed the average adoption rate, speed, and magnitude of diffusion at each step. To provide an encompassing depiction of overall process, tables 3-4 report the statistics of the model variables.

Table 3 reports the statistics of the network characteristics. The value of the degree highlights that each farmer is connected to 20 other farmers in mean, intercepts the shortest path length among 62 other farmers (BET), and is rather close to others (closeness). These values are the effect of a rather connected network, where the chances for a farmer to know others and influence theme or receive influence is very high. This relational structure represents a good premise for the innovation to spread.

Table 4 contains the statistics of simulated diffusion variables. They represent preliminary findings, since can give some initial indications for on a diffusion strategy. The first result is that spreaders achieve a 25% adoption rate in means, that is, a random chosen spreader is expected to cause adoption in 25% of other farmers. We found that the slowest spreader employs 389-time steps to reach its maximum adoption rate. In mean, the spreaders employ the 50% of this time to reach their maximum, that is the 194-time steps. The magnitude considers both diffusion rates and speed of diffusion in a synthetic indicators of diffusion effectiveness. In mean, spreaders reach a level of 0.11. But there is a huge variation among these performances. Considers, for instance the adoption rates. Table 4 reports that the maximum obtainable adoption rate employing a single spreader is 41%. This means that there are some effective spreaders capable of obtain high rates (>35%). We found 10 spreaders reaching this threshold. On the other side there are 11 spreaders reaching a zero-diffusion rate. This calls for a careful analysis in designing a diffusion campaign. Indeed, while some spreaders can accomplish an effective campaign, choosing the wrong spreaders can result to a *cul de sac* dynamic, where the financial and human energies deployed would lead to a zero-result campaign.

The diagrams of the density functions of three diffusion variables back up these findings (Figure 3).

They show that the speed of adoption and the adoption rate are bimodal, with the former showing a higher peak for low speeds, and the latter showing a higher peak for higher levels of adoption rate. This means that, in this context there are several good spreaders in terms of effectiveness (high adoption rates) but most part of them employ long time to completely accomplish the diffusion. On the other hand, there are some ineffective spreaders, characterised by low adoption rate which are relatively fast in covering their spreading. The third diagram confirm the initial findings. The magnitude (the interaction of speed and adoption rate) has a bimodal distribution as well with higher peak for lower values. The underlying process is that the speed of adoption

Table 4. Statistics of the dependent variables.

	Adoption rate (DIF)	Speed (SPE)	Magnitude (MAG)
Mean	0.25	0.50	0.11
Min	0.00	0.00	0.00
Max	0.41	1.00	0.33
Dev.st	0.01	0.23	0.07

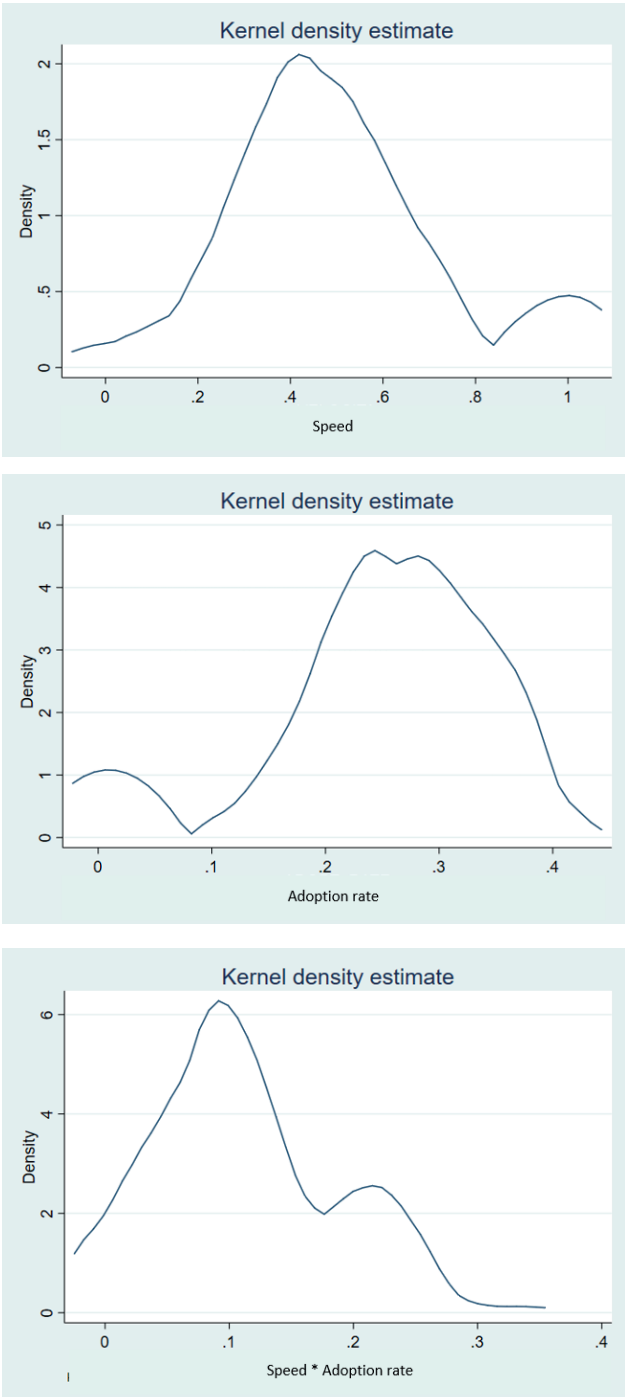

Figure 3.

dominates the adoption rate. Put differently, the share of spreaders capable of enhancing high and fast levels of adoption is rather limited (approximatively equal to one third of those that have average performance in terms of speed and rate of adoption).

We used the model in equation 1 to explain the three dependent variables, namely adoption rate, speed and magnitude. Table 5 reports the regression results.

The econometric analysis highlights the profile of the best spreader and, at the same time, provides deeper insights on the role of the network on the diffusion process. The model did not find any significant relation between the independent variables and the speed of diffusion. Moreover, none of the socio-demographics is able of influencing the performances in terms of rate of adoption and magnitude, possibly due to the fact that the spreaders have similar under socio-demographic characteristics so that these variables are unable to discern the best spreader. Likewise, four out of six network measures (i.e. DEG, BET, CLO and ARD) do not exhibit significant effects. This result is likely to depend on the use of macro characteristics of the network, which very dense and close, rather than of micro relational characteristics of the members.

On the contrary, EIG (i.e. eigenvector centrality) has a positive, significant and relatively high impact on the diffusion rates and on magnitude, while, surprisingly, LCC (i.e. local cluster coefficient) exhibits a negative, even though small, impact on the diffusion process. The eigenvector is a measure of how central the actors connected to the spreader are: it resulted the best predictor of an effective spreader. LCC measures the density of a local neighborhood and is high when the actor connected to the spreader are in turns themselves connected. The fact that this variable has a negative impact is due to the redundancy it produces at local level. In other words, since the acquaintances of the spreader are also acquaintances among themselves, the information on the innovation continue to circulate within a confined clique producing redundancy and waste of social reinforcement. All in all, this analysis shows that, in an agricultural context as the one investigated, the best measure to select effective spreader and increase the success chance of a diffusion campaign, is represented by the eigenvector, which identifies the central spreader who knows very central actors in turn.

4. DISCUSSION AND CONCLUSIONS

The innovations are catalysts of growth and their diffusion has been, during the last decades, a major driver of the economic development of the primary sector (Esposti, 2012; Scoppola, 2015; Viaggi, 2015; Moro et al., 2019): favoring a fast and complete spread of innovations should be a main goal in the policy agenda.

The paper aimed at finding the network characteristics that identify the best innovation spreaders. We fol-

Table 5. The results of the regression model.

	Adoption rate (DIF)			Speed (SPE)			Magnitude (MAG)		
	coefficients	σ	p-value	coefficients	σ	p-value	coefficients	σ	p-value
const	0,339	0,372	0,364	0,611	1,102	0,581	0,276	0,243	0,259
EDU	0,017	0,012	0,165	-0,031	0,035	0,380	-0,006	0,008	0,479
MAS	-0,008	0,009	0,406	0,019	0,027	0,479	-0,005	0,006	0,436
EXP	-0,007	0,010	0,502	0,045	0,030	0,137	0,004	0,007	0,581
AGE	0,000	0,001	0,857	0,000	0,003	0,905	0,000	0,001	0,751
SIZE	0,000	0,000	0,944	0,000	0,000	0,620	0,000	0,000	0,943
EMP	0,000	0,001	0,611	0,002	0,002	0,424	0,001	0,001	0,127
DEG	-0,005	0,008	0,528	0,021	0,025	0,403	0,001	0,005	0,846
BET	0,000	0,000	0,593	-0,001	0,001	0,187	0,000	0,000	0,447
CLO	-0,022	0,022	0,313	0,083	0,065	0,203	0,007	0,014	0,628
ARD	0,018	0,026	0,475	-0,082	0,076	0,282	-0,010	0,017	0,546
EIG	1,698	0,698	0,017**	0,248	2,069	0,905	1,504	0,456	0,001***
LCC	-0,100	0,047	0,034**	0,003	0,138	0,980	-0,079	0,030	0,011**
R-quadro	0,450			0,106			0,553		

lowed an integrated approach by using an ABM model to simulate the diffusion performances of alternative potential spreaders.

We found that the ARD, a measure of how much each node is close to the whole network, and the clustering coefficients, which are related to the density of the neighborhood of a given node, are the main important factors to forecast the successfulness of an innovation spreader. These findings indicate that the diffusion of innovations in agriculture is fostered by spreaders relatively close and well connected to the rest of the web. Furthermore, to enhance the diffusion of innovations in agricultural networks, the innovation spreaders should be highly clustered, so as to provide the needed information reinforcement required for the adoption to occur. We have also observed a low share of agents with a high level of adoption rate, a further proof that designing sets of spreaders capable of influencing the network areas is much in need to promote technologies adoption.

These findings have direct implications for the policy agenda. For instance, they may be included in the design of policy measures and, in particular, within the context of the admissibility and the selection criteria in rural development plans:in order to enhance the spread of innovations, exploiting the relationships linking farmers in rural areas, the future policies may promote the creation of social interactions among farmers (i.e. promoting public and private social events to interconnect farmers); second, the policies for rural development may prioritize the requests of funds coming that are solicited by the most performing innovation spreaders, in order to exploit the multiplier effect that they will produce; third, the innovations should be promoted in areas where the existing networks are likely to be more receptive, a feature that can be easily proxied by the measures discussed in our paper. All these suggestions can be easily translated in admission and selection criteria in rural development plans: our analysis has direct implications for a better implementation of the future interventions.

Few words of caution. The present paper focuses on a case study with specific characteristics in terms of density of the network and clusterization of farmers, therefore the conclusions on the effects that the individual characteristics have on the rate of adoption would be externally valid only for those cases that are reasonably similar to our case study. Thus, in order to further increase the external validity of our conclusions it would be recommendable the analysis of different network structures (e.g. high vs. low density, regular vs. randomized structure, high vs. low average degree, or so). To the extent that promoting innovations in agriculture is a priority for stakeholders in public and private sectors, similar studies should be encouraged.

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The co-evolution of policy support and farmers behaviour. An investigation on Italian agriculture over the 2008-2019 period

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Abstract. This paper investigates the co-evolution of the CAP expenditure and of the farms' performance and choices to assess whether and to what extent CAP assessment itself meets the requisites of Causal Inference. In order to identify some regularities in this co-evolution, the analysis is performed on a constant group of professional farms over a long enough time period. The Italian 2008-2019 FADN balanced sample is here considered. Results points to two major empirical implications. First of all, they question whether CAP expenditure is actually accompanied by any significant farmers' response. An exception may actually concern the support specifically focused on environmental standards. Secondly, they raises some major methodological issues about the applicability of the Treatment Effect logic to CAP assessment.

Keywords: Common Agricultural Policy, Farmers' Behaviour, Program Evaluation, Panel Data, Co-evolution.
JEL Codes: Q18, D04.

"Verum scire est scire per causas"

1. INTRODUCTION: TWO TOPICS, ONE OBJECTIVE

This paper deals with two distinct research topics and aims to join them into a unique research objective. The first topic consists in analysing the evolution of the Common Agricultural Policy (CAP) support, of the farmers' production choices and of their possible interdependence (henceforth, the *co-evolution*). The second topic has to do with the growing use of the so-called Program Evaluation Methods (PEM) (Imbens and Wooldridge, 2009) in assessing the impact of the CAP, its measures and reforms, on the farming activity (Dumangane *et al.*, 2021). The research objective that brings these two topics together is understanding whether and under which conditions investigating the farms' response to CAP support can be performed with the cause-effect logic implied by these PEM.

PEM have progressively emerged as the application of the general principles of Causal Inference (CI) to the assessment of public policies (Imbens and Rubin, 2015; Perraillon *et al.*, 2022). These methods are thus grounded on sound statistical concepts but, at the same time, they imply specific preconditions for an appropriate application to policy assessment (Khagram and Thomas, 2010). The bottom line is that an unambiguous cause-effect direction must occur between a well-defined policy measure (the *Treatment*) and a well-defined response (the *Treatment Effect*, or TE).

Such a direction (TE logic, henceforth) can be obviously assumed but it is not necessarily a good representation of the world especially in the case of many CAP measures. In particular, a correlation between some CAP measures (or reforms) and farmers' behaviour does not automatically make the latter a response to the policy. Not only because, as well known, correlation is not causation (Angrist and Pischke, 2009). More importantly, as stressed by the literature on the political economy applied to the CAP decision making process (Swinnen, 2015; Collantes, 2020), a potential endogeneity may occur within this process. The main aftermath of such endogenous relationship is that CAP and farmer's behaviour rather co-evolve, so the observed correlation might express a cause-effect relationship whose direction, in fact, is not clearly identifiable.

It follows that this paper is an empirical work but it is not an empirical application of some PEM to some CAP assessment. The empirical analysis rather aims to investigate the extent and nature of the abovementioned co-evolution in order to assess whether and how it is compatible with the application of the TE logic. The main research question underlying this study is thus the following: which empirical support do we really have to interpret farmers' behaviour as a response to CAP measures and, thus, to consistently and properly apply the TE logic to CAP assessment?

To answer these questions, the invariance of the field of investigation must be granted: a constant group (i.e., a balanced panel) of heterogeneous enough professional farms followed in its evolution over time together with the different CAP support they are recipients of. The Farm Accountancy Data Network (FADN) is helpful to perform this investigation, particularly in the Italian case where the FADN-RICA dataset contains most of the required information for the present analysis (Cagliero *et al.*, 2010). Moreover, Italy presents a very diverse agriculture, and it is often considered the most heterogenous agriculture within the EU (Baldoni *et al.*, 2021). Therefore, the 2008-2019 Italian FADN balanced panel is here used.

The abovementioned logic of the study also justifies its structure. Section 2 overviews the literature and the policy relevance underlying the present empirical investigation. Section 3 presents and discusses the balanced panel used for the analysis. Sections 4 examines the evolution of both CAP support and farms' production choices and performance. Then, section 5 presents the co-evolution hypothesis by connecting these two dynamics and wondering to what extent one can be considered a response to the other. Section 6 derives the main consequences of this co-evolution in terms of the methodological challenges in adopting the TE logic in this field. Section 7 concludes drawing some methodological implications.

2. THE POLICY ISSUE

With the EU approaching the first year of application of its n-th CAP reform, expected to enter into force in 2023, the debate among agricultural economists, policy experts and analysts remains essentially the same of the previous reforms. Positions range between two extremes. On the one hand, those (and the EU Commission itself) who support the idea that this reform, as the previous ones, contain substantial novelties and somehow radical changes (European Commission, 2021; Pupo D'Andrea, 2021). On the other hand, others consider it, as the previous ones, essentially a conservation of the same fundamental schemes (same money, same beneficiaries, same modalities,) with only marginal or "cosmetic" changes (ARC2020, 2020; Sotte, 2021a). A sort of "conservative revolution".

What is common between these two opposite views is that both see the CAP as a policy expected to produce an effect on (or a response by) the farming sector (OECD, 2011; Matthews, 2021).[1] Maybe, however, this is not the proper perspective from which the CAP and its reforms have to be evaluated. The very fundamental question is to what extent the CAP really conditions farmers' choices and, therefore, whether it is really worth to adopt a TE logic (Coderoni, Esposti and Varacca, 2021). In particular, the CAP presents three major problematic features in this respect.

First, CAP is a policy and not a program, that is, is made of a set of interdependent measures (Lassance, 2020). These may be separately assessed (Castaño *et al.*, 2019) but are not, usually, separately delivered to beneficiaries; and beneficiaries know this. In order words, the CAP is not a treatment, but it is a farm-specific (thus heterogeneous) combination of multiple treatments. Consequently, also the evaluation of individual measures

[1] "Agricultural economists have been more concerned with the how and how well food and agricultural policies should be designed to achieve specific objectives and how policies have succeeded in their aims" (Matthews, 2021, p. 185-186).

should be performed only within a complex multiple-treatment environment. Secondly, the CAP is not just a set of measures, but it is a menu of measures since beneficiaries (farmers) are not assigned to some measures but voluntarily select among them (Esposti, 2022).[2]

Thirdly, this policy being a menu of measures, it turns out (in fact, it aims) to be a "passive" policy in the sense that is tailored on the existent rather than on inducing a change or a behavioural response. "Active" measures are present, but they may take the form of conditionalities, that is, requirements to be met in order to be eligible to a support. These conditionalities are usually quite weak, if not actually purely apparent, in the sense that most beneficiaries already satisfy them or need just minimum adjustments to satisfy them (Latacz-Lohmann *et al.*, 2019).[3]

The key point here is that neither the CAP nor any CAP reform has a clear and univocal objective or target for which beneficiaries are expected to provide a specific response. CAP is a sort of "institutional environment" regularly accompanying, and not necessarily inducing, farms' evolution. Eventually, the CAP behaves as a welfare system reserved to the EU farming sector. Its universalism (though limited to the farming activity) is expressed by the fact that its menu of measures covers nearly all farms, as well as all their different activities and instances.[4] This does not exclude some more targeted measures, but it remains true that multiple targeted measures ultimately aim to be universalistic. The main consequence of this universalism is that the CAP tends to be conservative and passive in the abovementioned sense. Rather than being one the effect of the other, the CAP and the farming sector seem to actually co-evolve.[5]

The nature of the CAP as an all-encompassing policy is not, *per se*, at odds with an evidence-based design and implementation (Esposti and Sotte, 2013; Erjavec and Erjavec, 2015; Erjavec, 2016; Ehlers *et al.*, 2021). But this evidence concerns an expected effect (and, therefore, effectiveness and efficiency). Since this expected effect is unclear, the need of an evidence-based CAP inevitably raises the question: evidence about what? Waiting for the implementation of the new CAP reform (period 2023-2027), it seems useful to limit this question to the last 15 years. This is the period under investigation here and it has been interested by two major reforms, implemented in 2005 and 2015, and by some major further adjustments meanwhile (particularly in 2007 and 2008). It can be argued that these reform steps share the same three fundamental objectives (Frascarelli, 2020, 2021; Coderoni *et al.*, 2021): farm income support (or protection); farm competitiveness through (more) market orientation, i.e., (more) product diversification; larger and better public (mostly environmental) good provision by farms.[6]

In Italy, the decoupling of I Pillar support (the so-called Fischler Reform) was firstly introduced in 2005. It has been extended and reinforced in 2007 (with the introduction of the Single Common Market Organization, CMO) and in 2008 (the Health-Check Reform), and then progressively dissociated from historical direct payments in 2015 (the Ciolos Reform) (Sotte, 2021b). Consequently, the period under consideration here (2008-2019) starts from a year in which the full decoupling of direct payments was already under way. Meanwhile, II Pillar support has been strengthened in terms of overall support and of its share on the total CAP budget, but also

[2] The generalized voluntary nature of the CAP can be questioned. Here, voluntariness is intended in confront with the golden standard of randomized experiments where units assigned to the treatment do not choose whether or not to be treated. On the contrary, for all II Pillar measures the treatment is always the consequence of a voluntary choice. In the case of I Pillar direct payments, a difference has to be made between the period before and after 2015. After 2015, in practice all farms (but landless farms) have become entitled to apply for these payments. Before 2015, those farms that did not receive coupled payments before 2005 were not entitled to apply and, therefore, could not voluntary opt for the treatment. It remains true that, even when entitled, farms have to apply (so, to take a decision) and this also implies the respect of the cross-compliance conditions. Consequently, farmers that do not want to accept this conditionality may decide to do not apply even when entitled to do so.

[3] There may be significant exceptions to this conclusion due to large heterogeneity of agricultural systems across EU and Italy. For instance, in farming systems showing the prevalence of monoculture the introduction of green payments, and the consequent compliance, had a relevant impact on farmers' choices and behaviour (Bertoni *et al.*, 2018; 2021).

[4] This universalism does not conflict with the voluntary nature of most measures. It is rather the opposite: through a large set of voluntary measures, the CAP is able to provide assistance to all different kind of farmers according to their very different kinds of objectives. Voluntariness within universalism is, therefore, the obvious consequence of the large heterogeneity of beneficiaries.

[5] This is the empirical counterpart of the political economy argument on the endogeneity of the CAP (Swinnen *et al.*, 2015) which suggests that its design may depend on farmers' choices and behaviour more than the other way round.

[6] Matthews (2021, pp. 185-191) overviews the evolution of the fundamental objectives of the CAP over time. "Farm income", "Environment" and "Competitiveness" are among the most persistent. The objective of production diversification and market reorientation can be considered an explicitation of the competitiveness objective. In fact, these are not the only objectives of the CAP but are those that directly and exclusively refer to farmers' behaviour under scrutiny here. Other objectives could actually be added to this short list (European Commission, 2019; Coderoni *et al.*, 2021). In particular, two are worth noticing. One is favouring structural change or adjustment within agriculture. The other is supporting the rural economy. But these objectives are beyond the horizon and, above all, the field of investigation of the present study both for the limited time under consideration and for the use of balanced panel of farms (see below) that, evidently, do not cover all socio-economic aspects of the rural economy.

in terms of a progressively stronger orientation towards environmental goods provision.

With respect to the three abovementioned fundamental objectives, the decoupling of support (with the maintenance of the support level) was expected to induce market re-orientation while granting farmers' income (Anton, 2006; Esposti, 2017a,b; Ciliberti *et al.*, 2022). Also II Pillar had to facilitate market re-orientation (and structural change) and, at the same time, the environmental goods provision especially due to the strengthening of Agro-Environmental Measures (AEM) already introduced in the 1992 reform (MacSharry Reform). Pillar I itself has been designed to contribute to the environmental objectives with the introduction of the environmental conditionality already in 2005, then further enhanced with the novel Greening payments in 2015. Therefore, in principle, this sequence of reforms has been designed to get progressively closer to the abovementioned objectives. In practice, however, their actual implementation might not have generated a major impact.[7]

A lot of research work has been done in order to directly investigate, simulate, estimate the impact of these CAP reform steps on beneficiaries. This large body of literature is definitely helpful in better understanding the mechanisms through which the CAP operates and, therefore, in better designating and implementing it (Matthews, 2021). But analysing the possible impact of the CAP and its reforms with these approaches does not necessarily correspond to a program evaluation. Most studies are grounded on farm-level structural models used either for ex-ante (simulations) or ex-post (simulations or estimations) assessment (see, for instance, Mack *et al.*, 2019). Within their theoretical structure, these models somehow impose the existence, the form and sometime the direction of the response to policy measures.

Eventually, the problem is the lack of a counterfactual evidence. In most of these studies the counterfactuals are never observed, and they might not even exist, but the counterfactual case is just extrapolated from the estimated models parameters. The search of such counterfactual evidence may explain the emergence, in the last fifteen years, of a consistent body of empirical studies whose aim is to explicitly assess the CAP impact within a TE logic (just to mention a few: Chabé-Ferret and Subervie, 2013; Castaño *et al.*, 2019; Coderoni, Esposti and Varacca, 2021; Ciliberti *et al.*, 2022; Esposti 2017a,b, 2022). This research effort is commendable and promising. As mentioned, however, the actual characteristics of the CAP and of its reforms do not necessarily fit the strict requirements of this TE logic. In most of these recent studies its suitability for CAP assessment is given for granted and never really questioned. In principle, preliminary to any TE investigation, it would be desirable to scrutinize the empirical support about the applicability of this logic to the three abovementioned key objectives. Looking for this empirical support is the main purpose of the present study.

3. THE DATA: 2008-2019 FADN ITALIAN BALANCED SAMPLE

Another major issue in the investigation of farms' responsiveness and co-evolution with respect to CAP measures concerns the field of investigation. Several previous studies work on all farms, but this can introduce a bias as their response may be not fully observable for the presence of many very small farms (even "non-farms") (Sotte, 2006; Sotte and Arzeni, 2013) and may be also driven by long-term structural processes that are largely independent on the CAP support. A further limitation of the field of investigation of many previous studies is the lack of a long-enough time dimension. Most of them are, in fact, *ex ante* assessments thus they are a-temporal in the sense that are based on current farm-level data possibly on the basis of future scenarios. They seldom take the needed time until the farms' co-evolution or response is significantly revealed by data.

Here, we focus on a sample that take these issues into account: the Italian 2008-2019 FADN balanced panel.[8] A constant field of observation is clearly needed to investigate the co-evolution of the CAP support a farmers choice in order to get rid of the spurious effects simply generated by the change in the sample composition. This choice, however, may also have limitations and two of them are worth noticing here. The first limitation is that working on the FADN sample may miss some of the

[7] Studies on the distribution of the CAP support across regions and farms (see Sotte, 2014, and Terluin and Verhoog, 2018, to mention a few) have mostly concluded that the beneficiaries and the allocation among them did not change significantly over time. This can be considered an implicit demonstration that the (reform of the) CAP might not have had an effect. But this is not obvious. Maintaining the distribution of support but changing the forms and modalities may still induce a response.

[8] This balanced panel consists of 1585 farms observed over 12 years, thus 19020 total observations. Even if 2020 data were available, they are going to be problematic in terms of comparability due the effects of the COVID-19 pandemic also on the farming sector. The EU-wide FADN sample could be used instead but the information available over all countries are less comparable and, above all, less detailed than those reported in the Italian RICA-FADN dataset. The choice of working with a balanced panel also explains why some of the results here presented may also substantially diverge from what obtained in studies working on the same period but on a different fields of investigation (European Commission, 2019).

implications of CAP and its reforms as changes occurring in non-professional farms, numerically prevalent in the Italian context (Sotte, 2006; Sotte and Arzeni, 2013), remain unobserved as these units are excluded from the FADN field of survey. Structural changes may be also missing in the balanced panel. As the non-constant part of the FADN sample is excluded, the dynamics of entry/exit (i.e. deactivation) from the sector, as well as other changes somehow related to the entry/exit from the sample (for instance, change in size due to land acquisition or loss), are at least partially missed. However, none of this possibly missing information is at the core of the three CAP objectives here considered.

The second limitation concerns the possible lack of representativeness of the adopted balanced panel with respect to whole Italian agriculture even when only professional farms are considered (Mari, 2020; Vrolijk and Poppe, 2021).[9] Representativeness is evidently sacrificed when a balanced panel is extracted over a long-enough period since the FADN sample is rotating just in order to maintain representativeness over time. It is thus informative to make explicit how much the adopted dataset may over or under-represent some farms category compared to the whole Italian agriculture. Table A1 in the Annex compares the distribution of farms by Type of Farming (TF) and Economic Size class (ES) in the adopted sample (in year 2010) with the Italian 2010 agricultural Census.[10] For the sake of comparison, Census data are reported in two forms: the whole farm population and the population corresponding to the FADN field of survey, that is farms with a Standard Output (SO) higher than 8 thousand € (also called professional or market-oriented farms).[11]

It firstly emerges that the FADN sample always somehow misrepresents the whole Italian agriculture as about 63% of the farm population is excluded from the FADN field of survey. But limiting the attention to professional farms, the distribution of farms within the balanced FADN panel in terms of TF does not differ much from what observed in the Census data, even though a slight over-representation of grazing livestock activities (TF4) and under-representation of permanent crop farms (TF4) is observed. A more important bias concerns the ES as the balanced panel evidently self-select larger farms, in economic terms. This bias has to be taken in mind in commenting the following results and any generalization to the whole Italian agriculture requires caution.

However, it is worth stressing here that there is no feasible solution to this representativeness issue whenever a balanced FADN panel is adopted.[12] Even the vector of individual weights that accompany the FADN sample cannot be helpful in this respect. These weights allow to carry over the sample-level evidence to the population, at least for those dimensions for which the FADN sample is representative (Mari, 2020). Therefore, weights are useful to compute population-level aggregates, given representativeness, but it is not suitable to recreate this representativeness. Moreover, these weights refer to the whole FADN sample and not to the balanced FADN sample. They also vary any year and have to be redefined any time the underlying sampling scheme is changed as occurred, in particular, with the change of the professional farm threshold in Italy in 2014 and with the change of the TF classification in 2010. Applying these weights to the balanced panel over 12 years would incur the risk of generating an uncontrollable distortion rather than correcting for an observed misrepresentation.

Considering that working on a constant sample is a strict condition to properly investigate the co-evolution of CAP support and farms' behaviour, we prefer here to sacrifice representativeness rather than to generate artefacts in the attempt to correct for it. Also because representativeness is not a major concern with the respect of the major objective of the present paper. Evidently, any policy conclusion based on these data should be taken with major caution (Vrolijk and Poppe, 2021, p.10). But the main interest, here, is rather on the methodological implications of the co-evolution of CAP support and farms' behaviour. It may be the case that such co-evolution does not perfectly correspond to what observed in the whole Italian agriculture and may slightly overvalue the incidence of the outliers (in particular, farms with very high payments).[13] However, evidence here reported remains valid within the adopted field of investigation and, more importantly, with respect to its main methodological implications.

Within this sample, the empirical analysis is developed in a sequence of three steps. First, the evolution of the CAP support and of its distribution is investigated, considering both its total amount and its components (section 4.1). Then, the evolution of the farmers' choic-

[9] We wish to thank two anonymous referees for their helpful suggestions and remarks on this aspect.

[10] Together with the geographical district (regions in Italy), these are the two levels for which the representativeness of the FADN sample is granted (Mari, 2020).

[11] In Italy, this threshold was 4 thousand € up to 2014.

[12] In any case, it has been already noticed that also within the Italian FADN sample the full representativeness on the three abovementioned dimensions is more theoretical than actual (Mari, 2020, Tables 2 and 3).

[13] In the present case, however, what could be considered outliers are actually real farms. They might be peculiar and, for this reason, they are recipients of a very high CAP support. But this does not mean that they represent anomalous or aberrant cases.

es and performance is analysed (section 4.2). Finally, some stylised facts about the co-evolution of these two dynamics are derived (section 5).

4. THE EVOLUTION OF THE CAP SUPPORT AND FARMS' BEHAVIOUR

4.1. CAP support

The first question to be answered is whether the CAP support actually changed within the adopted field of investigation and how. Figure 1 displays the total and per farm public support considering all the possible sources.[14] The total support remains quite regular over the period (always ranging between 23 and 27 million €) with only limited oscillations due to the transition to one CAP regime to another. Overall, we observe an increase in total support (+17% from 2008 to 2019) in nominal terms, but this growth almost entirely vanishes (+4%) in real terms (2010 prices).[15] Consequently, the per farm average support passes from 14.4 thousand € to 16.9 thousand € per farm, in nominal terms. But in real terms this variation drops from 14.4 thousand € to 15.3 thousand € per farm.

Figure 2 reports the evolution of the composition of the total CAP support. It evolved as a combination of three dynamics:

1. I Pillar declined by 4% and II Pillar grew by 156% and this has made the share of I Pillar and II Pillar be gradually re-equilibrated with the latter moving from a 13% to 29% of total CAP support.

2. Within I Pillar, decoupled support remained stable (-0.4%) while coupled payments declined by -20% up to a final 15% in 2019 on total Pillar I payments (corresponding to 11% on total CAP support). The process of progressive decoupling of support actually stopped in 2012 since for the rest of period the shares of coupled and decoupled support remained quite stable.

3. Within II Pillar, the largest growth concerns AEM payments (+196%) while the other measures increased by 124% with AEM support passing from a share of 44% on the total II Pillar support in 2008 to 51% in 2019. The huge growth and the increasing relevance of the AEM support is investigated further in the Annex (Figure A1).

The synthesis that can be drawn from this general picture is that, at least from the farms' perspective, the evolution of CAP support in the 12 years under investigation really represents a sort of "conservative revolution": the different components of the whole expenditure changed significantly, but the support eventually delivered to farmers is more or less the same. Nonetheless, the key argument of the critics of this alleged conservatism of the CAP consists not so much in the amount of support but in its strongly uneven distribution across farmers. Table 1 reports some year-by-year distributional statistics of the total and CAP support, and of its different components, within the present sample. Overall, it is confirmed that values (but the maximum) are quite stable over time. At the same time, the distribution is very disperse with a standard deviation always much higher than the mean value as indicated by a greater than two Coefficient of Variation (CV). Moreover, the left tail of the distribution being truncated at 0, the presence of several extreme values generates a remarkable asymmetry with a very long right tail. This is clearly revealed by the difference between the mean and the median (2nd quartile) values, with the former being in all cases more than double than the latter.

High variability and asymmetry is observed in all the different policies but some specificities are worth noticing. In particular, both coupled I Pillar payments and non-AEM II Pillar payments show very high CV values. For both II Pillar subgroups the observed support is zero until the third quartile indicating that payments concentrate on a very limited number of farms.[16] It can be also concluded, however, that these specific asymmetries tend to compensate, at least partially, as dispersion and asymmetry observed in the total support are significantly lower than in the single components.

This apparent stability of the CAP support distribution over time does not mean that from any individual farm perspective nothing changed. By looking at the single farm percentage variation of the received support from 2008 to 2019 (bottom of Table 1), it emerges that several farms lost all the support (-100%) while for others the growth is maximum (in fact, it can not be computed simply because the initial value is zero). Between these extreme cases, we find most farms with a change in the support that ranges from a decline (the first quartile is -19%) to a huge increase (the third quartile is +370%). The mean value (the second quartile) indicates a

[14] Regional co-financing of II Pillar is included in CAP support. The remaining national support represents a very marginal part, always lower than 5%. For this reason, the national support will be neglected in the rest of the analysis.

[15] Following Matthews (2000), real values are computed using the official Italian GDP deflator released by the National Institute of Statistics (ISTAT).

[16] A similar, in fact more extreme, case can be found in national payments where also time variation is large. These distribution characteristics can be explained by the fact that national payments tend to have an emergency or exceptional nature: they are activated under very special conditions, for very specific farms and for a limited period of time.

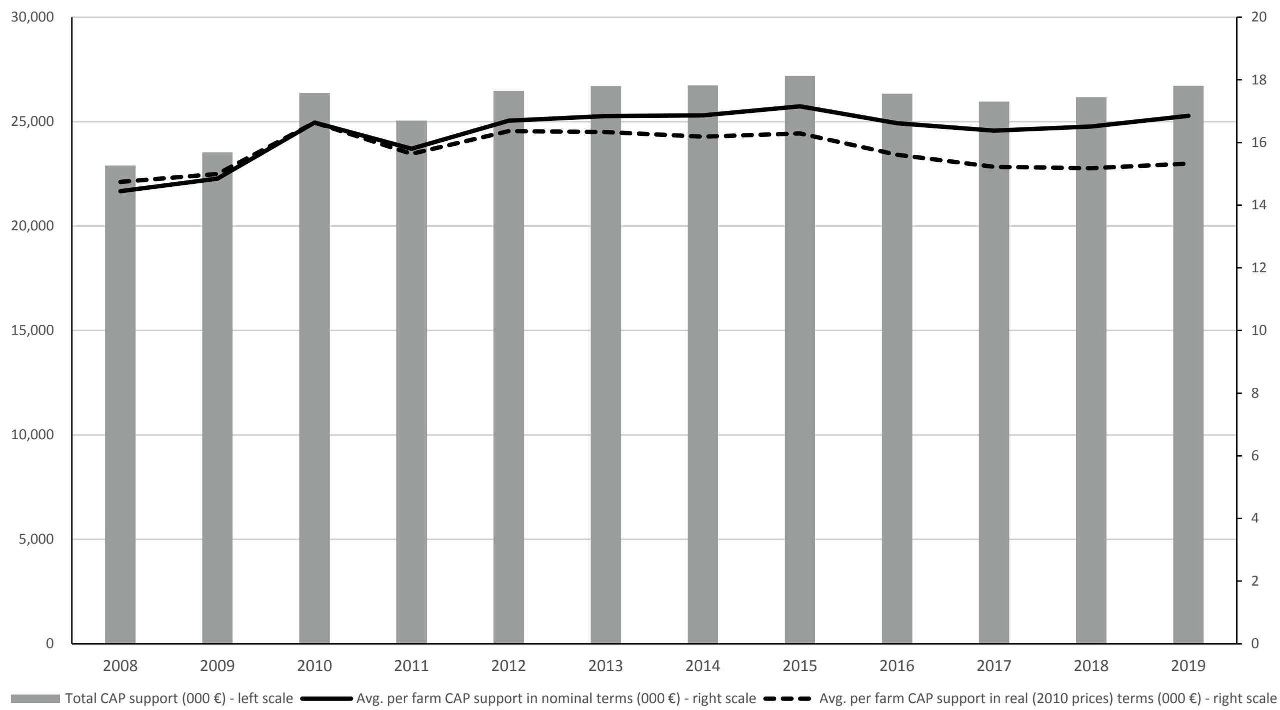

Figure 1. Total and per farm public support within the Italian 2008-2019 FADN balanced sample.

30% growth which is consistent with the growth of average support commented above. We should thus conclude that the evolution of the CAP over this period significantly redistributed the support across farms but did not make it more homogeneously distributed.

4.2. Farms' behaviour

4.2.1. Profitability

In order to assess whether or not this CAP evolution had any relevant impact on farms' performance and choices, the first question to be answered concerns farms' profitability. Here we proxy the farm's profit with the farm's net income simply computed as revenue plus policy support less all costs.[17] Therefore, in order to investigate the evolution of farms' profitability it is worth to analyse the evolution of its components. Figure 3 displays the dynamics of the average revenue and variable costs within the field of investigation. A selection of these costs is also shown. They concern what we design here as environment-using costs: fertilizers, pesticides (herbicides included), energy and water.

It firstly emerges a regular increase of both revenue and costs, but with the latter showing a larger growth than the former (+38% and +12%, respectively). It follows that the incidence of variable costs on revenue passes from 38% in 2008 to 47% in 2019. Among costs, environment-using ones maintain a quite constant share, always higher than 20% and lower than 25%. From these figures a quite regular profitability over the period can be deduced. Figure 4 shows that the average farm net income did not significantly change as it remains between 50 and 60 thousand €. A -10% variation is actually observed comparing 2019 with 2008, but this decline can be entirely attributed to the very last year.

If we express net income in real terms, however, a different conclusion can be drawn. Although inflation has been constantly low during this period, in real terms the average farm net income suffered a -20% decline from 2008 to 2019 that becomes a -9% if we stop the comparison at 2018. We should thus rather conclude that, on average, farms actually struggled to defend their profitability over this period. At the same time, however,

[17] In the FADN terminology what is here referred to as Net Income corresponds to the Entrepreneurial Income. As most agricultural production units are family farms, this also corresponds, for many units, to the Family Farm Income (European Commission, 2018a). The difference between net farm income and farm profit is that the former is defined as farm revenue, plus policy support, less all external costs; the latter as the difference between net farm income and the opportunity cost of factors of production (labour, land and capital) provided by the family farm. We wish to thank an anonymous referee for an helpful clarification on this point.

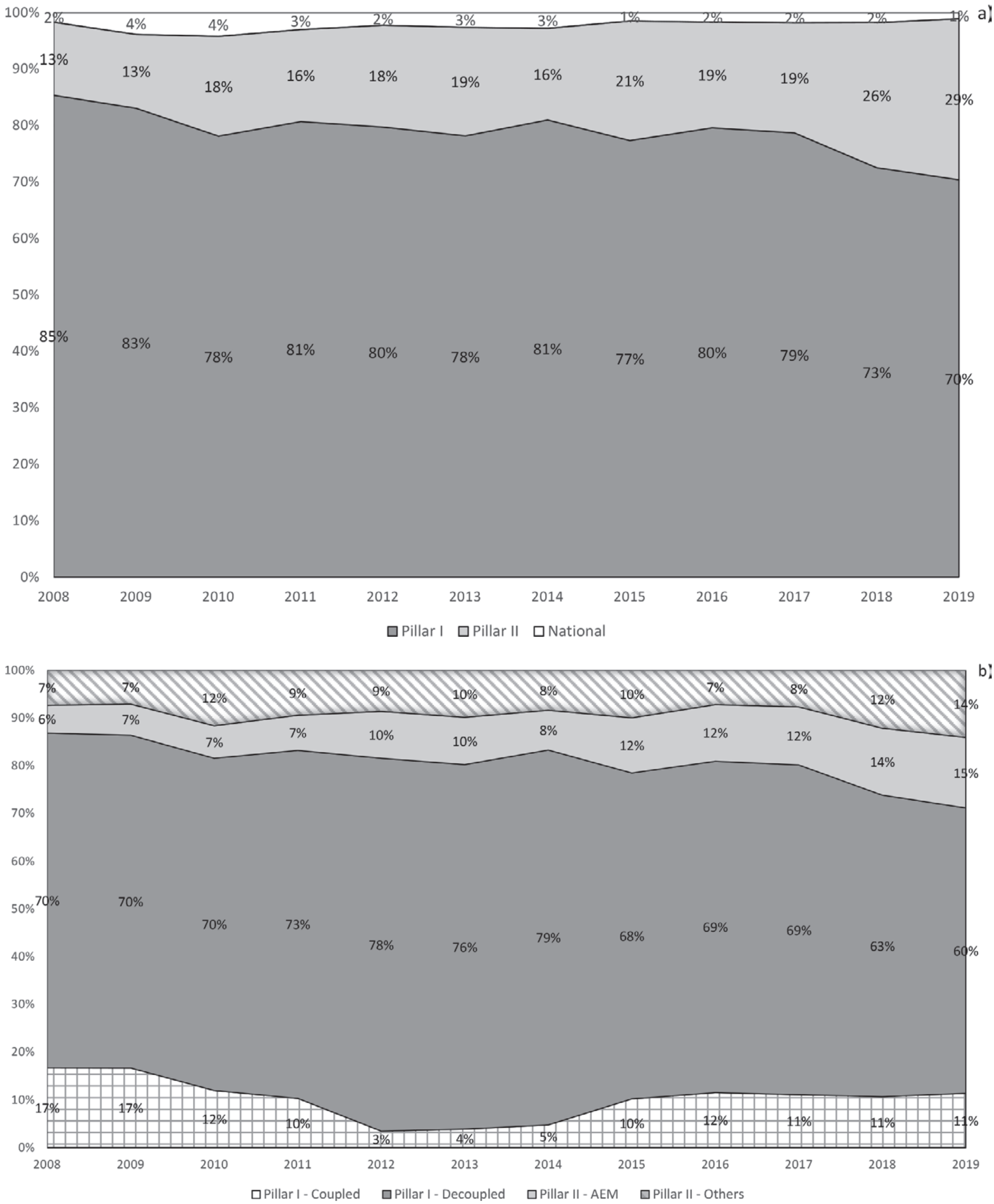

Figure 2. Composition of the total public (a) and CAP (b) support within the Italian 2008-2019 FADN balanced sample.

Table 1. Distribution of the public support (CAP included) within the Italian 2008-2019 FADN balanced sample (€).

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
TOTAL SUPPORT												
Mean	14,449	14,848	16,642	15,802	16,700	16,846	16,870	17,158	16,614	16,381	16,510	16,856
Standard deviation	31,844	31,258	41,230	38,001	39,722	38,967	42,899	42,205	41,005	40,174	36,552	34,645
Coefficient of Variation	2.2	2.1	2.5	2.4	2.4	2.3	2.5	2.5	2.5	2.5	2.2	2.1
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	755	1,014	1,666	1,860	1,924	1,844	1,904	1,508	1,501	1,532	1,804	2,325
2nd Quartile (Median)	5,065	5,498	5,920	6,341	6,545	6,536	6,329	6,470	5,941	6,185	6,449	6,826
3rd Quartile	14,824	15,904	17,100	16,878	17,634	17,607	17,431	18,625	17,807	16,971	17,813	18,489
Max	420,574	505,280	859,158	834,940	737,493	720,471	894,886	1,158,547	972,158	911,073	834,179	756,761
NATIONAL SUPPORT												
Mean	245	573	708	473	373	437	469	255	276	294	296	185
Standard deviation	1,883	4,874	8,621	4,410	3,126	3,396	4,983	2,219	2,408	2,233	1,974	2,379
Coefficient of Variation	7.7	8.5	12.2	9.3	8.4	7.8	10.6	8.7	8.7	7.6	6.7	12.9
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	0	0	0	0	0	0	0	0	0	0	0	0
Max	32,072	102,854	213,984	119,430	66,942	69,493	145,670	60,900	56,491	59,487	36,800	74,000
TOTAL CAP												
Mean	14,204	14,275	16,106	15,329	16,327	16,410	16,401	16,903	16,338	15,753	16,286	16,599
Standard deviation	31,763	30,850	38,511	37,724	39,512	38,714	42,579	42,135	40,897	37,516	36,501	34,463
Coefficient of Variation	2.2	2.2	2.4	2.5	2.4	2.4	2.6	2.5	2.5	2.4	2.2	2.1
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	724	947	1,622	1,840	1,892	1,750	1,814	1,491	1,461	1,497	1,770	2,286
2nd Quartile (Median)	4,957	5,144	6,395	6,125	6,478	6,325	6,130	6,340	5,727	5,955	6,257	6,701
3rd Quartile	14,611	15,320	17,745	15,969	17,132	17,157	16,961	18,337	17,253	16,514	17,417	18,245
Max	420,574	505,280	805,154	834,940	737,493	717,971	894,886	1,158,547	972,158	911,073	834,179	752,234
PILLAR I - DECOUPLED												
Mean	9,961	9,954	11,211	11,178	12,750	12,536	12,886	11,541	11,340	10,883	10,291	9,922
Standard deviation	21,774	21,001	33,082	31,119	35,614	34,153	36,599	32,735	30,054	26,924	24,078	21,307
Coefficient of Variation	2.2	2.1	3.0	2.8	2.8	2.7	2.8	2.8	2.7	2.5	2.3	2.1
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	98	215	507	768	886	830	878	739	925	1,028	1,204	1,242
2nd Quartile (Median)	3,477	3,483	4,015	4,199	4,231	4,171	4,068	3,568	3,614	3,644	3,682	3,830
3rd Quartile	10,715	10,992	11,718	11,772	12,412	12,095	12,179	11,040	11,008	10,519	10,445	10,378
Max	317,849	319,288	801,933	724,970	720,596	680,898	759,890	862,371	631,221	558,244	528,809	417,296
PILLAR I – COUPLED												
Mean	2,374	2,380	1,923	1,577	567	631	776	1,726	1,883	1,744	1,736	1,889
Standard deviation	11,566	12,675	8,401	8,003	3,357	3,786	5,307	8,515	9,999	10,320	8,860	9,275
Coefficient of Variation	4.9	5.3	4.4	5.1	5.9	6.0	6.8	4.9	5.3	4.9	5.1	4.9
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	690	794	0	0	0	0	0	975	1,087	1,034	1,221	1,120
Max	237,355	340,652	122,828	124,584	90,000	108,794	134,996	293,872	338,633	352,829	305,370	312,498
PILLAR II – AEM												
Mean	826	931	1,100	1,127	1,602	1,620	1,366	1,946	1,940	1,917	2,279	2,450
Standard deviation	2,991	3,300	4,132	4,430	5,390	5,585	5,043	6,552	6,674	6,555	7,528	7,862

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Coefficient of Variation	3.6	3.5	3.8	3.9	3.4	3.4	3.7	3.4	3.4	3.4	3.3	3.2
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	0	0	0	0	0	1	0	0	0	0	0	1,401
Max	38,115	51,974	77,603	77,603	77,598	99,500	100,000	73,863	77,341	92,541	92,541	120,010
PILLAR II – OTHERS												
Mean	1,043	1,010	1,872	1,447	1,408	1,622	1,373	1,690	1,175	1,208	1,980	2,339
Standard deviation	6,853	5,388	8,962	7,567	8,536	8,343	7,605	7,330	5,035	4,720	8,287	7,854
Coefficient of Variation	6.6	5.3	4.8	5.2	6.1	5.1	5.5	4.3	4.3	3.9	4.2	3.4
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	0	0	0	0	0	0	0	0	0	0	1,047	1,860
Max	184,212	140,000	133,700	149,093	240,000	215,000	240,000	110,000	87,000	83,265	176,513	161,758
% Variation CAP support (2019-2008)		Min		1st Quartile		2nd Quartile		3rd Quartile		Max		
		-100%		-19%		+30%		+370%		-		

the number of farms with negative net income did not increase. It amounted to 9% of the whole sample in 2008 and to 7% in 2019, and has remained always between 10% and 5% though with a clear drop after 2009.[18]

More generally, average values may be uninformative, and even misleading, due to the large heterogeneity occurring within the panel as also detailed in the Annex (Figure A3). Table 2 illustrates how during these twelve years the farm net income dispersion and asymmetry maintained the same basic features with no major evidence of a more uniform distribution. Such large dispersion is confirmed by a CV always around two or more, though it also shows a decline in the last three years under observation. The same does not occur for the asymmetry that remains large and constant over the whole period, with a very long right tail that motivates why the mean value is always more than double than the median value (2nd quartile).

4.2.2. Factor use and structural change

The fact that farm profitability did not change much over the period does not exclude that the behaviour and choices of farmers significantly responded to the change of external conditions (CAP included). In order to more deeply investigate this response is useful to assess whether factor endowment, use and intensities significantly changed within the adopted field of investigation. Four fixed (or quasi-fixed) factors are considered: land (UAA); labour (AWU) also including the farm family labour (FAWU); Machinery (KW); Livestock (LSU) (Sahrbacher *et al.*, 2008).

Figure 5 exhibits the evolution of these factors' endowment over the 2008-2019 period. To facilitate interpretation and comparison, values have been indexed with respect to the initial level (2008=1). For all factors a positive trend can be appreciated whose slope seems to be dependent on the respective degree of fixity. From 2008 to 2019 the average land endowment increased by only 6%, while the growth has been of 10%, 15% and 23% for AWU, LSU and KW, respectively. In fact, livestock endowment is the only case showing significant

[18] A classical issue in the analysis of farm profitability concerns whether the farming activity can grant agricultural workers and families a comparable income with respect to the rest of the economy. This issue has generated a long debate among agricultural economists, particularly in Italy (Rocchi *et al.*, 2012). Present results may provide some indication in this respect even though, as discussed, the net farm income here considered does not correspond, *stricu sensu*, to the family farm income for all units. In addition, as discussed, the adopted sample only consider commercial farms and tends to be biased upward, i.e., to have a little overrepresentation of larger farms in economic terms. Nonetheless, for the sake of comparison, it can be noticed that the mean net farm income in the last year of observation (51,440 €) is significantly higher than the average family income resulting, for the same year, from the Italian Statistics on Income and Living Conditions (SILC) (33,653 €). This remains true even when only families with prevalent autonomous work are considered (42,340 €). However, it should be also noticed that this positive gap can be a further consequence of the asymmetry within the sample. If the median net farm income is considered (23,154 €) the gap seems to be actually reversed. Moreover, while the average (or median) net farm income observed within the sample shows a decline in real terms over the period under analysis, the average real-term family income resulting from the SILC data show a very slight increase (+0.4%).

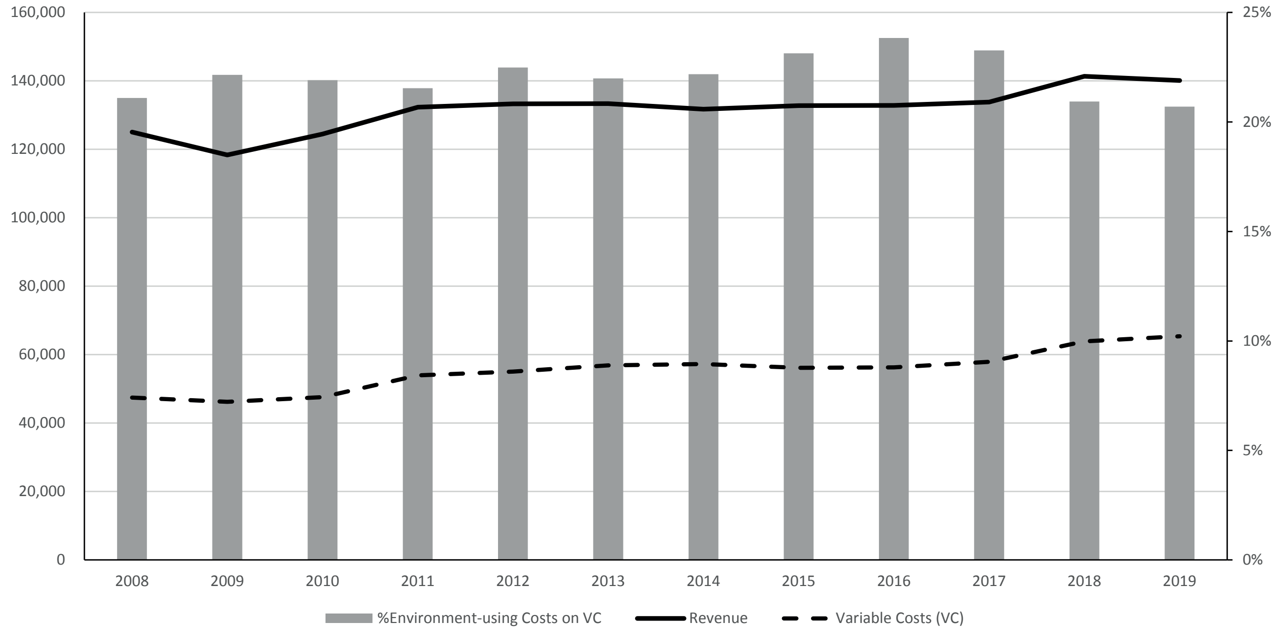

Figure 3. Average revenue, variable costs and environment-using costs (fertilizers, pesticides, energy, water) (€) over the 2008-2019 period within the Italian FADN balanced sample.

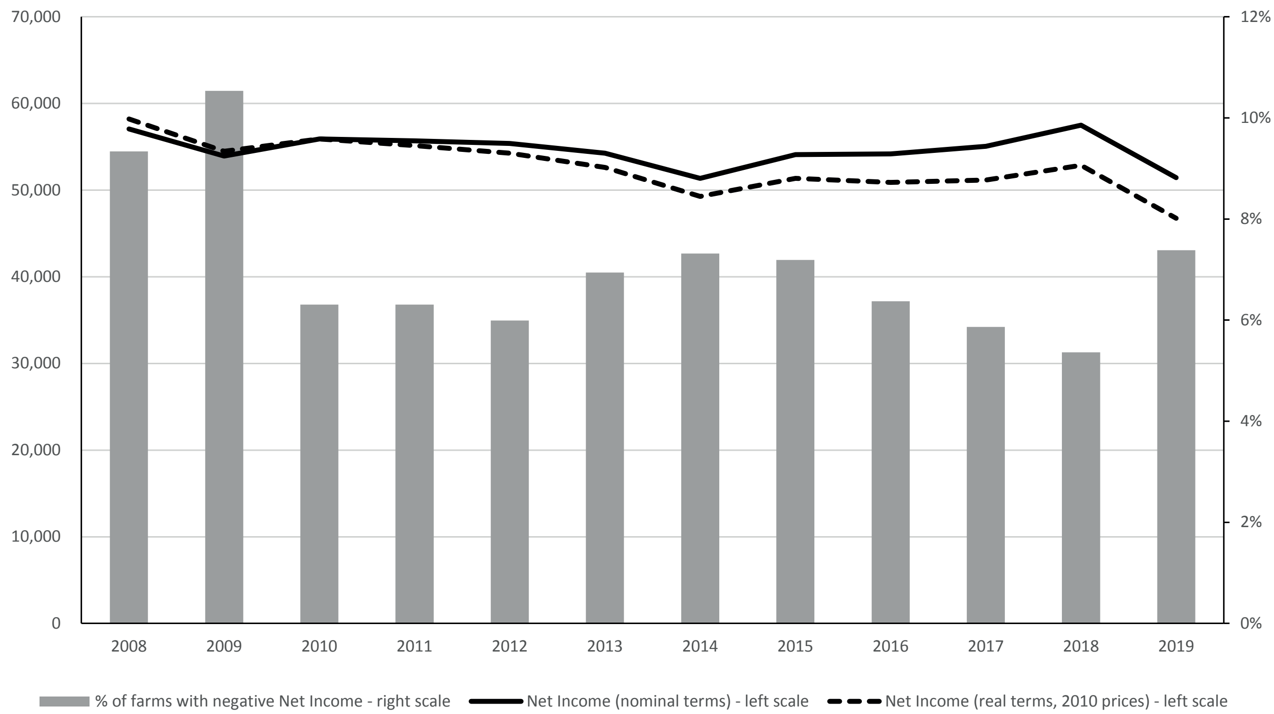

Figure 4.Average farm net income (€) over the 2008-2019 period within the Italian FADN balanced sample.

oscillations and, more importantly, an apparent trend reversal after 2015.

What emerges points to a substantial intensification in the use of these factors (in fact, the same was observed for the variable inputs). A more detailed analysis of the nature of this factors' intensification is available in the Annex (Table A2). It is worth emphasizing here that, combining the evolution of factors' use with

Table 2 – Distribution of the farm net income within the Italian 2008-2019 FADN balanced sample (€).

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	57,056	53,945	55,907	55,703	55,380	54,253	51,358	54,100	54,186	55,072	57,512	51,440
Standard deviation	139,843	134,874	135,000	142,913	127,696	119,818	123,255	132,212	133,324	109,159	106,696	106,542
Coefficient of Variation	2.5	2.5	2.4	2.6	2.3	2.2	2.4	2.4	2.5	2.0	1.9	2.1
Min	-160,758	-124,741	-143,652	-184,265	-66,484	-40,2051	-18,1687	-165,917	-205,180	-229,603	-121,842	-255,091
1st Quartile	8,969	6,542	9,042	9,147	9,669	9,702	8,423	9,399	9,172	9,573	10,065	8,424
2nd Quartile (Median)	24,802	21,723	25,506	24,741	25,537	25,001	23,146	23,966	24,972	25,785	26,229	23,154
3rd Quartile	58,698	52,296	58,763	57,760	59,681	58,205	53,101	57,595	62,726	6,1431	65,008	58,063
Max	2,429,572	2,075,403	2,333,829	2,228,093	1,983,041	2,019,809	2,100,850	3,368,715	3,691,632	1,815,441	1,939,388	1,930,918

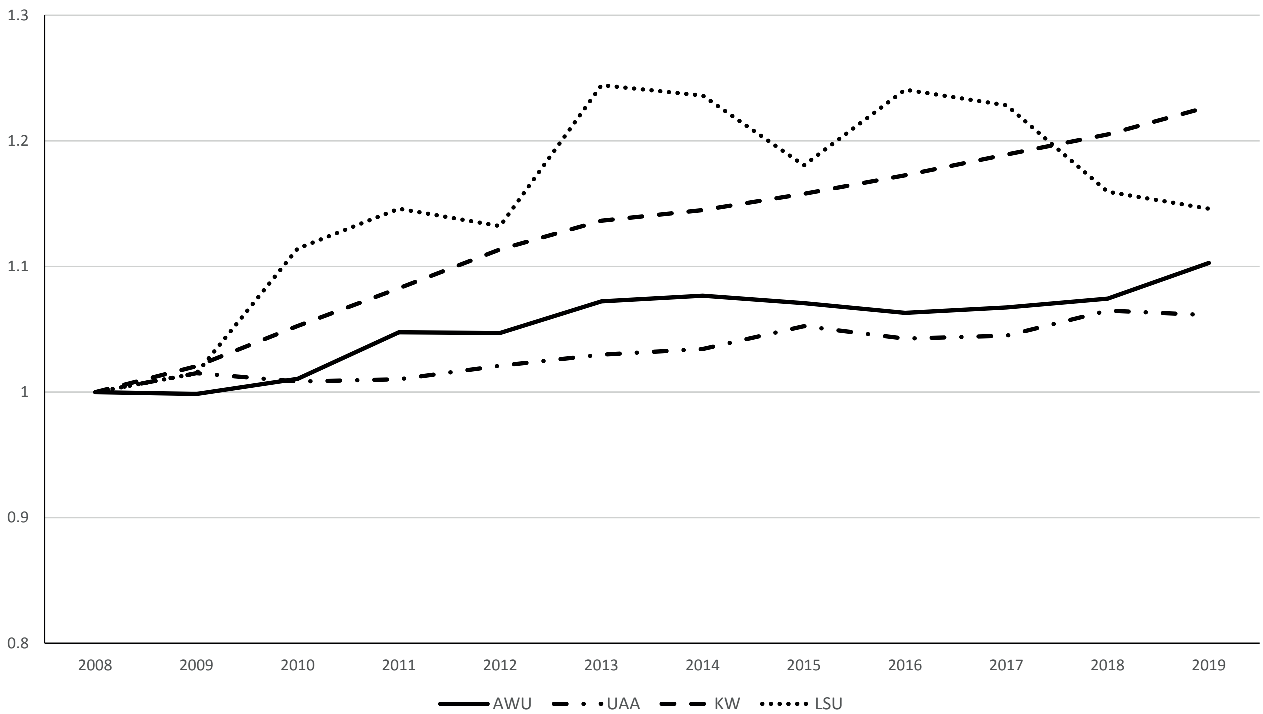

Figure 5. Evolution of main factors' average endowment (2008=1) over the 2008-2019 period within the Italian FADN balanced sample.

the profitability dynamics, a decline of factors' productivity is observed. Figure 6 displays the evolution of the farm net income per unit of labour. Labour productivity (or profitability) declined by 25% from 2008 to 2019, though most of the decline occurs in the very first years of the period. However, if the real term values are considered, the decline is more pronounced (-34%) and occurs quite regularly up to 2014.

It is finally interesting to assess whether this evolution in terms of factor endowment, intensities and profitability is associated to other structural adjustments concerning farm holders, their turnover and attitudes. Figure 7 reports the presence of female and young (<40 years old) farmers within the sample.[19] What emerges is a sharp decline of young holders (from 18% in 2008 to 6% in 2019) and a substantial stability of the presence of female holders (from 15% to 17%). Moreover, there is no

[19] It is worth noticing that this sample may significantly underestimate the holders' turnover. As entry and exit dynamics are excluded by definition within a balanced panel, here only the internal replacements are captured, that is, the possible substitution of the holder within the same farm. Although partial, however, this may still be a reliable representation of the actual structural change occurring within the professional farming sector. Considering agriculture as a whole may misrepresent the presence of female and young farmers as numbers are affected by the presence of very small (non)farms. In the Italian case, in particular, both the presence of female and of elder holders has been always altered by the persistence of these marginal (non)farms (Iacoponi, 2021).

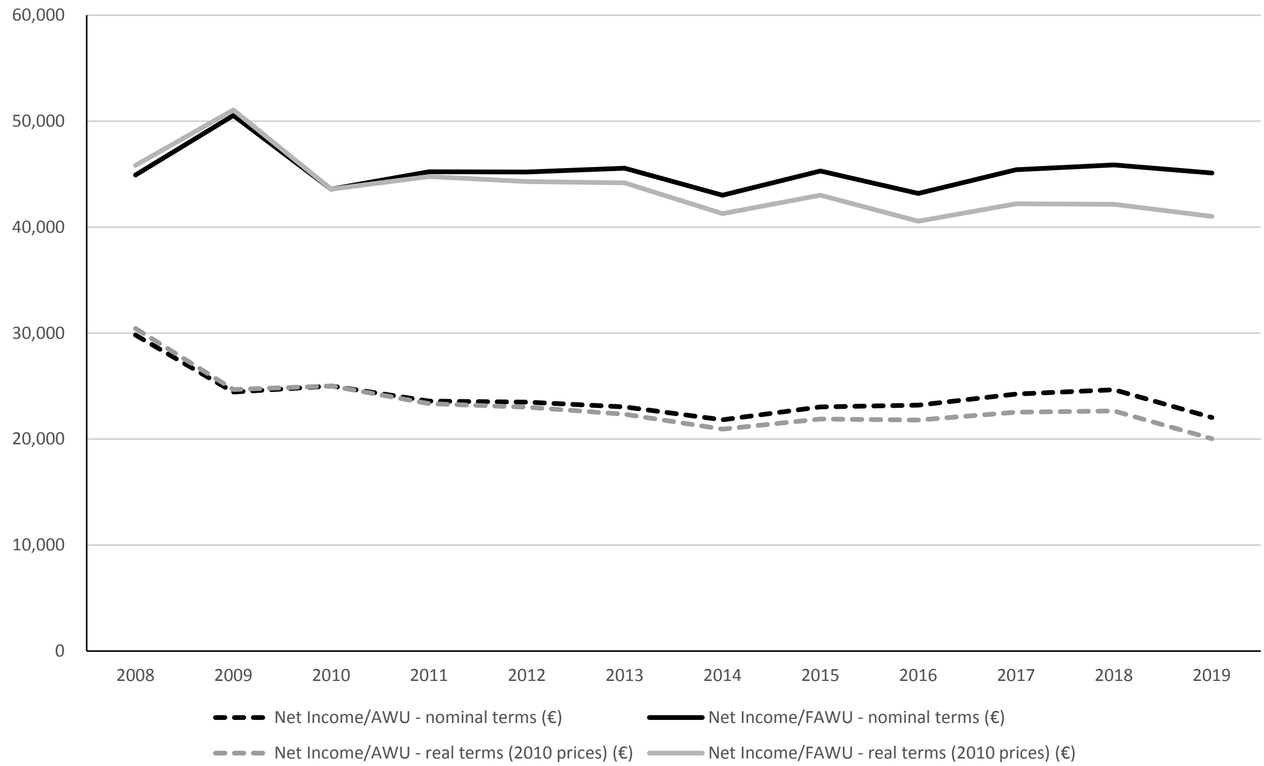

Figure 6. Evolution the farm net income per (F)AWU over the 2008-2019 period within the Italian FADN balanced sample.

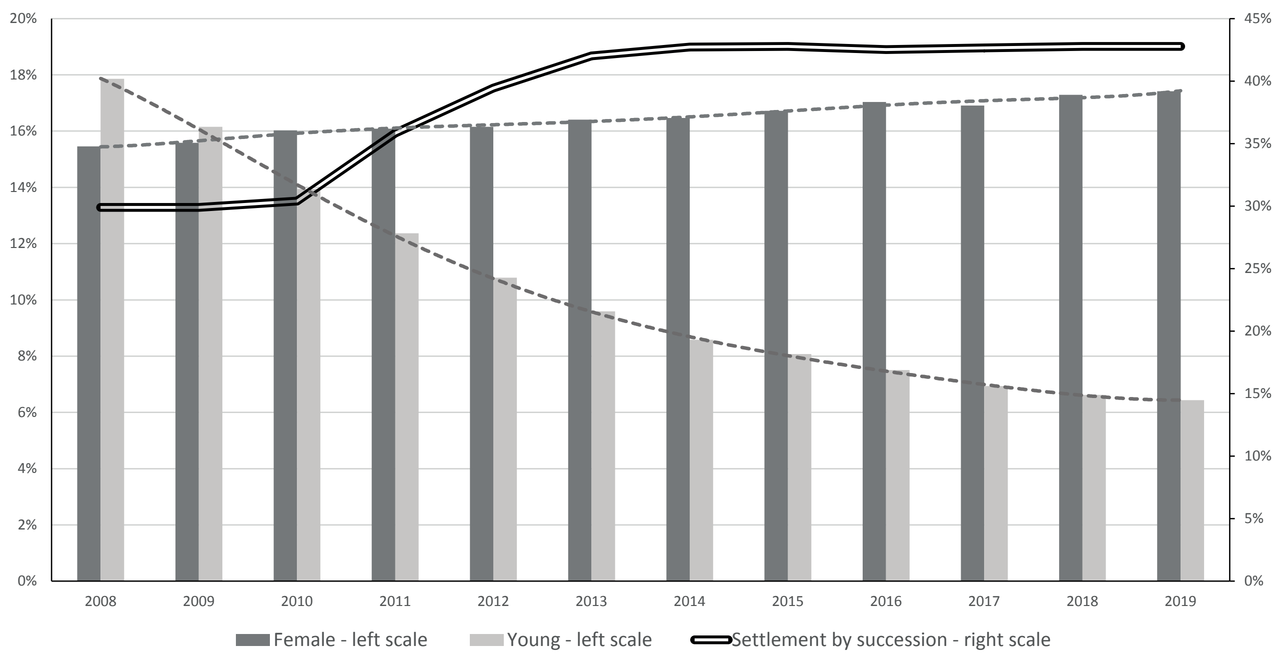

Figure 7. Evolution of the presence of the female, young and organic farmers over the 2008-2019 period within the Italian FADN balanced sample.

evidence of a correspondence between young and female holders as the average age of female and male holders is substantially the same.[20]

It thus seems difficult to interpret these figures as the progressive emergence of a new generation of farmers within the adopted sample. Nonetheless, the share of farmers settled by succession significantly increased from 30% in 2008 to 43% in 2019. This would indicate that 13% of farms experienced a succession during the period of observation. However, this succession is not apparently associated with the takeover of young and female farmers. In addition, most of these successions occurred between 2010 and 2012, thus it may be questioned whether it is real or it is just an artefact due to data collection or some other administrative reason.

4.2.3. Production choices

A final aspect of the evolution of farmers' behaviour concerns their production choices. The classification of agricultural holdings by Type of Farming (TF) can be informative in this respect. FADN classifies farms in eight TF categories: five main groups of specialist agricultural holdings and three mixed groupings.[21] Therefore, the first indicator of a production response is expressed by the TF dynamics: a switch from one TF to another evidently expresses the farmer's decision to change production orientation or specialization.

Figure 8 exhibits the evolution of the TF categories over the 2008-2019 period. The most frequent categories are field crops (TF1), permanent crops (TF3) and grazing livestock (TF4). None of the other Types of Farming (TFs) exceeds a 10% share. Overall, shares remain quite constant over time: TF1 remains at 26% even though a slight decline is observed between 2010 and 2016; TF3 remains constant at 30% up to 2014 and then slightly declines to 28%; TF4 starts from 21% and experiences an increase in the first years but then comes back to 22% in 2019. All other TFs show a very limited variation of their share (always lower than 2%). Even the combination of these TFs does not express any significant structural dynamics. For instance, TFs with livestock activities combined (TF4, TF5, TF7 and TF8) show the same share in 2008 and 2019 (31%) with minimum changes over the period.

Even though relatively few transitions from one TF to another are observed, it may be interesting to investigate further where these transitions occurs and speculate on the possible motivations. The Annex (Table A3) provides more details on the observed TF switches. Here, it seems interesting to define the proper dimension of this event. Figure 9 orders the farms per number of TF changes over the 2008-2019 period. For 1079 units (68% of the sample) no change is observed. For other 166 farms (about 10%) only one change is observed. It means that these are genuine switches, namely, in these observations a real change in production orientation has taken place. For all other units, multiple switches are observed during the period. In most cases, they are back-and-forth movements, that is, these farms are momentarily associated to another TF but then go back to the original category. Arguably, this peculiar behaviour does not express any relevant change in production farmers' choices. It can be interpreted as physiological oscillations of production activities in borderline farms between two TFs.

However, the switch of TF may be a poor indicator of farm production re-orientation. There could be more radical changes in farmer's output mix that are not captured by the TF classification. It is the case of the activation of unconventional farm activities usually designated as multifunctional diversification: farms combining agricultural production with market or non-market services (multifunctional farms). The FADN dataset provides information about the so-called "Other gainful activities", also defined as "agriculture-related activities" ("*attività connesse*") in Italian regulation.[22]

Figure 10 displays the evolution of the number of farms with other gainful activities, as well as their incidence on the SO both in the whole sample and in these multifunctional farms. For both the number of farms and the incidence on the whole sample, a sharp drop is observed between 2009 and 2010. After that, the trend regularly and consistently reverts to the initial 2008-2009 variation. It can be argued that this 2009-2010 drop is an artefact due to some changes in data collection as corroborated by the incidence of these activities within these multifunctional farms: it does not show any drop and it increases quite regularly, at least up to 2016.

Therefore, if compared to the 2010 level, in 2019 we observe a 3% growth in the number of multifunctional farms within the sample (from 14% to 17%), a 1.4% growth in the incidence of these activities within the full sample, and a 5% growth in the incidence within mul-

[20] See also Giampaolo *et al.* (2021) and Selmi (2021) for a comparison with analogous evidence on the whole Italian agriculture.

[21] The TF of an agricultural holding is determined by the relative importance of each production activity on the total farm SO. The eight groups are defined as follows: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

[22] They include agritourism and rural tourism, educational farms, active subcontracting, aquaculture, transformation of farm products, production of renewable energy, environmental services, agro-craft activities.

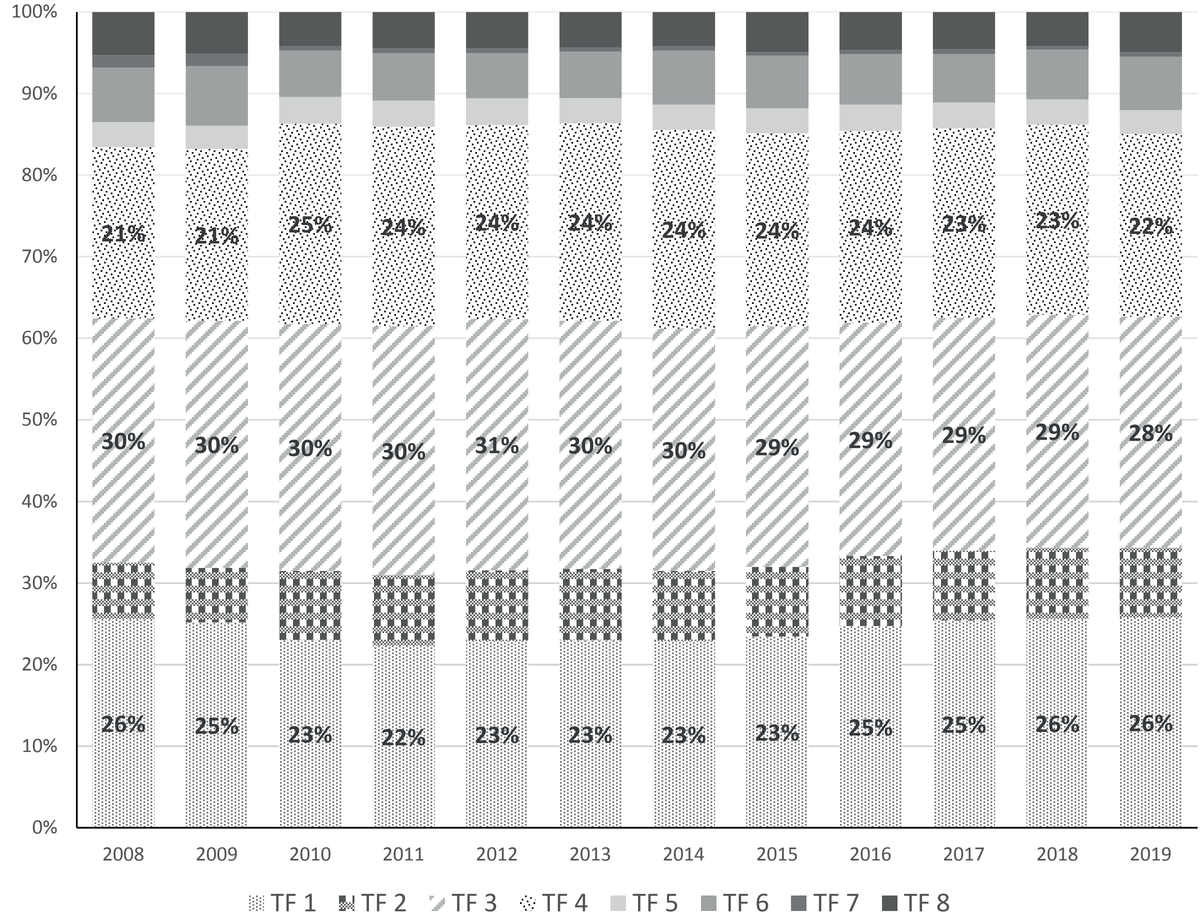

Figure 8. Evolution of the Type-of-Farming (TF) categories over the 2008-2019 period within the Italian FADN balanced sample (% is indicated only for FT >10%,). Legend: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

tifunctional farms. Therefore, the observed progress of multifunctional activities seems slow overall and it looks like more an increasing specialization of a limited group of farms. Eventually, it appears as a gradual and spontaneous structural evolution driven more by the market conditions than by some change in the policy support (see below).

5. THE CO-EVOLUTION

This section derives from the analysis above some stylised facts about nature and extent of the co-evolution of CAP support and farm behaviour. By co-evolution here we mean that the dynamics of the CAP and the change of farmers' behaviour concur (so they appear to be correlated) in such a way that it is very difficult, if not unfeasible in practice, to distinguish which is the cause and which is the effect. Therefore, with the term co-evolution we do not want to necessarily mean policy neutrality (or ineffectiveness) in promoting farm practice changes. It may be definitely the case that some agricultural practices are triggered by the change in the CAP support. However, empirically assessing this causal linkage, may be very challenging.

We want to motivate this conclusion more in detail by separately considering the three abovementioned major policy objectives (income support, production diversification, environmental goods provisions) to which we associate three respective research questions.

5.1. Farm income and CAP support

Is there any evidence that CAP payments did really protect the farm's net income in both level and variabil-

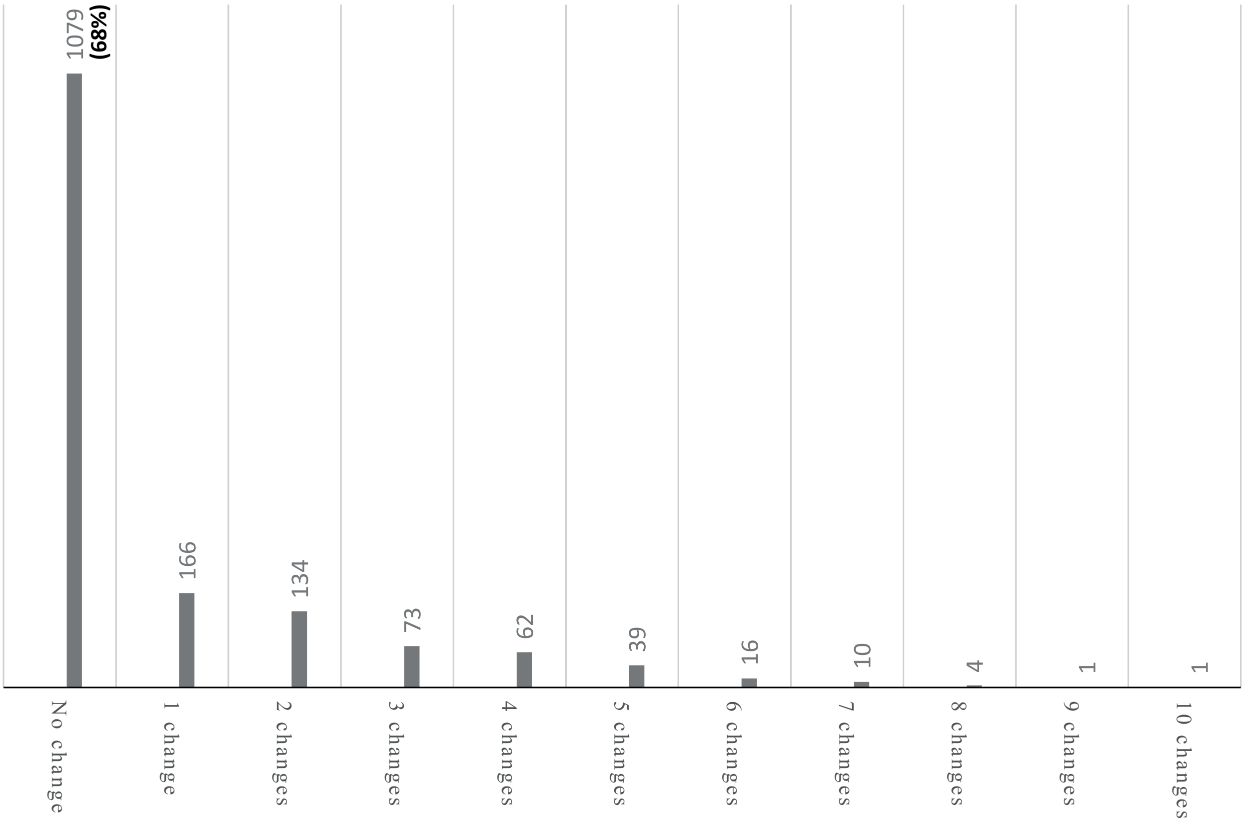

Figure 9. Farms per number of TF changes over the 2008-2019 period within the Italian FADN balanced sample.

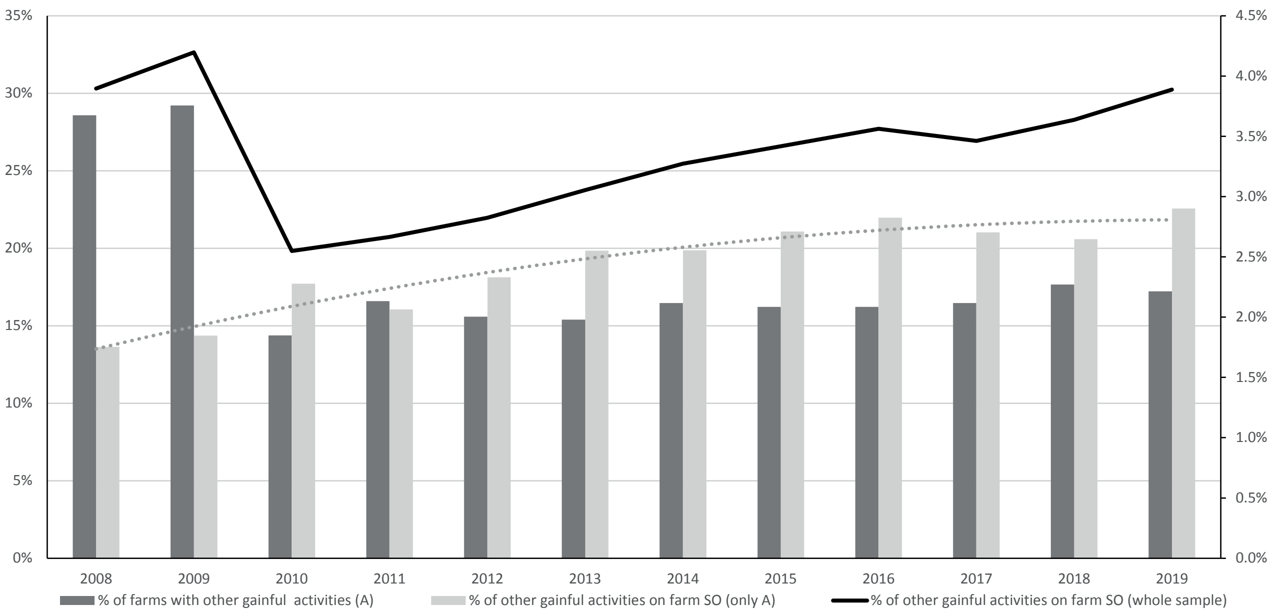

Figure 10. Evolution of the farms and of the incidence on farm Standard Output of other gainful activities within the Italian FADN balanced sample.

ity? An income-protection effect should imply a negative relationship between the level of CAP support and the farms net income, that is, a larger support for farms showing higher income problems. These problems can be expressed by a negative net income, by a net income that would be negative without the CAP payment (i.e., the ratio between CAP support and net income is >1) or, more generally, by a low labour profitability (i.e., net income per unit of labour). But income problems can be also intended as a large income variability.

In order to assess this question, it is worth measuring the intensity of support per unit of family labour (FAWU) both to eliminate the size effect and to focus on the actual farmers' objective variable. Table 3 provides detailed information about the evolution of the CAP support per unit of net income and of AWU and, above all, about its distribution within the sample. Figure 11 displays the CAP support and number of farms with a CAP support larger than the net income (included net income<0). Five major facts are worth noticing.

1. The support per unit of net income significantly oscillates due to the oscillations of the net income itself but, overall, it remains stable over time: 39% in 2008 and 40% in 2019, with a maximum of 66% in 2018 and minimum of 24% in 2014.[23]

2. The support per unit of FAWU increased by 21% in nominal terms (8% in real terms) from 2008 to 2019, but if the comparison is made between 2009 and 2019, the increase falls to 4% in nominal terms and becomes a decline (-7%) in real terms.[24]

3. The correlation between the CAP support per unit of FAWU and the respective unit net income is significantly positive[25] and it slightly reinforces over time with a maximum of 0.67 in 2018. It indicates that the incidence of the CAP support on net income per unit of labour tends to be stronger in farms that need it less as they show an higher labour profitability.

4. The number of farms with a CAP support greater than net income (negative net income included) is quite stable (around 20%). They receive an almost proportional share of support (between 20% and 30%) and the average support to these farms increased by 11% in nominal terms but remained constant in real terms (-0.6%).

5. The growth of unit CAP support[26] shows a weak but significantly positive correlation with family labour profitability. At the same time, a positive but much stronger correlation is observed between unit support and the variability the family labour profitability.

It can be concluded that a quite contradictory evidence emerges about the consistency of the CAP as an income protection policy. On the one hand, CAP support may have really supported the farms' income as its incidence is remarkable. On the other hand, however, support and support growth, though very disperse, go more towards farms that need less, i.e., more profitable farms.[27] Therefore, there is no clear indication that this policy is selective in favour of most problematic units but, at the same time, support itself is strongly oriented towards cases showing higher income variability. More than an income support policy, CAP thus seems to behave like an income stabilization policy at whatever income level a farm is.

5.2. Production diversification and CAP support

Is there any evidence that the change in CAP payments, either the decoupling of I Pillar payments and the increase of II Pillar payments, induced production diversification? To assess a diversification-inducing effect we need a metric to measure production diversification. Here we firstly follow the analogy with ecological studies where diversity is often measured using the Shannon (or Shannon-Wiener) and the Simpson indexes (Keylock, 2005). These indexes are here adapted to compute the farm-level Diversification Index for any i-th farm at any time *t* (DI_{it}) (Coderoni, Esposti and Varacca, 2021):

(1) Shannon
$$DI_{it} = -\sum_{c=1}^{C}\left[share_{it,c} * \ln\left(share_{it,c}\right)/\ln 2\right],\ \forall i, \forall t, \forall c \in C$$

(2) Simpson $DI_{it} = \sum_{c=1}^{C}\left(share_{it,c}\right)^2,\ \forall i, \forall t, \forall c \in C$

where *c* indicates a generic crop/animal species of the set of all observed crops/animal species *C*. These indexes are separately computed on crops (on the basis of the share on the total farm's UAA) and on animals (on the basis of the share on the total farm's LSU), and then averaged weighting by the respective share of crop and livestock products on farm revenue. For both indexes, more diversified farms are expected to show an higher DI_{it} and, more

[23] These figures confirm what emerged in previous studies also for Italian agriculture (European Commission, 2018b).

[24] Due the presence of negative values, In computing this indicator, farms with negative net income are attributed the highest incidence observed in the rest of the sample.

[25] It is worth reminding that, as detailed in section 4.2.1, the calculation of the net farm income includes the CAP support. Therefore, even when the latter shows a limited incidence on the former on average, a slight positive correlation between the two necessarily occurs.

[26] For farms with a zero initial CAP support, the attributed growth rate corresponds to observed maximum finite value.

[27] A similar evidence for the Italian FADN farms is obtained by Ciliberti *et al.* (2022).

Table 3. Evolution of the CAP support per unit of net income and of AWU within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A) CAP support/Net Income (%)												
Mean	39%	29%	54%	40%	43%	33%	24%	49%	47%	51%	66%	40%
Standard deviation	387%	1,207%	408%	270%	805%	628%	810%	363%	953%	11,234%	732%	266%
Coefficient of Variation	9.9	41.6	7.6	6.7	18.9	19.3	34.4	7.3	20.3	220.3	11.1	6.7
Min	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1st Quartile	0%	0%	3%	4%	5%	4%	4%	3%	2%	3%	4%	5%
2nd Quartile (Median)	17%	21%	24%	24%	24%	22%	25%	25%	22%	22%	24%	25%
3rd Quartile	55%	64%	61%	60%	60%	61%	62%	64%	62%	60%	61%	63%
Max	9,868%	16,679%	8,601%	3,553%	21,479%	17,270%	6,455%	9,591%	27,578%	2,388%	23,517%	3,902%
B) CAP support/FAWU (€)												
Mean	13,660	15,954	14,701	14,041	14,789	16,774	16,627	16,239	14,330	15,240	14,561	16,534
Standard deviation	33,102	45,784	40,671	32,212	34,684	53,774	61,150	43,461	36,434	42,160	37,633	39,940
Coefficient of Variation	2.4	2.9	2.8	2.3	2.3	3.2	3.7	2.7	2.5	2.8	2.6	2.4
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	556	800	1,096	1,244	1,470	1,330	1,350	1,164	1,043	1,175	1,386	1,754
2nd Quartile (Median)	4,038	4,802	4,519	4,525	5,165	5,369	5,238	5,303	4,414	4,893	4,954	5,592
3rd Quartile	12,498	14,468	13,835	13,489	15,083	14,765	15,201	16,545	14,457	13,841	14,328	16,522
Max	647,037	973,039	781,053	533,976	597,378	1,233,624	1,413,233	1,053,225	883,780	828,248	1,005,035	886,387
Correlation coefficient between B) and net income/FAWU	0.38*	0.36*	0.60*	0.39*	0.52*	0.64*	0.65*	0.51*	0.50*	0.46*	0.67*	0.54*
Correlation coefficient between net income/FAWU and the CAP support 2019-2008 growth rate								0.06*				
Correlation coefficient between avg. 2019-2008 CAP support/FAWU and standard deviation of net income/FAWU								0.52*				

[a] Farms with Net Income<0 are excluded.
*Statistically significant at 5% confidence level.

importantly, an increased production diversification within the sample is expressed by an higher average DI_{it}.[28]

Figure 12 shows the evolution of the average Shannon and Simpson diversity indexes within the adopted field of investigation. The two indexes behave similarly though the Shannon index evolves a little more smoothly: from 2008 to 2019, the Shannon index increased by 12%, the Simpson index by 10%. As usual, these average values may hide a major heterogeneity within the sample as can be better appreciated by looking at the descriptive statistics reported in Table 4. In both cases, the dispersion (as indicated by the CV) and the asymmetry (as indicated by the median-mean ratio) are limited compared to most variables investigated above. The growth of the lower quartiles is more intense than the higher ones, thus indicating that not only diversification increased, but also that it distributes more uniformly within the sample.

The bottom of Table 4 reports the correlation coefficients between these indexes and the CAP support per unit of FAWU. As expected, the two diversity indexes behave very similarly. Therefore, respective results can be commented on together. CAP support by itself shows a little linkage with diversity indexes, at least until 2016 when a positive relationship started to emerge. Apparently, this emerging relationship can be attributed to both the II Pillar support and to the I Pillar decoupled support, for which, in fact, the positive linkage emerges from the beginning of the period.

[28] The main difference between the two is that the Shannon index ranges between 0 and lnC/ln2, while Simpson index ranges between 0 and 1.

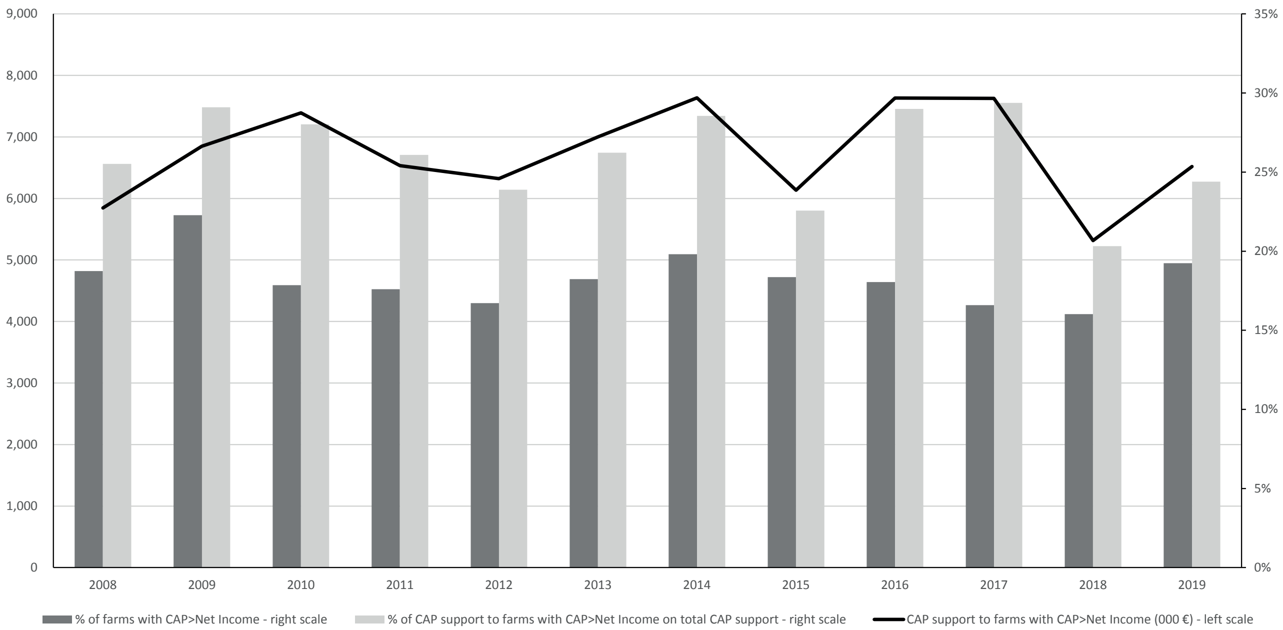

Figure 11. CAP support and number of farms with CAP support > net income (included net income < 0) within the 2008-2019 Italian FADN balanced sample.

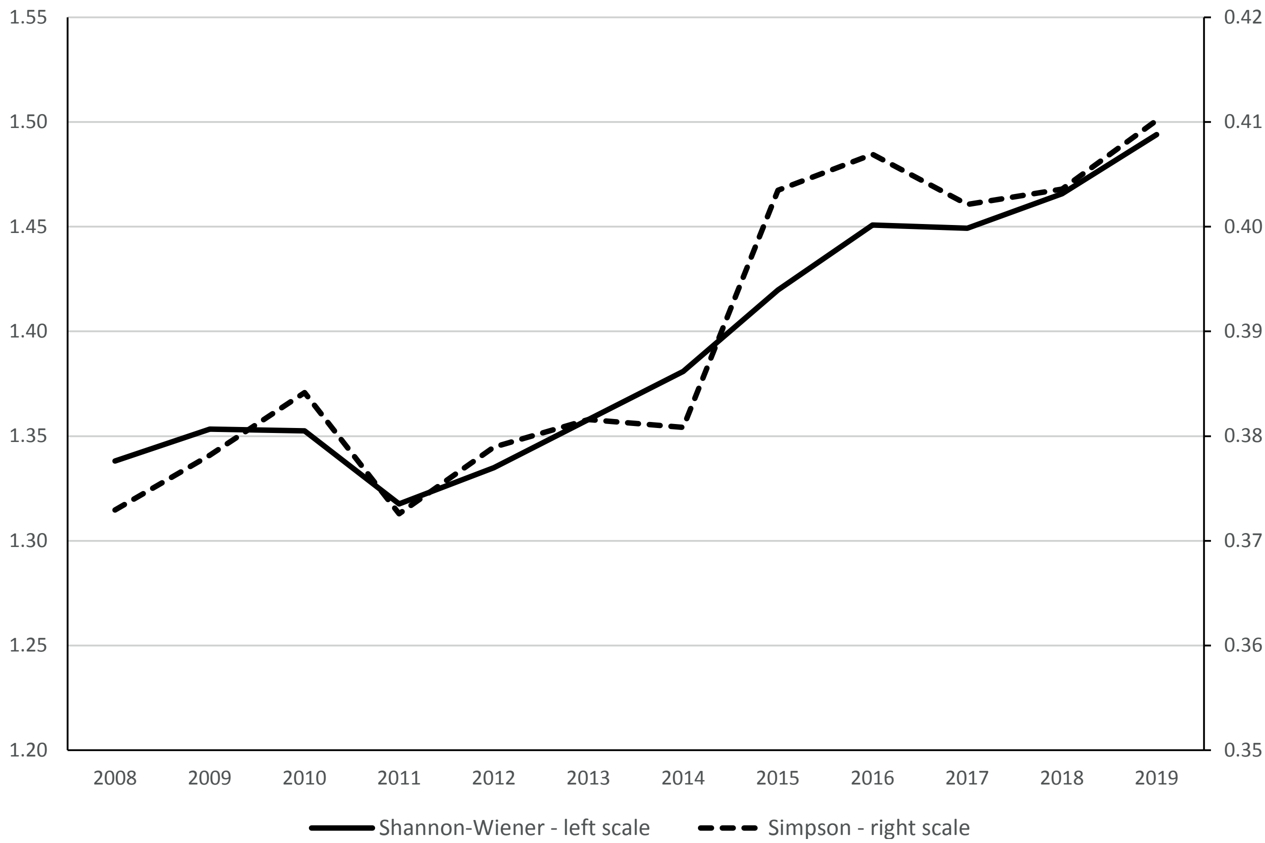

Figure 12. Evolution of the average Shannon and Simpson diversity indexes within the Italian 2008-2019 FADN balanced sample.

Table 4. Evolution of the Shannon and Simpson diversity indexes within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A) Shannon diversity index (>1)												
Mean	1.34	1.35	1.35	1.32	1.33	1.36	1.38	1.42	1.45	1.45	1.47	1.49
Standard deviation	0.94	0.96	0.93	0.94	0.94	0.95	0.97	0.95	0.98	0.98	0.99	1.00
Coefficient of Variation	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1st Quartile	0.66	0.66	0.66	0.62	0.64	0.65	0.65	0.72	0.76	0.73	0.74	0.75
2nd Quartile (Median)	1.27	1.31	1.31	1.30	1.31	1.37	1.40	1.44	1.45	1.43	1.44	1.48
3rd Quartile	1.94	1.96	1.96	1.92	1.94	1.99	2.02	2.04	2.09	2.10	2.12	2.14
Max	5.50	5.60	4.85	6.18	5.29	4.97	5.31	5.01	4.80	4.85	5.12	5.50
B) Simpson diversity index (0-1)												
Mean	0.37	0.38	0.38	0.37	0.38	0.38	0.38	0.40	0.41	0.40	0.40	0.41
Standard deviation	0.26	0.26	0.26	0.26	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
Coefficient of Variation	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1st Quartile	0.12	0.11	0.11	0.08	0.09	0.09	0.10	0.15	0.16	0.15	0.17	0.17
2nd Quartile (Median)	0.42	0.44	0.44	0.43	0.44	0.44	0.44	0.47	0.47	0.47	0.47	0.47
3rd Quartile	0.60	0.61	0.61	0.60	0.61	0.61	0.61	0.63	0.63	0.63	0.62	0.64
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Correlation coefficient btw A) and CAP support per FAWU	0.01	-0.02	0.03	0.01	0.00	0.03	0.05	0.04	0.09*	0.05*	0.11*	0.03
Correlation coefficient btw B) and CAP support per FAWU	-0.03	-0.03	0.02	-0.03	0.00	0.02	0.03	0.01	0.06*	0.04	0.09*	0.04
Correlation coefficient btw A) and I Pillar decoupled support per FAWU	0.05*	0.03	0.08*	0.07*	0.02	0.03	0.04	0.04	0.08*	0.06*	0.11*	0.04
Correlation coefficient btw B) and I Pillar decoupled support per FAWU	0.01	0.01	0.07*	0.04	0.02	0.01	0.03	0.01	0.07*	0.04	0.10*	0.06*
Correlation coefficient btw A) and II Pillar support per FAWU	0.01	-0.02	0.03	0.01	0.00	0.03	0.05	0.04	0.09*	0.05*	0.11*	0.03
Correlation coefficient btw B) and II Pillar support per FAWU	-0.01	-0.01	-0.02	0.00	-0.02	0.05*	0.04	0.05*	0.08*	0.02	0.06*	0.02

A similar analysis can be performed for another set of indicators of production diversification. In this case, it is not an "horizontal" diversification (more crops or livestock activities) but a "vertical" diversification, that is, higher production quality as expressed by process and production certifications and or by the activation of other gainful activities. Table 5 reports the correlation coefficients between CAP support (and its different components) per unit of FAWU and four indicators of this "vertical" diversification.[29] All these indicators can be expression of a generalized tendency of farmers to look for an improved allocation efficiency, i.e., to find the best output mix given the market conditions. In turn, this tendency can be affected by the CAP and its reform in two ways. On the one hand, the progressive decoupling of I Pillar support should enable this market reorientation (Esposti, 2017a,b). On the other hand, it can be also the consequence of the II Pillar support itself, as certifications and diversification activities are incentivized by several II Pillar measures.

Correlation coefficients reported in Table 5 only weakly support the linkage between the unit CAP support and these diversification indicators. The total CAP support is positively correlated with the organic farming certification (but this linkage is statistically significant only in the last four years) and negatively correlated with product quality certification. This evidence holds true also for decoupled I Pillar support, while any kind of statistically significant relationship seems to vanish when only coupled I Pillar support is considered.

II Pillar unit support shows a very strong positive linkage with organic farming that only slightly weakened from 2009 to 2014. A little weaker and more volatile, but still positive and mostly statistically significant, is the linkage with all environmental certifications. With only few exceptions concentrated in the initial years of the period, the correlation with II Pillar support statisti-

[29] Three has to do with certifications: organic farming certification; any kind of environmental certification (organic farming included); any product quality certification but organic certification (for instance, designation of origin). The last indicator is the already discussed multifunctional diversification, that is, the share of other gainful activities on farm's SO.

Table 5. Correlation coefficients between CAP support per unit of FAWU and different certifications within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total CAP support/FAWU												
Organic Farming	0.03	0.01	0.03	0.02	0.00	0.00	0.01	0.02	0.07*	0.09*	0.09*	0.08*
Environmental Certification (organic included)	0.01	-0.03	-0.01	0.00	-0.03	0.01	0.00	-0.01	0.02	0.00	0.03	0.04
Product Quality Certification (organic excluded)	-0.01	-0.03	-0.06*	-0.08*	-0.08*	-0.07*	-0.08*	-0.07*	-0.07*	-0.08*	-0.07*	-0.06*
% of other gainful activities	-0.03	-0.01	-0.03	-0.03	0.01	-0.01	-0.03	-0.02	-0.03	-0.02	-0.03	-0.04
Decoupled I Pillar support/FAWU												
Organic Farming	0.00	0.00	-0.01	-0.01	-0.02	-0.03	-0.02	-0.02	0.05*	0.05*	0.05*	0.02
Environmental Certification (organic included)	0.00	-0.04	-0.03	-0.03	-0.04	-0.02	-0.02	-0.04	-0.03	-0.01	-0.01	0.01
Product Quality Certification (organic excluded)	-0.04	-0.04	-0.06*	-0.08*	-0.08*	-0.08*	-0.07*	-0.08*	-0.09*	-0.10*	-0.08*	-0.07*
% of other gainful activities	-0.04	-0.01	-0.03	-0.03	-0.03	-0.02	-0.03	-0.03	-0.04	-0.04	-0.03	-0.04
Coupled I Pillar support/FAWU												
Organic Farming	-0.02	-0.02	-0.04	-0.04	-0.03	-0.02	-0.01	-0.03	0.00	-0.02	-0.01	-0.03
Environmental Certification (organic included)	-0.03	-0.03	-0.04	-0.05*	-0.03	-0.01	-0.01	-0.03	0.02	-0.03	-0.03	-0.03
Product Quality Certification (organic excluded)	0.02	-0.03	-0.05*	-0.08*	-0.03	-0.03	-0.03	0.00	-0.01	-0.03	-0.04	-0.03
% of other gainful activities	-0.04	-0.03	-0.03	-0.02	0.01	0.01	-0.01	-0.03	-0.03	-0.02	-0.02	-0.04
II Pillar support/FAWU												
Organic Farming	0.19*	0.08*	0.14*	0.10*	0.07*	0.10*	0.07*	0.16*	0.20*	0.13*	0.19*	0.18*
Environmental Certification (organic included)	0.11*	0.04	0.10*	0.07*	0.03	0.12*	0.05	0.13*	0.17*	0.06*	0.16*	0.12*
Product Quality Certification (organic excluded)	0.05*	0.02	-0.01	0.00	0.00	-0.04	-0.03	0.02	0.00	-0.02	0.01	-0.01
% of other gainful activities	0.06*	0.04	0.01	0.00	0.08*	0.01	0.01	0.02	0.01	0.01	0.01	0.02
AEM II Pillar support/FAWU												
Organic Farming	0.30*	0.17*	0.16*	0.14*	0.15*	0.11*	0.13*	0.19*	0.18*	0.19*	0.20*	0.19*
Environmental Certification (organic included)	0.23*	0.08*	0.13*	0.11*	0.08*	0.06*	0.09*	0.14*	0.15*	0.09*	0.14*	0.13*
Product Quality Certification (organic excluded)	0.08*	0.02	0.02	0.04	0.02	-0.01	-0.01	0.04	0.02	-0.01	0.02	-0.02
% of other gainful activities	0.03	0.00	-0.02	0.00	0.01	0.00	0.00	-0.01	-0.01	-0.01	0.00	-0.03
Other II Pillar support/FAWU												
Organic Farming	0.03	-0.01	0.06*	0.04	-0.01	0.03	0.03	0.06*	0.12*	0.04	0.11*	0.10*
Environmental Certification (organic included)	-0.02	-0.01	0.03	0.02	-0.01	0.12*	0.02	0.06*	0.12*	0.00	0.12*	0.06*
Product Quality Certification (organic excluded)	0.00	0.01	-0.02	-0.03	-0.02	-0.05*	-0.04	-0.01	-0.02	-0.03	-0.01	0.01
% of other gainful activities	0.06*	0.05*	0.01	0.00	0.10*	-0.02	-0.01	0.03	0.01	0.00	-0.01	-0.01

*Statistically significant at 5% confidence level.

cally disappears in the case of product quality certification and multifunctional diversification.

It can be concluded that there is some linkage between the increasing II Pillar support, the progressive decoupling of I Pillar support and production reorientation. However, the empirical evidence is not enough to interpret the observed linkage as an undisputable cause-effect relationship. It can be again interpreted as a co-evolution between market-driven production choices and the path-dependent CAP support.[30]

[30] Its negative linkage with product quality certifications, for instance, can be simply explained by the fact that most of these highly specialised farms were historically recipients of poor support. And of this remains a trace in both decoupled and coupled payments.

5.3. Environmental goods and CAP support

Did the change in the CAP support and composition (II Pillar in particular) really induce a greater provision of environmental goods? Also an environmental-good-provision effect of the CAP requires an appropriate metric, i.e., appropriate indicators (Janssen *et al.*, 2010).[31]

[31] This is a challenging task because environmental indicators often require detailed physical information that are hardly available at the farm level and only partially included in the FADN dataset. As part of "the Farm to Fork strategy", the European Commission has recently announced its intention to convert the FADN into a Farm Sustainability Data Network (FSDN) to expand the scope of the current FADN network by collecting farm level data also on environmental and social farming practices.

The diversity indexes discussed above may represent proxies of the provision of some environmental services, like the protection of biodiversity within the agro-ecological context. But they seem rough indicators of the provision of other environmental goods. At the same time, however, an explicit indication of the achievement of higher environmental standards comes from the abovementioned environmental certifications. Therefore, it is worth investigating further the linkage between these certifications and the CAP support.

Figure 13 shows the evolution of the share of farms with organic and environmental certifications. For the sake of comparison, also product quality certifications are reported. All certifications significantly grew over the whole period with +162% for organic farming, +52% for all environmental certifications and +47% for product quality certifications. In general terms, if we exclude organic farming, environmental certifications seem substantially stagnant compared to product quality certifications. Eventually, organic farming has become the prevalent form of environmental certifications over time as it was just 34% on the total in 2008 and reached 58% in 2019.

Table 5 presents the correlation coefficients between the two categories of II Pillar CAP support (AEM and other measures) per FAWU and the different certifications. As could be expected, it emerges a strongly positive and significant linkage between AEM payments and environmental certifications, in particular organic farming. On the contrary, there is no evidence of a regular and significant relationship between other II Pillar measures, product quality certifications and multifunctional diversification. Even for these measures, the only evidence concerns the linkage with environmental certification, organic farming in particular.

It could thus be concluded that a robust relationship between the AEM support and organic farming and, more generally, environmental certifications actually emerges. But, again, this does not imply a treatment effect as this linkage may be just apparent or, to be more precise, just a tautology. As a matter of fact, certification is not the consequence of a treatment (i.e., a II Pillar measure), but it is the treatment itself: untreated units cannot be certified whereas treated units are automatically certified. Therefore, the TE logic might not work properly because the treatment does not leave any behavioural trace, namely, it does not induce any observable behavioural response. In fact, the only behavioural trace is the farmer's voluntary choice of the treatment itself which inevitably implies certification.

6. CAUSAL INFERENCE, CAP ASSESSMENT AND THE CO-EVOLUTION HYPOTHESIS

We can now go back to the original question of the present study, i.e., the actual applicability of the TE logic to CAP assessment. Previous section points to some major features of the co-evolution of CAP support and of farmers' performance. As shown, this co-evolution does not necessarily exclude causation but makes it hardly identifiable. In practice, co-evolution is the consequence of the particular forms in which CAP measures are delivered to farmers and these latter progressively take decisions combining voluntary participation to these measures with production choices. These forms eventually enter in conflict with the prerequisites of a TE logic. Without entering into technical details, it must be reminded that almost all CI studies are based on the so-called Potential Outcome (PO) framework (Rubin, 1974; Imbens and Wooldridge, 2009; Imbens and Rubin, 2015). Within this theoretical framework, the empirical identification of the TE depends on the identification of counterfactuals mimicking the outcome variable of a treated unit in the case it was not treated (and the other way round) (Perraillon *et al.*, 2022). But empirical identification and estimation of the TE within this conceptual framework requires an appropriate quasi-experimental design[32] and imposes its conditions.[33]

In particular, six specific sources of conflict between these conditions and the abovementioned forms of co-evolution deserve detailed discussion. Not only they may be all encountered in CAP assessment exercises; more importantly, they may occur simultaneously. Let's discuss them from the more general (and problematic) to the more technical (and manageable) ones.

6.1. Voluntary and universalistic treatments

As discussed at the beginning of this paper, and as shown repeatedly in the empirical analysis, CAP meas-

[32] Here we refer to "quasi-experimental design" with the same meaning given by Perraillon et all. (2022) to "research design" on observational units, that is, the overall strategy used to answer a research question with non-experimental data.

[33] In particular, three assumptions are critical: the first is the *Conditional Independence Assumption* (CIA, or Unconfoundedness) that postulates the independence between the potential outcomes and the treatment conditional on a set of pre-treatment (exogenous) variables, or confounders. The second assumption is the *overlap* (also known as balance, or positivity, or common support) *condition* that empirically implies that there must be at least one treated unit and one control unit at each possible value of all confounders. The third condition is the *Stable Unit Treatment Value Assumption* (SUTVA) that rules out any interference of an individual's treatment status on another individual's potential outcome. If these conditions are satisfied, observational data can be regarded as generated by a "natural experiment".

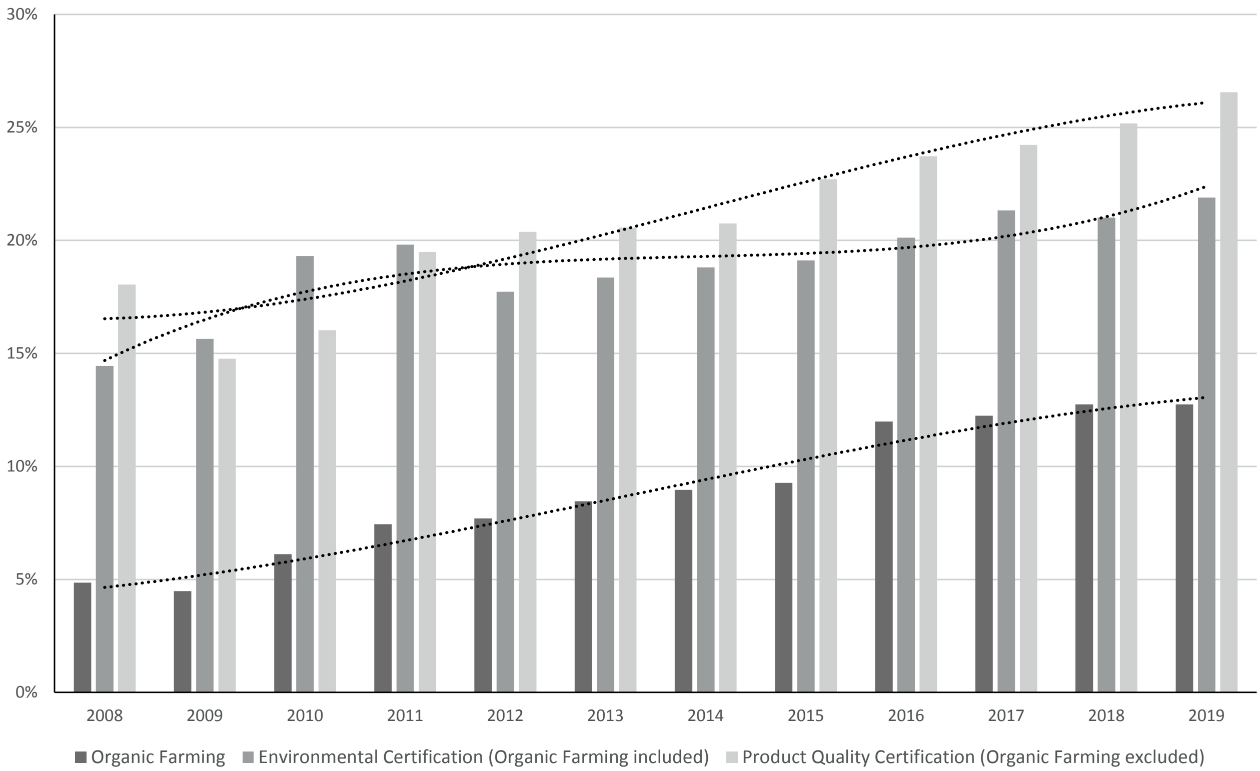

Figure 13. Evolution of the share of farms with certifications within the Italian 2008-2019 FADN balanced sample.

ures are tendentially universalistic and adoption is mostly voluntary. All or most farms can apply for these measures and, therefore, the treatment status can not be considered exogenous. This poses fundamental problems in finding suitable counterfactuals as they may not exist at all. Even when non-treated units are present and observable, they are so peculiar that can not be confronted with the treated ones: their peculiarity actually is the main reason for their exclusion (either voluntary or not) from the treatment. This makes the application of the TE logic to CAP assessment seriously questionable. Any possible way out of this problem relies more on a proper design of the quasi-experimental setting rather than on alternative or adapted TE estimation approaches. In practice, however, available datasets (like the FADN) might make these alternative settings unfeasible.

6.2. Outcome variable

The search of an appropriate quasi-experimental setting encounters another major issue. It has to do with the ambiguity about the outcome variable to be considered. The empirical analysis here performed clearly illustrate the point. On the one hand, for many CAP measures a policy target variable is simply neither explicit nor univocal. In such case, the present investigation had to identify, more or less arbitrarily, a suitable metric for the policy assessment. On the other hand, when measures are very clearly targeted (several II Pillar measures, for instance), the outcome variable is clear or univocal but it is just a tautology: the treatment adoption itself implies the outcome variable which automatically takes zero value for the non-treated units. As shown, this is the case, for instance, of certifications' adoption.

An outcome variable may not exist, may be unobservable, may be multiple or may be tautological. In any case, this poses a fundamental practical challenge for the consistent application of the TE logic to CAP assessment. Also in this case, the solution does not necessarily depend on some methodological adaptation or alternative to conventional TE estimation approaches. It rather requires a well suited quasi-experimental design based on a conceptualization of farmers' behaviour that eventually leads to the identification of the most appropriate outcome variable to be considered in the analysis.[34]

[34] For a theoretical and empirical investigation on how farmers select the policy and change their behaviour in order to take advantage of it within an utility-maximizing framework, see Esposti (2022).

6.3. Heterogeneity

Coexistence of the voluntaristic and universalistic nature of the CAP aims to cover very diverse farming conditions. As repeatedly emerged in sections 4 and 5, farms under investigation (treated or not) are characterized by vast heterogeneity. This has to do with their structural and geographical characteristics, but also with farmer's personal motivations. While the former features may be observed, the latter remain unobserved and can only be indirectly revealed by the observable farmer's behaviour (Esposti, 2022). Controlling for this heterogeneity requires many confounders, thus highly dimensional datasets that, in turn, imply remarkable computational complexity (the so-called *curse of dimensionality*). Literature in the field has proposed several solutions (Abadie, 2021) that have also widely adopted in CAP assessment (Esposti, 2017a,b).

But farm heterogeneity is challenging also for another more fundamental, and often disregarded, reason: the TE itself may be strongly heterogeneous. In such case, although the average TE (ATE) is correctly identified and consistently estimated, it simply remains uninformative. Under strong TE heterogeneity, estimating the group or the individual TE is needed for policy assessment and learning (Esposti, 2022). Recently proposed Machine Learning (ML) approaches seems interesting in this respect (Bertoni *et al.* 2021; Coderoni, Esposti and Varacca, 2021; Esposti, 2022). But they are also computationally demanding and complex making their outcome not always transparent and results not fully reliable (Knaus *et al.*, 2021). As a consequence, these approaches also requires a lot of additional validation work (Athey and Imbens, 2017).

6.4. Multivalued treatments

Most CI approaches have been designed and applied in a binary treatment context. But, as clearly shown, almost all CAP measures consist in interventions whose intensity varies across discrete or continuous range of possible values (i.e., they are *multivalued treatments*). A multivalued treatment can be still represented within an augmented PO framework but the empirical implications can be severe.

Imbens (2000) and Hirano and Imbens (2004) developed an extension of PO framework to continuous multivalued treatments and proposed an estimation approach based on the generalization of the Propensity Score Matching (PSM) of the binary case (Generalised Propensity Score, GPS, estimation) (Esposti, 2017a). However, it provides consistent estimates only whenever the treatment assignment can be considered exogenous once all confounders have been taken into account. The approach proposed by Cerulli (2015) admits this possibility of treatment endogeneity and the respective results are consistent even under this circumstance.

The application of both approaches, however, may encounter several practical problems for the computational complexity and, above all, for the likely violation of the overlap condition. Alternative non-parametric (or semi-parametric) estimation strategies can be helpful to overcome these issues, but they only apply to discrete (or categorical) multiple treatments (Cattaneo, 2010; Cattaneo *et al.*, 2013; Athey and Imbens, 2017; Esposti, 2017b). Therefore, they may require an arbitrary discretization of continuous treatments.

6.5. Multiple treatments

Almost all CI studies concentrate on single treatments. As shown, however, the main feature of the CAP and its co-evolution with the farmers' choices is that it delivers multiple treatments to farms. Identifying and consistently estimating the TE of any single treatment with the conventional approaches is possible only under the assumption of treatment independence. But the empirical evidence clarifies that this assumption is quite unrealistic as interdependence is likely to occur both in terms of treatment assignment and in terms of outcome variable. In particular, within the CAP both interdependencies may evidently occur between I and II Pillar measures. In this respect, it could be interesting to assess whether treatments reciprocally interfere by magnifying or offsetting the respective TE. At present, however, a viable empirical solution to this issue has not yet emerged (Frolich, 2004; Athey and Imbens, 2017).

6.6. Treatment timing

When panel data are available, as in the present case, units can be observed before and after the treatment. This allows TE identification and estimation via widely used approaches like the Difference-in-Differences (DID) estimation or the Two-Way Fixed Effects estimation (de Chaisemartin and D'Haultfœuille, 2020). However, though powerful, these approaches still require counterfactuals, with all the abovementioned complications, and imply an additional assumption (the so-called *parallel trend assumption*) that excludes that time behaves as an additional confounder.[35] But what really

[35] See Arkhangelsky *et al.* (2021), Chan and Kwok (2022), Cho *et al.* (2022), for recent developments in this field.

makes the timing of the treatment a challenging issue in CAP assessment is that it may differ (in fact, it usually differs) across the treated units. They enter the treatment in different moments of time (asynchronous policy adoption). This issue can become even more problematic in the agricultural context as the timing of the farms' response can be itself heterogenous across units depending on their structural characteristics: even under the same treatment timing, some farms can respond immediately others may take some years.

Recent generalizations of the DID approach tackle this issue under more than one pre- and post-treatment periods, but still a fixed treatment time (Cerulli, 2019), as well as under many post- and pre-intervention times and with the treatment itself that varies over time (Cerulli and Ventura, 2019; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

However, as shown in sections 4 and 5, CAP magnifies these issues and these methodological solutions may be insufficient or unfeasible. Even though, in principle, CAP reforms start at the same time for all farms (at least within a specific EU member state), their actual implementation can differ across space (for instance, regions) and farms may apply in different moments. Moreover, several measures are reiterated across successive CAP programming periods. Consequently, dealing with time-varying treatments is even more challenging because treatment itself may be reiterated on the same units in different periods of time, possibly melded with periods without the treatment.

7. SOME CONCLUDING REMARKS

Assessing the farm-level impact of CAP measures and reforms with a TE logic is potentially informative thus highly desirable. Unfortunately, it is also highly challenging. Major theoretical and methodological problems are more often overlooked that explicitly tackled. In this respect, a deeper and more critical discussion within the profession would be desirable. The present paper contributes to this discussion not by proposing an empirical application of methods based on this logic, but presenting an empirical evidence that poses doubts and conditions on their actual applicability.

Provided that the target of the policy to be investigated is clearly identified (in fact, it is often not clear at all) (Matthews, 2021), empirically assessing whether and to what extent this policy has been successful requires specific pre-conditions. Firstly, we need appropriate datasets. FADN surely is very helpful in this respect, but some of its limitations may reduce the application of these evaluation methodologies. Secondly, and more importantly, we need to investigate the co-evolution of the policy instruments and of the potentially treated units, that is, farmers' behaviour. Investigating co-evolution means finding enough support to the existence of a possible cause-effect relationships and to the feasibility of its investigation. In the meaning here given to the term, co-evolution implies that a correlation occurs but this does not necessarily imply causation as it may be the consequence of interdependence between the two processes making an unidirectional cause-effect relationship unidentifiable.

On the basis of the empirical investigation here presented and the observed co-evolution, we can conclude that the CAP has really moved in the right direction, that is, consistently with the declared objectives. And the farmers' changed their behaviour and performance, as well. At the same time, however, this does not mean that the policy induced the expected farmers' response. Achieving this conclusion within a TE logic requires conditions that are not always compatible with the CAP features. It does not follow that these approaches are and will be always inappropriate in this specific case. It rather implies that an acritical adoption of these approaches may not only lead to wrong policy conclusions but also procrastinates the search for more suited solutions. Moreover, it suggests that any consistent application of these approaches requires more attention on setting up appropriate quasi experimental design with the consequent appropriate datasets and theoretical representation of farmers' choices, and on suitable adaptations and refinements of these approaches.

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ANNEX

A1. Evolution of the AEM support

Figure A1 shows how AEM payments evolved in terms of number of beneficiaries and of average support per beneficiary. The growth of AEM support comes from the combination of two facts. On the one hand, the number of beneficiaries increased by 75% passing from 245 farms (15% of the whole balanced sample in 2008) to 428 units (27% in 2019). On the other hand, the average payment per farm increased almost with the same intensity (+70%) passing from about 5.3 thousand € in 2008 to 9.1 thousand € in 2019. In fact, the growth of the number of beneficiaries is not regular as it shows a fall from 2012 to 2015 and, then, a jump as a consequence of the transition from one regime to another. This sort of bureaucratic cycle is somehow compensated by the countermovement of the average payment per farm that reaches its peak exactly in 2015.

A2. The Lorentz curve of the farms' CAP support and income

To better illustrate the distributional characteristics of CAP support, and its evolution over time, within the sample, the Lorentz curves of the Pillar I and Pillar II support, respectively, are reported in Figure A2 for years 2008, 2015, 2019. The sharp concentration of the support on a very limited number of farms clearly emerges. As expected, it is higher in the case of II Pillar where 5% and 3% of farms (i.e., 79 and 48 farms) concentrate 50% of the support in 2019 and in 2008, respectively. But this over concentration is only a little lower for I Pillar with 8% and 6% (127 and 95 farms), respectively. Within the adopted field of investigation, the sequence of CAP reforms has slightly changed the distribution of the CAP support by making it a little bit more homogenous. But this change remains almost negligible.

Figure A3 presents the analogous Lorentz curves of the farm net income for selected years 2008, 2015 and 2019.[36] Two aspects are worth noticing. First, as expected, the distribution of net income within the sample is highly asymmetric with very few units concentrating most of the total (positive) net income. Second, no significant change in this distribution can be appreciated moving from 2008 to 2019. Eventually, in 2008 9% of farms concentrated 50% of the total (positive) net income; in 2019, this share has slightly increased to 11%.

[36] These curves are obtained considering only farms with a positive net income in the respective year.

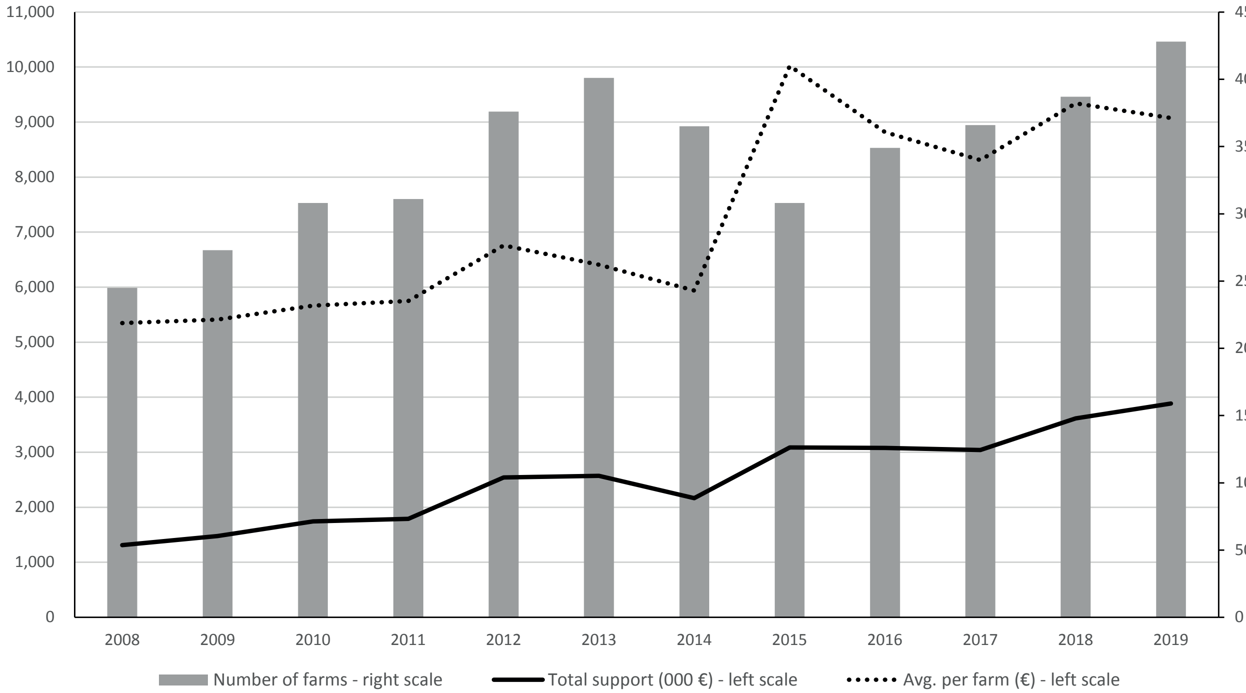


Figure A1. Evolution of the Agro-Environmental Measures (AEM) support within the Italian 2008-2019 FADN balanced sample: number of beneficiaries, total support and average support per beneficiary.

A3. Factors' intensification

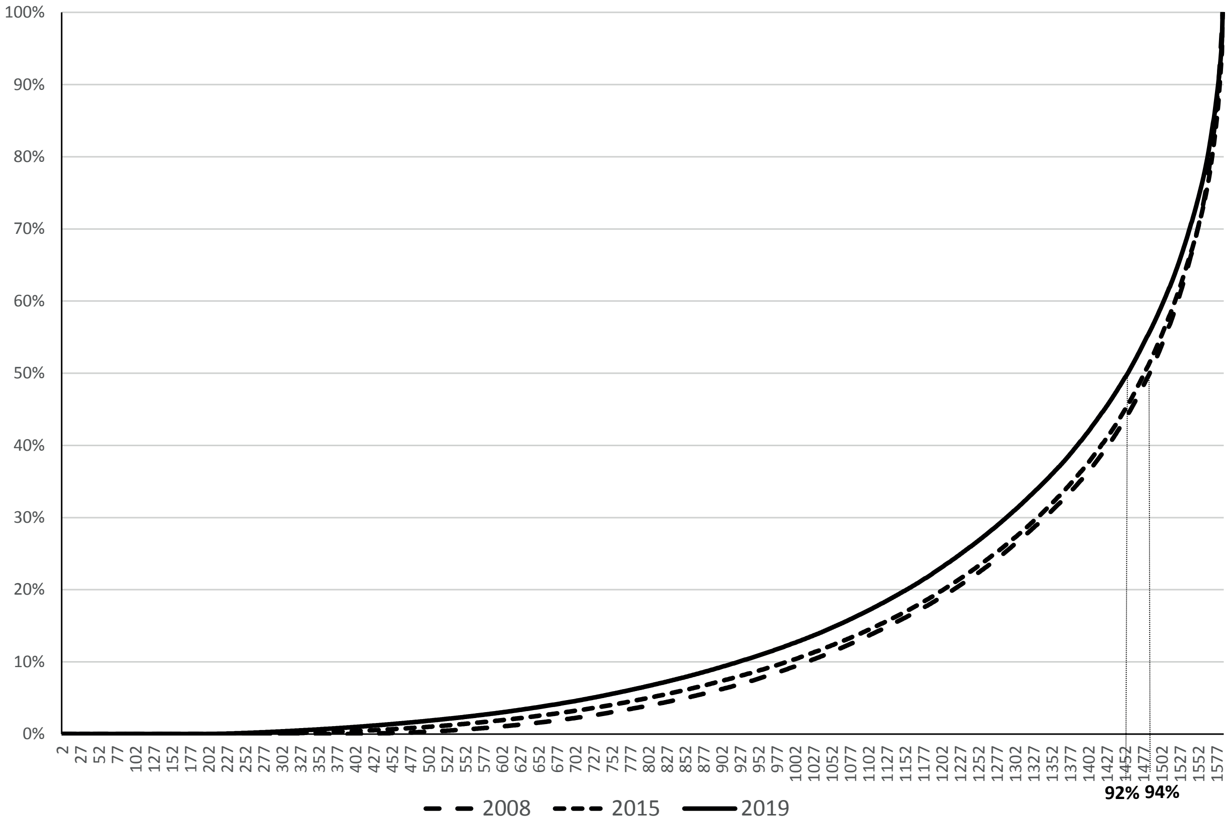
To better investigate the nature of factors' intensification, Table A2 reports the distributional characteristics of the factor intensities per labour unit (AWU) together with labour profitability. It firstly emerges that these structural characteristics remain quite stable over time as could be expected considering that adjustments in (quasi)fixed factors' endowment take time and may have a cost (Esposti, 2017a). It emerges a small reduction in the incidence of family labour on the total farm's labour use (-3.2%). Also the land endowment per unit of labour slightly declines (-4.8%). But for the other production factors, it emerges a gradual intensification with a 11% increase of machinery endowment, a 8% increase of the livestock endowment and, above all, a 18% increase of environment-using costs per unit of labour.

Although these ratios should get rid of the size effect, with the only exception of the FAWU/AWU ratio, they show a remarkable heterogeneity. Also for these structural characteristics and their evolution, a major dispersion (as expressed by CV) and asymmetry (as expressed by the median/mean ratio) emerges within the field of investigation. For instance, in the case of land endowment, we range from no-land farms to observations with hundreds of hectares per unit of labour. The bottom line of this large heterogeneity is expressed by the net income per unit of labour reported in the final rows of Table A2. Here we also find negative values and this makes the dispersion even more evident. Values range from a minimum of -345 thousand € per unit of labour in 2008 to a maximum 2372 thousand € per unit of labour in 2009. Only a little decline of dispersion of asymmetry is observed in the post 2015 period. More importantly, the mean value significantly declines over the 2008-2019 period (-13% in nominal terms; -22% in real terms) and this reveals a significant redistribution in favour of the more profitable farms: while 1st and 2nd quartiles decline by 15% and 20% respectively, the 3rd quartile declines by only 6% and the maximum value increases by 8%.

A4. TF switches

In order to only focus on real changes in production orientation, we limit our attention to those switches that make the initial TF of farm differ from the final one. These switches concern 187 farms (12% of the sample). These movements are positioned in a Source-Destination matrix by TF category (Table A3).[37] As could be

[37] Therefore, the diagonal elements indicate the non-switching units.

a)


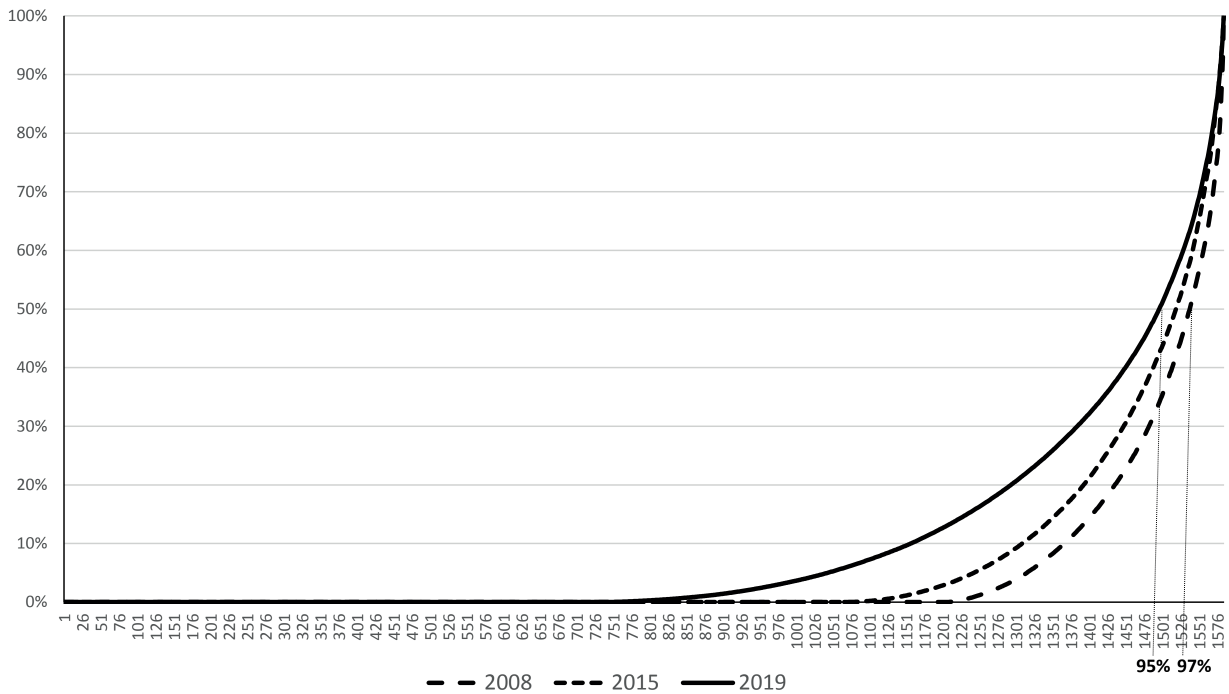
b)


Figure A2 – Lorentz curves of the Pillar I (a) and Pillar II (b) support within the Italian 2008-2019 FADN balanced sample: years 2008, 2015, 2019.

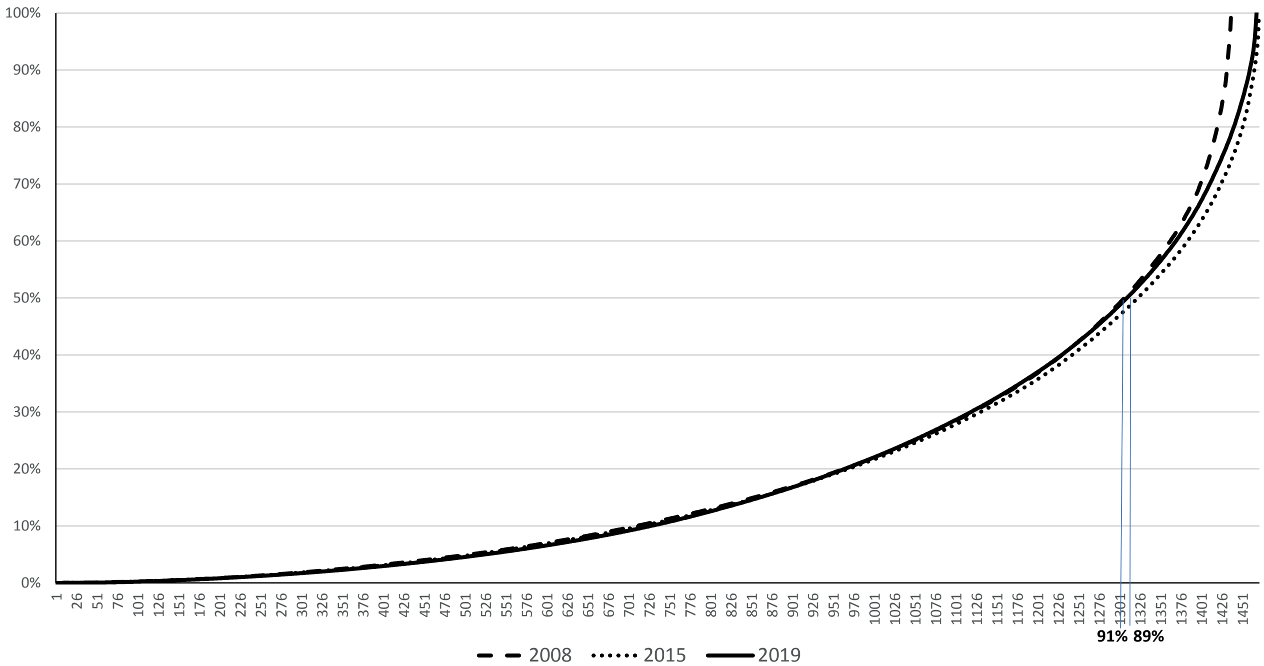


Figure A3. Lorentz curve of the (positive) farm net income within the Italian 2008-2019 FADN balanced sample: years 2008, 2015, 2019.

expected, flows mostly concern two kind of movements: one occur across the main TFs, (TF1, TF3 and TF4); the other concerns movements from more specialized TFs to the mixed ones (TF6, TF7 and TF8). Nonetheless, no prevalent migration emerges and this confirms that, over the period of observation, there is no prevalent evolutionary dynamic expressing a generalised reorientation of the farmers' production choices.

Table A1. Representativeness of the balanced FADN sample. Comparison of the Italian 2008-2019 FADN balanced panel (year 2010) with the Italian 2010 agricultural Census: distribution by Types of Farming (TF) and Economic Size (ES) classes (SO=Standard Output).

	FADN balanced sample	2010 Census (Total)	2010 Census (SO>8000 €)
TF classes:			
TF 1	23%	24%	23%
TF 2	8%	2%	6%
TF 3	30%	55%	43%
TF 4	25%	8%	16%
TF 5	3%	1%	1%
TF 6	6%	7%	7%
TF 7	1%	0%	1%
TF 8	4%	2%	4%
Not Classified	0%	1%	0%
Total	100%	100%	100%
ES classes:			
Small (SO <25,000 €)	30%	18%	49%
Medium-Small (SO=25,000-50,000 €)	19%	8%	21%
Medium (SO=50,000-100,000 €)	22%	5%	15%
Medium-Large (SO=100,000-250,000 €)	20%	4%	10%
Large (SO>250,000 €)	9%	2%	5%
Total	100%	37%	100%

Legend: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.
Source: FADN and ISTAT.

Table A2.Factor use and profitability per labour unit within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Family AWU/AWU												
Mean	0.71	0.68	0.73	0.71	0.70	0.70	0.70	0.69	0.73	0.71	0.72	0.69
Standard deviation	0.31	0.31	0.29	0.30	0.30	0.29	0.29	0.30	0.30	0.30	0.29	0.31
Coefficient of Variation	0.43	0.46	0.39	0.42	0.43	0.42	0.42	0.43	0.41	0.43	0.40	0.45
Min	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
1st Quartile	0.43	0.40	0.48	0.46	0.44	0.46	0.45	0.43	0.49	0.44	0.48	0.41
2nd Quartile (Median)	0.80	0.72	0.79	0.80	0.76	0.73	0.74	0.74	0.85	0.79	0.81	0.73
3rd Quartile	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
UAA/AWU (ha)												
Mean	18.5	18.5	17.8	17.4	17.4	17.3	17.5	18.3	17.7	17.8	18.1	17.6
Standard deviation	26.6	25.6	24.3	23.7	24.4	23.9	24.4	31.5	22.9	22.9	23.2	21.9
Coefficient of Variation	1.44	1.39	1.36	1.36	1.40	1.38	1.39	1.72	1.29	1.28	1.28	1.24
Min	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.1
1st Quartile	3.8	3.9	3.9	4.0	3.9	3.9	3.9	4.0	4.0	4.1	4.0	4.0
2nd Quartile (Median)	9.5	9.6	9.6	9.4	9.4	9.2	9.2	9.6	9.7	9.3	9.6	9.7
3rd Quartile	23.0	22.9	22.3	22.4	21.8	21.7	21.6	21.6	22.3	22.2	22.1	21.9
Max	486.4	387.3	387.3	421.8	421.8	421.8	387.3	803.6	274.5	200.5	192.4	179.1

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
KW/AWU (hp)												
Mean	113.1	112.4	112.2	112.7	114.0	114.0	116.4	124.0	120.3	123.0	123.7	125.7
Standard deviation	117.1	104.8	110.3	100.7	98.2	98.1	100.3	241.8	109.4	115.8	117.3	121.4
Coefficient of Variation	1.03	0.93	0.98	0.89	0.86	0.86	0.86	1.95	0.91	0.94	0.95	0.97
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1st Quartile	45.3	47.7	50.0	50.2	51.8	50.9	51.5	51.8	52.2	51.2	53.0	53.6
2nd Quartile (Median)	80.8	82.9	82.1	82.8	86.1	87.3	88.0	90.0	92.4	90.3	91.2	90.6
3rd Quartile	137.8	143.6	143.5	145.9	143.7	144.3	148.1	148.2	151.9	155.6	155.4	155.5
Max	1,341	1,010	2,010	812	798	926	846	8,560	1,488	1,123	1,488	1,488
LSU/AWU												
Mean	12.3	12.4	14.2	14.3	13.7	15.1	14.4	14.5	15.8	14.8	13.6	13.2
Standard deviation	36.4	41.3	44.5	57.8	40.7	55.1	46.8	56.3	62.4	56.2	43.6	46.9
Coefficient of Variation	2.97	3.32	3.13	4.03	2.98	3.65	3.25	3.87	3.95	3.81	3.21	3.54
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1st Quartile	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2nd Quartile (Median)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3rd Quartile	11.1	11.9	13.0	12.7	12.5	12.3	13.0	12.0	11.5	10.6	10.1	9.4
Max	528	1,032	992	1,782	580	881	860	1,042	1,125	1,291	604	723
Environment-using Costs/AWU (€)												
Mean	5,498	5,432	5,501	5,920	6,197	6,033	6,223	6,908	6,419	6,602	6,398	6,488
Standard deviation	8,373	7,237	8,036	7,993	8,199	7,813	8,101	19,089	9,226	11,042	9,776	9,830
Coefficient of Variation	1.52	1.33	1.46	1.35	1.32	1.30	1.30	2.76	1.44	1.67	1.53	1.52
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	1,452	1,444	1,543	1,737	1,856	1,827	1,938	1,873	1,669	1,688	1,670	1,705
2nd Quartile (Median)	3,068	3,184	3,199	3,484	3,598	3,634	3,743	3,678	3,602	3,608	3,691	3,764
3rd Quartile	5,940	6,072	5,957	6,428	6,838	6,635	6,914	6,960	7,002	6,927	7,031	7,018
Max	102,031	64,425	84,848	75,441	92,735	73,174	82,336	671,360	119,471	189,599	154,697	132,348
Net Income/Family AWU (€)												
Mean	44,928	50,549	43,592	45,238	45,209	45,561	43,007	45,313	43,174	45,413	45,861	45,113
Standard deviation	103,713	141,432	107,183	124,906	102,187	115,314	126,977	104,157	107,065	95,329	99,178	97,087
Coefficient of Variation	2.31	2.80	2.46	2.76	2.26	2.53	2.95	2.30	2.48	2.10	2.16	2.15
Min	-456,321	-166,321	-82,087	-80,300	-64,492	-181,104	-182,261	-162,664	-170,206	-229,603	-69,855	-208,142
1st Quartile	5,919	4,881	6,080	6,016	7,051	6,647	5,871	7,063	6,116	7,134	6,955	5,817
2nd Quartile (Median)	18,756	16,773	18,025	17,781	19,567	18,784	16,593	19,057	17,168	18,894	19,262	17,367
3rd Quartile	45,051	45,133	43,189	43,864	45,927	46,124	43,316	46,335	46,287	49,011	48,762	48,544
Max	1,454,834	3,459,005	1,944,858	2,197,699	1,246,851	2,693,079	3,166,903	2,041,645	1,986,362	1,609,615	2,085,363	1,821,656
Net Income/AWU (€)												
Mean	33,991	34,658	33,194	33,845	31,891	31,971	29,003	29,232	31,445	30,749	32,729	29,628
Standard deviation	78,467	96,969	81,619	93,450	72,083	80,916	85,630	67,193	77,978	64,547	70,778	63,762
Coefficient of Variation	2.31	2.80	2.46	2.76	2.26	2.53	2.95	2.30	2.48	2.10	2.16	2.15
Min	-345,243	-114,033	-62,508	-60,077	-45,493	-127,082	-122,912	-104,936	-123,965	-155,465	-49,852	-136,698
1st Quartile	4,479	3,346	4,630	4,501	4,974	4,664	3,959	4,556	4,455	4,831	4,963	3,820
2nd Quartile (Median)	14,190	11,500	13,726	13,303	13,803	13,181	11,190	12,294	12,503	12,793	13,746	11,406
3rd Quartile	34,085	30,944	32,888	32,817	32,397	32,365	29,211	29,891	33,712	33,185	34,799	31,881
Max	1,100,695	2,371,566	1,480,981	1,644,227	879,534	1,889,753	2,135,670	1,317,088	1,446,709	1,089,877	1,488,212	1,196,382

Table A3. Source-Destination matrix for TF category within the Italian 2008-2019 FADN balanced sample (in grey >10 elements).

Destination	Source								
	TF 1	TF 2	TF 3	TF 4	TF 5	TF 6	TF 7	TF 8	Total
TF 1	294	10	20	35	6	57	3	36	460
TF 2	10	96	22	0	0	14	0	0	142
TF 3	20	10	375	4	2	47	2	12	471
TF 4	33	0	5	272	2	6	17	46	382
TF 5	5	0	3	2	28	2	3	5	48
TF 6	55	6	58	5	3	9	0	5	141
TF 7	2	0	2	13	4	0	0	0	22
TF 8	35	0	15	36	7	6	2	5	105
Total	455	122	501	366	52	141	26	110	1772

Legend: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

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Price dependence of biofuels and agricultural products on selected examples

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Abstract. The growing demand for raw materials for the production of biofuels may lead to an increase in the prices of these raw materials and, due to the shortage of land, to an increase in the prices of other crops. This is due to the fact that the growing demand for raw materials for the production of methyl esters and bioethanol (the most widely used biofuels), such as rape and corn, is a form of competition on the food and feed markets. It should be mentioned that although the topic is not new, it is still very relevant, taking into account the expansion of energy crops, as well as national, European and world energy policy. Especially due to the fact that, as has already been mentioned, the use of plant products for the production of biofuels has an impact on the regulations of the food market.This study is to analyze the volatility and dependence of ethanol, biodiesel, maize and rapeseed prices in the period of 2016-2019 and aims at assessing the correlation between the agricultural and biofuel markets. In this paper, the investigation regarding co-integration of biofuel and agricultural commodity prices has utilized ethanol and commodity prices with the use of the vector error correction model (VECM). Price dependencies between the prices of biodiesel, rapeseed, maize and ethanol were found, indicating the existence of long-term causality in at least one direction between the analyzed prices. The results indicated that biodiesel prices during the period in question were influenced by the previous week's prices of biofuel and rapeseed. Moreover, biodiesel prices had an impact on the level of ethanol and rapeseed prices. In the case of rapeseed, the correlation between its prices and those of corn is also noticeable, while prices of corn may also affect prices of ethanol.

Keywords: Biofuels, Agricultural market, Biofuel market.
Jel Codes: Q16, Q4.

1. INTRODUCTION

To deal with the unprecedented pace of climate change caused by the accumulation of greenhouse gases in the atmosphere, there is a clear need to shift from an energy dependency on fossil fuels to renewable energy. Now, with environmental policy pushing to reduce greenhouse gas emissions, aided by recent advances in crop engineering and fermentation processes, the production of bioethanol and biodiesel has once again become viable and sustainable substitutes for petroleum-based fuels. Production of biofuels showed a growing tendency in the 1990s when the assumptions of the Common Agricultural Policy (CAP) indirectly supported the production of biofuels through guaranteed minimum prices, subsidies per hectare of production and compensation payments for set-aside land that, however, could be used to produce raw materials for biofuel production. Moreover, the 2003 CAP reform introduced a cultivation premium for production of energy crops on primary land (Lamers *et al*., 2011). It should be noted that in the case of the production of pollutants, more than a quarter of the total CO2 emissions are generated by the transport sector (Adams *et al*., 2020). To mitigate the effects of global warming caused by the accumulation of greenhouse gases from climate change, it is imperative to reduce CO2 emissions from fuel combustion in car engines and to switch to alternative and cleaner fuels. It should be noted that the development of road transport in the world has led to a rapid increase in the demand for fuels, especially those derived from crude oil. Increased greenhouse gas emissions are due to the burning of fossil fuels and to changes in land use caused by human activities. Therefore, alternative solutions are sought, especially biofuels that could actually compete with conventional energy sources (Kurowska *et al*., 2020, Klikocka *et al*., 2019). It should be emphasized that the known oil resources are limited resources. Various studies set the date of the world peak in oil production in 1996-2035. That is why it is so important to pay attention to biomass-based energy technologies, which use waste or plant matter to produce energy with lower GHG emissions than fossil fuel sources (Sheehan, 1988). Thus, biofuels entered the market as an option to reduce dependence on crude oil and as a way to pursue social, economic and environmental sustainability (Chavez *et al*., 2010, Kurowska *et al*., 2020). As noted by Janda *et al.* (2012), increased interest in the application of biofuels as an alternative to liquid fossil fuels was observed after the oil crisis that occurred on world markets in the 1970s. In addition, the use of biofuels (compared to fossil fuels) contributes to the mitigation of greenhouse gas emissions (Hallam *et al*., 2006). Moving on to the meaning of biofuels, it should be clarified that the term biofuel refers to liquid and gaseous fuels (bioethanol, biodiesel, biogas) and solids produced mainly from biomass (Demirbas, 2008). Biofuel is a non-polluting, locally available, sustainable and reliable fuel obtained from renewable sources (Vasudevan *et al*., 2005). Liquid biofuels are primarily used to power vehicles, but they can also power engines or fuel cells to generate electricity (Demirbas, 2007). Bioethanol and biodiesel are the two most popular biofuels used as substitutes for regular gasoline and diesel fuel (Clerici and Alimonti, 2015).

As already mentioned the global demand for biofuels such as ethanol and biodiesel is increasing mainly for environmental reasons (Goswamia and Choudhuryb, 2019; Ajanovic, 2011). This is in line with the expansion of this market and the rapid increase in their production worldwide (Banse *et al*., 2008). Biofuels are perceived as an essential element in the development of fuel markets (Ryan *et al*., 2006). In the transport sector, ethanol constitutes the most widely consumed liquid biofuel in the world (McPhail, 2011). It should be noted that the demand for biofuels is driven mainly by the transport sector (Fundira and Henley 2017). Brunschwig *et al.* (2012) as well as Balat (2011) indicated that biodiesel is an attractive alternative to diesel fuel. Sivakumar *et al.* 2010 noted that with population growth, industrial development, and fossil fuel transportation costs soaring, it seems reasonable that countries seek for solutions independent from non-renewable fuels for climatic and economic reasons (Reboredo *et al*., 2016), thus drawing the attention of many stakeholders related to this issue, i.e. decision makers, representatives of the industry, and the scientific community (Timilsina *et al*., 2011).

At the same time, the development of the biofuel market translates into a growing demand for the most important agricultural production factors (van Eijck *et al*., 2014). However, it should be taken into consideration that biofuels compete for renewable and non-renewable resources, and therefore may affect their sustainable growth and the market for agricultural products. Increased cultivation of biofuel crops will affect land utilization (Searchinger, 2007) which will have an impact on global natural resources and environmental sustainability (Zhang *et al*., 2009, Hausman *et al*., 2012), i.e. by generating indirect effects from their exploitation (van Noorden, 2013). Moreover, extending the cultivation area of biofuels with a simultaneous increase in population may lead to higher prices of agricultural raw materials on international markets. Thus, production of biofuels can pose challenges in terms of sustainable food production (Naylor *et al*., 2007). Moreover, in the case of biofuels, a crowding-out effect may appear (Vacha, 2013), redirecting food production to production of biofuel (Baffes, 2013). It should be emphasized that if part of the soil resources is occupied by the fields of energy crops, the potential for food production is weakened, which may result in an increase in food prices. Competition between energy crops and food crops has consequences such as rapidly rising food prices and a food deficit on a global scale (Gomiero, 2010, OECD-FAO). The problem of competition between bioenergy crops and plants intended for consumption, resulting from land use, was also noted by Vasile *et al.* (2016) and Cai *et al.* (2010), Tomei and Heliwell (2016). Therefore, the indirect effects of biofuel production have become the subject of research and discussion among economists, environmentalists, NGOs, and international organizations that call for an additional analysis of the outcomes related to biofuels (Bentivoglio and Rasetti, 2015; Oláh, 2017). It has been observed that the growing demand for raw materials for the production of methyl esters and bioethanol (the most widely used biofuels), such as rapeseed or corn, is a form of competition in the food and feed markets (Koizumi, 2015). It should also be noted that the activities related to the production of biofuels also have indirect negative effects of land use, such as the conversion of food crops into fuel (Humalisto, 2015). This phenomenon is known as indirect land use change, which, in combination with the conversion of carbon-rich lands, can lead to significant greenhouse gas emissions, which counteracts the previously indicated positive environmental importance of biofuels (Britz and Hertel, 2011, EC. Directive (EU) 2015 / 1513, Santeramo and Searle 2019, Kupczyk 2020). As the research by Searchinger *et al.* (2008), emissions of greenhouse gases from corn ethanol in selected locations may even double compared to the continued use of petroleum products. Then, the impact of the biofuel program on greenhouse gas emissions may be unfavorable (Britz and Hertel, 2011). In consequence, it raises doubts as to whether biofuels are a friendlier alternative to petrol (Chakravorty *et al*., 2017).

The issue of dependence between the agricultural market and the biofuel market plays a significant role, *inter alia*, due to the expansion of biofuels into global agricultural commodity markets (Drabik *et al*., 2016,Banase *et al*., 2008). The research conducted so far by, among others, Wright (2011), 2011 de Gorter and Drabik (2015) indicate a sharp increase in biofuel production as well as a strong and direct relationship between prices of energy and agricultural commodit.). The growing demand for raw materials for the production of biofuels may lead to an increase in the prices of these raw materials, and due to the shortage of land, to an increase in the prices of other crops (Searchinger, 2008). The price interdependencies between the food and biofuel market have therefore become an ongoing subject of discussion among energy, environmental and agricultural economists interested in the sustainability of biofuels (Kristoufek, 2012, Oladosu and Msangi, 2013, Kurowska *et al.* 2020). Drabik and *et al.* (2016) also notes that the global agriculture and energy sectors have become more interdependent due to the surge in biofuel production over the past two decades. At the same time, both sectors exhibit high price volatility. In contrast, the transmission of global price shocks to domestic markets, from agricultural commodities to food prices, might have a significant impact on income distribution and welfare for farmers and consumers. As a result, the issue of price transmission between agricultural markets and biofuel markets becomes relevant from the perspective of political economy.

This article analyzes the price relations between the biofuel market and the market of agricultural products. The price transmission between the prices of rapeseed, biodiesel, maize and ethanol was assessed.

The goal was to obtain answers to the following research questions:

1. How were the prices of biodiesel, ethanol, corn and turnip in the analyzed period ?
2. Is there a relationship between the prices of biodiesel, bioethanol, corn and turnip in the analyzed period ?
3. What is the relationship between the prices of biodiesel, bioethanol, corn and turnip in the analyzed period?

It should be mentioned that although the topic is not new, it is still very relevant, taking into account the expansion of energy crops, as well as national, European and world energy policy. Especially due to the fact that, as already mentioned, the use of plant products for the production of biofuels affects the condition of the food market.

2. METHODS AND DATA

The data set includes weekly wholesale prices of ethanol, biodiesel, rapeseed and maize, from the first week of 2016 to the last week of 2019, from global markets, i.e. the stock exchange: The Paris Stock Exchange oraz New York Mercantile Exchange Prices have been averaged and given in EUR. In order to standardize the currency, the average EUR rate in a given trading week was used. A period of no significant disturbances resulting from the COVID-19 pandemic was selected. The mutual integration of all prices was analyzed.

Prior to estimation of model parameters, it is necessary to determine the stationarity of the analyzed time series. For the purpose of this study, the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test was applied (Maddala, 2009; Welfe 2009). The direction of cointegrating relations between the analyzed prices was established based on the vector model of the VECM error correction, which determines the short-term dynamics of each price within long-term relations.

According to the Granger representation theorem, the equation of the VECM error correction model assumed the following form (Gujarati and Porter, 2009; Johansen and Joselius, 1990):

$$\Delta x_t = \Psi_0 D_t + \Pi x_{t-1} + \sum_{i=1}^{k-1} \Pi_i \Delta x_{t-1} + \varepsilon_t \quad (1)$$

where:

$$\Pi = \sum_{i=1}^{k} A_i - I \quad (2)$$

$$\Pi_i = \sum_{j=i+1}^{k} A_j \quad (3)$$

$X_t = [x_{t1} \ldots x_{tk}]^T$ – vector of observations on the current values of all explanatory variables,

D_t – vector of exogenous equation components such as intercept, time change, non-stochastic regression, delayed values of exogenous variables,
A_0 – matrix of parameters with vector variables Dt. (does not contain zero elements),
A_i – matrix of parameters with delayed *xt* vector variables (does not contain zero elements),
k – model row, specifying the maximum length of the delay,
$\varepsilon_t = [e1_t \ldots e_{kt}]^T$ – vectors of stationary random disturbances (residual vectors of the model equations).

In order to assess the response of individual variables to a change in the price level of another component, the Impulse Response Function (IRF) was applied, as presented below (Baillie, Kapetanios, 2013).

$$X_t = \sum_{i=1}^{\infty} \Phi_i \xi_{t-1} \quad (4)$$

where:
B – matrix of parameters standing at non-lagged vector values X_t,
Φ_i – response of the distinguished vector variable Xt to an impulse from another variable.

The choice of the order of variables in the model depends on the AIC information criterion. The length of the model lag has been 1.

The Granger causality test was used to analyse relations between the studied variables. Testing cau-sality in the Granger sense is based on the following system of equations:

$$Y_t = \beta_0 + \sum_{j=1}^{m} \beta_j Y_{t-j} + \sum_{k=l}^{n} \beta_k X_{t-k} + u_t \quad (5)$$

$$X_t = \beta_0 + \sum_{j=1}^{m} \beta_j X_{t-j} + \sum_{k=l}^{n} \beta_k Y_{t-k} + u_t \quad (6)$$

where:
Y_t – values of the variable Y;
X_t – values of the variable X;
β – structural parameters of the model;
u_t– random component of the model (Granger, 1969).

The null hypothesis in the Granger Causality test assumes that all βk coefficients are equal to zero, which means that there is no causality, while the alternative hypothesis assumes the occurrence of causality in the Granger sense.

3. RESULTS

In 2021, the global production of biofuels reached the level of 1,747 thousand. barrels of oil equivalent per day, compared to 187 thousand barrels of oil equivalent per day, produced in 2000. Production of biofuels, given the belief that it can provide energy security and reduce greenhouse gas emissions in the relevant sectors. The global biofuel market is expected to reach over $ 200 billion by 2030 (statista.com, 2022).

As noted, price developments in the four markets in question appear to be correlated. The evolution of rapeseed, maize, biodiesel, ethanol prices and their volatility in years 2016-2019 is depicted in Figure 2. In the analyzed time period, a gradual decline in biodiesel prices was observed. This situation stabilized in the first quarter of 2016. A similar situation occurred in the case of ethanol prices. Throughout years 2016-2019, there were significant fluctuations in the prices of ethanol and biodiesel. In the case of rapeseed and maize, the differences were milder.

Studying the interdependencies of time series requires an examination of their stationarity. The level of integration of the analyzed time series was tested using the KPSS test. The calculated value of the test statistics presented in Table 1 with the included lags at significance level α = 0.01 indicates rejection of the null hypothesis which suggests the stationarity of the tested

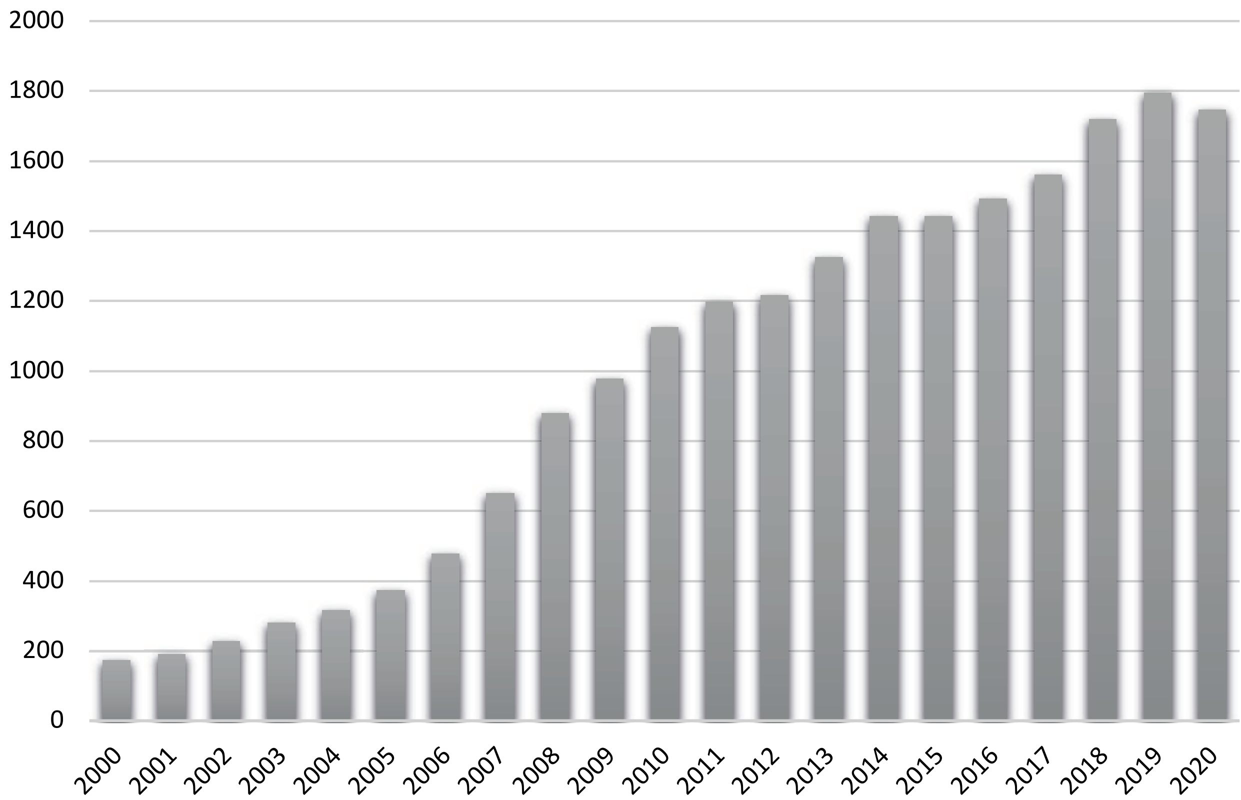

Figure 1. Biofuel production worldwide from 2000 to 2021(in 1,000 barrels of oil equivalent per day). Source: Own elaboration based on statista.com.

time series, proving the non-stationarity of the analyzed prices.

The performed test using the Johansen method shows that at the significance level equal to 0.05, the null hypothesis of no cointegrating relation should be rejected. The test results included in Table 2 indicate the existence of three dependence relations between the examined prices.

The existence of relationships between prices proves the existence of long-term causality in at least one direction between the analyzed prices. However, it does not indicate the direction of causality in price developments. This causality can be determined using the vector model of the VECM error correction (Table 3). The results of the model estimation for the analyzed prices suggested the existence of numerous relationships between the analyzed prices (statistically significant relationships between the price levels have been marked in grey). Namely, the price level of biodiesel in the said period was influenced by prices of this biofuel from the previous week and prices of rapeseed. At the same time, biodiesel prices influenced the price level of ethanol and rapeseed. In the case of rapeseed, the estimation of the

Table 1. Results of stationarity tests with regard to the analyzed time series.

	Biodiesel	Ethanol	Maize	Rapeseed
KPSS test statistics / Critical value	1.724***	1.581***	0.852***	0.965***
p-value = 0,01	0.587	0.587	0.587	0.587
p-value = 0,05	0.399	0.399	0.399	0.399
p-value = 0,1	0.311	0.311	0.311	0.311

Source: Own calculations and analysis with the use of EViews software.

Table 2. Occurrence of correlations between the analyzed time series - Johansen's test.

The number of cointegrating vectors	Test trace	Critical value p=0,05
0*	66.05	47.99
1*	36.61	28.99
2*	14.99	13.11
3	3.44	4.74

Source: Own calculations and analysis with the use of EViews software.

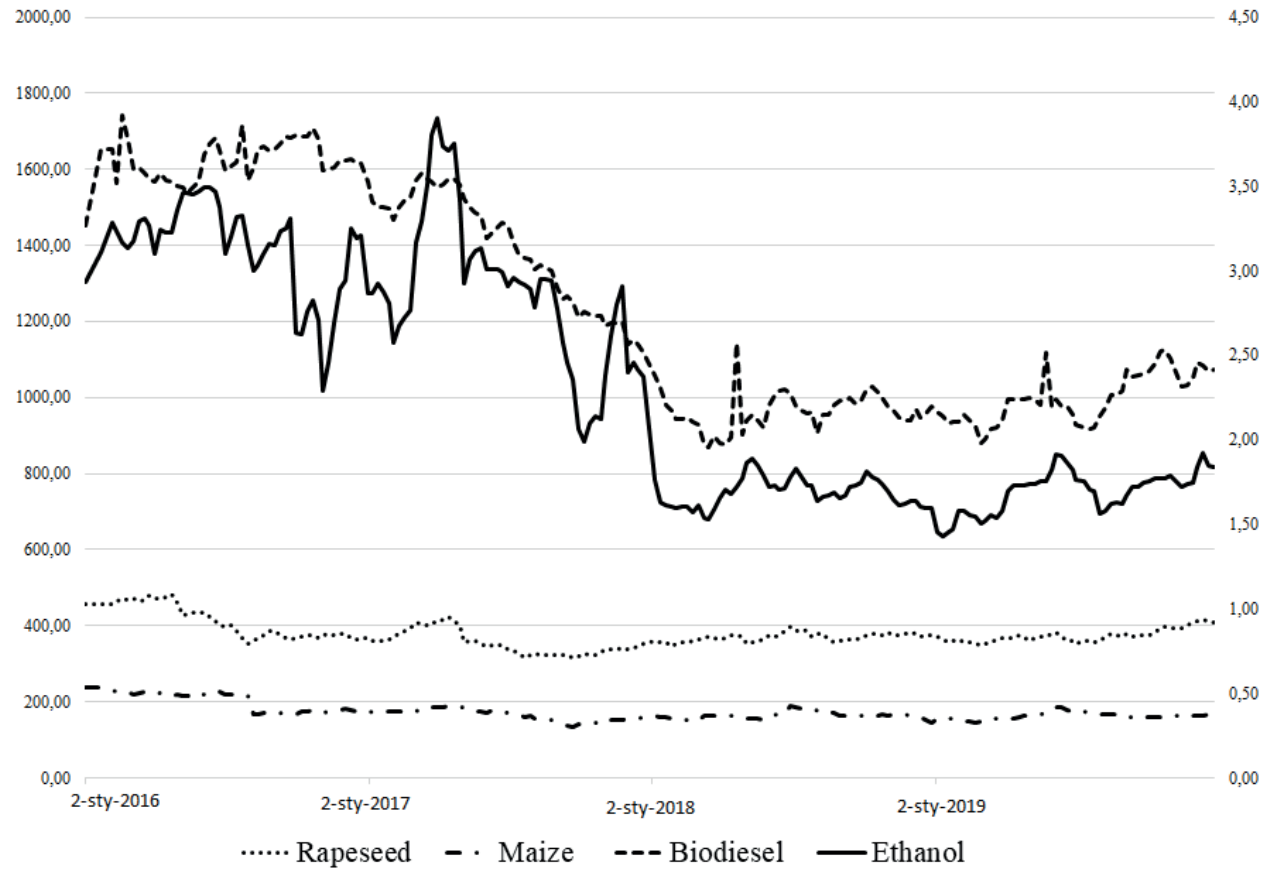

Figure 2. Price level of rapeseed, maize, biodiesel and ethanol prices in the analyzed period in nominal terms (in EUR). Source: Own calculations and analysis with the use of EViews software.

Table 3. The results of the VECM model parameters estimation.

	Biodiesel	Rapeseed	Ethanol	Maize
CointEq1	-32.05	24.25	-0.31	-13.14
	27.24	8.15	0.21	5.88
	[-1.24]	[2.31]	[-2.19]	[-2.74]
Δ_biodiesel	0.41	0.07	0.01	0.01
	0.09	0.04	0.01	0.02
	[2.74]	[2.11]	[1.11]	[0.40]
Δ_rapeseed	0.73	0.31	0.01	0.11
	0.62	0.06	0.01	0.05
	[2.13]	[3.88]	[0.99]	[2.87]
Δ_ethanol	-24.75	-0.20	0.17	-6.412
	18.11	6.01	0.07	3.31
	[-1.74]	[-0.02]	[-1.51]	[-1.74]
Δ_maize	-0.24	-0.27	0.01	-0.07
	0.42	0.14	0.001	0.08
	[-0.81]	[-1.81]	[1.64]	[-1.07]

Source: Own calculations and analysis with the use of EViews software.
Δ – price of given product from previous period.

VECM model showed a connection with maize prices. Nonetheless, it should be noted that maize prices may also cause changes in ethanol prices. In this case, the obtained results indicate the existence of a two-way relationship.

The impulse response function determined on the basis of the estimation of VECM parameters illustrated the occurrence of reactions between individual variables, as depicted in Table 3 (Figure 2). The IRF functions were determined by the results of the VECM model parameter estimation for the levels. The course of the IRF function confirms the interaction of prices, for which the VECM model estimation indicated the presence of interdependencies in their formation.

Based on the analysis of the course of the IRF function, the reaction to the impulse appears up to 2 weeks after its occurrence while individual functions expire within 3-4 weeks, rebalancing the system.

The Granger causality test was used to determine which prices are interdependent in terms of price formation. The test results are presented in Table 4.

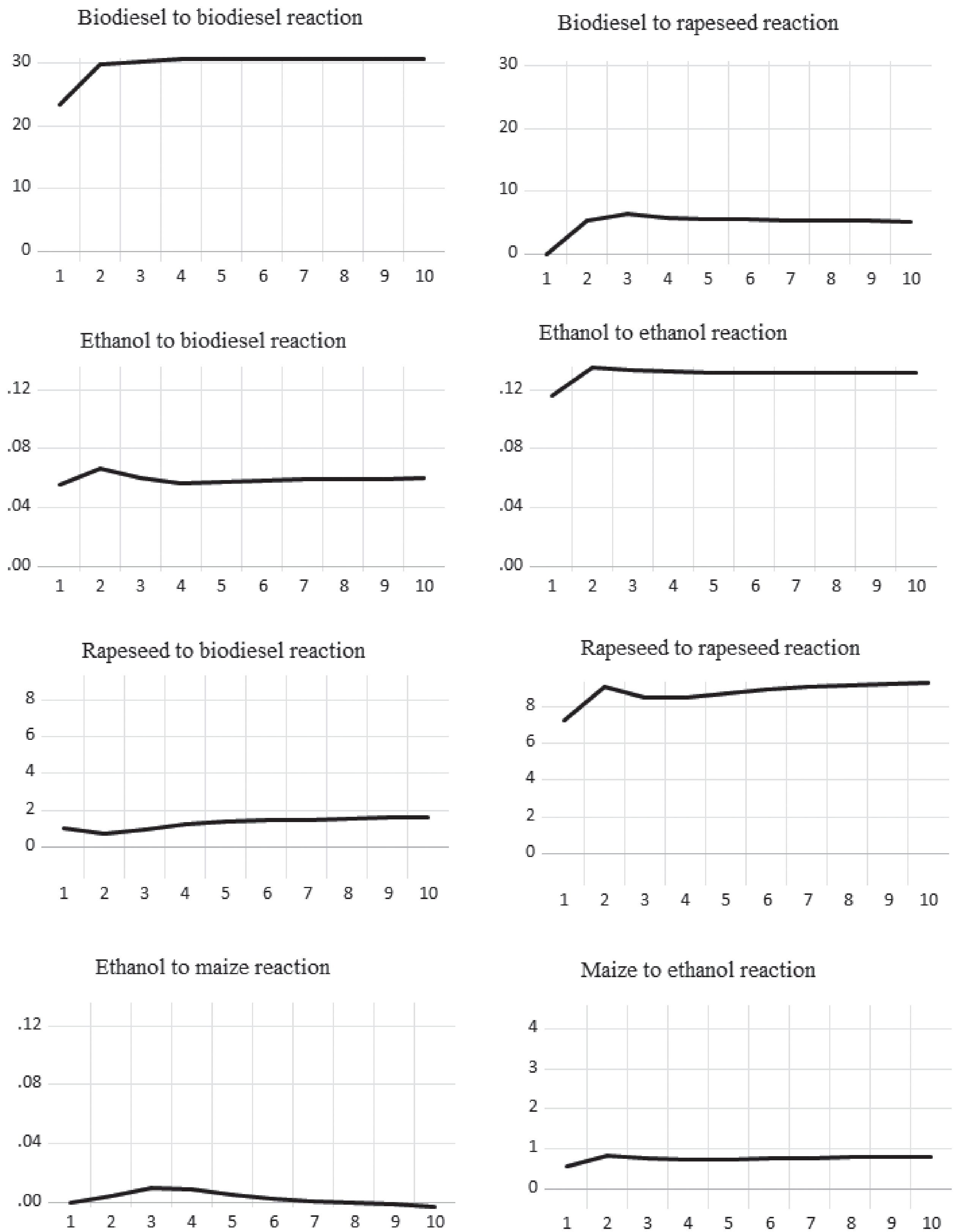

Figure 3. The reaction of individual markets to an impulse in the form price level changes. X axis - days; Y axis - price in EUR. Source: Own calculations and analysis with the use of EViews software.

Table 4. The results of the Granger causality test.

Null Hypothesis:	F-Statistic	Prob.	
Etanol does not Granger Cause Biodiesel	0.154	0.856	Accepted
Biodiesel does not Granger Cause Etanol	**6.285**	**0.002***	**Rejected**
Corn does not Granger Cause Biodiesel	1.358	0.259	Accepted
Biodiesel does not Granger Cause Corn	1.276	0.281	Accepted
Rape does not Granger Cause Biodiesel	**4.769**	**0.009***	**Rejected**
Biodiesel does not Granger Cause Rape	0.880	0.416	Accepted
Corn does not Granger Cause Ethanol	1.467	0.232	Accepted
Ethanol does not Granger Cause Corn	0.955	0.386	Accepted
Rape does not Granger Cause Ethanol	**3.439**	**0.034***	**Rejected**
Ethanol does not Granger Cause **Rape**	1.152	0.317	Accepted
Rape does not Granger Cause Corn	**2.020**	**0.001***	**Rejected**
Corn does not Granger Cause Rape	1.806	0.166	Accepted

*Probability 0.05 then Null Hypothesis is rejected.
Source: Own calculations and analysis with the use of EViews software.

The analyzes of the Granger causality test showed that there was a relationship between the prices of biodiesel and ethanol, the impact of rapeseed prices on biodiesel prices, the price of rapeseed and ethanol prices, as well as the prices of rapeseed and corn prices..

DISCUSSION AND CONCLUSION

The obtained results indicate that further research is necessary in order to provide a detailed description of the multiple dependencies that occur in the biofuel market as well as their connection with fossil fuel and agricultural markets. The presented research results on price volatility and price response of selected biofuels and agricultural products could have been measured more thoroughly with higher frequency data (e.g. daily), as well as taking into account products such as soybean, palm oil, rice or sugar. In addition, it is worthwhile to examine the problem from a broader perspective and to consider to what extent the price interdependence in these markets is a natural phenomenon and how much action is taken to promote the bioeconomy. Literature provides many studies on the relationship between the biofuel market and the agricultural raw materials market, e.g. Ciaian and Kancs, (2011), Janda *et al.* (2012), Serra and Zilberman *et al.* (2013), Kristoufek *et al.* (2014), de Gorter *et al.* (2013), de Gorter *et al.* (2015), Goswami and Choudhury (2019). However, due to the dynamic character of the market, this area should be the subject of continuous study. The conducted analyses indicated relationships between the prices of biodiesel, rapeseed, maize and ethanol, proving the existence of long-term causality in at least one direction between the analyzed prices. Based on the results of the estimation of the VECM model parameters, biodiesel prices in the period in question were influenced by prices of this biofuel from the previous week and prices of rapeseed. Moreover, biodiesel prices influenced the price level of ethanol and rapeseed. In the case of rapeseed, one may also observe the dependence of its prices on the prices of maize, while the prices of maize might be cause changes in ethanol prices. Moreover, in this case, the obtained results indicate the existence of a two-way relationship.

This study may add value to previous studies, showing the relationship between the prices of biofuels and agricultural products, and thus become the basis for further considerations on the analysis of the impact of energy crops and biofuel production on the prices of agricultural and food products. It should also be mentioned that obtaining fuels from bio sources is becoming more and more important. Particular attention in this direction has been paid recently, when there has been a strong increase in the prices of fossil fuels resulting from the pandemic situation in recent years and the ongoing war in Ukraine.

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