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Full Research Article

The role of trust and perceived barriers on farmer's intention to adopt risk management tools

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Abstract. This paper adds to the ongoing debate about low farmers' uptake of risk management (RM) tools subsidised by the Common Agricultural Policy (CAP). In particular, the research pioneers the investigation of whether and how trust towards the relevant intermediaries and the perceived barriers to adopting may influence farmers' intention to adopt the insurance and to participate in mutual funds (MF) and in the Income Stabilisation Tool (IST). In the light of the current CAP reform, as a novel contribution this paper also questions the efficiency of the new operating rules established by the Omnibus Regulation. The research proposes a conceptual framework to simultaneously assess these underinvestigated factors and several other determinants of the intention to adopt (e.g. risk attitude). Data were gleaned from direct interviews among 105 Italian farmers and analysed through structural equation modeling. The results confirm the positive role of trust in influencing the intention to adopt the insurance, which is notoriously affected by problems of information asymmetry. Similarly, trust is a key element in influencing the intention to participate in the IST, which is a collective instrument based on solidarity and mutuality indeed. Moreover, the higher the perceived barriers to adopting, the lower the intention to participate in a mutual fund, for which therefore further informative initiatives (e.g. on benefits from the adoption and the ease of use) are required. Interestingly, the results show a positive impact of the new CAP policy changes on the intention to both take out the insurance and participate in the IST, thus opening up to positive prospects for the EU risk management strategy post-2020. To conclude, this study paves the way for new research avenues in the field of farmers' adoption of subsidised RM tools.

Keywords. Insurance, mutual fund, income stabilisation tool, trust, structural equation modeling.

JEL codes. D81, G22, Q18.

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Authors' contributions: Samuele Trestini (ST) and Elisa Giampietri (EG) conceived and designed the research idea; EG collected data and analysed them with support from Xiaohua Yu (XY); all authors discussed the results; EG wrote, reviewed and edited the manuscript under the supervision of ST.

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1. Introduction

Risk is embedded in the agricultural production, leading to adverse outcomes as yield and income losses for farmers (Komarek *et al.*, 2020). Particularly, nowadays agricultural risk sources can be mainly identified in the increased severity and frequency of extreme weather conditions, pests and diseases that strike farm yields, and in the global phenomenon of price volatility that determines growing pressures on farmers' income (EC, 2017a). To cope with multiple risks, in the European Union (EU) farmers can resort to adopting subsidised risk management (RM) tools. Accordingly, the Common Agricultural Policy (CAP) has recently emphasized the role of these tools (Meuwissen *et al.*, 2018): in addition to supporting insurances and mutual funds (MF) to cover yield losses, it has introduced the so-called Income Stabilisation Tool (IST) to cope with income drops (El Benni *et al.*, 2016). As opposite to the most part of the other member states, Italy allocated a specific budget for each of these tools for the period 2014-2020. However, despite the pervading exposure to risks for farmers (Trestini *et al.*, 2017a) and the advantages that these instruments provide to farms (Enjolras *et al.*, 2014; Severini *et al.*, 2019a), in Italy the participation rate in subsidised insurance schemes is currently below what policy makers hope for, and the uptake is not homogeneous (Coletta *et al.*, 2018). As opposite, hitherto only several private MFs existed at national level, while both the subsidised mutual fund and the IST did not take up; however, it is worth noting that new initiatives (i.e. four MFs and three ISTs) will be available soon in Italy (these are currently requiring the approval). Nowadays, there exists a policy interest in understanding how to enlarge the adoption of subsidised tools among the potential beneficiaries in Italy.

In line with this, nowadays the understanding of farmers' decision-making process when choosing their preferred risk management tools represents a significant issue for many stakeholders (i.e. academics and researchers, private insurance companies, policy makers, etc.) (Cao *et al.*, 2019; Meraner and Finger, 2019). In particular, as regards the EU RM toolkit this may be useful to provide new insights for reversing the low demand and thus enhancing the efficiency of the RM policy at EU level.

A burgeoning effort was given to studying the determinants of crop insurance uptake over the last years. As broadly demonstrated (Goodwin, 1993; Mishra *et al.*, 2005; Enjolras and Sentis, 2011), moral hazard and adverse selection represent two major reasons to explain the poor development of insurance market, also justifying the policy intervention through public subsidies by the governments. In recent years the literature extensively discussed the role of several factors affecting farmers' demand for agricultural insurance: first of all, farmer's risk attitude and risk perception (Hellerstein *et al.*, 2013; Menapace *et al.*, 2012 and 2016; van Winsen *et al.*, 2016); the adoption of self-coping strategies (Enjolras and Sentis, 2011); off-farm income and direct payments (Finger and Lehmann, 2012); expected indemnity from the insurance (Liesivaara and Myyrä, 2017); prior indemnification (Wąs and Kobus, 2018); previous experience with farm losses and the level of farm's debts (Wąs and Kobus, 2018); direct and indirect experience with the insurance (Santeramo, 2018); finally, farm and farmer's characteristics (Ogurtsov *et al.*, 2009; Farrin *et al.*, 2016; Santeramo *et al.*, 2016).

Further to the above, in 2017 Castañeda-Vera and Garrido drew attention on farmers' willingness to adopt as a relevant factor to investigate. Furthermore, many authors (see e.g.

Marr *et al.*, 2016) called for the necessity not to overlook the effect of behavioural indicators, alongside the most commonly investigated neoclassical determinants (i.e. risk aversion). For instance, this supports the importance of studying the intention to adopt (i.e. antecedent of the decision makers' behaviour); in addition, opportunities exist to further knowledge in this area, e.g. by exploring the role of other potential determinants that are still underinvestigated. Hence, a serious reflection follows: are other not yet explored factors reducing the interest of EU farmers in adopting these tools? Further, it is worth noting that both MFs and the IST received only limited empirical attention both in terms of demand and research, thus representing a relevant focus of investigation to address nowadays.

Given the above, as a novel contribution this paper aims at investigating whether and how trust towards the relevant intermediaries and the perceived barriers to adopting may influence the intention to adopt the subsidised insurance, and also to participate in the mutual fund and the new IST (these two forms of mutual funds are separately investigated in this work). Finally, in the light of the current CAP reform, this analysis questions the efficiency of the new RM toolkit's operating rules provided by the Omnibus Regulation as follows: do these policy changes affect the intention to adopt?

The paper is structured as follows: paragraph 2.1 includes a description of the agricultural risk management at EU level, while the literature and conceptual framework with the hypotheses underlying the analysis are developed in paragraph 2.2; next, data collection, the questionnaire and the methodology are described in paragraph 3.1, 3.2 and 3.3, respectively; moreover, the empirical results are presented and discussed in paragraph 4; finally, the paper concludes with paragraph 5.

2. Background

2.1 The EU agricultural risk management strategy

In Italy, the participation in subsidised RM instruments dates back to 1970, with the creation of the National Solidarity Fund (Law n. 364), then reformed in 2004 (Legislative Decree n. 102). In particular, the recourse to the insurance tool recorded a long history, also by reason of premium subsidies to farmers (up to 80%). With the Health Check reform[1], in 2009 European reserves were added to national resources, in order to support (up to 65%) the insurance (i.e. the premium) and the mutual fund (i.e. administrative expenses for the setting up) covering for losses caused by adverse climatic events, animal or plant diseases, pest infestations, or environmental incidents. Within the EU borders, the policy debate on supporting RM in agriculture has progressively evolved over the last decade: the most recent demonstration comes from both the last CAP 2014-2020 reform[2] and further its middle-term revision known as Omnibus Regulation[3]. In particular, the reform in 2013 has introduced the new IST in the form of a mutual fund to support farmers facing a severe income drop (El Benni *et al.*, 2016; Castañeda-Vera and Garrido, 2017; Trestini *et al.*, 2018a; Cordier and Santeramo, 2019; Severini *et al.*, 2019b). In 2017, the

[1] Regulation (EC) n. 73/2009.
[2] Regulation (EU) n. 1305/2013.
[3] Regulation (EU) n. 2393/2017.

Omnibus Regulation has introduced new operating rules: for instance, the increase of the support rate to 70% for each tool and the introduction of sectoral ISTs with a threshold for compensation lowered at 20% (from 30%). Finally, the more recent proposal for the CAP post 2020[4] confirms the possibility for a financial contribution to the aforementioned RM toolkit under national strategic plans.

Turning to the market of RM tools, the Italian agricultural insurance sector grew rapidly over the last 15 years. The most recent data (ISMEA, 2018) depict this as highly concentrated in terms of products and characterized by a strong imbalance between the North (that concentrates up to 81% of the insured value and 86% of the insured areas), the Central Italy (10% and 8%, respectively) and the South (9% and 6%, respectively). Nevertheless, nowadays the participation rates to subsidised insurance in Italy are still below those desired, although the recent history shows a substantial level of public intervention (with a budget of 1,4 billion euro for the period 2014-2020) dedicated to the insurance market, and an ascertained high level of income losses for the Italian farms (Trestini *et al.*, 2017b). Furthermore, it is worth noting that both subsidised MFs and the IST do not yet exist in Italy at the moment, even if 97 million euro have been budgeted for each of these tools over the 2014-2020 period. To this purpose, the major difficulties recurrently encountered are related to pre-implementation issues (e.g. design of sectorial or multi-sectorial funds, initial capital stock, organisation) (Trestini *et al.*, 2018b), to the lack of a dedicated legislation (actually, with the official approval of specific national legislative decrees, improvements have been recently made on this), and to questions on benefits and limits from the farmers' side (EC, 2017b). Moreover, a major constrain to the development of the IST was represented by the difficulty to correctly and objectively assess farmers' income losses, due to the current lack of a formal accountancy in the farm sector in Italy; however, this has recently been overcome with the introduction of an index-based costing method that opens up new development opportunities for this instrument.

As opposite, several private MF initiatives exist in the North of Italy (i.e. in Trentino province and Veneto and Friuli Venezia Giulia regions): these run without subsidies and are promoted by the Defence Consortia, i.e. producers' associations based on consolidated mutual agreements and established reciprocity between members, that are historically rooted in those areas. To conclude, it is noteworthy that there are no available observational data on subsidised MFs and the IST to the present time.

2.2 Literature and conceptual framework

Research on this topic has been extensively rooted in the standard expected utility theory: as refers the insurance tool, we know that the expected utility maximizing farmer's choice to subscribe the contract must be greater from profit with insurance than from profit without it (Goodwin, 1993). However, many authors (e.g. Kahneman and Tversky, 1979) raised an objection to its predictive power of decision-making under risk. Based on this, the present study considers several determinants and investigates their simultaneous effect on farmers' intention, hereafter referred as INT, to adopt the subsidised RM tools. This is to satisfy the necessity for a reference frame that is most likely that in which farm-

[4] COM (2018) 392 final.

ers behave under uncertainty. Indeed, to our knowledge the use of consolidated frameworks studying the combined action of several factors contemporaneously (as actually happens in a decision-making process) is rare in the literature on RM tools' adoption and the most part of the studies focuses on one strategy or instrument, and very few exceptions to this exist, e.g. van Winsen *et al.* (2016) and Meraner and Finger (2019). Inspired by the study by van Winsen *et al.* (2016) that explores the role of risk perception and risk attitude as determinants of farmer intended behaviour, in this research we propose three different conceptual models: other things equal, the first (model 1) regards the intention to adopt the insurance whereas, as a novel contribution, the second model (model 2) refers to the mutual fund and the third model (model 3) to the new IST. Furthermore, this study focuses on the intention to behave (i.e. the intention to adopt each instrument) as a proxy for actual behaviour (i.e. adoption) (Lobb *et al.*, 2007), due to the fact that no forms of subsidised MFs and IST operate in Italy to date, as opposite to the insurance.

In the literature on farmers' adoption of RM tools, especially those subsidised by the CAP, hitherto scarce attention has been paid to the role of trust, with very little exceptions: e.g. Cole *et al.* (2012) argued that farmers' mistrust in the insurance market can represent a friction to the uptake. Grebitus *et al.* (2015, p. 85) argued that "the role of trust is considered to be of particular importance where information is sparse, hard to assess or complex; in these situations, trust can substitute for full knowledge". Accordingly, Pascucci *et al.* (2011) highlighted how trust is a relevant factor to efficiently cope with problems of asymmetric information, that notoriously lower the insurance demand due to two major problems as adverse selection (i.e. the tendency of riskier farmers to purchase the insurance) and moral hazard (i.e. the tendency of insured farmers to adopt a riskier behaviour). Hence, here we refer to trust as the farmer's belief in the reliability of relevant intermediaries involved in those settings characterized by imperfect or asymmetric information (i.e. a situation where one actor has greater information than the other actor), as the relationship between principal and agent (Jensen and Meckling, 1976; Eisenhardt, 1989). With regards to the RM tools, farmers are likely to show limited knowledge and a reduced ability to perfectly evaluate if both the insurance contract and the membership rules of mutual funds are adequate for the own interest; at the same time, they tend to assume opportunistic behaviour (e.g. moral hazard). For example, in the insurance market farmers do not always show complete trust that they will receive the payout from the insurance company in return for the premium paid to subscribe the contract, and this can inhibit the contract purchase. Therefore, the intermediaries (e.g. insurance providers, local agents, etc.) play a key role in this respect: they gain and retain trust from farmers and, based on this, they match the farmer and the insurer (Cummins and Doherty, 2006) and encourage farmers' participation in the insurance program (Ye *et al.*, 2017). To summarise, it is reasonable to assume that trust can represent a solution for those situations that are inherently characterized by increasing complexity (see the insurance contract), uncertainty and reciprocal lack of knowledge (this characterizes the insurance, by nature), scarce experience, and the necessity for membership control (as for mutual funds, where members derive utility from a good conduct of all members and a good exercise of the instrument[5]). As regards

[5] This is especially true for mutual funds that, according to a recent Ministerial Decree (n. 10158/2016), in Italy can be created and managed by cooperatives, consortia, producers' organizations, farm associations, etc. Mutual funds are voluntary alliances among members who formalize an agreement related to duties and rights, membership rules, etc.

the mutual funds, a recent document of the European Commission (2017b) reported that farmer's reluctance to trust these collective instruments represents a principal ambiguity that justifies the failure to create mutual funds in Italy. In fact, since the fund implies the creation of a financial reserve by the annual contribution by all the members, the potential beneficiaries may question the level of solidarity and mutuality between who benefits and who loses within the fund, and raise questions as who is paying for whom. As opposite, the same document highlighted that the high level of trust between members is conducive to the good operation of those mutual funds run by the Defence Consortia (see e.g. in Trento Province in Italy), but little empirical evidence exists on this nonetheless. To conclude, since uncertainty is inherent in the choice of RM tools (as farmers may not fully understand the instruments or may have harbour doubts about the behaviour of intermediaries), it is reasonable to suppose that trust represents a catalyst for the adoption of these instruments. Following this, we test this hypothesis:

H1: trust significantly affects the intention (i.e. the intention to adopt the insurance or to participate in a mutual fund or in the IST).

Similarly, evidence into the role of farmers' perceived barriers on farmers' adoption are limited, with the exception of a recent paper by Ye *et al.* (2017) on crop insurance, thus stimulating our interest in this field. Indeed, farmers often know little about the benefits of using RM tools primarily because they receive little education about the instruments. As opposite to this, the literature shows that farmers who are better-informed on the operating rules of the insurance contract and its benefits, thus showing lower perceived barriers, are more willing to purchase the coverage (Santeramo, 2019). In line with this, it is worth investigating the role of farmers' perceived barriers to adopting (that here serve as proxy for the lack of understanding), and we reasonably expect a negative role on the intention for all the investigated tools. Based on this, we test the following hypothesis:

H2: perceived barriers to adopting significantly affect the intention.

Nowadays, a further important but still unanswered question is the extent to which policy interventions actually influence farmers' choice to adopt the CAP's RM toolkit. To this purpose, another innovative element of this study is the investigation of the effect of the changed operation rules established by the agricultural package of the new Omnibus Regulation as potential drivers of the intention. In our opinion, this may provide interesting insights on CAP's effectiveness to encourage the adoption of subsidised tools.

As alluded to in the introduction, the core contribution of this paper is represented by the pioneering investigation of the role of trust and perceived barriers. In addition to these, the conceptual model that we propose considers some other determinants of the intention to adopt the three subsidised tools: their role on farmers' insurance uptake has already been found to be relevant by the literature, as opposite to their role on the intention to participate in a MF and in the IST that is still unclear at the moment, to the best of our knowledge.

Inspired by the extant literature on insurance, we investigate the role of past adoption of RM tools on the intention. To this purpose, in line with some other authors (see e.g.

Enjolras and Sentis, 2011; Cole *et al.*, 2014), Santeramo (2019) found that farmers who experienced the insurance tool in the past are more likely to buy it further, with respect to uninsured farmers. Moreover, as the previous experience in using RM tools can change farmers' perception of these instruments (Ye *et al.*, 2017), we also test the influence of past adoption on perceived barriers; similarly, we analyse the effect of previous adoption also on trust, for an explorative purpose.

Furthermore, this study tests whether farmers' attitude towards risk has power in explaining their intention to purchase the insurance tool or to participate in MFs or the IST. Indeed, risk attitude influences many decisions in a farm management context (Vollmer *et al.*, 2017): it follows that its understanding is essential to explain and predict farmers' risk behaviour (i.e. how they act upon risk) and any related policy implications (van Winsen *et al.*, 2016; Iyer *et al.*, 2020). Against this background, we consider the individual risk attitude (namely, the individual orientation towards taking risks) as a fundamental determinant of farmer's INT. Based on the standard expected utility theory and thus assuming farmers' rational behaviour, we expect that more risk averse individuals are more likely to insure (Cao *et al.*, 2019).

In addition, several authors (Enjolras and Sentis, 2011; Lefebvre *et al.*, 2014) emphasized that farmers facing a higher risk exposure (e.g. a greater frequency of insurable risks) are expected to insure, being the demand positively related to past risky occurrences. Thus, we test the role of the perceived risk frequency at farm level (namely, their perceived exposure to risks), assuming that it positively affects INT.

Also, this study investigates the impact of the perceived risk control on INT for an explorative purpose, inspired by the literature: coherently with other authors that they cited, Wauters *et al.* (2014) recalled the link existing between people's behaviour and their degree of control over something. However, no study has yet experimentally explored this link. As intuition suggests, we can assume that farmers with a lower perceived control over risks may be more willing to adopt RM tools.

In addition, farmers can adopt several self-coping strategies for coping with risks in order to minimise their losses (Bowman and Zilberman, 2013; Meraner and Finger, 2019): these includes (but are not limited to) production contracts (i.e. contracts that ensure that the product will be bought at a set price), diversification and investments for new farm structures and new technologies. To this purpose, Marr *et al.* (2016) stated that the higher is the variety of risk mitigation strategies and the lower the demand for insurance is. Hence, our model combines self-coping strategies and INT in a unique framework to better fit the real context of farmers' risk behaviour.

Finally, we also take into account some individual indicators as gender, age and the level of education, analysing their effect on both the intention to adopt and the attitude towards risk. In particular, the literature suggests that elder farmers, i.e. more experienced, and the better educated ones are expected to be insurance users (Sherrick *et al.*, 2004), probably because they can better understand the insurance product (Ye *et al.*, 2017) or because they can assess risks more precisely (El Benni *et al.*, 2016). As regards risk attitude, Franken *et al.* (2017, p. 42) argued that "risk attitudes have been shown to vary systematically with socioeconomic and individual characteristics, such as age, education, gender". In particular, van Winsen *et al.* (2016) showed that age has a positive relation with risk aversion, while education can have both a negative and a positive effect.

Summarising the above discussion, we also test the hypotheses included in table 1 and figure 1. It is worth highlighting that, among the investigated variables, trust, perceived barriers, perceived risk frequency and risk control, self-coping strategies, past adoption and the effect of CAP changes are not observable by scholars, whereas the attitude towards risk is not observable neither by farmers nor by researchers.

Table 1. Hypotheses on relations among variables.

Relation	Sign*
H1: trust significantly affects the intention (i.e. the intention to adopt each subsidised RM tool)	(+/-)
H2: perceived barriers to adopting significantly affect the intention	(+/-)
H3: perceived risk frequency significantly affects the intention	+
H4: perceived risk control significantly affects the intention	(+/-)
H5: risk attitude significantly affects the intention	+
H6: past adoption of RM tools (whatever) significantly affects the intention	+
H7: policy change provided by the Omnibus Regulation significantly affects the intention	(+/-)
H8: self-coping strategies (Past_strat1; Past_strat2; Past_strat3) significantly affect the intention	-
H9: past adoption significantly affects the trust	(+/-)
H10: past adoption significantly affects the perceived barriers	(+/-)

* The sign here reported represents the expected positive (+) or negative (-) influence, as evidenced by the existing literature (related to the insurance tool); however, there is also a possible double effect (+/-) and the reason is twofold: i) because the effect has not yet been investigated by the existing literature or ii) because the literature reports both a positive and a negative effect.

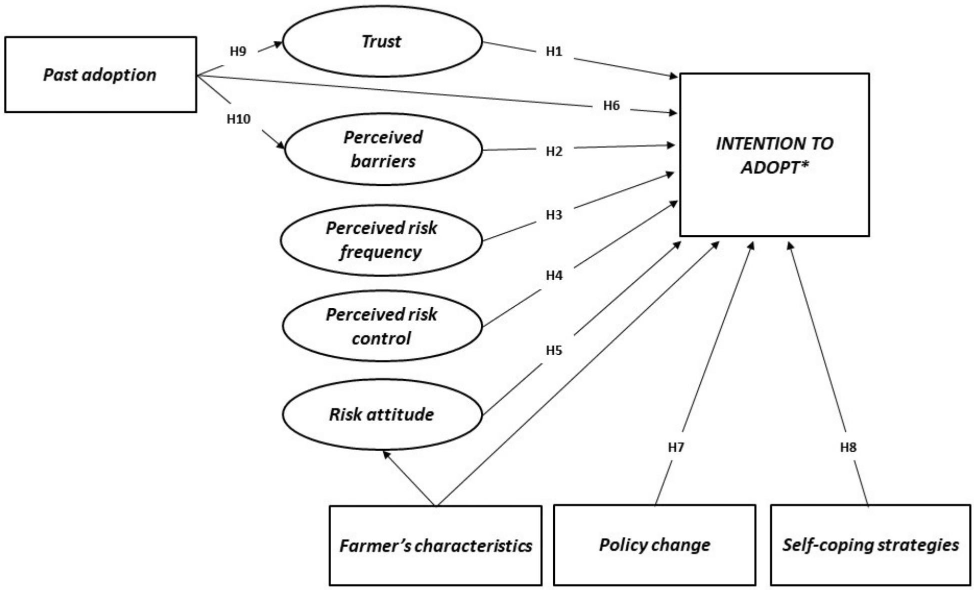
3. Data and method

3.1 Data collection

From December 2017 to March 2018 a survey collection was conducted among 127 Italian farmers in Veneto[6] region through direct interviews. Respondents who freely accepted to answer the questionnaire were the participants of some training courses organized by a farmers' association. Consistent with Wauters *et al.* (2014), it was indeed a purposive sampling, as the authors needed informed respondents who, based on their farming experience and understanding of RM tools, could provide reliable answers (Flick, 2006). The data collection recovered 105 fully completed questionnaires representing the final sample[7]. A structured questionnaire, pre-tested on a small sample (N = 15), was designed based on the existing literature on this topic and on a preliminary survey[8] previously conducted among 23 Italian farmers. In the final questionnaire, farmers were pro-

[6] Veneto region is the first in terms of value of crop-hail insurance coverage (with over 1.4 billion euros) (https://www.statista.com/statistics/818978/value-of-crop-hail-insurance-coverage-by-region-in-italy/).
[7] This sample size is in line with similar studies (see Iyer *et al*., 2020).
[8] Some open-ended questions asked for: major sources of income and production risks occurring at farm level; most important barriers preventing farmers' adoption of subsidised RM tools; main self-coping strategies employed to manage risk at farm level.

Figure 1. Conceptual path model with hypotheses.



* Intention refers to: insurance adoption (INT_INS) in model 1; participation in a mutual fund (INT_MF) in model 2; participation in the IST (INT_IST) in model 3. The figure does not represent the standard graphical representation of SEM: indeed, measured variables (i.e. those determining latent variables, namely indicators) are not shown. In the figure there are two types of unobservable variables as antecedents of the intention: one measured through the lottery task (i.e. risk attitude - shown as an oval) and some measured through the indicators within the survey (i.e. trust, perceived barriers, perceived risk frequency, and perceived risk control - shown as ovals). Finally, past adoption, policy change, self-coping strategies and farmers' characteristics are observed variables shown as squares.

vided with a short description of the RM tools subsidised by the CAP (i.e. insurance, MFs, IST) to ensure a full understanding.

3.2 Questionnaire

The questionnaire was divided into four sections investigating: i) the intention; 2) the antecedents of the intention; 3) risk attitude; 4) farm's and farmer's characteristics and past strategies to cope with risks at farm level. In particular, in the first one, it was asked to self-assess the individual intention to adopt a subsidised agricultural insurance (*INT_INS*) or to participate in a MF (*INT_MF*) or in the IST (*INT_IST*): more in depth, the average value from three items (5-point scales) was transformed into a dummy (1 if the value was greater than 3, 0 otherwise) to measure each type of intention[9]. Furthermore,

[9] As regards the intention to adopt the insurance tool, the agreement with the following items was asked: "Next year, I will consider the adoption of the subsidised agricultural insurance to face yield risk", "For the next year, I plan to adopt the agricultural insurance to face yield risk", and "Next year, I will adopt the agricultural insur-

the second section of the questionnaire included: several statements to elucidate all the latent variables that cannot be directly measured; a binary yes or no question asking for the past adoption of RM tools (at least once) during the previous five years (*Past adoption*); a five-point psychometric scale (1 = not at all important; 5 = very important) to measure the subjective relevance of the new rules for indemnification provided by the Omnibus Regulation in order to further adopt the three subsidised tools (*Policy change*). As regards latent variables, for each item respondents were asked to score their agreement on several five-point Likert scales. For instance, participants were asked to self-assess their trust (*Trust*) by scoring their agreement with three statements on a Likert scale from 1 (strongly disagree) to 5 (strongly agree); these statements were based on Hartmann *et al.* (2015), with adjustments. Furthermore, three items were used to elucidate the barriers for each tool (*Perceived barriers*), ranging from 1 (not at all a barrier) to 5 (a very important barrier). Finally, with regards to risk frequency (*Perceived risk frequency*; five items) and risk control (*Perceived risk control*; five items) farmers were asked to score the likelihood (1 = very unlikely; 5 = very likely) of six different risk sources identified through the above mentioned preliminary survey (i.e. storm, hail, ice, heavy rain, other negative weather conditions, plant diseases) and the degree of control (1 = no control; 5 = very much control) they exerted on them at farm level, respectively. Particularly, the items related to risk frequency derived from Wauters *et al.* (2014) with adjustments. The third section of the questionnaire included a lottery task to measure farmers' risk attitude (*Risk attitude*) (Menapace *et al.*, 2012; Vollmer *et al.*, 2017; Iyer *et al.*, 2020). We used a lottery choice task inspired by Eckel and Grossman (2008) and assumed constant relative risk aversion (CRRA) for which the utility is defined as $U(x)= x^{(1-r)}/(1-r)$. In order to measure their subjective preferences for taking risks, respondents were asked to imagine to have 28€ and to gamble over this sure amount: they were asked to select, among six different gambles, the one they wished to play[10]. With the exception of the first gamble showing a sure outcome (28€) in both cases, every other gamble involved a 50% chance of receiving a low payoff and a 50% chance of a high payoff (expressed in €) as an outcome; gambles from 2 to 6 presented risky outcomes where the expected payoff and risk linearly increased. This method, derived from Charness *et al.* (2013), represents a simple way of eliciting risk aversion: in particular, risk averse respondents choose gamble 1-4, whereas those who choose gamble 5 and gamble 6 are risk neutrals and risk seekers, respectively. Following Menapace *et al.* (2012), we considered CRRA lower bound for the analysis. Finally, the last section of the questionnaire investigated farmer's and farm's characteristics (i.e. gender, age, education, average farm revenue, utilised agricultural area) and the previous adoption of self-coping strategies as diversification (*Past_*

ance to face yield risk" (composite reliability: 0.88). In relation to the intention to participate in a mutual fund we used: "Next year, I will consider the participation in a mutual fund to face yield risk", "For the next year, I plan to become a member of a mutual fund to face yield risk", and "Next year, I will be a member of a mutual fund to face yield risk" (composite reliability: 0.88). Finally, with regards to the intention to participate in the IST we used: "I will consider the participation in the IST to face income risk", "I plan to become a member of a IST to face income risk", and "I will be a member of the IST to face income risk" (composite reliability: 0.88).

[10] We chose this easily comprehensible lottery task derived from Dave *et al.* (2010) as it is simple, easy to explain and implement, while retaining a reasonable range of risky choices, and it is totally understandable by the respondents.

strat1), production contracts (*Past_strat2*), investments for new farm's structures and new technologies (*Past_strat3*).

3.3 Methodology

The analysis applied a structural equation model (SEM) that deals with a system of regression equations. Indeed, this multivariate analysis consists of a set of linear equations that simultaneously estimate two or more hypothesized causal relationships between several variables (Bollen, 1989): by including them in a single model, SEM traces the structure of the decision-making process. In SEM models, variables can be both exogenous (independent) and endogenous (dependent), both observed and latent variables (namely, unobservable variables that require two or more measured indicators) as perceptions, self-reported behaviour, or personality traits; moreover, in some cases a variable can be both a predictor and a dependent variable at the same time, whereas the relationship can be direct or indirect. Within SEM it is possible to distinguish both structured models (that represent the relationship between latent variables) and measurement models (that represent the relationship between the latent variable and its observable indicators). In the model, the parameters to estimate are the regression coefficients, the variances and the covariances of the independent variables. As above mentioned, the popularity of this technique derives from the possibility to concurrently test different impacts among variables (i.e. multiple and simultaneous testing), as opposite to ordinary regression analysis (Schreiber *et al.*, 2006); another main advantage is the capability to handle latent variables, which can be both dependent variables and predictors, while controlling for farm's and farmers' characteristics. However, an adequate (i.e. large) sample size is required[11]; moreover, only identified models can be estimated. The interested reader may want to read Ullman (2006, p. 40) for a more extensive description and a more extended model statistical specification. Following Ullman (2006), SEM can be expressed as follows:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{1}$$

where η is a vector of endogenous variables, B is a matrix of coefficients between endogenous variables, Γ is a matrix of regression coefficients denoting the effect of exogenous variables on endogenous variables, ξ is a vector of exogenous variables, and ζ is a vector of the measurement errors. Although widely tested in many different contexts, this approach has been only recently proposed in the field of study on farmer's risk behaviour and the work of Pennings and Leuthold (2000) represents a pioneering example. More recent applications to risk behaviour analysis are the study by van Winsen *et al.* (2016) and the study by Franken *et al.* (2017): this latter analyses the impact of farm socio-economic and farmer individual characteristics on risk attitude. Against this background, our paper represents an innovative attempt to use a SEM in explaining the potential relationships of several factors with farmers' intention to adopt risk management strategies. The descriptive analysis was performed using SPSS version 24, whereas SEM was performed using AMOS package. In SEM models,

[11] To overcome this limit, it is worth noting that Bentler and Yuan (1999) developed test statistics for small sample sizes.

the goodness-of-fit statistics assess the model-data matching; to do this, we used the following indexes: the ratio between χ^2 and the degrees of freedom (CMIN/DF), the comparative fit index (CFI), and the root mean square error of approximation (RMSEA).

4. Empirical results and discussion

As shown in table 2, the average age of respondents is 40 years and the majority of the sample are men (72%), with an upper secondary school level of education (63%) and an

Table 2. Sample descriptive statistics.

Categories	Description	N. Obs	%	Mean	S.D.
Gender (*Sex*)	(0) female	29	27.6		
	(1) male	76	72.4		
Age (*Age*)	n. years			40.12	13.55
Education (*Education*)	(1) primary school	3	2.9		
	(2) secondary school	14	13.3		
	(3) upper secondary school	66	62.9		
	(4) university degree	22	21.0		
Average farm revenue (*Revenue*) (gross income from farming/year)	(1) less than 50,000€	62	59.0		
	(2) 50,000€ - 100,000€	28	26.7		
	(3) 100,000€ - 250,000€	11	10.5		
	(4) more than 250,000€	4	3.8		
Utilised Agricultural Area (*Uaa*)	n. hectares		14.25	17.04	
How relevant are the changes to RM policy provided by the Omnibus Regulation, in order to adopt risk management tools in your farm? (*Policy change*)	(1) not at all important	6	5.7		
	(2) scarcely important	6	5.7		
	(3) neutral	52	49.5		
	(4) sufficiently important	27	25.7		
	(5) very important	14	13.3		
Intention to adopt the agricultural insurance (*INT_INS*)	(0) no	47	44.8		
	(1) yes	58	55.2		
Intention to participate in a mutual fund (*INT_MF*)	(0) no	57	54.3		
	(1) yes	48	45.7		
Intention to participate in the IST (*INT_IST*)	(0) no	50	47.6		
	(1) yes	55	52.4		
Previous adoption of RM tools at farm level (past 5 years) (*Past adoption*)	(0) no	73	69.5		
	(1) yes	32	30.5		
Adoption of diversification (*Past_Strat1*)	(0) no	92	87.6		
	(1) yes	13	12.4		
Adoption of production contracts (*Past_Strat2*)	(0) no	98	93.3		
	(1) yes	7	6.7		
Previous investments for new farm structures and new technologies (*Past_Strat3*)	(0) no	101	96.2		
	(1) yes	4	3.8		

average farm revenue lower than 50,000€ per year (59%). The average utilized agricultural area of farms is 14 hectares and these are heterogeneous in terms of production orientation: permanent crops' production represents the majority of the sample (50%), followed by livestock (28%), arable crops and horticulture (23%), and only a minority are mixed farms. Moreover, up to 70% of the respondents declares no previous adoption of RM tools at farm level. Finally, on average respondents show a positive intention to adopt subsidised agricultural insurance schemes (55%) and to participate in the IST (52%) in the near future (i.e. the next year), as opposite to MFs (46%). Interestingly, 36% show a positive intention to both subscribe the insurance and to participate in a mutual fund, 38% to both subscribe the insurance and to participate in the IST, 37% to participate in both a MF and the IST, and finally 29% show a positive intention with regard to the three tools.

As shown in table 3, all the items present mean values above the scale mean, with the exception of perceived risk control, as expected. Hence, the majority of farmers perceive a high risk frequency and considerable barriers to the adoption of subsidised RM tools, are endowed with a scarce control over adverse weather events striking their farm and display a high trust towards the intermediaries. Cronbach's α scores are higher than 0.75 for each considered latent variable, denoting an adequate internal consistency. Moreover, the standardized regression weights of the items are significant at 1% level and show values ranging from 0.320 to 0.916.

As expected and consistent with the literature (Iyer *et al.*, 2020), table 4 shows that our farmers' sample mainly consists of risk averse subjects (84.8%) who chose gamble 1, 2, 3 and 4, whereas only 6.7% are risk neutral and 8.6% are risk seekers.

Goodness-of-fit indexes of the estimated models are acceptable, with a root mean square error of approximation (RMSEA) of 0.05 (model 1) and 0.06 (model 2 and 3), a comparative fit index (CFI) of 0.9 and CMIN/DF always lower than 2 in each model. Hence, our results demonstrate the usefulness of SEM in exploring the relationships of intention and other decision-making attributes with regard to risk management behaviour, consistent with van Winsen *et al.* (2016). Furthermore, the variance of farmers' intention, risk attitude, perceived barriers and trust is explained in the measure of 25%, 15%, 6% and 5% in the first model, respectively; whereas in the measure of 27%, 15%, 1% and 5% in the second model. To conclude, the third model explains up to 25% the intention, 15% the risk attitude and 4% the trust, whereas it does not explain the barriers at all.

Interestingly, the results (table 5) show a positive effect of trust on the intention in model 1 and 3 (H1 - $\boldsymbol{\beta}_{\text{Trust}}$ = 0.22 and 0.24 respectively, significant at 5% level), showing that a greater individual trust increases the intention to adopt the insurance and to participate in the IST. Consistently with this, Karlan *et al.* (2014) argued that the more farmers are confident the payout will be properly made by the insurance company and the greater their demand for insurance is. The evidence that trust tends to increase the intention to participate in the IST let us assume that this personality trait might be considered as a substitute for farmers' need to understand this new instrument (that is currently unfamiliar to them), at least during the setting-up: the greater the amount of trust, the lower the perceived uncertainty linked to these tools (operating rules, management, etc.); however, this deserves further investigations. Consequentially, if reinforced (by the bodies responsible for its management, e.g. Defence Consortia), we can assume that trust might overcome farmers' original reticence about participating in the IST and foster its progressive

Table 3. Latent variables.

Measure	Item code	Mean	S.D.	Std. factor loading
Trust[a] (Cronbach's *α = 0.86)*				
I perceive the intermediaries who support me for the adoption of the agricultural insurance to be reliable	*trust1*	3.17	0.87	0.73***
I am confident that the intermediaries which I refer to for the adoption of agricultural insurance take care of my interest	*trust2*	3.05	1.01	0.86***
I trust in the intermediaries who support me for the adoption of agricultural insurance	*trust3*	2.85	0.89	0.86***
Perceived barriers to insurance adopting[b] (α = 0.79)				
I have a scarce perception of the benefits of agricultural insurance's adoption	*ins_barr1*	3.31	1.17	0.73***
There is low transparency in the mechanisms of agricultural insurance	*ins_barr2*	3.53	1.07	0.78***
I think that the management of agricultural insurance tool is difficult at farm level	*ins_barr3*	3.02	1.05	0.74***
Perceived barriers to participating in a mutual fund[b] (α = 0.78)				
I have a scarce perception of the benefits of my participation in a MF	*mf_barr1*	3.54	0.94	0.89***
There is low transparency in the mechanisms of MFs	*mf_barr2*	3.45	0.96	0.87***
I think that my participation in a MF is difficult to manage at farm level	*mf_barr3*	3.17	0.86	0.48***
Perceived barriers to participating in the IST[b] (α = 0.80)				
I have a scarce perception of the benefits of my participation in the IST	*ist_barr1*	3.53	0.93	0.92***
There is low transparency in the mechanisms of the IST	*ist_barr2*	3.50	0.85	0.83***
I think that my participation in the IST is difficult to manage at farm level	*ist_barr3*	3.15	0.83	0.57***
Perceived risk frequency[c] (α = 0.80)				
Storm	*freq1*	3.56	1.11	0.59***
Hail	*freq2*	4.20	0.88	0.68***
Ice	*freq3*	3.79	1.00	0.68***
Heavy rain	*freq4*	3.47	1.15	0.59***
Other negative weather conditions	*freq5*	3.36	0.96	0.66***
Plant diseases	*freq6*	3.85	0.96	0.52***
Perceived risk control[d] (α = 0.84)				
Storm	*cont1*	2.04	1.22	0.74***
Hail	*cont2*	2.19	1.39	0.84***
Ice	*cont3*	2.08	1.22	0.82***
Heavy rain	*cont4*	2.09	1.23	0.73***
Other negative weather conditions	*cont5*	2.35	1.03	0.56***
Plant diseases	*cont6*	3.10	1.22	0.32***

*** Significant at 1% level.
[a]5-pt Likert scale (1=strongly disagree; 5=strongly agree); [b]5-pt Likert scale (1=not a barrier; 5=very important barrier); [c]5-pt Likert scale (1=very unlikely; 5=very likely); [d]5-pt Likert scale (1=no control; 5=very much control).

Table 4. Gamble task experiment and CRRA measure of risk aversion and share of farmers choosing each gamble.

Gamble	Low payoff (50%)	High payoff (50%)	Expected payoff	Risk[a]	CRRA ranges[b]	Farmers (%)
1	28 €	28 €	28 €	0	r>7	11.4%
2	24 €	36 €	30 €	6	1.2<r<7	18.1%
3	20 €	44 €	32 €	12	0.8<r<1.2	34.3%
4	16 €	52 €	34 €	18	0.5<r<0.8	21.0%
5	12 €	60 €	36 €	24	0.1<r<0.5	6.7%
6	2 €	70 €	36 €	34	0.09<r<0.1	8.6%

[a] The risk is calculated as the standard deviation of the expected payoff.

[b] CRRA ranges are calculated as the range of r in the function $U(x)= x^{(1-r)}/(1-r)$ for which the subject chooses each gamble assuming constant relative risk aversion utility.

development. Also, the mutual nature of the IST considers the risk sharing among farmers, thus the need to support and cover other members' losses (Meuwissen *et al.*, 2013): for that reason, farmers need to feel assured and a deep trust can play a crucial role for this. Interestingly, trust increases if the individual has formerly made use of subsidised RM tools (H9 - $\boldsymbol{\beta}_{\text{Past adoption}}$ = 0.21 at 5% level), suggesting that the previous experience somehow positively drives farmers to be more confident. This result somehow considers the importance of the quality (positive / negative) of past experience which, to the best of our knowledge, has not yet been considered by the extant literature (see e.g. Enjolras and Sentis, 2011; Santeramo, 2019) that focused on investigating direct or indirect experience, or distinguishing between long or recent experience over time: indeed, increased trust is necessarily linked to a positive past experience.

So far, the literature highlighted how several bureaucratic and administrative hurdles, as for instance the difficulty in monitoring the historical farm income, constrain the development and demand of MFs and the IST (Cordier and Santeramo, 2019). To this purpose, our results reveal that the individual perceived barriers also matter: in fact, the higher is the perceived existence of barriers to adopting and the lower is the intention to participate in a MF (H2 - $\boldsymbol{\beta}_{\text{Perceived barriers}}$ = -0.20 at 5% level); as opposite, no significant effect emerges in model 1 and 3. This foreshadows the hypothesis that our respondents would make use of this instrument if they were provided with practical knowledge about it. In this regard, the competent authorities eligible for setting up and managing MFs in accordance with the national law could play a key role in providing farmers with adequate information (e.g. benefits and transparency in the functioning mechanism), and in reassuring them about the streamlined management rules at farm level, in order to encourage the participation.

As regards the perceived frequency of risk occurring at farm level, we can appreciate a positive effect on the intention to both adopt the insurance ($\beta_{\text{Perceived risk frequency}}$ = 0.19 at 10% level) and participate in a mutual fund (H3 - $\beta_{\text{Perceived risk frequency}}$ = 0.21 at 5% level), as expected. This is consistent with Meraner and Finger (2019) who argue that more risk literate farmers are more likely to resort to off-farm measures as insurance contracts. In

Table 5. Standardized regression weights for model 1, 2 and 3.

	Model 1 (INT_INS)				Model 2 (INT_MF)				Model 3 (INT_IST)			
	INT	RA	BAR	TRU	INT	RA	BAR	TRU	INT	RA	BAR	TRU
	β	β	β	β	β	β	β	β	β	β	β	β
TRU	0.224**				-0.039				0.239**			
BAR	-0.151				-0.197**				0.023			
RF	0.193*				0.210**				0.127			
RC	-0.065				0.156				0.016			
RA	0.197**				-0.012				-0.028			
PAST	0.107		-0.234**	0.212**	-0.074		-0.032	0.212**	-0.225**		0.006	0.208**
PO	0.104				0.261***				0.271***			
STRA1	0.100				0.020				0.008			
STRA2	-0.036				0.031				0.149*			
STRA3	0.187**				0.155*				0.130			
EDU	-0.038	0.267***			0.192**	0.267***			0.115	0.267***		
SEX	0.098	0.091			0.138	0.091			0.146*	0.091		
AGE	-0.104	0.271***			0.097	0.271***			-0.022	0.271***		
R^2	0.25	0.15	0.06	0.05	0.27	0.15	0.01	0.05	0.25	0.15	0.00	0.04
	χ2 = 436.981; df = 339; p < 0.000 CMIN/DF = 1.29; CFI = 0.87; TLI = 0.86; RMSEA = 0.05				*χ2 = 449.736; df = 339;* p < 0.000 CMIN/DF = 1.33; CFI = 0.86; TLI = 0.84; RMSEA = 0.06				*χ2 = 449.675; df = 339;* p < 0.000 CMIN/DF = 1.33; CFI = 0.86; TLI = 0.85; RMSEA = 0.06			

Significant levels are under the coefficient: *** significant at 1% level; ** significant at 5%; * significant at 10%.
RA = Risk attitude; BAR = Perceived barriers; TRU = Trust; RF = Perceived risk frequency; RC = Perceived risk control; PAST = Past adoption; PO = Policy change; EDU = Education; SEX = gender; AGE = Age; STRA1 = Past_strat1; STRA2 = Past_strat2; STRA3 = Past_strat3.

this study, farmers that more often face some major risks (e.g. storm, hail, ice, heavy rain, other negative weather conditions, plant diseases) are more likely to use those instruments that are specific to cope with yield losses, indeed. As opposite, no significant effect emerges with respect to the IST, which aims at facing income losses instead. As regards the perceived risk control (H4), our findings do not show significant effect in every model.

Also, the results show that the individuals who are less willing to take risks (namely, more risk averse) are more likely to subscribe an insurance contract (H5 - $\beta_{\text{Risk attitude}} = 0.20$ at 5% level), being consistent with the more recent literature on crop insurance uptake in Italy (Santeramo, 2019), while contrasting some other authors (Hellerstein *et al.*, 2013; van Winsen *et al.*, 2016). Conversely, we find no significant effect of risk attitude on the participation in both MF and IST.

Surprisingly, we found that the most important contributor of farmers' intention to participate in both MFs and to the newly established IST is represented by the changed operating rules provided by the agricultural part of the Omnibus Regulation (H7 - $\boldsymbol{\beta}_{\text{Policy change}} = 0.26$ in model 2 and = 0.27 in model 3, both at 1% level). When adequately informed about the existence of advantageous conditions for the adoption, farmers show a positive intention to make use of these tools. Hence, this reinforces the importance of information (Santeramo, 2019).

Not surprisingly, the results show a significant and negative effect of past adoption on perceived barriers in model 1 (H10 - $\boldsymbol{\beta}_{\text{Past adoption}} = -0.23$ at 5% level): this is to indicate that having a previous experience with a subsidised RM tool facilitates the understanding (Ye *et al.*, 2017), thus reducing the reluctance to adopt the insurance in the future (Santeramo, 2019). As opposite, no significant results emerge in model 2 and 3. Furthermore, we find no significant effect of past adoption on the intention to subscribe the insurance and to participate in MFs, contrary to Enjolras and Sentis (2011) and Santeramo (2019). As opposite, in model 3 we find a significantly negative effect on the intention to participate in the IST (H6 - $\boldsymbol{\beta}_{\text{Past adoption}} = -0.23$ at 5% level): this may suggest that the farmers in our sample who previously experienced tools other than the IST, in other words unsubsidised MFs' initiatives or subsidised insurance, are less inclined to experiment with this innovative tool.

Regarding the hypothesis H8, the results show that the individuals who already apply some risk reduction actions (i.e. self-coping strategies) as investments for new structures and technologies are more likely to adopt the insurance ($\beta_{\text{Past\_strat3}} = 0.19$ at 5% level) and to participate in a MF **(**$\boldsymbol{\beta}_{\text{Past\_strat3}} = 0.16$ at 10% level). On the other hand, farmers in our sample who already use production contracts to secure their income show a higher intention to participate in the IST ($\beta_{\text{Past\_strat2}} = 0.15$ at 10% level), as expected: indeed, this latter is designed to satisfy farmers' growing request to protect their income from losses at farm level. A similar finding is shown by Lefebvre *et al.* (2014) on insurance adoption in Bulgaria.

Also, findings reveal that the intention to participate in a MF is higher for farmers with a higher education ($\beta_{\text{Education}} = 0.19$ at 5% level), whereas men are more likely to participate in the IST, compared to women ($\beta_{\text{Sex}} = 0.15$ at 10% level). The effect of education in relation to the insurance found no significant evidence, coherently with Menapace *et al.* (2016) and van Winsen *et al.* (2016), as well as the IST. A second line of findings shows that elder and higher educated individuals are more risk averse ($\beta = 0.27$ at 1% level for both education and age), thus corroborating the findings of previous research (see e.g. Harrison *et al.*, 2007; Nielsen *et al.*, 2013; van Winsen *et al.*, 2016).

5. Conclusion

In the wake of the contingent debate on farmers' adoption of subsidised risk management tools, this contribution contrasts three conceptual models to test the simultaneous effect of some major interrelated factors on farmer's propensity to adopt RM tools, as pertains to a real decision-making process: namely, subsidised insurance and, for the first time, mutual funds and the new IST. Instead of relying on secondary data as the most part of the existing literature in Europe, this study presents the results from a field investigation: this allowed to collect relevant determinants as trust and perceived barriers, that the existing literature on EU risk management in agriculture has not experimentally addressed so far. It is worth to note that the investigation of trust and barriers represents a novelty, similarly to the inclusion of the new IST and the adoption of a SEM approach. Moreover, it is worth highlighting that this represents an ex-ante analysis which does not consider farmers' behaviour after the practical introduction of the IST in the agricultural sector.

As the scarce attention to trust mainly inspired this study, the most intriguing result is represented by its positive influence on the intention to both subscribe an insurance contract and to participate in the IST. This confirms the key role of this personality trait in decision-making under uncertainty, and suggests that trust probably works as a substitute for knowledge as pertains to the insurance, while it can overcome the lack of experience for the new IST, whose functioning mechanisms and rules are still unfamiliar to farmers. Even if we do not focus neither on the nature of trust, nor the context in which it arises, we can suppose that the subsidised RM tools' adoption may be incentivized in the future by building trust nonetheless. Indeed, trust may be essential for the demand of the insurance (e.g. between the farmer and the insurance sale agent), that is notoriously affected by information asymmetry, and the IST especially. In fact, this latter represents a fund that creates a financial reserve through the annual contributions by all members and that compensates only farmers who lose beyond a certain threshold: it follows that farmers can hesitate to participate in such collective tools, compared e.g. with individual instruments. To this purpose, it is recommendable to build strong interpersonal relationships, also confirmed over time, within whichever body designated for the IST's management (e.g. farmers' cooperatives or organizations or Defence Consortia). Accordingly, this may represent a trust-making strategy useful to guarantee farmers' positive expectations regarding the other members' behaviour, and thus to attract more beneficiaries just fading their initial reticence. The evidence that trust can play a role let us assume that this represents a promising area of research regarding the agricultural risk management, deserving further research to analyse its determinants and to understand how to increase it, in order to provide practical policy recommendations. Generally speaking, we can only assume that several strategies implemented by both the insurance companies and the mutual fund's managers or Defence Consortia might positively affect farmers' trust by decreasing the uncertainty linked to RM tools. Among these, establishing reputation, increasing transparency on losses and indemnities' monitoring, and promoting a greater comprehensibility of contracts' conditions or the operation and membership rules (as regards the new mutual funds), and about the advantages (both in terms of risk coping and affordability) for farmers to adopt RM instruments. Furthermore, we found that trust is positively affected by previous adoption, thus evoking the importance of personal satisfaction from past experience (e.g. with previous compensations or from the participation in a mutual fund); this confirms the definition of trust by Mutti (1998), that is "an expectation born from experiences deemed positive by the individual, developed under conditions of uncertainty". In addition, our results show an indirect effect of previous experience with RM tools on the intention to adopt (at least for the insurance), mediated by trust. Based on this, we can assume that efforts should be made to promote the initial adoption of RM instruments (e.g. encouraging farmers to use these tools through information campaigns or incentives as the reduction of the participation fee for the first year) in order to increase trust and, as a consequence, to positively impact the intention to adopt RM tools further.

Moreover, this study confirms that the changed rules recently established by the Omnibus Regulation positively influence the intention to participate in a mutual fund and the IST. On the other hand, we can suppose that the insurance decision is not sensitive to these policy changes probably because of its greater understanding among farmers, as it boasts a long-standing tradition in Italy, compared to the other instruments that are less known. Since our results show that these recent policy changes are perceived as relevant and suitable by the beneficiaries, it seems increasingly important to bridge the gap between the current policy efforts in implementing specific measures to encourage farmers' adoption of subsidised RM tools and the lack of knowledge among the potential beneficiaries; indeed, this represents a friction to enlarge the audience of farmers. Thus, we merely conclude that a greater information about the operating rules is advocated among farmers, as a greater support to the advisory systems that mainly drive initiatives to increase the knowledge among farmers. In line with this, another interesting evidence comes from the negative effect of perceived barriers on the intention to participate in a mutual fund in our sample: this highlights the necessity of spreading the knowledge about this tool among the potential beneficiaries, as they reasonably have difficulties in evaluating the benefits properly and in understanding the operation of the instrument in depth without an advice.

Although this paper presents many innovative cues on the heterogeneous literature on RM tools' adoption, some limitations exist. Firstly, the hypothetical nature of the gambles and the absence of a context specification for the measure of risk attitude. To this purpose, despite many authors may criticize this, we remind that many others (e.g. Rommel *et al.*, 2019) argue that adding context does not necessarily improve the ability to predict real-world decision-making. Nevertheless, due to the fact that risk attitude is not central in our study, this may not necessarily represent a strong limitation at the moment. Secondly, the non-representativeness of the Italian population prevents our results from being generalizable: for this reason, we cannot discuss policy implications at this stage. In line with this, we highlight that the overarching objective of this research is to provide new evidence on the potential role of factors not yet explicitly explored before, and therefore to pave the way for new research avenues in the field of farmers' adoption of subsidised RM tools: accordingly, if supported by a wider and more representative sample, further research would reasonably lead to relevant policy implications, e.g. informing policy makers to devise and plan more adequate strategies and initiatives to foster farmers' adoption. Moreover, the analysis does not consider several relationships and factors that the literature found to be significant determinants, due to the necessity to keep the models as parsimonious as possible; this limitation could be overcome in further studies that may also focus on farmers' real uptake (i.e. behaviour) instead of intention, by using also framing techniques.

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Full Research Article

Drivers and barriers of process innovation in the EU manufacturing food processing industry: exploring the role of energy policies

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Abstract. This paper investigates the driving forces that can promote or impede process innovation adoption in the European food manufacturing industry. The study uses a logit model applied to Community Innovation Survey (CIS) data containing information on innovation at the industry level for 15 EU Member States. Results suggest the relevance of many factors, internal and external to the enterprise, such as size and organization of business practices on one hand, and networking activities and cooperation agreements within the supply chain on the other hand. We also focus on energy policy variables as process innovation determinants. Energy policies implementation, energy price and the availability of public funds, show a significant impact on process innovation adoption in the European food processing industry.

Keywords. Environmental Regulation, Energy policy, Innovation, Cooperation activities, Food manufacturing industry, EU.

JEL codes. L66, O3, Q4, Q16.

1. Introduction

In October 2014 the European Council agreed on a new 2030 Framework for climate and energy, including EU-wide targets and policy objectives. This strategy aims to help the EU achieve a more competitive, secure and sustainable energy system and to meet its long-term 2050 greenhouse gas reductions target. The figures for renewables and energy efficiency have subsequently been increased in the Targets for 2030 context including, among others, a 40% cut in greenhouse gas emissions compared to 1990 levels and an indicative target for an improvement of at least 32.5% energy efficiency at EU level.

The food processing industry makes a significant and increasing contribution to the overall energy consumption and GHGs emitted in the food chain (OECD, 2017). Eurostat considers the total energy consumed by the food processing industry (including bever-

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ages and tobacco) to be 29178.5 Mtoe in 2015. This amount represents 28% of the energy embedded in the food chain (Monforti- Ferrario *et al.* 2015), 2.7% of the average final energy consumption and the 10% of the average energy consumption in the manufacturing industry, with Denmark and Croatia having the larger shares. Although the European food processing and beverage sector has gradually improved its energy efficiency – measured as the ratio value added/energy consumption - gaining competitiveness and reducing GHGs emissions in the last decades, still it has a strong potential for decreasing energy consumption both as a result of process optimization and plant system improvements (OECD, 2017; Ladha-Sabur et al, 2019). Technical potential energy savings have been estimated to be 22% (compared to 2004) by 2030 (Altmann et al, 2010; ICF, 2015). Energy use reduction and energy recovery from waste are two important methods to reduce production costs in the food processing industry (OECD, 2017; Altmann *et al.* 2010; Monforti- Ferrario *et al.* 2015). Kaminski and Leduc (2010) have identified the most important systems and processes where significant energy-efficiency improvements can be achieved in the EU's food industry: steam, motor and pump, compressed air systems, process cooling and refrigeration, and buildings heating and lighting.

The EU Lisbon Strategy considers innovation as one of the most important factors to enhance productivity, competitiveness, and sustainability in the economy. Literature, starting from Schumpeter's studies (1934, 1942) has tried to understand what the internal and external factors influencing process innovation are (Cohen, 1996; Galende and de la Fuente, 2003). Many factors determine the firm's capacity to innovate, ranging from technical capabilities, financial structure, market needs, network relationships, regulations, and subsidies. Enterprises, however, can also be deterred from engaging in innovation or fail to bring in new processes or products because existing barriers. Recognizing the nature of these barriers is important both from a policy and a management point of view (D'Este *et al.* 2012).

Literature on innovation has focused mainly been on high tech industries and only a few studies have considered low-tech traditional sectors such as the food processing industry.

Some specificity characterizes innovation in the food processing industry. Firstly, food firms are mainly process innovation oriented (Minarelli *et al.*, 2014). Secondly, the production of new technologies is usually developed by upstream industries and R&D expenditure is low compared to other sectors (Garcia-Martinez and Briz, 2000; Triguero *et al.*, 2013). Thirdly, most innovations are incremental rather than radical (Garcia-Martinez and Briz, 2000). Fourthly, product typologies and process phases are extremely differentiated and difficult to uniform (Capitanio *et al.*, 2010). Finally, SMEs are characteristically prevalent in the agri-food sector. Literature shows that SMEs behave differently with respect to large enterprises relative to innovation adoption, with larger firms being more innovative than smaller ones (Galizzi and Venturini, 1996). This distinction has important policy implications for policy design. Recent research (Minarelli *et al.*, 2014) indicates that, in the EU, SMEs are a very heterogeneous group regarding their innovation profile, particularly in the food sector. The relation between size and innovation is not straightforward, as other factors influence firms' behaviour as workforce in-house capabilities and the engagement in R&D activities (Avermaete *et al.* 2004). The small average size is considered one of the main barriers to innovation in Southern European countries (Garcia-

Martinez and Briz, 2000; Capitanio *et al.* 2010).

Nevertheless, the food processing industry is becoming more technologically intensive to maintain better process control, exploit economies of scale and guarantee food safety and quality, facing market competition through new products and processes development.

Capitanio *et al.* (2009) analysing the driving factors of innovation in the Italian food processing industry conclude that the determinants can be found both in internal and external factors. Among the first, there is the human capital qualification, a clearer orientation to quality products, organizational changes, and relation capacity development. On the external side, factors such as the increasing competition and demand have a relevant role in shaping the innovation process. Different determinants emerge when analysing process and products innovation separately. In the first case, the of human capital and market relationships qualities are the most important drivers, while in the of process innovation case, the firm's financial structure and capital intensity are the most relevant. The firm's location, meaning socioeconomic context relevance, has a positive and significant impact on process or product innovation adoption. With regard to Spain, research has underlined the machinery and equipment suppliers contribution to innovation diffusion (Garcia Martinez and Briz, 2000), together with significant path dependence (Triguero *et al.*, 2013). Environmental and market factors role seems higher in the food processing industry compared to other manufacturing industries. Cleaner technologies[1] can improve the production process efficiency by reducing materials and energy consumption, improving firm's productivity and competitiveness (Del Rio, 2005; Frondel *et al.*, 2007; Arimura *et al.*, 2007). Regarding the adoption of cleaner processes in the Spanish food industry, such as material recycling and water management processes, Cuerva *et al.* (2014) find that firm organizational capabilities - i.e. the implementation of an environmental management system - are an important driver, while no significant relationship with public support is found. The same result is confirmed in other studies on France and Germany (Belin et. al. 2011) and for the EU-27 (Triguero *et al.* 2013).

Small food firms contribute substantially to the food processing industry economic performance and are considered to play a key role in achieving sustainable economic growth in local economies.

In the EU, the food and drink sector turnover, in 2017 was 1,192 billion with 294,000 firms. The food processing industry is dealing with several challenges related to the sustainability productive processes, being a large surface water and energy user. However, as previously mentioned, it has a strong potential of decreasing energy consumption both a result of process optimization and plant system improvements (OECD, 2017; Ladha-Sabur et al, 2019).

On the same vein, we focus on the food processing industry investigating for factors that can statistically be associated with the firm's innovation process. We study the adoption of process innovation in the food processing industry in the EU, considering the role of energy prices and policies[2] role. According to the CIS 9 survey, 30% of firms in the

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[1] Process innovations are usually grouped in clean technologies and end-of-pipe technologies (Kemp and Volpi 2008; Rave et al, 2011).

[2] The main limitation of this study concerns the fact that it does not exploit the endogeneity issues; the panel is too short and the use a lagged variable may overfit the endogenous lagged dependent variable-

F&B industry that have innovated have reduced their energy consumption while 20% have contributed to reduce energy use or the CO2 "footprint" during the consumption or use of a good or service by the end-users.

Financial measures count for half of the policies addressing energy efficiency in industry. The Odyssee- MURE project shows that in many countries the policies in place include a broad mix such as co-operative measures (e.g. agreements among enterprises on energy efficiency), cross-cutting measures with sector-specific characteristics (e.g. industry eco-tax with reduced rates); fiscal/tariff measures (e.g. tax deduction for energy saving investments in businesses); information/education/training (e.g. advice programs for industry, energy management systems); legislative/informative (e.g. Mandatory execution of energy audits in large enterprises); legislative/normative (for e.g. CO2 emission fee for large emitters; new market-based instruments. About 10% of overall measures have been introduced under the Energy Efficiency Directive (2012/27/EU), especially measures introduced under Article 7 (energy efficiency obligations and/or alternative measures), mandatory audits (Article 8) and new certification/qualification schemes. Nevertheless, most energy measures are not EU-related but national measures, particularly those rated with a high impact (Odyssee-Mure, 2015).

The main questions addressed in this paper are: i) Are networking and cooperation activities between research institutions and food companies relevant in generating and promoting process innovation? ii) Is the high energy price a driver for boosting process innovation? iii) Does environmental regulation together with policy stringency stimulate the process innovation introduction? iv) If yes, what is the most effective driver?

The paper is structured as follows. Section 2 presents the hypothesis that will be tested in the model. Section 3 introduces the dataset mainly based on the Eurostat Community Innovation Survey and the empirical model. Section 4 reports the econometric estimates. Section 5 shows the main conclusions.

2. Conceptual background and hypotheses

The empirical literature on the determinants of innovations focuses on four groups of factors impacting production and innovation adoption: technological capabilities, organizational capabilities, market pull and external influences related to the regulatory push/pull and potential existence of networks (Cuerva *et al.*, 2014, Horbach, 2008, Wagner, 2009). Technological capabilities refer to knowledge resources, human skills and access to internal or external funds and are common drivers for all kinds of innovation. Organizational capabilities have a strong impact on green innovations; for example, the quality management systems adoption is often linked to the implementation of environmental management systems (Mazzanti *et al.* 2008). Market pull factors relate to consumers' preferences or customers' requirements for new products as well as the search for new niche markets. Among external innovation sources, literature considers the regulatory push/pull effect as very relevant (Rennings, 2000). Regulations have been found to be significantly more important for environmental innovation compared to other innovation (Horbach *et al.* 2012).

At the same time, government policies play a role in inducing the creation of new cleaner technologies and also in the adoption of already existing technologies by firms

(Veugelers, 2012). The EU growth strategy Europe-2020 seeks to booster innovation and collaboration across actors in the supply and innovation chains and private companies, and to strengthen cooperation among research institutions and firms, in addition to promoting more effective and efficient public financial support for innovation activities. Furthermore, the EC Green Deal Communication notes the role of new technologies in providing additional benefits in the transition to a sustainable economy.

A recent OECD (2017) study on energy efficiency in the agri-food sector identifies four broad groups of barriers: structural, behavioral, availability and policy. Structural barriers encompass issues such as limited know-how on implementing energy-efficiency measures, or fragmented and under-developed supply chains. Such barriers prevent an end-user from adopting an energy-efficient technology or practice: for example, low educational attainment and ageing farmers impede the adoption of new potentially energy-efficient technologies. Behavioral barriers include situations in which limited awareness or end-user inertia inhibit an opportunity pursuit. Inertia represents the resistance to change and risk, and the more radical the change, the higher the barrier will be (Sorrel *et al.* 2000). It can lead to preferring interventions with quick and low investments and returns, thus slightly modifying the production system with short pay-back criteria may be explained by risk aversion (Jaffe and Stavins, 1994). An unfavorable perception or treatment of risks can inflate energy-efficiency projects costs or lead to the underestimation of risks associated with changes in energy prices. Uncertainty about energy prices can also limit energy efficiency measures because of higher perceived risks. Risks management associated with energy costs and availability in agri-food businesses are largely determined by business size, with larger businesses being more likely to be proactive in managing risks from volatility in energy and commodity prices (OECD, 2017).

Availability barriers include situations in which the decision-maker is interested in and willing to innovate, but barriers, for example, a lack of capital access might prevent an upgrade to a new heating system or the availability and diffusion of technology and innovations (OECD, 2017).

Policy barriers are policy-induced market distortions which result in market conditions hindering energy efficiency. For example, energy subsidies can crowd-out public spending and private investment, encourage excessive energy consumption, reduce incentives for investment in renewable energy, and accelerate the depletion of natural resources (McKinsey and Company, 2010) i.e. encouraging more fossil fuels or energy usage intensive production .

Cagno *et al.* (2013) find that the major perceived barrier for Italian manufacturing SMEs in the food processing industry, regarding the adoption of energy efficiency technologies, is represented by high investment costs. Same or also insufficient profitability and low capital availability.

The identification of barriers to innovation is crucial for effective policy design. According to the Eurobarometer survey of SMEs in the EU (Eurobarometer, 2016), most common barriers are represented by uncertain market demand and returns. Other causes are the lack of funds or qualified personnel and in general, low technological capabilities. This barriers typology is expected to be more pervasive for SMEs, particularly in sectors with non–energy-intensive production processes (Fleiter *et al.*, 2012, Trianni *et al.*, 2013) such as the food processing industry.

Hence, we explore the following research hypotheses:

H1a) Networking and cooperation activities between research institutions and food companies are positively associated with process innovation.

Research shows that networking and cooperation effects are unclear, indeed some SMEs benefit from positive effects from cooperation to achieve innovations (De Jong and Vermeulen 2006; Van Gils and Zwart, 2004; Batterink *et al.*, 2010; Omta, 2002); while others experience problems (Hoffmann and Schlosser, 2001; Caputo *et al.* 2002; Kaufmann and Todtling, 2002). The importance of cooperation has risen steadily alongside the complexity, risk and cost of innovation activities. Innovation cooperation influences innovation activities through the pattern of collaborative relationships and partner type involved (Vinding 2002). This relationship is mutually reinforcing - external linkages facilitate innovation, and at the same time innovative outputs attract further collaborative ties (Powell and Grodal 2005). Companies that continuously cooperate with different external subjects such as suppliers, customers, competitors, and research organization improve both knowledge sharing and market knowledge acquisition by the firms, resulting in expansion of the firm's existing knowledge base, which in turn advances a firm's innovation capability (Zhou & Li, 2012). Such collaboration has been identified in literature as one of the most important external predictors of innovations (Alexiev *et al.*, 2016; Clauss and Kesting, 2017; Heirati *et al.*, 2016). In addition, a company may establish collaboration with other business partners, such as technology providers and researchers (Bigliardi and Galati, 2013). In fact, through networking, a company can extend its range of skills by an effective contractual arrangement (Martino and Polinori, 2011). Vertical cooperation offers more possibilities for innovation SMEs because cooperation is often used to acquire external know-how, in particular where firms have neither R&D employees nor the special technical requirements necessary to engage in R&D activities (Gellynck *et al.*, 2007; Gellynck and Khüne, 2010; Laperche and Liu, 2013). Collaborative innovation networks are defined when members participate in new product development and innovation processes (Alexiev *et al.*, 2016; Möller & Halinen, 2017). The role of firm network relationships and internationalization has been investigated by Cainelli *et al.* (2011) for Italian firms, finding to have a strong effect on the environmental innovations adoption by internationalized firms while being less clear for locally oriented firms.

Yet, scholars show that when firms cooperate with universities or research institutes, the overall effects on innovation capacity is positive (Hájek and Stejskal, 2018). Research also demonstrates that participating in cooperation networks makes companies more prone to undertaking sustainable oriented innovation (Melano-Levado, 2020; Klewitz and Hansen, 2013). Resorting to cooperation agreements (e.g. Cainelli *et al.* 2012; DeMarchi 2012; Del Río *et al.* 2013) and external knowledge sourcing (e.g. Del Río *et al.* 2013; Ghisetti *et al.* 2015) are thus particularly important and "complement" investments made in organizational and technological capabilities (e.g. Horbach 2008; Demirel and Kesidou 2011; Horbach *et al.* 2012).

H1b) Information is positively associated with a process innovation.

This hypothesis follows the previous one. Even in this case, several studies reveal that access to information facilitates the use of scientific knowledge, enhancing innovation and increasing the food processing industry competitiveness (Ciliberti *et al.* 2016). However, firm size matters in this regard, where small companies rely on universities or research institutes while larger enterprises might have the capabilities needed to put new ideas into practice (King et al, 2003; Ciliberti *et al.* 2016). Lasagni (2012) suggested that innovation performance in SMEs can be higher when they strongly collaborated with users, customers and suppliers. His results also showed that SMEs can be more successful in product development when they closely work with research institutes. This suggests that there can be specific types of partners preferred by SMEs. Gomez et al (2016) examine a panel of manufacturing firms in Spain to verify the extent to which the use of internal and external sources of information generate product and process innovation. Their results show that, although internal sources are influential, external sources of information are key to achieve innovation performance. Furthermore, the importance of external sources of information varies depending on the type of innovation (product or process) considered. To generate process innovation, firms mainly rely on suppliers while, to generate product innovation, the main contribution is from customers.

H2a) The higher energy price stimulates process innovation.

A relatively higher energy price in a country, as a result of country's energetic structure and energy taxation, will induce a technological change heading to higher energy efficiency. Ghisetti and Rennings (2014) found that innovation leading toward reductions in the use of energy or materials per unit output positively affect the firm's competitiveness, while externality-reducing innovations hamper the firm's competitiveness. Cainelli & Mazzanti (2013) find that policies targeting the manufacturing sector are likely to induce innovation adoption in the services sector, especially when considering innovation practices aimed at abating CO2 emissions and improving energy efficiency. Yet, the study of Popp (2002), on the standard inducement mechanism, confirms that both energy prices and the quality of knowledge exert a significant and positive effect on patenting.

H2b) Environmental Policy Measures stimulate firms' process innovation adoption.

The relevant contribution of Porter and Van der Linde (1995b) has paid attention to "Porter hypothesis", according to which a good environmental innovation can lead to an increase in firms' performance, for instance through a reduction in energy or materials use. However, since firms are not always aware of the opportunities from eco-innovation, a strict and effective environmental regulation is required in increasing this awareness. Therefore, environmental policy seems to be an important eco-innovation driver and deserves specific attention.

According to Porter and van der Linde (1995a), environmental standards can foster innovation but under three well established conditions. Firstly, they must create maximum opportunities for eco-innovation, letting the industry choose its own approach to innovation. Secondly, regulation should foster continuous improvement in any technology. Thirdly, the regulatory process should not leave uncertainty at every stage of implementation. The type of regulation or policy and the way in which it is implemented is important. It could lead firms to effectively address environmental problems. The stringency of the policy and the terms in which it is defined are equally important, since uncertainty depends on these factors. Several empirical studies (ZEW, 2001; Rehfeld at al. 2006; Reid *et al.* 2008; Belin at al. 2009) find a positive correlation between innovation and regulations. Porter and van der Linde, (1995a/b), Kemp *et al.* (2001) and Jänicke *et al.* (2002) show that strict environmental regulations stimulate innovation in several ways, such as advantages created by the development of "green" technologies. However, firms are not able to recognize the environmental innovation cost saving potentials as in the case of energy or materials savings (Horbach and Rennings, 2007). This leads many of them to believe that an environmentally virtuous behavior is a burden rather than an asset (Kemp and Andersen, 2004). Therefore, regulations and policies can be a catalyst and help them to understand the potential benefits of environmental innovations. Popp (2009) argues that in general, market-based policies are thought to provide greater incentives for innovation, as they provide rewards for continuous improvement in environmental quality. Conversely, command-and-control policies penalize polluters who do not meet the standard, but do not reward those who do better than mandated as the command-and-control regulations direct a specific level of performance.

3. Dataset, Variable and estimation methods

3.1 Data

The dataset used in the analysis is based on the biennial CIS surveys carried out from 2010 to 2014 (CIS 8 and CIS 9). The CIS questionnaire addresses several elements of firms such as size, i.e. firm's size, turnover, employees, cooperation activities, source of information, public financial supports, innovation expenditures, and innovation activities.

The CIS survey provides information on sectors innovativeness, different types of innovations and various aspects of innovation development. The survey allows to distinguish firms that can easily be categorized into innovating and non-innovating.

Table 1 reports data on process innovation implemented by enterprises across the EU-28 between 2012 and 2014. The highest proportion of enterprises that have developed process innovation is observed for Belgium (46,8%), Netherlands (33,4%), Portugal (37,2%) and Lithuania (42,3%) in 2012/2014, while rates are lower for Bulgaria, Hungary, Romania and Slovakia , ranging from 5% to 9%.

Our panel (CIS 8 and CIS 9) includes all the in the firms belonging to the food manufacturing industry (NACE Code C10-12). For data availability reasons, we have restricted the analysis to the following EU countries: Bulgaria, Cyprus, Croatia, Czech Republic, Germany, Estonia, Hungary, Italy, Lithuania, Portugal, Spain, Romania, Slovenia, Slovakia and Norway. After removing missing value, the sample contains 4618 observations which are used in the analysis.

Data on energy policy come from the MURE project (Mesures d'Utilisation Rationnelle de l'Energie)[3] which provides information on energy efficiency policies and their impact assessment in EU countries.

The score classifies the EU member states based on scoring energy efficiency policies and trends. It aims to provide comparison indicators and comparable characteristics helping countries to understand whether their policies are comparable or better than in

[3] https://www.odyssee-mure.eu

Table 1. Enterprises in the food processing industry that have introduced process innovation.

	2010/2012	2012/2014		2010/2012	2012/2014
Belgium	35.5	46.8	Lithuania*	18.4	42.3
Bulgaria*	9.6	9.2	Luxembourg	43.8	22.6
Czechia*	27.2	25.3	Hungary*	6.1	7.4
Denmark	26.8	19.0	Malta	:	29.8
Germany*	22.3	17.4	Netherlands	27.0	33.4
Estonia*	37.3	21.9	Austria	20.0	26.0
Ireland	:	51.7	Poland	8.1	8.5
Greece	29.0	30.3	Portugal*	35.8	37.2
Spain*	20.0	18.5	Romania*	5.1	5.1
France	25.0	26.3	Slovenia*	23.1	28.7
Croatia*	15.2	21.8	Slovakia*	9.1	17.3
Italy*	32.6	31.7	Finland	38.4	30.1
Cyprus*	26.9	:	United Kingdom	17.0	23.6
Latvia	21.2	14.3			

The * symbol is indicating the countries used in the analysis.
Source: Eurostat, Community Innovation Survey

other countries or whether they can learn from other countries to improve their policies. It ranges between 0 and 5, with 0 meaning "*worst*" and 5 "*best*". Countries with a lower score are Cyprus, Hungary and Croatia; conversely, Spain, Norway and Slovenia reported the highest score.

The energy price yearly data come from Eurostat database available at the following link: "https://ec.europa.eu/eurostat/web/energy/data/database". Prices are provided without taxes, with VAT and with all taxes included.

A detailed explanation of the variables definition and measurement is reported in appendix (Table A.1).

3.2 Model and estimation

The choice to adopt a process innovation is represented by a binary logit model where the dependent variable (process innovation adoption hereafter *proc_inno_adop*) is a binary variable (yes=1/no=0) based on the response – at the firm level - on the introduction of innovations in the previous three years.

Let y the dependent variable observed and the latent variable satisfying the single index model

$$y_j^* = x_j'\beta + \varepsilon_j \tag{1}$$

Even if is not observed, we do observe

$$y_j = \begin{cases} 1 \ if \ y_j^* > 0 \\ 0 \ if \ y_j^* \leq 0 \end{cases} \tag{2}$$

(0 for non-innovative firms and 1 for the otherwise). From 1 and 2 we have:

$$\begin{aligned} \Pr(y_j = 1) &= \Pr(x_j'\beta + \varepsilon_j > 0) \\ &= \Pr(-\varepsilon_j < x_j'\beta) \\ &= \mathrm{F}(x_j'\beta) \end{aligned} \tag{3}$$

Where $F(x'\beta)$ is the cumulative distribution function of $-\varepsilon_j$. The logit model specifies that cumulative standard logistic is:

$$\Pr(y = 1|x) = \frac{e^{x'_j\beta}}{1+e^{x'_j\beta}} = \frac{1}{1+e^{-x'_j\beta}} = \Lambda(x_j'\beta) \tag{4}$$

and the marginal effect is:

$$\frac{\partial p}{\partial x} = \Lambda(x_j'\beta)\{1 - \Lambda(x_j'\beta)\}\beta \tag{5}$$

Thus, we estimate the following equation:

$$proc\_inn\_adop_{it} = \alpha + \beta_1 \ln(turnover_{it}) + \beta_2 funds_{it} + \beta_3 lmarket_{it} + \beta_4 rmac_{it} + \beta_5 gnewmkt_{it} + \beta_6 orgbup_{it} + \beta_7 co_{it} + \beta_8 int\_info\_sources_{it} + \beta_9 other\_info\_sources_{it} + \beta_{10} policy\_m_{it} + \beta_{11} ep_{it} + fe_i + fe_t + \varepsilon_{it} \tag{6}$$

where *i* denotes countries, t = 2010, 2012 and fe_i and fe_t represent country and time fixed effects respectively.

The dependent variable (*proc_inn_adop*) is a dummy that has been built using three indicators of the CIS: a) INPSD which considers the introduction onto the market of a new or significantly improved production method ; b) INPSLG which considers a new or significantly improved logistic, delivery or distribution system; c) INPSSU that considers the introduction onto the market of a new or significantly improved supporting activities. It takes a value of 1 if a new or significantly improved method of process or distribution has been introduced, 0 otherwise.

We have included the following control variables chosen on the basis of their relevance for firm characteristics and strategies:

- *lnturnover*, measured as the natural logarithm of the turnover. Literature has found that size affects the propensity to innovate, emphasizing the difficulties for small and medium enterprises. Indeed, the small average size is considered one of the main barriers to innovation in Southern European countries (Garcia-Martinez and Briz, 2000; Capitanio *et al.* 2010). Yet, scholars find that farm size has a positive, albeit small, effect on innovation, which is in line with the general innovation adoption literature (Lapple *et al.*, 2015; Feder *et al.*, 1985; Sauer and Zilberman, 2012). Moreover, as highlighted in the Diederen *et al.* (2003) study, agricultural farm size explains differences in adoption. Similarly, the work of Hashi and Stojcic (2012) show that larger firms are more likely to embark, to invest on innovation activities but with decreasing innovation output depending on the firm's size;

- *funds* reflecting the availability of public support to innovation. It takes a value of 1 if enterprises have benefited from public (Regional, National, European) support to innovation and 0 otherwise. Marzucchi and Montresor (2017) note that public funding for innovation generally increases the innovation adoption and environmental innovation particularly. Hyytinen and Toivanen (2003) analyze the effects of public policy, measured by government funding, on the behavior of privately owned, small and medium sized enterprises (SMEs) in Finland. Their findings pointed out that government funding disproportionately helps innovation and growth of firms in industries that are dependent on external finance;
- *lmarket* representing firm's prevalent market. It is a dummy variable equal to 1 if firms operate in the EU/international market and 0 for national/regional market. Regarding the access to foreign markets, literature has pointed out that international has been associated with successful innovation development (Oliveira and Carvalho, 2010; Salavisa *et al.*, 2012; de Faria *et al.*, 2010; Romijn and Albaladejo, 2002);
- *orgbup* representing organizational practices. It includes new business practices or new method of organizing work responsibilities and external relationships. A part of the literature supports the view that having a structured organization is important in achieving innovation. Laursen and Foss (2003), find that interdisciplinary teams, quality circles[4], employees' proposals collection system, planned job rotation, delegation of responsibility, integration of functions and performance related significantly lead to innovation. O'Connor and DeMartino (2006) agree that organizational structure and incentive systems are key elements in the innovation success. Prester and Bozac (2012) in analyzing companies over 20 employees on the European Manufacturing Innovation Survey (EMIS) in Croatia report findings similar to Laursen and Foss (2003). Therefore, organizational practices have impact in achieving innovation.

We test our hypothesis by considering the following variables:

- *co* is the variable cooperation agreements which includes active participation among companies or institutions on innovation activities. The aim of any cooperation agreement is that of introducing external knowledge to the firms. Studies show an uncleared networking and cooperation effect. Some SMEs benefit from positive cooperation effects to achieve innovations (De Jong and Vermeulen 2006; Van Gils and Zwart, 2004; Batterink *et al.*, 2010; Omta, 2002); while others experience problems (Hoffmann and Schlosser, 2001; Caputo *et al.* 2002; Kaufmann and Todtling, 2002);
- *int_info_sources* considers the internal sources of information; it is equal to 1 if its CIS score is more than 2 and 0 otherwise. Scholars find that innovations are developed by using knowledge from a diverse set of internal and external sources of information

[4] Jones *et al.* (2008) define quality circles in a following manner: "The company uses quality circles, defined as regular meetings between employees where they discuss issues related to immediate job tasks and make suggestions to improve production processes".

(Gomez *et al.*, 2016; Amara and Landry, 2005). Furthermore, the influence of each source is different depending on the innovation type. Internal sources and suppliers are the main contributors in the case of process innovation (Gomez *et al.* 2016);

- *other_info_sources* takes into account external sources of information. It considers information from suppliers, competitors, consultant or from other sources as scientific journal, which allows firms to generate new ideas and developing innovations by merging this kind of information with their internal ones (Lefebvre *et al.*, 2015; Lee *et al.*, 2010). This variable considers all the information sources other than internal one. It takes a value of 1 if all the information sources report a CIS score more than 2 and 0 otherwise;
- *policy_m* represents the score attributed to policies and measures at national level in terms of success in achieving energy efficiency in the industry end-use sectors (see data description). Regulations and policies can be a catalyst and help firms to understand the potential benefits of environmental innovations.
- *ep* refers to yearly energy price data. Energy prices are considered together with the policy measures. We include prices with taxes in the model. A relatively higher energy price in a country will induce a technological change in favor of higher energy efficiency. (Ghisetti and Rennings, 2014; Cainelli & Mazzanti, 2013; Popp, 2002).

Descriptive statistics on selected variables used in the estimated model are shown in appendix (Table A.2).

About 64% of the considered firms have introduced process innovations. Data show the importance of internal sources of information (68%) and the machinery and equipment acquisition (52%). At the same time, most of the enterprises in the sample operate in the EU markets (89%). Only 26% of the firms in the sample are engaged in cooperation activities or received public funds for innovation (26%). Energy price (with tax) has high variability in the EU countries ranging from a minimum value of 0.07 and a maximum value of 0.25. Finally, the successful policies in energy saving show high variability ranging between 0 and 4.38.

The correlation matrix is reported in table 2. Correlations are moderate implying that there is a low collinearity risk issues and redundancies in this set of variables. All the control variables are positively correlated with the dependent variable except for "other information sources" and "energy price".

4. Results and Discussion

We have run three different models with the scope of investigating the energy policy variables effect on process innovation, (Table 3). The first one considers the main innovation process drivers and barriers and the successful policy measures (*policy_m*); the second one takes into account the effect of energy policy variables (*ep)*; while the third one considers the two policy variables effects (*ep* and *policy_m*). Most of the hypotheses are confirmed by the results with models 1, 2 and 3, satisfying all the tests.

The discussion below concerns model 3 in table 3. The variable *lnturnover* displays a positive and significant coefficient (+0.1288). This result is different from the study of Garcia-Martinez and Briz (2000) or Capitanio *et al.*, (2010), where the small average size hamper innovation. As regards to the other control variables we find a positive and sig-

Table 2. Correlation Matrix.

	Process innovation adoption (inno_proc_adop)	Internal information sources (int_info_ss)	Other information sources (other_info_ss)	Acquisition machinary (rmac)	Funds	Cooperation (co)	Business organization (orgbup)	Turnover (lnturnover)	Policy measures (pm)	Energy price (ep)
Process innovation adoption (inno_proc_adop)	1									
Internal information sources (int_info_ss)	0.1375*	1								
Other information sources (other_info_ss)	-0.1363*	0.2417*	1							
Acquisition machinary (rmac)	0.3102*	0.0928*	-0.0484*	1						
Funds	0.1677*	0.0789*	-0.0158	0.1284*	1					
Cooperation (co)	0.1841*	0.1931*	0.0424*	0.1005*	0.2466*	1				
Business organization (orgbup)	0.2585*	0.1557*	-0.0265*	0.1369*	0.1021*	0.1996*	1			
Turnover (lnturnover)	0.2036*	0.0746*	-0.2040*	0.0357*	0.1269*	0.2678*	0.2134*	1		
Policy measures (pm)	0.1119*	0.0151	-0.0185	-0.2215*	0.0085	-0.0124	0.0583*	0.0639*	1	
Energy price (ep)	-0.1534*	-0.0479*	0.2090*	-0.0901*	0.0188	-0.0639*	-0.0354*	0.0380*	-0.0541*	1

nificant influence in fostering process innovation adoption for machinery acquisition (rmac), business practices organization (orgbup) and public funds (funds). As regards to the machinery acquisition (rmac +1.8995), our result is in line with the main literature which shows that machinery acquisition foster process innovation adoption. (Ciliberti et al 2016). Business practices organization reports a positive and statistically significant coefficient (orgbup +0.8891). This result is supported by the following studies Laursen and Foss (2003); O'Connor and DeMartino (2006); Prester and Bozac (2012); while Silva *et al.* (2008) find a negative relationship between the propensity to innovate and the organizational rigidities. Public financial support for innovation seems to be a process innovation driver (+0.2613) with a positive and statistically significant coefficient. The opening of new markets (*gomkt*) and market localization (*lmarket*) report insignificant coefficient.

Focusing the discussion on the first two hypothesis, results reveal that the presence of cooperation agreements (co +0.3929) and networking activities are positively associated with innovation process. As literature points out, these activities facilitate learning about new opportunities and can improve market access and economies of scale and scope (de Faria *et al.* 2010; Cassiman and Veugelers, 2002; Lopez, 2008). Quantitative empirical studies on external knowledge sourcing provide evidence that involving a large number of external sources of knowledge in innovation is a promising choice for large firms (Lakhani *et al.* 2006; Laursen and Salter 2006).

Information sources reveal a different pathway depending on their nature. Our analysis suggests a relevant role for the internal sources (*int_info_sources +0.2622*); while the others (*other_info_sources -0.5494*) are negatively correlated with the process innovation. The impact of various information sources is not straightforward as their use can be public and private – universities, journals, conferences and suppliers among many others - which may generate costs that must be considered. In some cases, the over-search of external sources may take too much time and slow down the innovation process. Additionally, excessive reliance on external information sources can increase coordination and monitoring costs and could affect the creation of knowledge stocks within the firm. Comparing results with existing literature, we find that the information sources affect the generation process innovation as in Ciliberti et al 2016. However, this finding is dissimilar to other empirical evidence which shows that firms should always look for external information which can then be embodied into innovation (Köhler *et al.* 2012; Costa *et al.* 2015). In some cases in acquiring external information, companies demonstrate openness and ability to scan the market and identify opportunities which allow them to be more efficient in implementing innovation and decrease the risk of product failure (Stewart-Knox and Mitchell 2003; Avermaete *et al.* 2004; Wei and Wang 2011). As underlines by Tether and Tajar 2008; Lee *et al.* 2010, diverse information sources (from suppliers, competitors, consultants) are complementary and, if merged with the existing knowledge, allow to create new knowledge useful for innovation.

The third and fourth hypothesis have tested through the impact of the implementation at the country level of energy saving policy measures *(policy_m)*. The positive and statistically significant coefficient of *policy_m* (+3.3934) indicates that energy policies adopted by EU countries boost innovation. Firms innovated, i.e. adopting new or making changes to the organization of the productive process. Very similar is the energy price effect (*ep +7.8284*), which clearly shows that a high energy price is an incentive to modify

Table 3. Logit regression result from panel data.

	(1) Proc_inn_adoption	(2) Proc_inn_adoption	(3) Proc_inn_adoption
Proc_inn_adoption			
lnturnover	0.1274***	0.1288***	0.1288***
	(0.0243)	(0.0244)	(0.0244)
funds	0.2605**	0.2613**	0.2613**
	(0.0994)	(0.0992)	(0.0992)
lmarket	-0.0088	-0.0087	-0.0087
	(0.0865)	(0.0865)	(0.0865)
rmac	1.8986***	1.8995***	1.8995***
	(0.0903)	(0.0903)	(0.0903)
gnewmkt	0.0599	0.0517	0.0517
	(0.0376)	(0.0381)	(0.0381)
co	0.3934***	0.3929***	0.3929***
	(0.1073)	(0.1073)	(0.1073)
orgbup	0.8888***	0.8891***	0.8891***
	(0.0919)	(0.0918)	(0.0918)
Inte_info_sources	0.2620**	0.2622**	0.2622**
	(0.0896)	(0.0896)	(0.0896)
Other_info_sources	-0.5122***	-0.5494***	-0.5494***
	(0.1208)	(0.1237)	(0.1237)
policy_m	1.9569**		3.2951**
	(0.8876)		(1.133)
ep		7.8284*	7.8284*
		(4.5457)	(4.5457)
N	4645	4645	4645
adj. R^2	0.41	0.40	0.40
chi2	1191.8519	1196.1113	1196.1113
BIC	4559.1268	4564.8505	4564.8505
VIF	1.20	1.21	1.21

Time dummies and country dummies are included in the model. Standard errors in parentheses. Variable statistically significant at $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ respectively.

the productive process. Our results are also consistent with what is found in Rennings and Rammer (2009) revealing that process innovations are more strongly aimed at cost reduction, since increasing energy and/or material efficiency are associated with lower costs per unit. On the same vein, Popp (2002) exposes the strong and positive impact energy prices on new innovations. Similarly, Rennings *et al.* (2008), Del Rio Gonzalez (2005) find that regulation pressure and corporate image are the main drivers for adopting green technologies in the Spanish pulp and paper industry.

Table 4 merges the results of the model with the underlying hypothesis, showing that the model performs reasonably well, with energy policy, cooperation activities, financial public supports, and technical capabilities play an important role in creating a favourable environment for processes innovation.

Table 4. Merging Hypothesis and results.

Hypothesis	Results
H1a) Networks and cooperation activities promote process innovation	**YES** ⇒ + and significant
H1b) Sources of information stimulate process innovation	**Internal** ⇒ **YES** ⇒ + and significant **Other** ⇒ **YES** ⇒ - and significant
H2a) Successful policies measures stimulates firm to introduce process innovation	**YES** ⇒ + and significant
H2b) Energy price is positively associated with process innovation	**YES** ⇒ + and significant

4.1 Robustness Check

In order to test the robustness of our results, further elaborations are provided (Table 5). Results were confirmed when we ran the logit model considering the original variables of the CIS survey instead of the transformed variables used in section 3. Again, cooperation, information sources, policy variables and energy price, are positively associated with process innovation. Results were also confirmed when we used variables acting as barriers instead of drivers.

The estimated models are consistent; indeed, the impact of most explanatory variables is statistically significant and different from zero. Results of the confusion matrix[5], which describes how many actual and predicted values exist for different classes predicted by the model, indicate that the model fit quite well with both estimation techniques having a percentage of corrected classified value about 78% (Table A.3 in appendix).

Results from VIF test suggest that variables are uncorrelated with each other. Tolerance is different from zero and the variance inflation is low.

Evidence of good fit is reflected in a ROC curve (figure 1 in appendix), the area under the ROC curve is equal to 0.83 meaning that 83% of the observations are correctly classified.

5. Conclusions

The food processing industry is a sector mainly constituted by SMEs, with a low propensity to adopt process innovation. It represents one of the four sectors that consumes more energy in Europe although, at a large extent, it is not considered energy intensive and therefore covered by the EU Emissions Trading System (ETS); it also is considered to have a high energy saving potential. A major barrier that literature finds is the low importance attributed to energy consumption in non-energy intensive industries as in the case

[5] A confusion matrix is a table used to describe the performance of a classification model on a set of test data for which the true values are known. It tells us how many actual values and predicted values exist for different classes predicted by the model.

Table 5. Robustness Logit estimation.

	(1) Proc_inn_adoption	(2) Proc_inn_adoption	(3) Proc_inn_adoption
Proc_inn_adoption			
lnturnover	0.1163***	0.1100***	0.1052***
	(0.0248)	(0.0255)	(0.0259)
funds	0.0878	0.0881	0.0902
	(0.0992)	(0.0996)	(0.0996)
lmarket	-0.0453	-0.0343	-0.0449
	(0.0885)	(0.0889)	(0.0893)
rmac	1.5594***	1.5537***	1.5553***
	(0.0914)	(0.092)	(0.092)
gnewmkt	-0.0017	0.0011	-0.0001
	(0.039)	(0.0393)	(0.0392)
orgbup	0.7801***	0.7812***	0.7771***
	(0.0929)	(0.0936)	(0.0937)
ssup	0.3931***	0.3991***	0.3996***
	(0.0431)	(0.0433)	(0.0433)
scom	-0.0871	-0.0888	-0.089
	(0.0452)	(0.0456)	(0.0456)
sins	0.1445**	0.1416**	0.1395**
	(0.0478)	(0.0479)	(0.048)
co	0.2694*	0.2749*	0.2677*
	(0.1071)	(0.1078)	(0.1079)
policy_m	4.8399***	4.5146**	4.4198**
	(1.2369)	(1.3724)	(1.3801)
ep	15.4363**	15.3776**	15.0575**
	(4.8897)	(4.8956)	(4.9124)
obsprs		0.0219	0.0241
		(0.0455)	(0.0454)
obsfin		-0.0441	-0.0429
		(0.0384)	(0.0384)
empedu			0.1113
			(0.1003)
N	4425	4398	4398
adj. R-sq	0.346	0.34	0.34
chi2	998.4058	994.3702	999.5503
BIC	4358.8634	4345.35	4352.528

Time dummies and country dummies are included in the model. Standard errors in parentheses. Variable statistically significant at * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ respectively.

of food processing industry. Another barrier is the lack of high expected returns ad short payback times. Furthermore, SMEs have limited access to information, low energy share on their expenditures, too high transaction costs for fund searching, cost disadvantages in obtaining or developing innovation. All these problems need to be specifically addressed by policy measures. In particular, small food firms contribute substantially to the food processing industry economic performance and are considered to play a role in achieving sustainable economic growth in local economies. Nevertheless, the small size of the industries and their less energy intensive use clarifies why it is difficult to apply energy policy measures and, why the optimization process is often not a priority for company managers.

Being among the largest users of surface water and energy among the manufacturing sectors, the food processing industry needs to reduce its energy consumption and improve its energy efficiency. However, changes in energy efficiency are often difficult because they depend on several factors such as the energy used technical performance, the importance of energy trans-formations, climate conditions, the structure of each economic sector that uses energy (MEDENER, 2013).

In this study, we have addressed the following issues: a) the role of cooperation agreements between food processing industries and research institutes in promoting process innovation adoption; b) whether or not the high price of energy encourages process innovation adoption; c) whether or not the environmental regulation and the severity of the policies stimulate process innovation adoption; d) which of these two factors, energy price and successful policy measures, are the most effective tool in promoting process innovation adoption. Through our models, we have addressed the issues related to process innovation adoption in the EU food processing industry. As regards to the first two hypotheses, namely the role of cooperation and network activities, on the one hand (H1a) and the role of information (H1b), our study confirms that cooperation agreements encourage SMEs to adopt new process innovations. Networking activities in this regard are relevant because they allow SMEs to acquire all the knowledges that is unavailable within the firm. The role of different information sources is uncertain. Indeed, the internal sources availability seem to encourage the adoption of new processes innovation. External sources information availability shows a negative sign that could be due to the higher costs related to the acquisition of this kind of knowledge and the manager's or owners' attitudes.

Concerning the role energy policy, results confirm the key role of energy prices and energy policies, with the energy price coefficient having a higher weight.

Furthermore, results confirm the role and the relevance of drivers like financial resources availability at the enterprise level, the presence of new organizational methods, the positive role of R&D firms' engagement and cooperation activities. These are important findings, in particular, if we consider that SMEs have limited access to information, low energy share on their expenditures, too high transaction costs for fund searching, cost disadvantages in obtaining or developing innovation.

Our results support previous research in identifying the main areas for policy action. Process innovation adoption in the food processing industry could be enhanced by measures addressed to:

- information cost reduction in order to support informed choices. One example is the support energy auditing in SMEs as a tool to track energy consumption and costs throughout a facility and identify opportunities to reduce energy use, increasing entrepreneurs' awareness.
- Contrasting the low private investment in R&D in SMEs for process and energy saving innovations through public-funded R&D or promoting enterprises aggregation

in networks. This action can take several forms research public of financing activities that require partnership with the private sector including technology providers and or facilitating partnership agreements between sectoral entrepreneurs and technology providers.

- Promoting policy coherence in EU policies impacting on energy use and innovation i.e. CAP, EU Cohesion policies, Energy and Climate policies as well the Bioeconomy and the Circular economy Strategies.
- Reinforcing the role of partnership tools along the whole supply chain in the agri-food sector enhancing cooperation towards sustainable production, thus creating the necessary conditions by which green labels could deliver and increase the demand for sustainable products.
- Considering that policy instruments are located at different government levels (EU, MS, regional or local) when dealing with the appropriate policy mix, and increase policy coherence through the whole governance system in which policy tools operate (Borràs and Edquist 2013).

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APPENDIX

Table A.1. Variables' description.

Variable CIS	Description	Variable in the model	Re-coded Variable	Expected sign
INPSPD	Introduced onto the market a new or significantly improved method of production	Dependent Variable: process innovation adoption	dummy variable: 0=No; 1=Yes	
INPSLG	Introduced onto the market a new or significantly improved logistic, delivery or distribution system			
INPSSU	Introduced onto the market a new or significantly improved supporting activities			
TURN	Total turnover	Size	total turnover in euros	+
FUNDS	Public funding from local or regional authorities	External Financial capacity	dummy variable: 0=No; 1=Yes	+
MOTHER	Local/regional market (within country)	lmarket	dummy variable: 0=No; 1= Yes	+
RMAC	Acquisition of machinery	RMAC		+
GOMKT	Increase market share	GOMKT		+
ORGBUP	New business practices for organizing work or procedures	ORGBUP	dummy 0= No , 1=Yes	+
CO	Cooperation arrangements on innovation activities	Cooperation activities	dummy variable: 0=No; 1=Yes	+
SENTG	Sources from within the enterprise or enterprise group	Int_info_sources	dummy variable: 0=not important; 1=important	+
SSUP	Suorces from suppliers of equipment, materials etc	other_info_sources	dummy variable: 0=not important; 1=important	+
SCOM	Sources from Competitors and other enterprises of the same industry			
SINS	Sources from consultants, commercial labs or private R&D institutes			

Variable CIS	Description	Variable in the model	Re-coded Variable	Expected sign
SUNI	Sources from Universities or other higher education institutes			
SCLUP	Clients or customers from the public sector			
SCON	Sources from professional conferences, trade fairs, meetings			
SJOU	Sources from Scientific journals, trade/ scientific publications			
SPRO	Sources from Professional and industry associations			
Policy_m	Energy saving successful policy measures	Policies	0<score<4.389	+
ep	Energy price (including not-refundable taxation)		value of energy price Euros/kw	+

Source: CIS 2010 - 2012.

Table A.2. Descriptive statistics of the Panel sample.

Variable	Obs	Mean	Std. Dev	Min	Max
proc_inn_adop	4,651	0.641	0.480	0	1
lmarket	4,646	0.890	0.313	0	1
rmac	4,651	0.526	0.499	0	1
co	4,651	0.258	0.438	0	1
orgbup	4,651	0.344	0.475	0	1
gnewmkt	4,651	2.009	1.105	0	3
turnover	4,651	42400000	141000000	12645	3.10E+09
int_info_sources	4,651	0.697	0.459	0	1
others_info_sources	4,651	0.1163	0.320	0	1
funds	4,651	0.258	0.438	0	1
ep	4,651	0.118	0.036	0.07045	0.2504
policy_m	4,651	3.539	0.939	0	4.389
year	4,651	2010.722	0.961	2010	2012

Source: CIS 2010 - 2012.

Table A.3. Confusion Matrix.

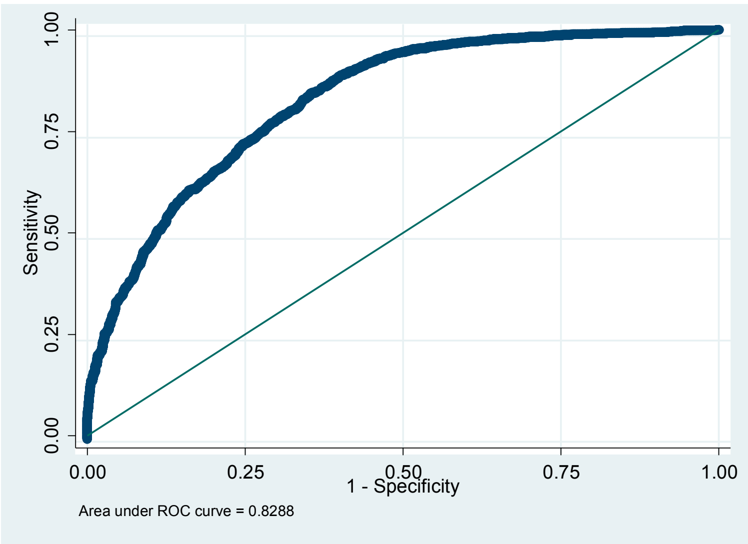
Classified	True		Total
	D	~D	
+	2726	730	3456
-	254	935	1189
Total	2980	1665	4645

Classified + if predicted Pr(D) >= .5
True D defined as dipend_1 != 0

Sensitivity	Pr(+| D) 91.48%
Specifity	Pr(-|~D) 56.16%
Positive predictive value	Pr(D| +) 78.88%
Negative predictive value	Pr(~D|-) 78.64%

False + rate for true ~D	Pr(+|~D) 43.84%
False - rate for true D	Pr (-| D) 8.52%
False + rate for classified +	Pr(~D|+) 21.12%
False - rate for classified -	Pr(D| -) 21.36%
Correctly classified	78.82%

Figure 1. ROC Curve.



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Full Research Article

Step-by-step development of a model simulating returns on farm from investments: the example of hazelnut plantation in Italy

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Abstract. Recent literature reviews of empirical models optimizing long-term investments in agriculture see gaps with regard to (i) separating investment and financing decisions, (ii) considering explicitly risk and temporal flexibility, and (iii) accounting for farm-level resource endowments and other constraints. Inspired by real options approaches, this paper therefore stepwise develops a model extending a simple net present value calculation to a farm-scale simulation model based on mathematical programming, which considers time flexibility, different financing options and downside risk aversion. We empirically assess the different model variants by analysing investments into hazelnut orchards in Italy outside of traditional producing regions. The variants suggest quite different optimal results with respect to scale and timing of the investment, its financing and the expected NPV. The stepwise approach reveals which aspects drive these differences and underlines that considering temporal flexibility, different financing options and riskiness can considerably improve traditional NPV analysis.

Keywords. Perennial crop; real options; stochastic dynamic modelling; stochastic optimization.

JEL codes. C61, Q12.

1. Introduction

Recent literature reviews on empirical models for long-term investment analysis see gaps with regard to separating investment and financing decisions (e.g., Trigeorgis and Tsekrekos, 2018) and explicit consideration of associated risk and temporal flexibility (e.g., Shresta *et al.*, 2016). Furthermore, opportunity costs, farm-level resource endowments, multiple risk sources and risk preferences are also rarely taken into account. This paper

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illustrates how to include all these aspects into farm-level investment analysis and highlights resulting differences based on an empirical example of investing into hazelnut trees.

The vast majority of research modelling farm-level investment behaviour opts for the classical investment theory, which maximizes the net present value (NPV) or alternatively the internal rate of return (IRR), or minimizes the pay-off period, subject to technological and resource constraints (e.g., Schweier and Becker, 2013; Shresta *et al.*, 2016; Bett and Ayieko, 2017). Two major limitations of this approach are well known (among others see Freixa *et al.*, 2011; Robinson *et al.*, 2013; Badiu *et al.*, 2015; Sgroi *et al.*, 2015; Stillitano *et al.*, 2016). First, the risk underlying the investment project is not explicitly represented and can be reflected only by increasing the discount rate above market levels. Other data determining cash-flow changes of the operation related to the investment enter with their expected values, only, neglecting their riskiness including potential correlations. Second, the classical investment theory depicts a "now exactly as defined or never" decision problem where neither future adjustments to the investment project under, for instance, changing market, policy or technological environments, nor its postponement are considered. This easily overestimates necessary investment triggers and thus suggests a lower investment scale (Wolbert-Haverkamp and Musshoff, 2014). The new investment theory aims to overcome these limitations. In particular, the application of the real options approach to agricultural investment projects has gained interest (e.g., Wossink and Gardebroek, 2006; Hinrichs *et al.,* 2008; Maart-Noelck and Musshoff, 2013; Spiegel *et al.,* 2020). But its empirical application is still limited, for instance, in the domain of perennial crops. While quantitative analysis of investments into perennial crops has a long history (e.g., Jackson, 1985), it mainly sticks to the classical investment theory. Despite considerable market and production risk in orchard production, only a few recent studies, such as Sojkova and Adamickova (2011), consider risk. Not astonishingly, they find substantial differences in optimal investment levels compared to the classical NPV approach and suggest that deterministic models may provide flawed estimation of investment dynamics and scale.

Consideration of risks in investments is also beneficial for their social and behavioural analysis. Social analysis mainly focuses on social networks and their effects on investment decision, for instance, via learning experience (Marra *et al.*, 2003; Ghadim *et al.*, 2005). Dynamic social analysis is more promising and benefits from explicit consideration of risks, as learning and social interactions usually affect not only expectations, but also associated subjective risk; and optimal behaviour was found to be sensitive to strategic uncertainty (Morreale *et al.*, 2019). Behavioural investment analysis studies subjective factors, including irrationality, subjective beliefs, and risk attitude (see e.g., Chavas and Nauges, 2020; Weersink and Fulton, 2020). Also here, explicit consideration of risks in dynamics is beneficial as it allows adjusting risk perception and risk preferences (Coelho *et al.*, 2012). As for optimal financing behaviour, many studies investigate with other methods different aspects and determinants of farm-level demand for credits, such as present risk management strategies (Katchova, 2005), credit source (Farley and Ellinger, 2007), interest rate (Turvey *et al.*, 2012; Fecke *et al.*, 2016), farmer's personal characteristics and farm structural variables (Howley and Dillon, 2012). While financing behaviour is found to affect farm performance, financial risk, resilience, and their links to investment behaviour is still understudied.

Building on this literature, we develop models for valuing and analysing long-term investment decision on farm, starting with a simple net present value calculation. We stepwise expand this model to a final dynamic stochastic farm-scale simulation model inspired by real options approaches, which considers different financing options and downside risk aversion in the form of minimum household withdrawals. To this end, the paper focuses on economic analysis of farm-level investment and financing options, while some social and behavioural aspects might be incorporated in follow-up research as discussed in the concluding chapter. Accordingly, the objectives of the paper are twofold. First, we aim to illustrate how additional investment drivers can be stepwise incorporated into models of increasing complexity, and second, we aim to demonstrate sensitivity of results across the model variants to underline their relevance. The novelty of the paper is threefold. First, we explicitly consider factors that are still widely ignored when modelling farm-level investment decision, namely temporal flexibility, flexibility in terms of financing options, and downside risk aversion of the farm household. Second, we stepwise introduce these factors to quantify their impact on optimal scale and timing of investments in a case study. Third, the case study refers to perennial crops, a domain where advanced quantitative assessments are lacking.

Hazelnut production was chosen for the empirical application. It presents an interesting case study as it requires long-lasting expensive investments in form of a plantation, specialized machinery and irrigation. The different models are all set up for the same case study farm located in Viterbo, a central Italian region, where hazelnut production is not traditional, but becomes an increasingly important agricultural activity. The farm is assumed to currently manage rainfed annual crops. It is representative by its size and farm program for farms that are investing into new hazelnut plantations in the region. Since hazelnut production was found to be characterized by a relatively high level of risks (Zinnanti *et al.*, 2019), we explicitly quantify considerable market (Pelagalli, 2018), weather, and other production risks affecting product quality and quantity.

Taking hazelnut production in the Viterbo region as an example is motivated by further facts. Firstly, with 13% of global hazelnut production, Italy is the second largest producer worldwide after Turkey with ca. 65% (FAO, 2019). Global demand for hazelnut and derived products increased over the last decades and is projected to expand further. This triggers new investments in different producing countries, partially initiated by international food industry companies, of which a major one is located nearby our case study region. In Italy, further expansion of hazelnut orchards in the traditional hilly production districts under rainfed systems is not possible. New plantations are now set-up in surrounding lower areas where irrigation is necessary to ensure relatively stable production and quality levels. Over the years 2016-2019, the Italian National Institute for Statistics (ISTAT) recorded a 15% increase in the total area devoted to hazelnut cultivations. Further investments are likely in coming years, according to major companies involved in hazelnut-based food production which foresee and foster the cultivation of 90.000 hectares in Italy alone. The trend of investing into hazelnuts as an alternative land use option also reflects decreased profitability of so far dominating annual crops such as grains and oilseed. Both socio-economic and environmental consequences of this ongoing land use change are lively debated (Boubaker *et al.*, 2014; UTZ, 2016). So far, economic assessments of investments into hazelnuts at farm level draw on data from specialized producers in the traditional districts, only. Several authors therefore stress the need to better evaluate investments in new producing regions (Bobic *et al.*, 2016; Pirazzoli and Palmieri, 2017; Frascarelli, 2017). The empirical analysis conducted in this paper closes the gap.

The paper is organized as follows. Section 2 step-by-step develops four models where each one expands the previous one by relaxing some assumptions to further improve the analysis. Section 3 introduces data and assumptions used in our case study which also shows the additional data required for the model expansions. Section 4 presents main empirical results to highlight differences across the model variants. Section 5 concludes with a discussion of pros and cons of the different model variants and provides suggestions for further research on farm investments.

2. Building-up a stochastic dynamic farm-level model

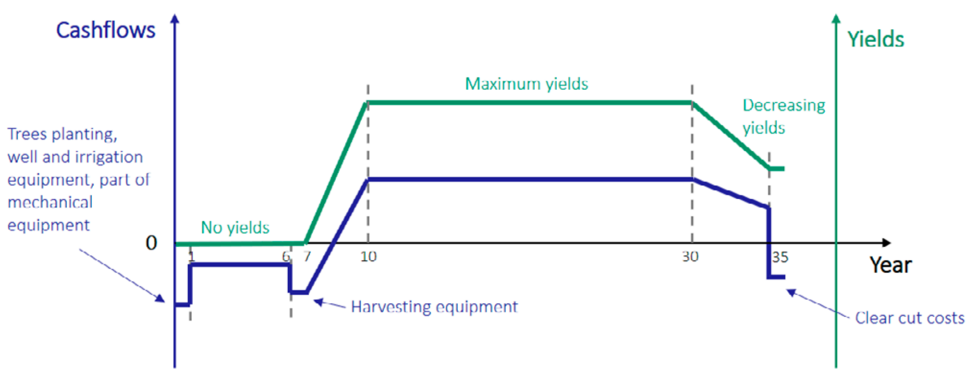
2.1 Farm-level endowments, economy-of-scale and alternative crop (ClassNPV)

We start with simulating discounted cash flows at farm level for either investing now or never – the still dominant approach in literature. In the case of hazelnuts, the nominal cash flows in each year depend on the age of the plantation (Fig. 1).

A newly set-up hazelnut orchard can be first harvested in its seventh year. From there to the tenth year, yields increase linearly from zero to a maximum yield level (*max-Yields*) which is maintained until the trees are thirty years old. Afterwards, there is a linear decrease in annual yields to 50% of the maximum up to the year 35. The resulting formula for the yields in year y is:

$$yield_{hazel,y} = \begin{cases} 0 & \forall\, y \le 6 \\ 0.2 * (y-6) * maxYields & \forall\, 6 < y \le 10 \\ maxYields & \forall\, 10 < y \le 30 \\ 0.1 * (40-y) * maxYields & \forall\, 30 < y \le 35 \end{cases} \tag{1}$$

Figure 1. Evolution of a new hazelnut orchard, with related investments points. Source: Own elaboration based on Liso *et al.* (2017) and Frascarelli (2017).



where y depicts the year after the initial set-up and thus the age of the plantation; $yield_{hazel,y}$ the hazelnut yields at age y in tonnes per hectare [t ha^{-1}]; $maxYields$ refers to the maximum hazelnut yield [t ha^{-1}].

Multiplying hazelnut yields with their price and deducting variable costs defines the gross margin per hectare. We capture the difference between the farm-gate and the average regional market price *marketPrice* by so-called quality index *qi*, which reflects specific quality of hazelnuts, farmer's negotiation power, and other related factors. Both the quality index and the market price are represented in the NPV calculation by their expectations. We also distinguish between harvesting costs per tonne harvested, and other costs per hectare, which include irrigation and fertilization costs. At each age of the plantation y, the cash flow per hectare equal to the gross margin is thus defined as:

$$E[gm_{hazel,y}] = yield_{hazel,y} * E[qi_{hazel,y}] * E[marketPrice_{hazel,y}] - yield_{hazel,y} * harvCost - otherCost \qquad \forall\ y \leq 35 \tag{2}$$

where $E[\cdot]$ is the expectation operator; $gm_{hazel,y}$ stays for the gross margin of hazelnuts [€ ha^{-1}]; $qi_{hazel,y}$ for the hazelnuts quality index; $marketPrice_{hazel,y}$ for the average market price of hazelnuts [€ t^{-1}]; *harvCost* for the variable harvesting costs [€ t^{-1}]; *otherCost* for the other quasi-fixed costs related to hazelnut cultivation, including irrigation and fertilization costs [€ ha^{-1}]. Furthermore, we consider two (quasi-)fixed resources endowments: land and labour. Additional demand for labour can be satisfied via hired labour. The farm resources are distributed between hazelnuts and durum wheat - an alternative crop to hazelnuts. The acreages of hazelnut and durum wheat can jointly not exceed the given land endowment:

$$area_{hazel} + area_{wheat} \leq \overline{end_{land}} \tag{3}$$

where $area_{hazel}$ depicts land under hazelnuts [ha] and $area_{wheat}$ land devoted to durum wheat [ha]; $\overline{end_{land}}$ stays for the total fixed and given land endowment [ha].

Labour requirement for the crops are expressed per hectare; for hazelnuts, additional labour hours per harvested tonne are considered. Total labour requirement can be covered by on-farm or hired labour:

$$area_{wheat} * \overline{lab_{wheat}} + area_{hazel} * \overline{lab_{hazel}} + area_{hazel} * yield_{hazel,y} * \overline{lab_{hm}} \leq end_{lab} + hiredLab_y \qquad \forall y \tag{4}$$

where $\overline{lab_{wheat}}$ stays for labour requirements for durum wheat [hours per hectare, h ha^{-1}]; $\overline{lab_{hazel}}$ for quasi-fixed (i.e., independent of yields) labour requirements for hazelnuts [h ha^{-1}]; $\overline{lab_{hm}}$ for variable labour requirements for hazelnuts [hours per tonne, h t^{-1}]; end_{lab} for on-farm labour use [hours, h]; $hiredLab_y$ for additionally required labour that can be hired [h]. The gross margin of the alternative crop is defined in a similar way as the one of hazelnuts, namely, based on expected yield, quality index, market price and variable costs:

$$E[gm_{wheat}] = E[yield_{wheat}] * E[qi_{wheat}] * E[marketPrice_{wheat}] - E[cost_{wheat}] \tag{5}$$

where gm_{wheat} stays for gross margin of durum wheat [€ ha^{-1}]; $yield_{wheat}$ for its yields [t ha^{-1}]; qi_{wheat} for its quality index; $marketPrice_{wheat}$ for its average market price wheat [€ t^{-1}]; and $cost_{wheat}$ for its quasi-fixed costs [€ ha^{-1}].

While durum wheat is rain-fed, hazelnuts require irrigation water, such that farmers have to invest into a well and irrigation equipment in addition to the establishment costs of the plantation (Fig. 1). Furthermore, harvesting machinery for hazelnuts must be available prior to the first harvesting of hazelnuts. Harvesting machinery is physically depreciated while other machinery is depreciated by lifetime. The formula for NPV then becomes:

$$E[NPV] = \left(-iniCost + \sum_y \frac{E[gm_{hazel,y}]}{(1+dr)^y} - \frac{reconvCost}{(1+dr)^{35}}\right) * area_{hazel} + \sum_y area_{wheat} * \\ * E[gm_{wheat}] - invCostWell - \sum_y \frac{\sum_m invCostMach_{m,y} + hiredLab_y * E[wage]}{(1+dr)^y} \tag{6}$$

where NPV stays for the net present value over the overall planning horizon $\sum_y$ [€]; $iniCost$ for the costs associated with initial establishment of hazelnut plantation [€ ha^{-1}]; dr for the discount rate [%]; $reconvCost$ for the costs associated with final clear-cut of hazelnut plantation [€ ha^{-1}]; $invCostWell$ for costs of well and irrigation equipment for hazelnut [€]; $invCostMach_{m,y}$ for investment costs of machinery m{*smaller;standalone;irrigation;tractor; operating*} [€]; $E[wage]$ for expected costs of hired labour [€ h^{-1}]. We optimize the farm-level NPV under endowment constraints (Eq. 3 and 4) by solving for the following decision variables: area of hazelnuts, area of durum wheat and investments into machinery m at each age of the plantation y.

The model advances by accounting for all required investments as well as resource endowments. It also captures the associated economy-of-scale; in our example, via lifetime and capacities of machines and via fixed costs for a well and irrigation equipment. In another case study, the gross margin of the alternative land use option could also represent average returns from a portfolio of alternative crops instead of one crop, only, as in here durum wheat. As the result, we simulate the maximum possible farm-level NPV under given conditions and constraints.

This model still suffers from limitations as seen in literature. First, it operates with expected variables, ignoring their underlying riskiness when maximizing the NPV. Second, it implies investing into hazelnuts now or never. Yet, in the case of uncertainty and high sunk costs of an investment project, investors might prefer to wait for new information before making a decision. Here, sunk costs relate to setting up the plantation and investments into a well, irrigation equipment and specialized machines while future prices, yields, and costs are uncertain, and the first yield is generated only seven years after the investment. These circumstances might create an additional value of waiting and of getting more information, such as on price developments of hazelnut, and motivate using the real options instead of a classical NPV approach.

2.2 Risk and flexibility in timing (RealOpt)

Spiegel *et al.* (2018; 2020) demonstrate the advantages of stochastic-dynamic programming for farm-level investment analysis, since it also considers risks besides (quasi-fixed) assets, such as land and on-farm labour already found in the model *ClassNPV* above, and addresses both time and scale flexibility as elements of a real-options approach. Spiegel *et al.* (2018; 2020) overcome the curse of dimensionality found in binary lattices or similar scenario tree approaches by employing a scenario tree reduction technique. Building on their work, we transform the *ClassNPV* model developed in the section above into a stochastic-dynamic farm-level model. In contrast to Spiegel *et al.* (2018; 2020), we consider a second replantation period in order to expand the finite planning horizon so far in the future that differences to an infinite one become marginal from a numerical perspective.

We assume the following aspects of management flexibility. The farmer can decide during the first five years to introduce hazelnut or to continue cultivating durum wheat as an alternative annual crop (*time flexibility 1*). After reaching an age between thirty-two and thirty-five years, the hazelnut trees must be removed; afterwards the land can be either planted again with new hazelnut trees or cropped with durum wheat (*time flexibility 2*). The subsequent plantation must be closed down again after thirty-two to thirty-five years (*time flexibility 3*). This results in a finite planning horizon of seventy-five years such that differences between an infinite and this finite planning horizon should be negligible for any reasonable private discount rate. In order to increase computational speed, we divide the total land endowment into distinct plots of sizes 2^n with $n = 0,1,2\ldots$ which in combination allow any integer plantation size between 0 and the land endowment (*scale flexibility*). Using fixed plot sizes instead of a continuous fractional plantation size allows for a mixed integer program instead of a mixed non-linear integer one. Integers are needed anyhow to capture indivisibilities in investment (well, machinery). Time flexibility is considered separately for each plot.

Differences compared to the previous model *ClassNPV* are threefold. First, we consider now not only the expected values of stochastic variables, but also the associated riskiness. More specifically, all expected values are replaced by probability distributions or stochastic processes, represented by a scenario tree. Each node of the tree contains a vector of stochastic variables' realizations. Second, we now distinguish between the time period and the age of the plantation. In the previous simpler model, hazelnuts could only be planted in the first year such that the plantation's age was equal to the year. Due to the time flexibility in *RealOpt* model, time and plantation age become two different dimensions as the time flies regardless of the farmer's decision to introduce hazelnuts or not. Accordingly, a plantation now can consist of plots of different age. As a consequence, in the expanded model, decision variables and risky parameters carry now both a time and node indices, such that the gross margins of both crops are defined as follows:

$$gm_{hazel,p,t,n} = ha_{hazel,p,t,n} * [\, yield_{hazel,p,t,n} * qi_{hazel,t,n} * marketPrice_{hazel,t,n} - yield_{hazel,p,t,n} * harvCost - otherCost] \tag{7}$$

$$gm_{wheat,t,n} = yield_{wheat,t,n} * qi_{wheat,t,n} * MarketPrice_{wheat,t,n} - cost_{wheat,t,n} \tag{8}$$

where $gm_{hazel,p,t,n}$ stays for the gross margin of hazelnuts [€ ha^{-1}] on plot p in time period $t\{t_1,t_2,\ldots,T\}$ and node of the scenario tree n; $yield_{hazel,p,t,n}$ for hazelnut yields [t ha^{-1}] on plot p in time period t and node of the scenario tree n. The hazelnut yield depends on the difference between current year t and the year $\tilde{t}$ when they were planted on this plot on the same path from the root to the current node n according to Eq.(1). $ha_{hazel,p,t,n}$ stays for a binary variable of devoting a plot p into hazelnuts in time period t and node of the scenario tree n (1 = the plot is cultivated with hazelnuts; 0 = otherwise); $qi_{hazel,t,n}$ for the hazelnuts quality index in time period t and node of the scenario tree n; $marketPrice_{hazel,t,n}$ for the market price of hazelnuts in time period t and node of the scenario tree n [€ t^{-1}]; $gm_{wheat,t,n}$ for gross margin of durum wheat [€ ha^{-1}] in time period t and node of the scenario tree n; $yield_{wheat,t,n}$ for yields of durum wheat [t ha^{-1}] in time period t and node of the scenario tree n; $qi_{wheat,t,n}$ for quality index of durum wheat in time period t and node of the scenario tree n; $MarketPrice_{wheat,t,n}$ for the market price of durum wheat [€ t^{-1}] in time period t and node of the scenario tree n; $cost_{wheat,t,n}$ for quasi-fixed costs for durum wheat [€ ha^{-1}] in time period t and node of the scenario tree n.

The farm's operating income is thus defined as follows:

$$\begin{aligned} operInc_{farm,t,n} &= area_{wheat,t,n} * gm_{wheat,t,n} + \sum_p size_p * gm_{hazel,p,t,n} - \sum_p ini_{p,t,n} * iniCost * \\ size_p &- \sum_p reconv_{p,t,n} * reconvCost * size_p - invWell_{t,n} * invCostWell - \sum_m invMach_{m,t,n} * \\ invCostMach_m &- hiredLab_{t,n} * wage_{t,n} \qquad \forall t,n \end{aligned} \tag{9}$$

where $operInc_{farm,t,n}$ stays for farm's operating income in time period t and node of the scenario tree n [€]; $area_{wheat,t,n}$ for land area under durum wheat in time period t and node of the scenario tree n [ha]; $size_p$ for the size of the plot p [ha]; $ini_{p,t,n}$ for a binary variable of exercising the initial establishment of a hazelnut plantation on plot p in time period t and node of the scenario tree n (1 = hazelnuts are introduced; 0 = otherwise); $reconv_{p,t,n}$ for a binary variable of exercising clear-cut of hazelnuts plantation onto a plot p in time period t and node of the scenario tree n (1 = hazelnuts are clear-cut; 0 = otherwise); $invWell_{t,n}$ for a binary variable of exercising investments into a well and irrigation equipment in time period t and node of the scenario tree n (1 = investments into a well and irrigation equipment are exercised; 0 = otherwise); $invMach_{m,t,n}$ for a binary variable of exercising investments into required machinery m in time period t and node of the scenario tree n (1 = investments into machinery are exercised; 0 = otherwise).

The discounted operating income is the objective variable to be maximized, defined as follows:

$$NPV = \sum_{t,n} prob_n * \frac{operInc_{farm,t,n}}{(1+dr)^t} \tag{10}$$

where $prob_n$ stays for the probability of the node to occur [percentage points].

At each node of the constructed scenario tree, the model takes into account available time and scale flexibility, the state of the stochastic variables, as well as resources endowments, and provides the following output:

- Land distribution between hazelnuts and durum wheat. Observing changes in land distribution between different nodes of the tree allows to observe (re)planting decisions, as well as decisions to expand or clear-cut hazelnut plantations;
- Investments into a well and harvesting and other machinery for hazelnuts, the latter differentiated by size;
- Related economic variables such as costs and revenues.

Although the *RealOpt* model is fairly complex and presumably closer to real world decisions on investments, it has still two major drawbacks considering gaps found in literature. First, due to high costs related to the initial investments, the farmer will face considerable negative cash flows during the first years after a plantation is set up. Related costs for financing are most probably underestimated by the average discount rate in the model. Second, the model neglects downside risk aversion, while the production cycle of hazelnuts implies significant negative cash flows in several time periods and related financing costs. We address these drawbacks stepwise in the two final models.

2.3 Costs of financing (RealOptFin)

The *RealOptFin* model introduces a current account of the farm operation. It serves as the source to cover variable and investment costs and receives subsidies and the operating income from selling products. In order to finance investments beyond accumulated cash, the model considers different types of loans with fixed repayment times and interest rates. The benefit for the farmer from the farm operation is represented now by annual profit withdrawals from the current account of the farm, discounted by his private discount rate. Accordingly, the private discount rate now does not longer need to reflect the costs of financing. Instead, the market based discount rate is implicit and endogenously determined depending on the financing decisions.

The farmer now optimizes the expected net present value of future profit withdrawals from the farm operation, considering simultaneously investment and financing decisions. Farm operating income *operInc* enters the current account as follows:

$$curAcc_{t,n} = \sum_{n1-n=1} curAcc_{t\text{-}1,n1} + operInc_{farm,t,n} - withdraw_{t,n} + \sum_{loans} newLoans_{loans,t,n} - \sum_{loans} repaym_{loans,t,n} - \sum_{loans} intpaym_{loans,t,n} \qquad \forall t, \tag{11}$$

where $curAcc_{t,n}$ stays for the current account in the year t and node n [€]; $withdraw_{t,n}$ for annual farm household withdrawals [€]; $newLoans_{loans,t,n}$ for the loans acquired in the year t and node n [€]; $repaym_{loans,t,n}$ for the debt to-be-paid in the year t and node n [€]; and $intpaym_{loans,t,n}$ for the interest to-be-paid in the year t and node n [€]. The household withdrawals are defined for each combination $\{t,n\}$ based on investment and financing decisions.

The reader should note that introducing endogenous financing decisions implies and requires a more accurate simulation of cash flows. In particular, if the previous two models could omit cash flows independent of investment decisions, such as decoupled subsidies under the Common Agricultural Policy's (CAP) first pillar, all cash flows related to the farm operation have to be included now, since they affect the required financing. The operating income is hence defined as:

$$operInc_{farm,t,n} = area_{wheat,t,n} * gm_{wheat,t,n} + \sum_{p} size_p * gm_{hazel,p,t,n} - \sum_{p} ini_{p,t,n} * iniCost$$
$$* \; size_p - \sum_{p} reconv_{p,t,n} * reconvCost * size_p - invWell_{t,n} * invCostWell$$
$$- \sum_{m} invMach_{m,t,n} * invCostMach_m - hiredLab_{t,n} * waget,n + end_{land} * prem \qquad \forall t,n \quad (12)$$

where *prem* stays for the Common Agricultural Policy (CAP) first pillar direct payments [€ ha^{-1}].

The discounted household withdrawals are now the objective variable to be maximized and defined as follows:

$$NPV = \sum_{t,n} prob_n * \frac{withdraw_{t,n}}{(1+dr)^t} \qquad (13)$$

2.4 Downside risk aversion (RealOptFinRisk)

Explicitly considering profit withdrawals allows introducing a lower limit of income from the farm operation such as to ensure household survival. This limit also acts as risk floor. The previous *RealOptFin* model assumes such minimum withdrawals to be zero, i.e. there are combinations of years and nodes possible where the household will not receive any income from the farm. This is likely to occur especially in the first years after setting up the plantation where high investment costs coincide with zero or low yields of hazelnuts. Our final *RealOptFinRisk* model instead assumes a minimum withdrawal level in each year and each node of the scenario tree. It is calculated by multiplying the level of the farm resource endowments with assumed minimum risk-free returns:

$$withdraw_{t,n} \geq end_{lab} * minWage + end_{land} * prem \qquad (14)$$

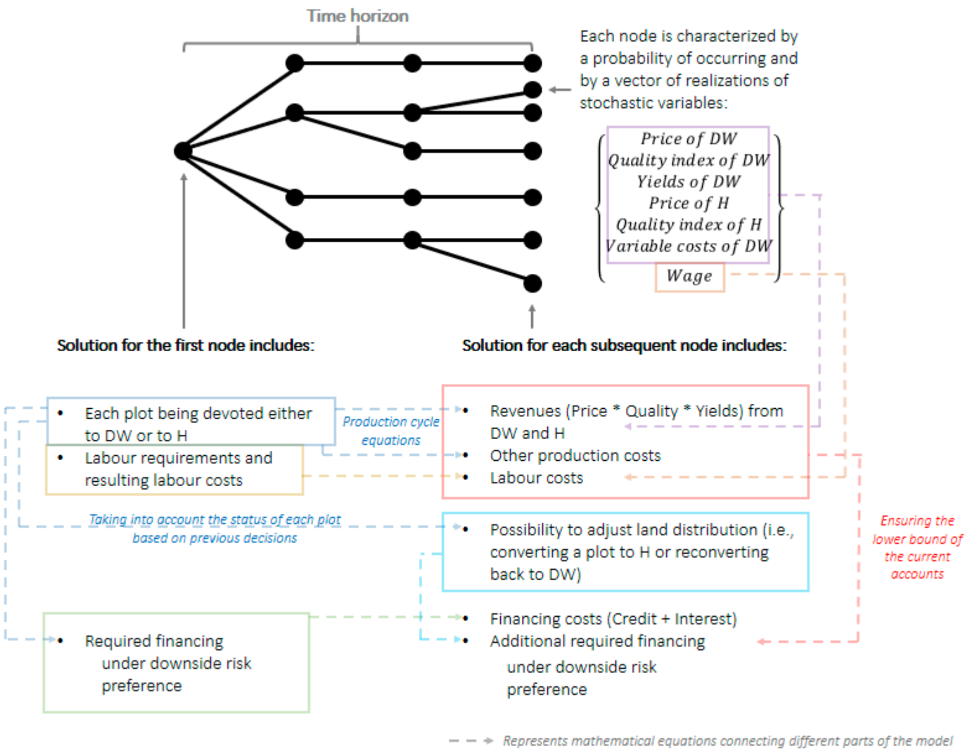
where *minWage* is a minimum risk-free off-farm wage [€ h^{-1}]. Similar, the minimum withdrawal limits above assumes that the farmer would be able to receive at least the premium of the first pillar of CAP as returns to its land, for instance, by renting it out. Different assumptions to define minimum withdrawals could clearly be chosen.

Financing and deciding on the annual withdrawals are hence also measures of risk management. While we ensure that the amount of new long-term loans cannot exceed investment costs in a year – assuming that bank will link such loans to a business plan – short-run loan and postponed withdrawals allow flattening the impact of stochastic operational cash flows from the farm on household withdrawals, i.e. income. The reader should note further that we assume that the quality indices, yields and prices of hazelnut and durum wheat are not correlated. Combining arable farming and a hazelnut plantation thus by itself reduces risk due to natural hedging.

We consider a lower limit on annual household withdrawals as a rather transparent and easy to communicate measure of risk aversion. Changing the limit in sensitivity analysis can help to inform a decision taker on the trade-offs between ensuring a minimum income level under any potential future development and his expected discounted income level. It does not require to introduce explicitly a risk-utility function in the framework above which is another avenue to develop the model further, for instance, to introduce behavioural aspects.

Figure 2 graphically represents the model variant and its major components. Each node of the scenario tree contains a vector of realizations of the seven stochastic variables. These realizations enter the calculations of net revenues in each node of the tree, which also reflect set-up and removal decisions with respect to hazelnuts made in this one and its ancestor nodes. These decisions translate into the future according to the production cycle and determine required future financing, as well as future costs of adjusting these production decisions. Financing decisions need to ensure minimum household withdrawals and a non-negative current account. The model simultaneously solves for optimal behaviour in all its nodes, maximizing the net present value (Eq. 13) under endowment and other constraints.

Figure 2. Graphical representation of the *RealOptFinRisk* model's major components and relations between them.



Note: H stays for hazelnuts; DW stays for durum wheat.

2.5 Comparison of the models

Fig. 3 and Table 1 below give an overview on the four model variants. *ClassNPV* calculates discounted annual cash flows at farm level under the assumption to convert a part of land into hazelnuts now or never, i.e. it considers scale flexibility under endowment constraints. Consequently, it also considers that additional labour might be needed depending on available farm family labour and the chosen investment program. *RealOpt* adds time flexibility, i.e., it captures and optimizes returns from investments at different time points, drawing on a real options approach. That model is next expanded to *RealOptFin* by introducing a difference between the private discount rate, used by the farmer to discount cash flows, and the costs of financing investments, i.e. it also optimizes financing decisions. *RealOptFinRisk* finally ensures that the farm household can withdraw in each year a minimum sum of money from the farming operation. It is also worth to mention that *ClassNPV* does not require a scenario tree as only the expected realizations are needed in each time period. However, the tree realizations can be used post-model to report on the riskiness of the NPV optimized without considering risk.

Figure 3. Comparison of components of the four model variants.

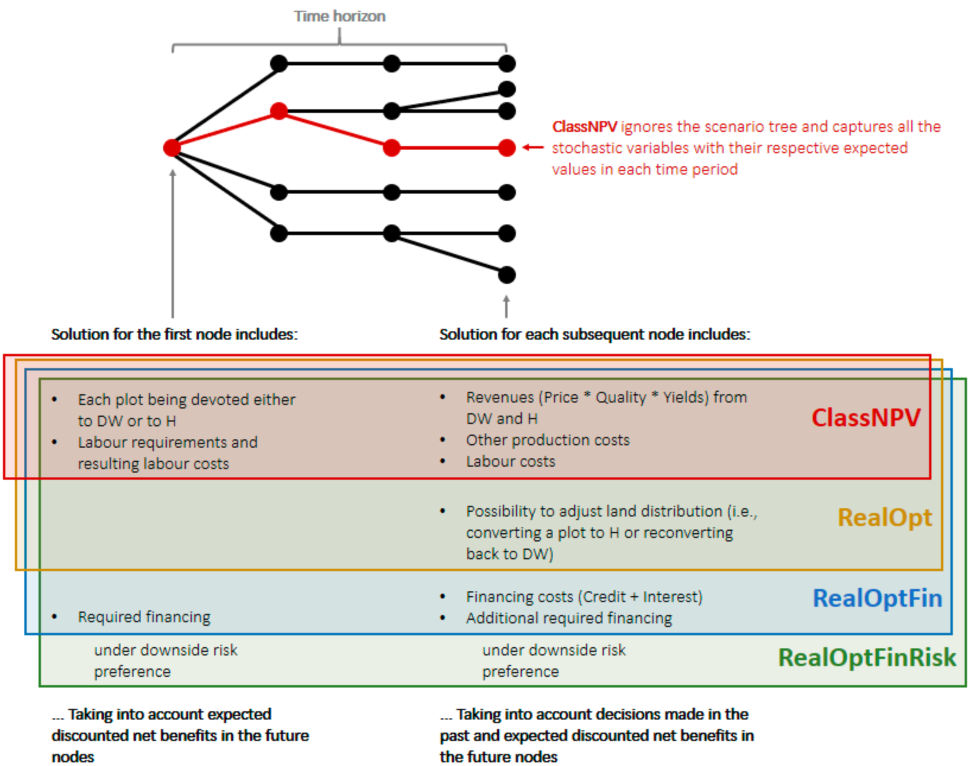


Table 1. Comparison of the four model variants.

		ClassNPV	RealOpt	RealOptFin	RealOptFinRisk
(i)	Production cycle	Yes	Yes	Yes	Yes
(ii)	Spatial flexibility	Yes	Yes	Yes	Yes
(iii)	Economy-of-scale	Yes	Yes	Yes	Yes
(iv)	Resources endowments	Yes	Yes	Yes	Yes
(v)	Time flexibility	No	Yes	Yes	Yes
(vi)	Optimising financing costs	No	No	Yes	Yes
(vii)	Downside risk preferences	No	No	No	Yes

2.6 Solution approach

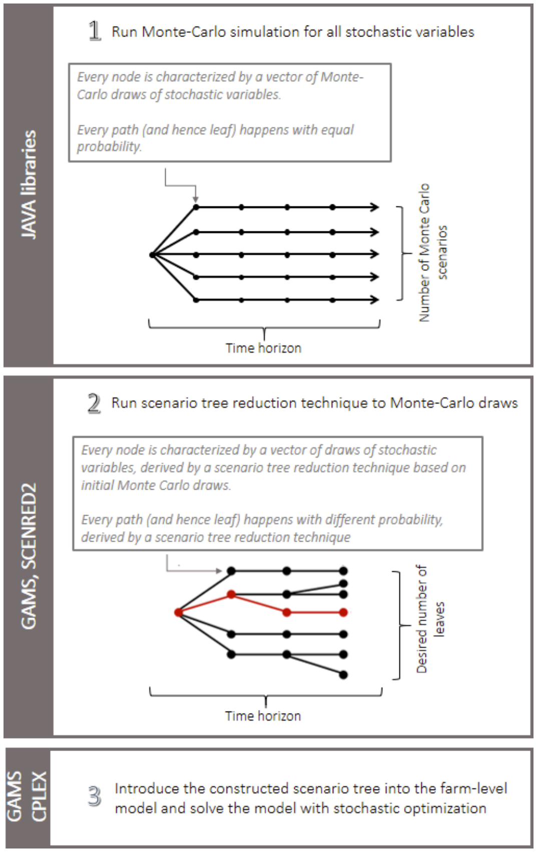
We use the solution approach suggested by Spiegel *et al.* (2018; 2020), which combines Monte-Carlo simulation, a scenario tree reduction technique, and stochastic-dynamic programming (Fig. 4). First, 5’000 Monte-Carlo draws are obtained for all the stochastic variables, using empirically predefined stochastic processes and distributions. Jointly this results in a huge scenario tree with 5’000 equally probable independent paths and a realization vector for the seven stochastic variables in each node. This step is done in Java based on standard libraries and own developed code to overcome speed limitations in GAMS. The GAMS-package SCENRED2 by Heitsch and Römisch (2009) reduces this scenario tree in the second step. The underlying scenario reduction technique merges selected paths and nodes and provides new outcomes (i.e., the expected mean of merged outcomes) and the respective probabilities (i.e., the thickness of merged paths). The relation between nodes across time in a scenario tree is captured by an ancestor matrix, generated by SCENRED2. The final step combines the obtained scenario tree with the farm-level model and solves for the optimal investment behaviour using stochastic programming. Due to manifold dynamic relations between endogenous variables, all nodes on the same path to a final leave are interrelated. As all paths start with from the same root node, that implies that all nodes need to be simultaneously solved. The code of scenario tree composition and the farm-level model is available online.

3. Data and parameters

The parameters of the model draw on multiple data sources, including the Italian Farm Accountancy Data Network (FADN-CREA), Eurostat, World Bank, Census data (ISTAT, 2010), agricultural output prices (ISTAT, 2018) and the Italian Central Bank, as well as available literature (Frascarelli, 2017; Liso, 2017; Ribaudo, 2011) and expert judgement. The FADN data are only available for the period 2008-2016; the data from ISTAT, Eurostat, and the World Bank were selected for the period 2000-2016. All monetary values were deflated using the GDP deflator for Italy provided by the World Bank (2015=100) to ensure comparability over time.

Traditionally, hazelnut orchards were found in a specific district of the Viterbo province, only, which is specifically suitable for hazelnut cultivation but nowadays doesn’t offer

Figure 4. Graphical representation of the solution process. (Source: based on Spiegel *et al.*, 2018; 2020).



any additional space for new hazelnut cultivation. Therefore, new investments are located in municipalities close by, following a gradient of falling hazelnut yields depending on soil characteristics, climate conditions and often higher irrigation requirements, which mostly depends on the distance to the traditional growing zone. Data have been retrieved from the individual farm FADN database (2008-2016) considering only 21 municipalities of the province of Viterbo[1] (Lazio region) where hazelnut represents a limited share of the Utilized Agricultural Area according to 2010 Census data (less than 5%), but which have recently experienced relevant relative increases due to new plantations. We furthermore filter FADN data to account for two factors. First, observations referring to years at or close after the establishment of hazelnut plantations were excluded to reflect that no yields occur in the first six years

[1] Arlena di Castro, Bassano in Teverina, Blera, Castel Sant'Elia, Celleno, Civita Castellana, Gradoli, Graffignano, Marta, Monte Romano, Montefiascone, Monterosi, Oriolo Romano, Orte, Piansano, Tuscania, Vejano, Vetralla, Villa San Giovanni, Vitorchiano in Tuscia, Viterbo.

after planting (Frascarelli, 2017). Second, only observations above 1 ha are included to neglect non-commercial activities in form of "hobby farms". The regional focus and the two filters led to 62 observations in total. Census data suggest a representative farm size of 30 ha, and, for the considered municipalities, cropping of rain-fed arable crops with durum wheat as the dominant one as the benchmark before considering a hazelnut plantation.

Table 2 provides an overview of the parameter values and underlying data sources. For durum wheat and hazelnuts, expected yields are derived from the FADN sample based on total production and area. Since there is no information on the age of the respective plantations, we corrected the resulting average hazelnut yields by a coefficient of 1.25 and assumed it to be the maximum hazelnut yields. That coefficient reflects the average relation between the maximal yield and the yield developments depicted in Eq.(1). Also, due to limited data on hazelnut yields, we assume no riskiness in maximum hazelnut yields *maxYields* and the yields derived thereof $yield_{hazel,p,t,n}$. Instead, stochasticity in hazelnut production is captured by a stochastic quality index and market price. In order to estimate the expected market prices of unshelled hazelnuts and durum wheat, the market prices in Italy provided by ISTAT (for hazelnuts) and Eurostat (for durum wheat) were used.

Furthermore, we correct the expected hazelnut price derived from historical observations by a multiplicative coefficient of 1.18. Assuming higher future prices seems appropriate due to increasing global demand of hazelnut, while production is expanding into less suitable production areas with a lower yield potential and higher costs, such caused by the required irrigation. Furthermore, all four models suggest no investments at all into hazelnuts under the expected historical price level. This contradicts observed farmers' behavior, and suggests that farmer expect higher future prices. We used sensitivity analysis to find a suitable future expected mean price level where some but not all land was devoted to hazelnut in at least one of the models, reflected by the factor of 1.18.

For quality indices, the FADN data were used to derive annual per unit farm specific prices of hazelnuts and durum wheat by dividing crop revenues by sold quantities. These calculated farm-gate prices were normalized by the market prices in Italy provided by ISTAT (2018) for hazelnuts and durum wheat to define samples of farm specific quality indices.

We differentiate two sizes of a specialized harvester for hazelnuts between which the model can chose endogenously. The cheaper harvester is drawn by a tractor ordinarily used for other activities. The more expensive self-driving harvester reduces per ha labour needs and has a longer lifetime measured in harvested area.

Compared to the *ClassNPV* model, the other models require converting expectations of stochastic variables into stochastic processes or distributions. All the stochastic variables are assumed to be mutually independent, i.e. a correlation coefficient between any two stochastic variables of zero is chosen. In particular, the market prices of hazelnuts and durum wheat are captured by uncorrelated mean-reverting stochastic processes defined as follows:

$$dprH_t = \mu_{hazel} \, (\theta_{hazel} - prH_t)dt + \sigma_{hazel} \, dW_t^{hazel} \tag{15}$$

$$dprDW_t = \mu_{wheat} \, (\theta_{wheat} - prDW_t)dt + \sigma_{wheat} \, dW_t^{wheat} \tag{16}$$

where t is the time period; *hazel* indicates hazelnuts and *wheat* durum wheat; prH_t is the natural logarithm of hazelnuts price; $prDW_t$ the natural logarithm of durum wheat price;

Table 2. Overview of parameters of the four models, their assumed values, and respective references.

Model	Parameter	Notation used in equations above[1]	Value	References
ClassNPV	Expected yields of durum wheat	$E[yield_{wheat}]$	3.9 t ha^{-1}	FADN
	Expected variable costs of durum wheat	$E[cost_{wheat}]$	371.75 € ha^{-1}	FADN
	Expected market price of durum wheat	$E[marketPrice_{wheat}]$	237.22 € t^{-1}	Eurostat, Word Bank
	Expected market price of hazelnuts	$E[marketPrice_{hazel}]$	2,549.66 € t^{-1}	ISTAT, Word Bank
	Expected quality index of durum wheat	$E[qi_{wheat}]$	0.9247	FADN, ISTAT
	Expected quality index of hazelnuts	$E[qi_{hazel}]$	0.9817	FADN, ISTAT
	Expected wage of hired labour	$E[wage]$	10 € h^{-1}	Local collective contracts for hired labour
RealOprFinRisk RealOptFin RealOpt	Available annual labour endowment	end_{lab}	350 h	Own elaborations
	Available land endowment	end_{land}	30 ha	FADN
	Hazelnut establishment costs	$iniCost$	8,000 € ha^{-1}	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Investments for a smaller harvesting machinery	$invCostMach_{smaller}$	8,000 €	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Labour requirements for a smaller harvesting machinery		32 h ha^{-1}	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Maximum land area that can be harvested per year with a smaller harvesting machinery		5 ha	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Total endowment for a smaller harvesting machinery			
	In terms of lifetime		12 years	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	In physical terms		2,000 h	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Investments for a stand-alone harvesting machinery	$invCostMach_{standalone}$	40,000 €	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Labour requirements for a stand-alone harvesting machinery		15 h ha^{-1}	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Maximum land area that can be harvested per year with a smaller harvesting machinery		15 ha	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Total endowment for a smaller harvesting machinery			
	In terms of lifetime		12 years	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	In physical terms		3,000 h	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Other labour requirements for hazelnut (excl. labour required for harvesting machines)			

Model	Parameter	Notation used in equations above[1]	Value	References
	Age of plantation: below 7 years (without production)		49.5 h ha^{-1}	Expert based information
	Age of plantation: equal to or more than 7 years		89.5 h ha^{-1}	Expert based information
	Variable harvesting costs of hazelnuts	*harvCost*	50 € t^{-1}	Ribaudo, 2011
	Other production costs of hazelnuts, incl.	*otherCost*	1,700 € ha^{-1}	Expert based information
	Costs of fertilization and chemical treatments		800 € ha^{-1}	Expert based information
	Operational costs for other machinery (excl. harvesting)		600 € ha^{-1}	Expert based information
	Irrigation costs		300 € ha^{-1}	Expert based information
	Investments into a well	*invCostWell*	12,000 €	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Investments into irrigation equipment for hazelnuts	$invCostMach_{irrigation}$	2,000 € ha^{-1}	Liso *et al.*, 2017; Ribaudo, 2011; Frascarelli, 2017
	Investments into tractor	$invCostMach_{tractor}$	20,000 €	Expert based information
	Lifetime of tractor		20 years	Ribaudo, 2011
	Investments into operating machinery for hazelnuts	$invCostMach_{operating}$	10,000 €	Expert based information
	Lifetime of operating machinery		10 years	Ribaudo, 2011
	CAP direct payment	*prem*	300 € ha^{-1}	Own elaboration
	Annual discount rate	*dr*	2%	Own elaboration
	Laplace distribution for yields of durum wheat (see Appendix for further details)			
	Mean		3.9120	FADN
	Standard deviation		1.1984	FADN
	Expected maximum yields of hazelnuts	*maxYields*	2.9 t ha^{-1}	FADN
	Mean-reverting stochastic process for natural logarithm of market price of durum wheat (see Appendix for further details)	$marketPrice_{wheat}$		
	Long-term mean		5.4690	Eurostat, Word Bank
	Speed of reversion		3.1053	Eurostat, Word Bank
	Standard deviation		0.4808	Eurostat, Word Bank
	Starting value		5.4036	Eurostat, Word Bank

Model	Parameter	Notation used in equations above[1]	Value	References
	Mean-reverting stochastic process for natural logarithm of market price of hazelnuts (see Appendix for further details)	$marketPrice_{hazel}$		
	Long-term mean		7.6782	ISTAT, Word Bank
	Speed of reversion		0.9219	ISTAT, Word Bank
	Standard deviation		0.1933	ISTAT, Word Bank
	Starting value		8.0669	ISTAT, Word Bank
	Laplace distribution for quality index of durum wheat (see Appendix for further details)	qi_{wheat}		
	Mean		0.9817	ISTAT
	Standard deviation		0.2580	ISTAT
	Laplace distribution for quality index of hazelnuts (see Appendix for further details)	qi_{hazel}		
	Mean		0.9247	ISTAT
	Standard deviation		0.2398	ISTAT
	Gamma distribution for variable costs of durum wheat (see Appendix for further details)	$cost_{wheat}$		
	Shape		3.8286	FADN
	Scale		97.098	FADN
	Uniform distribution for costs of hired labour	$wage$		
	Minimum		7.50 € h^{-1}	Expert based information
	Maximum		12.50 € h^{-1}	Expert based information
	Annual interest rate for			
	Short-term credit [1 year]		7%	Own elaboration
	Middle-term credit [5 years]		6%	Own elaboration
	Long-term credit [10 years]		5%	Own elaboration
	Minimum off-farm risk-free wage rate	$minWage$	6 € h^{-1}	Expert based information

[1] Indices *y*, {*t*,*n*} and {*p*,*t*,*n*} are omitted for simplicity.

μ the speed of reversion; θ the long-term logarithmic average level of price; σ the standard deviation; and dW_t^{hazel} the standard Brownian motion independent from dW_t^{wheat}. Other stochastic variables, namely a quality index of hazelnuts and a quality index, yield and variable costs of durum wheat are captured by distributions that were selected based on Akaike Information Criteria (AIC) (Akaike 1998) using @RISK software. More details on deriving the stochastic processes and distributions based on historical data are presented in the Appendix.

4. Results and discussion

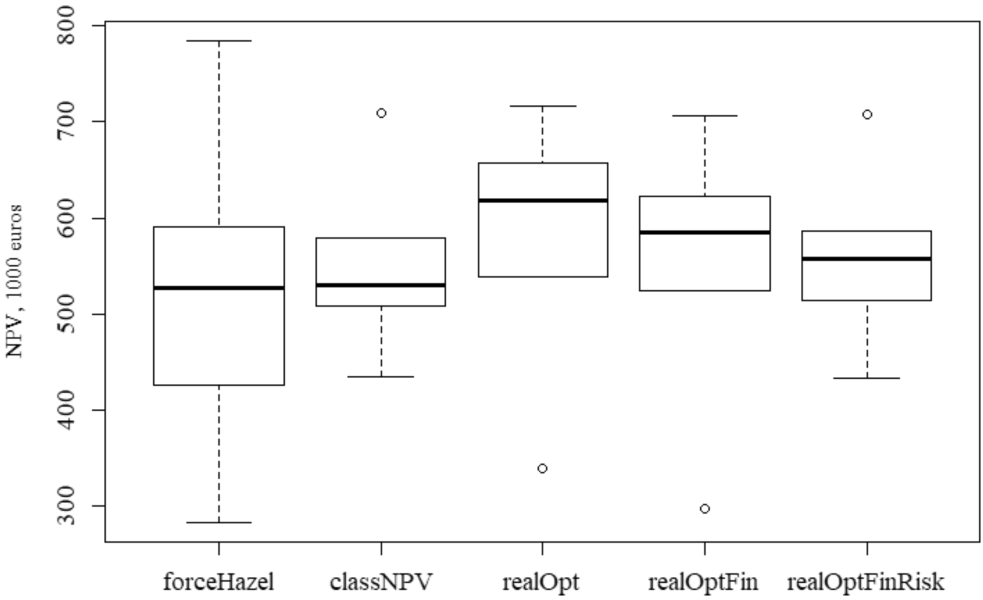
We focus in this section on differences between the models with respect to key results: scale and timing of optimal hazelnuts introduction, expected NPV, as well as financing decision (Table 3). In particular, according to the *ClassNPV* model, hazelnuts cannot compete with the representative alternative arable crop durum wheat. Accordingly, the expected NPV of *ClassNPV* (rows 4-5 in Table 3) reflects returns from cultivating durum wheat only and hazelnuts are never introduced. In contrast, a hazelnut plantation might be set-up in later years in the *RealOpt* model which considers temporal flexibility. Specifically, that model suggests that a land share of about 48% of hazelnuts in the second year or later is optimal. This does not imply that in any future stochastic scenario hazelnuts are cultivated. Temporal flexibility means that the farmer can wait, observe how the stochastic environment evolves, and take an investment decision depending on which node of the scenario tree is realized in the future. The 48% is hence an expected share. Row 2 in Table 3 reports the earliest time point where any hazelnuts are introduced (if at all). While both *RealOpt* and *RealOptFin* imply waiting at least for two years before setting up the first time a plantation, *RealOptFinRisk* suggests even longer postponement as the minimal year profit withdrawal is increased from zero in *RealOptFin* to opportunity costs reflecting off-farm wages and renting out land. Durum wheat exceeds these opportunity costs in any year and node, but hazelnuts do not. Accordingly, the *RealOptFinRisk* model has to postpone investments until hazelnuts are only introduced on such nodes where the minimal income of farming exceeds opportunity costs. For the remainder of the stochastic tree, only durum wheat is cropped. Compared to *RealOpt* or *RealOptFin*, this implies a lower average discounted household income at however reduced downside risk.

The temporal flexibility introduced in *RealOpt* allows increasing the expected NPV by 9.5% compared with the *ClassNPV* model. Note that generally the NPV can never decrease when additional flexibility is considered if all other assumptions are equal. Explicitly considering the costs of financing in *RealOptFin* slightly decreases the competitiveness of hazelnuts and reduces the NPV by 4.4% compared with the *RealOpt* model. That means that the discount rate used in *RealOpt* underestimates the true costs of financing under assumed loan conditions. Yet, considering downside risk aversion in the *RealOptFinRisk* model has an even stronger effect: only around 6% of the total land is converted to hazelnut in the third year or later. The expected NPV drops by 8.2% compared with the *RealOpt* model and by 3.9% compared with the *RealOptFin* model. However, the expected NPV under *RealOptFinRisk* still slightly exceeds the one of the *ClassNPV* model by 0.6%. Fig. 5 compares the riskiness of the resulting NPV in the four models described above, plus the *forceHazel* variant which forces immediate conversion of the whole farm

Table 3. Comparison of empirical results of different models.

		ClassNPV	RealOpt	RealOptFin	RealOptFinRisk
(1)	Expected area under hazelnuts, % of total farm land endowment	-	48.07	40.80	6.03
(2)	Time period when introducing hazelnuts for the first time	-	(in 2 years)	(in 2 years)	(in 3 years)
(3)	Is earlier reconversion applied?		yes	yes	yes
(4)	Expected NPV at farm-level, €	541,740.32	593,267.05	567,052.33	544,800.89
(5)	Expected NPV per hectare, € *[calculated as (4) divided over the total farm land endowment]*	18,058.01	19,775.57	18,901.74	18,160.03
(6)	Used harvesting machine(s)	-	Large	Large	Large
(7)	Total expected amount of new loans over the planning horizon, €			Short: 110,534.94 Middle: 2,602.33 Long: 1,720,204.63	Short: 140,573.06 Middle: 11,792.54 Long: 432,047.90
(8)	Total expected amount of interest paid, €			481,262.14	130,775.94

Figure 5. Distributions of maximized net present values in the five model variants, incl. *forceHazel* – an additional model variant that forces immediate conversion of the whole farm into hazelnuts. The *forceHazel* model assumes no financing constraint, as it has no feasible solution otherwise. Both *forceHazel* and *classNPV* models ignore the associated risk and treat all the stochastic variables as their expectations, yet we recovered the riskiness of resulting NPVs based on the optimal behaviour that the models suggest.



into hazelnuts. The *forceHazel* model considers no financing options, as otherwise it has no feasible solution. The *forceHazel* model is therefore similar to the *classNPV* model except for having no scale flexibility. The models *forceHazel* and *classNPV* hence represent the two corner solutions: the former suggests devoting all resources to hazelnuts, the latter to the alternative crop. Both deterministic models *forceHazel* and *classNPV* ignore any risk by using expected values, only, for any stochastic variable related to both hazelnuts and the alternative crop durum wheat. We however recovered the associated riskiness in resulting NPVs post-model by applying the optimal behaviour in both models to the constructed scenario tree (Fig. 5). One can observe that hazelnuts imply much more risk of the resulting NPV, while also leading to a slightly lower expected NPV (compare *forceHazel* and *classNPV* in Fig.5). In contrast, the other three models directly report the riskiness of the NPV and consider it when searching for the optimal investment and financing behaviour. While *realOpt* and *realOptFin* are quite similar in terms of the spread of the NPV, the model *realOptFinRisk* clearly outputs a less risky NPV due to its lower limit on annual household withdrawals, however as noted already above, at the costs of a lower expected NPV (Fig. 5). The *realOpt* and *realOptFin* show some outliers (indicated as dots in the box-and-whisker charts) with quite low NPVs that are removed at the *RealOptFinRisk* model, which however also considerably reduces upside risk.

Figure 6 visualizes the riskiness of the four models in greater details. *ClassNPV* implies no hazelnuts and reflects the moderate riskiness of durum wheat cultivation, only. The upper panel shows that quite clearly, as the cloud with the points showing the different outcomes for the farm income is quite dense. In contrast, *RealOpt* implies much more risky withdrawals, including considerable positive and negative outliers. Moreover, annual withdrawals implied by *RealOpt* echo the production cycle of hazelnuts: negative withdrawals in the beginning of the time horizon (establishment of the first plantation) and between time periods 35 and 40 (establishment of the second plantation), combined with high positive withdrawals that are associated with periods of maximum yields of the hazelnut plantation.

Both models with financing (the lower part of Fig. 6) cut off the negative withdrawals by covering them with short-term credits or by not withdrawing all profits in some years, i.e. using a retained profit position. Without these internal and external financing options, a lower limit of household withdrawals of zero or above in any year under all potentially considered futures cannot be achieved. This is visible from the upper panel as even under the *classNPV* where only durum wheat is grown, there are some years where farm profits become negative. These last two models differ mainly in financing behaviour. The *RealOptFin* model only needs to maintain a positive current account of the firm but can reduce household withdrawals in certain years down to zero. As a consequence, it uses almost solely long-term credits (Table 3, row (7)) to finance the initial investment costs of plantation set-up and the well, as well as in some later years investment in a harvester. The costs relate to an expected 41% land share under hazelnuts (Table 3, row (1)). In contrast, the *RealOptFinRisk* model ensures minimum annual withdrawals above opportunity costs and has to use also short- and especially middle-term credits to balance annual fluctuations in withdrawals (Table 3, row (7)). These reflect foremost the production cycle, i.e. plantation ages of no or low hazelnuts yields, but also relate to nodes in scenario tree with lower than average prices and/or quality indices. Since only 6% compared to 41 % of

Figure 6. Distributions of annual withdrawals across the planning horizon in the four models.

total land is in the expected mean devoted to hazelnuts, the required investment costs are considerably lower such that the amount of long-term credits decreases substantially compared with the *RealOptFin* model.

The empirical results are in line with the available literature. Comparison of the results of *ClassNPV* and *RealOpt* models indicate that uncertainty and time flexibility leads to later investments at a higher expected scale. Trigeorgis and Reuer (2017) and Musshoff (2012) confirm that managerial flexibility usually increases the value of waiting, hence leading to postponement of investments; the reader should note here that relatively small uncertainty might lead to no value of waiting and hence immediate investments. As for investment scale, Hassett and Metcalf (1993) confirm that if immediate investment is worthless, uncertainty could create its value in the future. However, the effect of uncertainty might be the opposite if immediate exercising of investment is profitable in a risk-free environment. In this case, considering temporal flexibility might lead to lower expected investment scale depending on how the stochastic environment evolves. The resulting effect would depend on the underlying uncertainty, as well as on relationship between stochastic variables and the optimal investment scale. In this regard, our empirical results stating that uncertainty leads to larger expected area under hazelnuts shall be treated as a special case. Trigeorgis and Reuer (2017) also report that managerial flexibility reduces downside riskiness of investment, which is confirmed by our results, in particular the upper part of Fig. 6. Comparison of the results of *RealOpt* and *RealOptFin* models suggest that explicit consideration of financing behaviour reduces investment scales, yet does not affect the earliest time of investments. The results can indirectly be confirmed by Chen (2003) and Lin (2009), both claiming that a higher debt ratio leads to a higher investment threshold. However, we explicitly highlight here that the literature focusing on financing of investment under uncertainty is extremely limited. Finally, comparing the results of *RealOptFin* and *RealOptFinRisk*, one can conclude that consideration of downside risk aversion leads to later investment at a lower scale, as well as lower resulting riskiness. Previous studies confirm that risk aversion, and downside risk aversion in particular, reduces incentives to invest (e.g., Chronopoulos *et al.*, 2011).

5. Discussion and conclusion

Our case study results highlight that the assumptions underlying the different model variants can considerably affect key results. The comparison confirms that more advanced models are more informative: they provide additional insights and can provide more detailed advice to decision takers, such as on how to best finance an investment and how to buffer income fluctuations from production and market risks. The step-by-step development of the advanced farm-level models allows to identify the relative importance of the additional elements considered and to illustrate their value added. For instance, the simple NPV calculation suggests not planting hazelnut at all while all the other more complex models suggest doing so, however at varying time periods and scales. Constraining the downside risk of income from the farm operation in the most advanced models not only highlights the trade-off between mean income and reduced downside risk, but also shows the resulting consequences on the scale and timing of investments, as well as on financing behaviour.

Clearly, there is a trade-off between additional insights and potentially more realistic results on the one hand, and increased data demands (Table 2) and model complexity on the other one. Additionally, higher data requirements imply typically also higher uncertainty. For instance, the more advanced model with explicit financing costs does not simply require one average interest rate, but interest rates for different finance instruments which depend on a number of factors, such as credit amount or farmer's credit scores. The results – both additional ones and the ones also found in simpler models – are sensitive to what is assumed here in detail on top of the parameter found also in simpler models. Compared to sensitivity to one average discount rate only, the more advanced model distinguishes between different components of discount rate, i.e., time preferences, risk preferences, costs of financing, etc., which all can be subject to sensitivity analysis to inform on their importance individually. Furthermore, such sensitivity analysis could also help to find a set of parameters which best fits the observed behaviour (e.g. Troost and Berger, 2014). In our case, expected hazelnuts yields and market prices as well as their riskiness would be obvious first candidates for such an analysis.

As a word of caution, we remind the reader that using more advanced methods such as real options does not necessary imply a better fit to observed behaviour. Indeed, especially the full rationality assumption inherent in optimization approaches might be questioned. A potential promising avenue here is to complement the optimization model with other methodologies (Colen *et al.*, 2016), for instance, to expose farmers facing investment decisions to results of such models in order to learn more, e.g., on how they frame the decision problem including which results matter to them most, or to contrast subjective perceptions of market developments and related risk with findings from statistical analysis. The detailed what, how and when view of dynamic programming approaches might ease that kind of dialogue as it might be similar to the one used by the farmer itself. Alternatively, results obtained with other methodologies, e.g., econometric or experimental techniques for objective or constraint functions, can serve as input for optimization model and allow introducing behavioural aspects, for instance in form of a risk utility function (Chronopoulos *et al.*, 2014). Finally, further research might put greater focus on how learning affects future expectations, for instance, how experiences of rare but catastrophic events shape expectations, and how this can be reflected, for instance, in a scenario tree.

Overall, our paper underlines that the conceptual and technical elements are readily available to build farm-scale models based on dynamic stochastic optimization. This allows to determine scale and timing of long-term investments under production and market risk and endowment constraints, drawing on real options. We also highlight that such models are extensions of the widely used farm programming approaches and show the additional insights which can be gained from their application. We demonstrated the different models using the example of hazelnut production in an Italian region. An application to, for instance, other perennials can draw on the basic model structure and solution approach. But it will clearly require other data, and potentially also adjustments in some model detail, for instance introducing variables and equations to reflect additionally required investments such as relating to storage or post-harvest treatment.

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Appendix. Capturing stochastic variables with stochastic processes and distributions based on historical data

Market price of hazelnuts and durum wheat

In order to estimate the stochastic processes for market prices of unshelled hazelnuts and durum wheat, the market prices in Italy provided by ISTAT (for hazelnuts) and Eurostat (for durum wheat) were used (Fig.A1).

We omit the observations from the years 2008 and 2014-2016 for hazelnuts, as they do not fit the general trend and hence should be excluded when estimating stochastic processes. We ran the following stationarity tests: Augmented Dickey-Fuller (ADF) test; Phillips–Perron (PP) Unit Root test; and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. For both data samples, non-stationarity hypothesis cannot be rejected based on the ADF and PP tests, while the KPSS test concludes that stationarity hypothesis cannot be rejected. In light of the conflicting results of these tests, we decide on the appropriate method based on economic reasoning and therefore apply an MRP estimation. This assumes stationarity

Figure A1. Real durum wheat (DW) and hazelnut (H) prices, € 100kg^{-1}. Source: ISTAT and Eurostat; the prices are deflated (2015=100) using the GDP deflator in Italy provided by the World Bank.

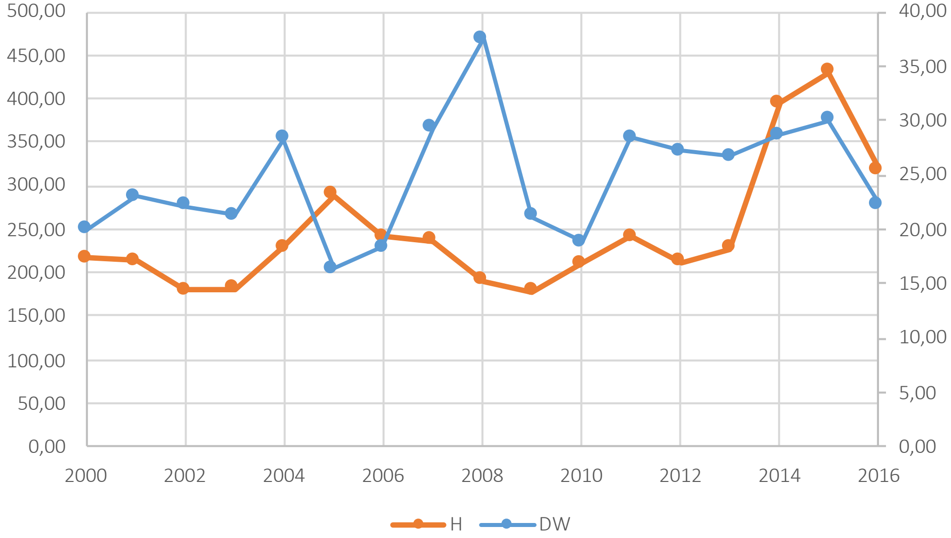


Table A1. Estimated parameters of mean-reverting processes for hazelnut and durum wheat prices. Source: own estimation based on the ISTAT (for hazelnuts, years 2000-2013) and Eurostat (for durum wheat, years 2000-2016, excl. 2008) data. The prices were deflated (2015=100) using the GDP deflator for Italy provided by the World Bank.

	Natural logarithm of hazelnut price	Natural logarithm of durum wheat price
Long-term mean	7.6782	5.4690
Speed of reversion	0.9219	3.1053
Standard deviation	0.1933	0.4808
Starting value	8.0669	5.4036

reflecting that the market price likely fluctuates around a constant long-term per unit production cost. The result of the MRP estimations are summarized in the Table A1.

Furthermore, as above, we correct every price draw by a multiplicative coefficient of 1.18 in order to account for expected increase in hazelnut price due to increasing demand. This price level also leads to introduction of hazelnut in some but not all model variants and also to highlight differences.

Quality index for hazelnut and durum wheat

The FADN data were used to derive annual per unit farm specific prices of hazelnuts and durum wheat by dividing crop revenues by sold quantities. These calculated farm-gate

Figure A2. Distribution fitting for the quality index of hazelnut. Source: own elaboration based on FADN and ISTAT data.

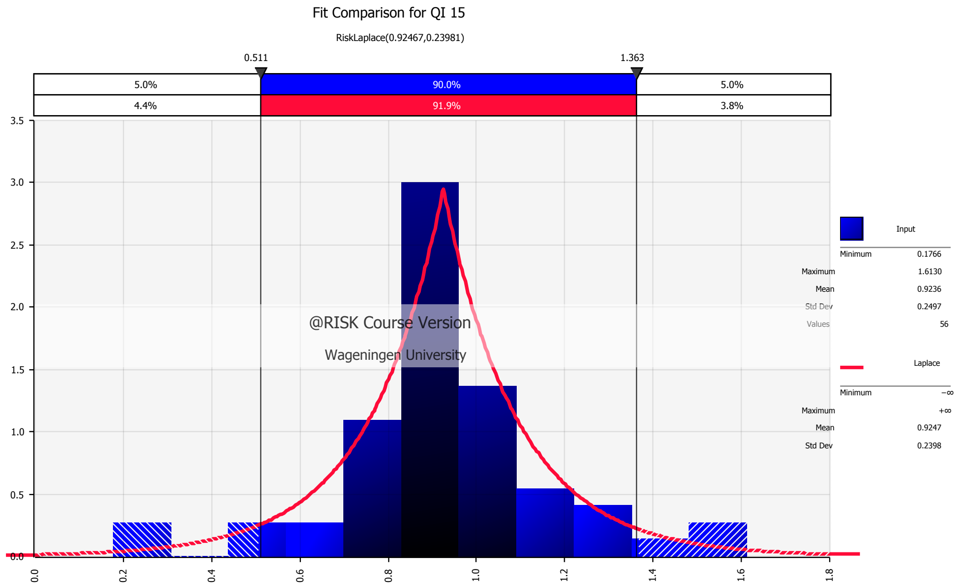
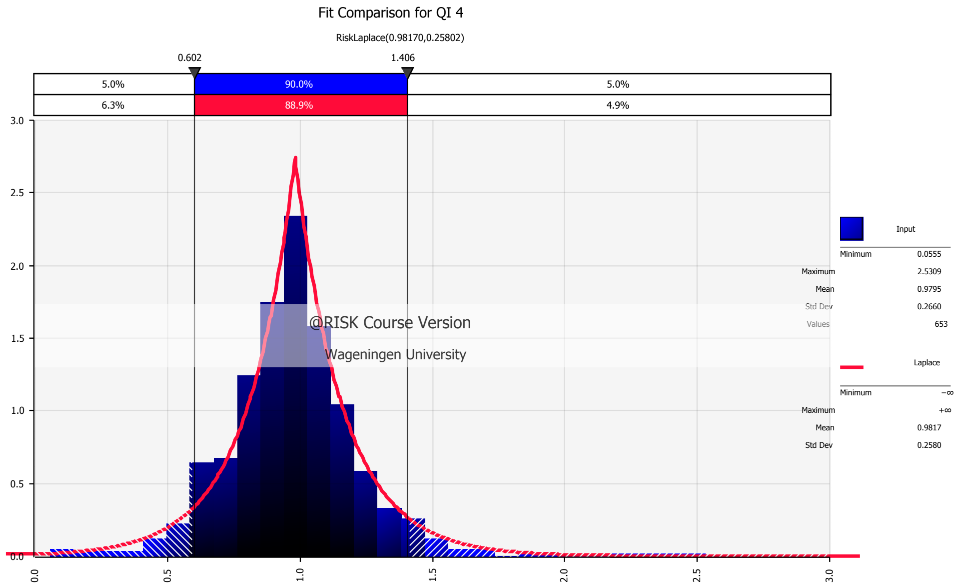


Figure A3. Distribution fitting for the quality index of durum wheat. Source: own elaboration based on FADN and Eurostat data.



prices were normalized by the market prices in Italy provided by ISTAT for both hazelnuts and durum wheat to define samples of farm specific quality indices. These observations for quality indices were fitted to a Laplace distribution with a mean of 0.9247 and standard deviation of 0.2398 (Fig.A2) for hazelnut, and mean of 0.9817 and standard deviation of 0.2580 (Fig.A3) for durum wheat.

Yields and variable costs for durum wheat

For durum wheat, yields derived from the FADN sample based on total production and area were fitted to a Laplace distribution with a mean of 3.9120 and standard deviation of 1.1984 (Fig.A4). The observations for durum wheat costs were fitted to a Gamma distribution with a shape parameter of 3.8286 and a scale parameter of 97.098 (Fig.A5).

Figure A4. Distribution fitting for the yields of durum wheat. Source: own elaboration based on FADN data.

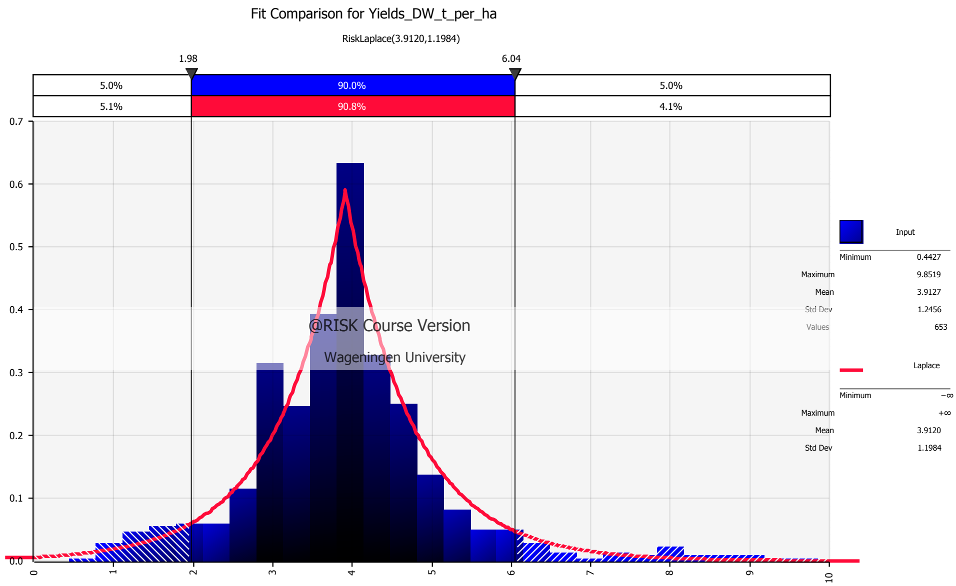
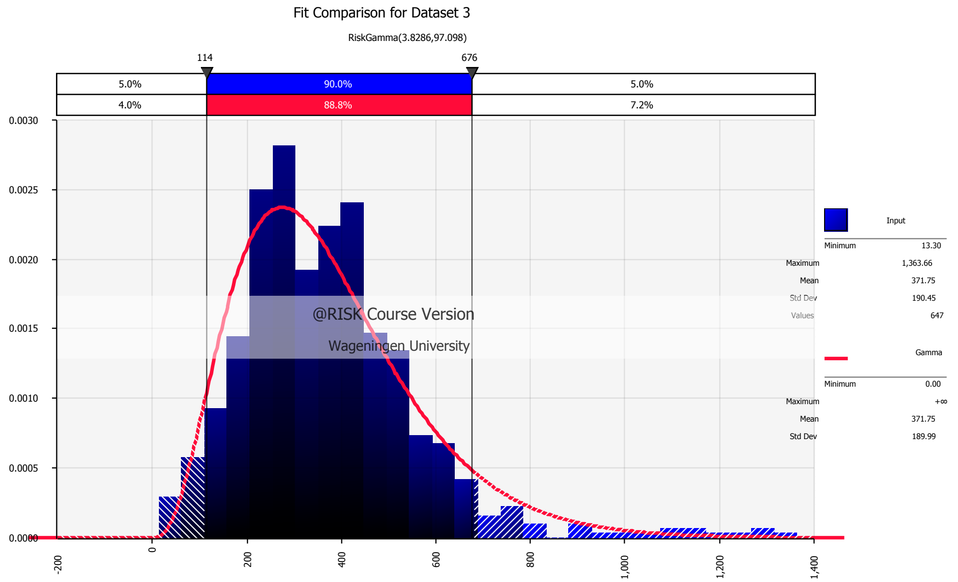


Figure A5. Distribution fitting for the variable costs of durum wheat. Source: own elaboration based on FADN data.



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Full Research Article

The role of group-time treatment effect heterogeneity in long standing European agricultural policies. An application to the European geographical indication policy

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Abstract. In recent years, the European Union is stressing the importance of monitoring and evaluating its policies, among which the common agricultural policy plays an important role. Policy evaluation, in order to provide reliable results on which to take important legislative decisions, should rely on robust methodological tools. A recent strand of literature casts some doubts about the reliability of the two-way fixed effect estimator when the effect of a treatment is heterogeneous across groups of units or over time. This estimator is widely used in agricultural economics to estimate the effect of policies where effect heterogeneity may be at stake. Using the European geographical indication (GI) policy, we compared the two-way fixed effects estimator with a novel non-parametric estimator that accounts for the issues created by effect heterogeneity. The results show that the two estimators, consistently with the concerns expressed by the technical literature, may lead to different estimates of the policy effect. This suggests that treatment effect heterogeneity is likely a concern when assessing the impact of GI-type policies. Therefore, the use of the standard estimator may lead to misleading conclusions and, as a result, to inappropriate policy actions.

Keywords. Treatment heterogeneity; geographical indications; impact assessment; two-way fixed effects; policy evaluation

JEL codes. Q18, Q56.

1. Introduction

In recent years, the European Union (EU) is stressing the need to move toward an ever more evidenced-based policy making. Despite the renewed attention it is attracting nowadays, evidence-based policy making is not a new concept. The discussion about the need to use empirical evidence to understand how policies work and to identify their results was already in place in the 1990s (e.g., OECD, 1994; Pawson and Tilley, 1997).

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Sanderson (2002) claims that two kinds of evidences are required to improve the governmental action. On the one hand, it is necessary to understand whether the policy action is effective. On the other hand, acquiring knowledge about how a certain policy works is of fundamental importance. In the language of Yin (2013), this corresponds to answer, respectively, a "what" and a "why" question.

Especially the former aspect plays an important role in the current EU Common Agricultural Policy (CAP), where the legislator stresses the importance of a constant monitoring and evaluation of its measures, also providing indicators and methodological guidelines, as well as some ex-ante evaluations on quantitative goals. On the verge of the new CAP programming period (2021-2027), the policy course that aims at providing evidences about the effectiveness of the policies and measures of the CAP is confirmed and stressed. The new CAP Regulation proposal states that "the current Common Monitoring and Evaluation Framework (CMEF) and the current monitoring system of Direct Payments and Rural Development would be used as a basis for monitoring and assessing policy performance, but they will have to be streamlined and further developed" (European Commission, 2018: pg. 9).

The rising interest in evidence-based policy making, however, requires proper tools to collect evidences, analyze them and interpret the results. In this respect, a useful reservoir of approaches, methods and techniques to be used in the evaluation process is represented by quasi-experimental approaches. Adopting an *ex-post* perspective (i.e., after the policy has been implemented), the main goal of quasi-experiments is to identify the effect that a certain policy, program or treatment produces on some indicator that measures the policy objectives. Basically, this requires to clearly identify the causal relationship between the treatment and the outcome, in order to isolate the effect of the policy from the role played by other confounding factors (Khandker et al., 2009). The identification of this causal link, however, constitutes the major effort in real socio-economic contexts. Different policy settings have different pitfalls that hinder the correct identification of the causal effect. To overcome these issues, researchers came up, over the years, with strategies and techniques tailored to specific policy settings. To cite some examples, regression adjustment and matching are ways to account for the effect of observable covariates; instrumental variables and difference-in-differences (DID) can get rid of the influence of unobservable factors (Cerulli, 2015); the regression discontinuity design is well suited in contexts where the administration of the treatment is based upon certain thresholds. As a result, before starting an impact analysis, the researcher should pay attention to the policy he/she aims at evaluating and to the setting where the policy is implemented.

The ideal policy setting for impact analysis involves a binary treatment that is administered to one group of individuals, while another group can be used as a control. The two groups can be observed at a single point in time or over a couple of periods. However, some policies are characterized by more complex settings, as is the case of several EU agricultural policies. This is especially the case of long-standing policies, where the participation is voluntary, the enrollment in the treatment not simultaneous, and individuals can be observed for multiple time periods. The policy we refer to in our article, the geographical indication (GI) policy, is an example of this situation. Provided that their farm is located in the area of origin of a GI product, farmers do not have any obligation about whether or when to join the specific GI system.

Policy settings where the treatment administration is based on voluntariness and is not simultaneous can be included in the category that is referred to as event study designs (Borusyak and Jaravel, 2017) or staggered adoption designs (Athey and Imbens, 2018). An important aspect in event study designs is that the effect of the treatment might not be constant across groups of individuals or time periods, a condition that is referred to as group-time treatment effect heterogeneity. The standard econometric model that has been used so far to deal with this kind of policy frameworks is the two-way fixed effects (TWFE), a panel fixed effect estimator with group (or individual) and time effects. De Chaisemartin and D'Haultfoeuille (2019) noted that the TWFE was used in 20% of the empirical articles published on the American Economic Review between 2010 and 2012. This tool is used in agricultural economics as well, where is exploited to study a variety of topics. Dawson (2005), for example, used a TWFE regression to measure the contribution of agricultural exports in less developed countries, finding a positive effect of agricultural exports on economic growth. Lien and Hardaker (2001), in a study on Norwegian farmers, showed that, in the choice of the optimal farm plans, subsidy schemes, market conditions and available labor have more importance than the farmer's risk attitude. In the context of the GI policy, Raimondi et al. (2019) investigated the effect of these quality labels on trade, highlighting that the GI policy promotes the export of agri-food products and has positive effects on export prices, while it has weak negative effects on imports. Despite the wide use of the TWFE, however, a recent bunch of literature questions the validity of this estimator when estimating the impact of the treatment in presence of group-time effect heterogeneity, claiming that it does not provide easy-to-interpret estimates (Goodman-Bacon, 2018; Athey and Imbens, 2018; Imai and Kim, 2019) and, more important, that this estimator can produce, in some cases, biased results (de Chaisemartin and D'Haultfoeuille, 2019; Borusyak and Jaravel, 2017; Abraham and Sun, 2018).

Given the practical relevance of impact analysis, biased results are a serious concern, especially when institutions stress the link between policy making and empirical evidence, as in the European case. Moreover, the European agricultural context is quite rich in policies that have an event study structure, such as the GI policy, the organic certification, or the rural development programs. Some studies tried to investigate the effects of these policies. Torres et al. (2016) compared, over a 25 years period, the performance of organic and conventional citrus farms in Spain using profitability indicators to evaluate farms investments. Nordin (2014) and Nordin and Manevska-Tasevska (2013) assessed the impact of the grassland support on agricultural employment in Sweden at the municipality and farm level, respectively. Within the GI context, Cei et al. (2018a) and Raimondi et al. (2018) estimated the impact of GIs at the regional level, respectively, on agricultural value added in Italy and on agricultural value added and employment in Italy, France and Spain. To our knowledge, however, so far, no study explored the relevance of group-time treatment effect heterogeneity in measuring the impact of this kind of policies and measures in Europe. In light of this, the objective of this paper is to understand whether group-time treatment effect heterogeneity is a concern when estimating the effects on the agricultural value added of the GI policy, an EU agricultural policy characterized by both voluntariness, not-simultaneity of the treatment and persistence of the treatment over time. This is done comparing the results of the standard TWFE estimator with the results obtained using a novel estimator proposed by Callaway and Sant'Anna (2018) that specifically accounts for the presence of group-time treatment effect heterogeneity. Ideally, if group-time treatment effect heterogeneity is not an issue in the studied context, the results of the two estimators should coincide. Understanding the relevance of group-time treatment effect heterogeneity would help in identifying the best strategies to correctly assess the impact of this kind of EU policies.

In the next section, we provide a brief overview of the GI policy in the EU and of the economic effects of this policy on the rural economy, and we review the technical literature addressing the issue of group-time effect heterogeneity in impact analysis. Here, we also present the novel non-parametric estimator that we will use as a comparison for the TWFE estimator. The third section describes the data and methods we used in the analysis, while in the fourth section we present our results, that will be discussed in a critical way in the fifth section. We end the article drawing some conclusion and highlighting the relevant research and policy implications of our work.

2. Policy and technical background

2.1 Geographical indications in Europe and their economic impact

Geographical Indications (GIs) are defined as "indications which identify a good as originating in the territory of a Member, or a region or locality in that territory, where a given quality, reputation or other characteristic of the good is essentially attributable to its geographical origin" (WTO, 1994, article 22). In Europe, geographical indications were given a common legal framework in 1992, but some countries (especially Mediterranean ones) already had in place, by that time, national provisions regulating GIs. According to the European definition of GIs, the quality of a GI product directly stems from specific and unique characteristics of the area where the product is produced, i.e. from the *terroir*. The GI policy regulates two types of GIs, the protected designation of origin (PDO) and the protected geographical indication (PGI), but the link between the product quality and the *terroir* is stronger for the PDO, whose entire production process must take place in the delimited area of origin, while the PGI just requires that at least one of the production steps takes place in the area of origin. The distinctive sign of the EU GI policy is that, in contrast to what happens in other countries, where the protection of GIs is mainly based on trademarks, PDO and PGI are public-owned signs. Farmers are thus free to join GI schemes, provided they are located within the area of origin and they comply with the rules contained in the product specification.

The strong link between GI products and the territories from which they originate is reflected in the objectives of the policy. Reg.(EU) No 1151/2012, that currently regulates the European GI system, places a considerable importance on the value adding function of the GI certification, claiming that this legislative tool is able to improve the income of local farmers. In turn, this would reflect in positive effects for the local economy and rural development.

The idea that GIs can positively affect the economy of the area where their production takes place relies on several economic foundations. First, GIs are widely recognized to be market instruments that reduce the information gap between producers and consumers (Marette et al., 1999; Josling, 2006; Anania and Nisticò, 2004). Providing additional information to consumers is expected to raise their willingness to pay for the product. If this added value manages to be transferred up the supply chain, it will turn into an economic benefit for producers. Another function fulfilled by the GI certification is to act as a substitute for producer's reputation (Menapace and Moschini, 2012), which, according to Shapiro (1983), needs time to be built, but eventually grants a price premium on the market. Finally, GI-type certifications are able to create a rent for a limited number of producers because of the excluding mechanisms that operate in this kind of systems (Moran, 1993; Perrier-Cornet, 1990; Josling, 2006; Thiedig and Sylvander, 2000) as a consequence of area restrictions, yield limits, or both (Landi and Stefani, 2015; Hayes et al., 2004).

The value-creation function of GIs and quality schemes in general is supported by several studies that approach the problem from a theoretical and modeling perspective (Anania and Nisticò, 2004; Menapace and Moschini, 2014; Moschini et al., 2008; Zago and Pick, 2004). On the other hand, however, empirical studies offer a more controversial scenario. Consumers usually attach a greater value to GIs, despite the occurrence of positive label effects is heterogeneous across GI products (see Deselnicu et al. (2013), Leufkens (2018) and Santeramo and Lamonaca (2020) for some meta-analysis of studies on GIs and regional products, Garavaglia and Mariani (2017), Menapace et al. (2011) and De-Magistris and Gracia (2016) for specific studies) However, some difficulties are identified for that value to be transferred to agricultural producers (Cei et al., 2018b). With respect to proper impact evaluation analysis, to our knowledge, to date, only two studies have addressed the topic from this perspective. Cei et al. (2018a), found a positive impact of the GI protection on regional agricultural value added in Italy while Raimondi et al. (2018) estimated a positive impact of GIs on regional employment in France, Italy and Spain, and a positive effect on labor productivity in Spain.

2.2 Group-time treatment effect heterogeneity in impact evaluation

The GI policy allows farmers to voluntarily start the production of a GI product provided they are located in the area of origin and they comply with the GI product specification. Moreover, the policy has been continuously in place for more than 25 years, so that its activity has been observed for several periods. These characteristics create suitable conditions for the presence of group-time treatment effect heterogeneity. While treatment effect heterogeneity is defined as "the degree to which different treatments have differential causal effects on each unit" (Imai and Ratkovic, 2013), in line with the relevant literature (see, for example, Athey and Imbens (2018), Borusyak and Jaravel (2017), Abraham and Sun (2018)), group-time treatment effect heterogeneity arises when the effect of the treatment varies across groups of individuals (group heterogeneity), over time (time heterogeneity), or both. In this respect, group-time treatment effect heterogeneity can be considered a specific case of the general treatment effect heterogeneity, where the effect varies not at an individual level, but at the level of groups of individuals (e.g., groups that receive the treatment in the same year, groups for which the effect is estimated in a certain year). Three types of group-time heterogeneity can be distinguished according to Callaway and Sant'Anna (2018). The first type, which they refer to as *Selective treatment timing*, is the pure group heterogeneity case, where the effect of the treatment depends on when an individual is treated for the first time (groups are made of individuals who receive the first treatment at the same time). Time heterogeneity is decomposed into a *Dynamic treatment effect* and a *Calendar treatment effect*. The former considers the possibility that the effect of the treatment may depend on the amount of time an individual has been exposed to the treatment. The latter lets the treatment effect vary according to the moment (period) when the effect is measured.

In contexts where group-time treatment effect heterogeneity can show up, researchers usually exploit a standard parametric way to measure the average treatment effect on the treated (ATT), the two-way fixed effects model. The TWFE model, whose specification is reported in (1), is a modification of the classical fixed effects regression.

$$Y_{it} = \alpha_i + \delta_t + \beta D_{it} + \theta X_{it} + \varepsilon_{it} \tag{1}$$

In (1), i and t are the individual/group and year subscripts, Y is the outcome, X is a set of covariates that account for possible confounders, and ε denotes the error term. α_i and δ_i are, respectively, the unit/group and time fixed effects. β, the coefficient associated to the treatment variable D_{it}, is the estimator for the ATT.

The TWFE is a regression-based DID estimator (Abadie, 2005) and as such is able to get rid of the selection bias introduced not only by observable factors (which can be directly included in the set of covariates X), but also by unobservable factors, provided that these factors are constant over time. This characteristic makes the classical fixed effects the perfect parametric counterpart of the DID method in the basic impact analysis setting where two groups (treated and controls) are observed over two periods (before and after the treatment). Similarly, working with multiple groups and multiple periods, the TWFE is expected to provide an average estimate of the treatment effect. This average estimate is the result of the aggregation of the various group-time ATTs, i.e. the ATTs for each group of individuals measured in a specific time period[1]. The aggregation of the group-time ATTs, however, involves a not linear weights structure, which makes the interpretation of the β coefficient not straightforward (Imai and Kim, 2019; Athey and Imbens, 2018; Goodman-Bacon, 2018). More importantly, in contexts characterized by group-time treatment effect heterogeneity, some of the group-time ATTs can receive negative weights when aggregated into the TWFE estimator (Abraham and Sun, 2018; Borusyak and Jaravel, 2017; de Chaisemartin and D'Haultfoeuille, 2019). Negative weights are a potential risk not only for the interpretation, but also for the reliability of the estimator, since they alter the sign of some ATTs that form the aggregated estimate and thus introduce a bias.

To face this issue, several authors suggested some novel estimators, either parametric (Imai and Kim, 2019) or non-parametric (de Chaisemartin and D'Haultfoeuille, 2019; Callaway and Sant'Anna, 2018), that do not involve negative weights. In our study, we use the one suggested by Callaway and Sant'Anna (2018) (hereinafter referred to as the CSA estimator) and we compare its results with the estimates obtained using the TWFE. The CSA estimator computes the ATT for each group of treated units (g) in each time period (t). Treated units are those observations that receives the treatment at some point in time during the observation period and they are assumed to not withdraw from the treatment

[1] The group-time ATTs are not actually estimated by the TWFE, but some authors offer several decompositions of the TWFE estimate in terms of group-time ATTs (Imai and Kim, 2019; Athey and Imbens, 2018; Goodman-Bacon, 2018).

once they received it. Each group g of treated units is composed of individuals that are treated for the first time in period g (i.e., they are not treated at $t < g$). Controls are the units that never receive the treatment.

The authors provide two versions of the estimator, one for balanced panel data, reported in (2), and one for repeated cross sections.

$$ATT(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}_g(X)C}{1-\hat{p}_g(X)}}{E\left[\frac{\hat{p}_g(X)C}{1-\hat{p}_g(X)}\right]}\right)\left(Y_t - Y_{g-1}\right)\right] \tag{2}$$

In (2), G_g is a group binary indicator that identifies individuals first treated at time g, C is a binary variable identifying control units, Y is the outcome variable, and $\hat{p}_g(X)$ is the generalized propensity score[2], estimated on a set of covariates X, that estimates the probability of a certain unit to be first treated at time g. The idea behind the estimator resembles the one in Lemma 3.1 in Abadie (2005) for the classical two groups-two periods setting. Basically, control units are weighted down when they have characteristics that are uncommon in the treated group, and weighted up when their characteristics are frequent in the treated group. This mechanism guarantees the balancing of the covariates between the treated (g) and the control group (Abadie, 2005; Callaway and Sant'Anna, 2018).

Basically, the CSA strategy computes, for each (g,t) pair, a DID estimate weighting control units on the basis of a propensity score measure. The propensity score is estimated for each (g,t) sample, i.e. using all control units and those treated units that form group g. It is important to note that the ATT can be estimated even for pre-treatment periods, i.e. with $g > t$. Because the treatment is supposed to not affect the outcome before it is administered, the analysis of the pre-treatment ATTs allows to verify that the conditional parallel trends assumption (i.e., the trends of the outcome variable in the treated and control groups are parallel conditional on X for all g and t) holds. The parallel trend assumption is common in DID settings, where we assume that the change in the outcome variable would have been the same in the treated and control group had the treatment not been administered. In a setting with multiple groups and multiple periods, it is required that the parallel trends assumption holds for all $g \leq t$. This assumption is fundamentally untestable (Callaway and Sant'Anna, 2018), but once we extend it to cover also pre-treatment periods it can be tested looking at the significance of the pre-treatment ATT estimates.

The means through which the CSA strategy addresses the group-time treatment effect heterogeneity issue are the avoidance of making "functional form assumptions about the evolution of potential outcomes" (Callaway and Sant'Anna, 2018, p.9) and the devising of several summary measures that avoid the drawback of negative weights. The main summary measures suggested in Callaway and Sant'Anna (2018) are reported in Table 1. The first measure (*Simple weighted average*) is a simple average where each ATT(g,t) is weighted by the number of treated observations in the respective (g,t) subsample. The *Selective treatment timing*, the *Dynamic treatment effects* and the *Calendar treatment effects* meas-

[2] This definition is provided in Callaway and Sant'Anna (2018), despite the term "generalized propensity score" is used with different meanings in the literature. In Rosenbaum and Rubin (1984), it refers to a form of the propensity score that accounts for missing data in the covariates, while Hirano and Imbens (2004) use the same term to indicate a propensity score that also accounts for cases when the treatment is not a binary variable.

Table 1. Summary Parameters of the ATT Proposed by Callaway and Sant'Anna (2018).

Summary parameter	First level	Second level
Weighted average[1]	$\theta = \frac{1}{k}\sum_{g=2}^{T}\sum_{t=2}^{T} 1\{g \leq t\}ATT(g,t)P(G=g)$	
Selective treatment timing	$\theta_s^*(g) = \frac{1}{T-g+1}\sum_{t=2}^{T} 1\{g \leq t\}ATT(g,t)$	$\theta_s = \sum_{g=2}^{T} \theta_s^*(g)P(G=g)$
Dynamic treatment effects[2]	$\theta_d^*(e) = \sum_{g=2}^{T}\sum_{t=2}^{T} 1\{t-g+1 = e\}ATT(g,t)P(G = g \mid t-g+1=e)$	$\theta_d = \frac{1}{T-1}\sum_{e=1}^{T-1} \theta_d^*(e)$
Calendar time effects	$\theta_c^*(t) = \sum_{g=2}^{T} 1\{g \leq t\}ATT(g,t)P(G = g \mid g \leq t)$	$\theta_c = \frac{1}{T-1}\sum_{t=2}^{T} \theta_c^*(t)$
Selective + Dynamic[3]	$\theta_{sd}^*(e,e') = \sum_{g=2}^{T}\sum_{t=2}^{T} \delta_{gt}(e,e')ATT(g,t)P\big(G = g \mid \delta_{gt}(e,e')=1\big)$	$\theta_{sd}(e') = \frac{1}{T-e'}\sum_{e=1}^{T-e'} \theta_{sd}^*(e,e')$

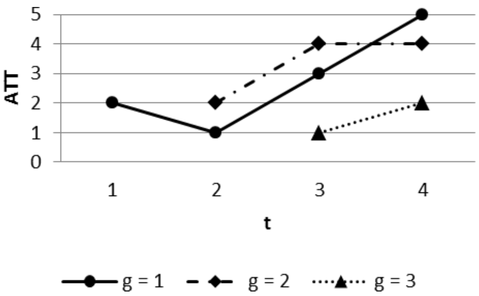
1. The weighted average parameter had a single level of aggregation. The term k assures the normalization of weights, and is equal to $\sum_{g=2}^{T}\sum_{t=2}^{T} 1\{g \leq t\}P(G=g)$.
2. e represents the number of periods (years) after a group g of units receive the first treatment.
3. e' is a specific number of periods, selected by the researcher, after a group g of units receives the first treatment. $\delta_{gt}(e,e')$ abbreviates the logic function $1\{t-g+1=e\}1\{T-g+1 \geq e'\}1\{e \leq e'\}$.

ure the three types of heterogeneity that we mentioned in the first part of this subsection, where the effect is thought to vary according either to the group, to the length of exposure to the treatment, or to the moment when the effect is estimated, respectively. The last summary measure, *Selective + Dynamic*, is a combination of *Selective treatment timing* and *Dynamic treatment effects*. Each of these summary measures has two levels of aggregation. The first level indicates the ATT within each group (g), number of periods after the treatment (e), or period (t). The second level measure is an average of the first level measures. As we can see from Table 1, to obtain these measures, the group-time ATTs are weighted on the basis of the size of the samples of interest (which vary according to the different summary measures). In this way, weights are assured to be always positive and meaningful, thus avoiding the occurrence of any bias or difficulty in their interpretation.

To better clarify the meaning of the summary measures, we propose a simple practical example. In Figure 1, we report hypothetical ATTs for three groups of individuals. One group (bold line) is first treated at period 1 (g = 1), the second group (dashed line) at period 2 (g = 2) and the last group (dotted line) is treated for the first time at period 3 (g = 3).

According to the formulas in Table 1, these ATTs are aggregated into the first level summary measures, which are reported in Figure 2. The *Selective treatment timing* ("Selective" pane of Figure 2) highlights that the average effect is larger for the group that receive the

Figure 1. Hypothetical group-time ATTs: each line identifies a group of treated units that receive the treatment in a specific time period.



first treatment in the second period. The *Dynamic treatment effect* ("Dynamic" pane) shows that, on average, the longer individuals stays in the treatment, the higher the treatment effect. Finally, the *Calendar treatment effect* ("Calendar" pane) suggests that the effect measured in the last periods (t = 3 and t = 4) is higher. For this simple example, all this information were easily retrievable from Figure 1, but the summary measures gain importance when the number of groups and periods gets large.

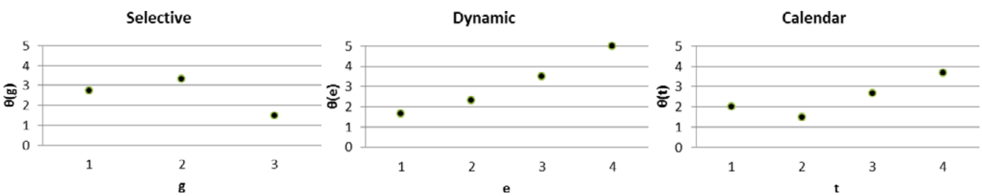
A final major contribution of Callaway and Sant'Anna (2018) is the derivation of the respective asymptotic theory for both the ATT(g,t) estimators and the summary parameters. Specifically, they derived both a consistent estimator of the variance and a specific bootstrap procedure. The suggested bootstrap procedure in particular has some advantages over traditional bootstrap. It avoids the re-estimation of the propensity score in each draw; it includes, in each iteration, observations from each group; and it allows to compute confidence bands simultaneously valid in g an t.

3. Data and methods

3.1 Data sources and samples

In our study we used two data sources: the Italian Farm Accountancy Data Network (FADN) and the EU *eAmbrosia* database[3]. The FADN data we worked with cover a nine years period, from 2008 to 2016. FADN is an unbalanced panel collecting farm-level data using a stratified sample design common to all EU Member states[4]. The database reports

Figure 2. First-level summary measures for the hypothetical group-time ATTs reported in Figure 1.



[3] The *eAmbrosia* database is accessible at: https://ec.europa.eu/info/food-farming-fisheries/food-safety-and-quality/certification/quality-labels/geographical-indications-register/

[4] The FADN field of observation consists of commercial farms, which are defined according to country-specific economic size thresholds (see Reg.(EC) 1242/2008). For Italy, the threshold is set to 4000 euros until 2014

data on farm structure, the farmer and workforce characteristics, the production process and several economic indicators. A specific section of the database reports whether a farm is involved in GI production and details which crop (or animal type, in case of livestock production) is under PDO and/or PGI certification.

eAmbrosia (formerly DOOR), is an European database where all the registered GI products are listed. For each product, several information is reported, including the product specification.

To identify the GI case studies on which to perform the analysis, we crossed the information from the two databases. Specifically, we know, from FADN, whether a farm is involved in the GI production, to which crop/animal type the certification refers, and where the farm is located. Rearranging the information from product specifications, we know which GIs can be produced in the area where the farm is located. Using this information, we selected two cases, based on: *i)* no overlap between GIs of the same product category in the same area; and *ii)* presence of control farms (i.e., farms producing the same product without the certification) in the GI area. Considering also the need for sufficiently large sample sizes, we selected two GIs: Mela Val di Non PDO (apple) and Riviera Ligure PDO (extra-virgin olive oil).

As mentioned in the previous section, a form of the CSA estimator for unbalanced panel has not been provided yet, thus we needed to balance the samples to conduct our analysis. Since FADN data cover a nine-years period, we created several balanced panels selecting different time spans and dropping units that were not observed in all the years included in the selected span. This balancing procedure will affect our results, because we are dropping treated units. However, as we discuss in the fifth section, this is not a concern for our purpose of comparing the two estimators. The balancing provides a data structure that complies with all the assumptions required by Callaway and Sant'Anna (2018) to implement their technique.

3.2 Impact analysis

In each sample, the treatment variable, GI_{it}, is the binary indicator showing whether a farm *i* produces the GI product in year *t*. Treated units are those farms for which $GI_{it} = 1$ in at least one year *t*, that is, farms that at some point in time certify their production as a GI[5]. In line with the CSA assumptions, once a farm adopts the certification, it is not sup-

and to 8000 euros afterward. The stratification is based on three levels: geographical location (European NUTS2 regions), economic size, and type of farming. Further details can be found at https://ec.europa.eu/agriculture/rica/index.cfm.

[5] It could be the case that some farms produce two versions of the same product certifying a part of the production and commercializing the remaining share without the GI sign. In these cases, the structure of the FADN dataset does not allow to distinguish between the two kinds of production. In the analysis, whenever a farm is reported to use the GI certification for a certain product, is considered to produce "only" GI-certified product. Therefore, farms that possibly has a "mixed" production (GI and non-GI) for the same crop are always considered as treated. It must be noted that this issue is probably more relevant for apple farms than for olive oil farms. In the Mela Val di Non PDO origin area the production of non-certifiable varieties is possible and common, while olive varieties grown in the Riviera Ligure PDO area are quite exclusively the ones admitted by the product specification.

posed to withdraw from the GI scheme, i.e., the treatment is irreversible[6]. On the other hand, a farm is included in the control group if it is never treated, i.e. $GI_{it} = 0$ in every year *t*. Control units are selected only among farms located in the same region (NUTS2 level for Riviera Ligure PDO and NUTS3 level for Mela Val di Non PDO), and producing the same product of treated farms (e.g., apple farms without the certification for the Mela Val di Non PDO sample). This allows us to perform our analysis in a sufficiently homogeneous socio-economic and legislative setting.

To measure whether the GI certification is actually able to increase the added value of the crop to which it applies, the crop gross margin per hectare is used as the outcome variable. The use of this variable has several advantages for our aim. In contrast to farm-level economic indicators, crop-level indicators are not affected by the economic performance of other processes or by the organization of the farm as a whole, and this allows to isolate the effect of the certification[7]. In addition, the crop gross margin indicator is defined as the difference between the total crop production and total variable costs. Measuring the certification impact on the crop gross margin thus allows to consider the effects of the certification both on the crop revenues (e.g., increased prices) and on the variable costs associated to that specific crop (e.g., inputs and certification costs). In turn, this definition of crop gross margin does not account for other EU subsidies that farms might benefit[8]. The exclusion of other subsidies from the indicator is important to isolate the effect of the GI certification from the possible effects of other CAP measures connected to product quality (e.g., second pillar measures).

Another possible option would have been to use farm prices to measure the effect of the certification, thus focusing on the expected ability of GIs to increase these prices, supposing that this is the main effect of the certification. However, it must be noted that the certification usually entails additional costs (e.g., the certification cost to be allowed to use the GI sign). Even if one assumes that those additional costs have just a minor importance with respect to the possible effects on farm prices, disregarding the cost side would inevitably lead to a bias in the estimation of the ability of the GI certification to generate an additional value.

With respect to the outcome variable, we decided to focus on relative performance improvements rather than on absolute ones. For this reason, since in the DID setting results are not scale invariant (Lechner, 2010), we use the crop gross margin per hectare in the logarithmic form.

The analysis proceeded creating two completely balanced panels, one for each sample. In each sample the effect was first estimated using the TWFE and then implementing

[6] In the original samples, few farms exit the certification scheme. In these cases, we dropped, before creating the balanced panels, the observations of receding farms from the year when the certification is removed onward. Similarly to the reduction in farms due to the balancing, we deem this is not an issue for our purpose of comparing the two estimators.

[7] Had the objective of the study been to measure the effect of the certification on farm profitability, the crop gross margin would have been a poor choice because it does not allow to attribute to the GI process the costs of factors shared between different farm processes (e.g., labor and capital). This indicator does in fact include the remuneration of these factors. However, the inclusion of these remunerations is exactly what one seeks in estimating the effects on the value added of the GI-certified crop, as in our case.

[8] In the FADN database, subsidies are included in the computation of farm-level indicators, such as farm gross margin, farm net value added or farm net income.

the CSA procedure. Initially, for each sample, we performed basic analysis using models without covariates. In a second stage, we included some independent variables to consider also the role of other factors that may confound the relationship between treatment and outcome. The identification of these factors was based both on previous studies investigating the determinants of GI adoption (van de Pol, 2017; Marongiu and Cesaro, 2018; Niedermayr, Kapfer and Kantelhardt, 2016) as well as on our knowledge of GI systems. We reported these factors in Table 2 (first column), where the type of each variable and their summary statistics are also shown.

In the last two columns of Table 2, we specified how, in the two methods of analysis that we compared (TWFE and CSA), we controlled for each factor. The unobservable factor (*Individual characteristics of the farmer*) is automatically controlled for by the DID structure of the two estimators (*Estimator structure* in columns 4 and 5 of Table 2), under the assumption that farmer's characteristics do not change over time (at least in the period considered in the analysis). The structure of the estimators accounts for the *Less favored area* (*LFA)* variable and for the *Year of observation* as well. The location of a farm in a less favored area does not change over time and the DID framework differences out its effect. On the other hand, the *Year of observation* is controlled by the time fixed effects in the TWFE estimator and by the within-year propensity score estimation in the CSA estimator. We controlled for the other observable factors in three different ways. Most of them are included in the TWFE equation as covariates and in the propensity score equation of the CSA estimator (*Covariate* and *Propensity score* in columns 4 and 5 of Table 2, respectively). On *Direct selling* and *Organic* a sort of direct matching is performed (*Direct matching* in Table 2). Because, in the two samples, none or very few treated farms adopt organic farming or directly sell their products, we dropped organic and/or direct selling farms from both the treated and control groups (this procedure explains the absence of sample variation for these variables in Table 2). Dropping organic and direct selling farms is like directly matching farms on a specific value (i.e., zero) of these variables. This strategy, therefore, allows to control for these factors without including them among the regressors of the TWFE model or in the CSA propensity score equation[9]. Finally, the definition of the control group (*Control group* in Table 2) allows to control for the *Type of GI product* variable, because control units are selected among farms that produce the same type of product of treated farms.

4. Results

The analysis were conducted on the two samples (Mela Val di Non PDO and Riviera Ligure PDO) for different time spans, first using basic models without covariates and then adding independent variables[10]. The first one is the Mela Val di Non PDO sample in a seven years period (from 2008 to 2014). In this sample, 15 farms join the certification system in 2009 and 13 farms enter the GI scheme in 2010. The control group consists of

[9] It should be noted that, in this way, only specific farm types are compared (i.e., non-organic and non-direct selling), which makes the results of the analysis not extendable to organic or direct selling farms. Again, the objective of our analysis makes this issue irrelevant.

[10] The whole analysis was performed using the statistical software R. Callaway and Sant'Anna (2018) provide a specific R command to implement their methodology.

Table 2. Factors to be controlled for in the models.

Factor	Type	Summary statistics[1]						Method (TWFE)	Method (CSA)
		Mela Val di Non PDO			Riviera Ligure PDO				
Age of the farmer	Continuous	[min;max]	Mean	St.dev	[min,max]	Mean	St.dev	Covariate	Propensity score
Farm located in a less favored area	Binary	[1.00;1.00]	1.00	0.00	[0.00;1.00]	0.71	0.45	Estimator structure	Estimator structure
Farm performing direct selling	Binary	[0.00;0.00]	0.00	0.00	[0.00;0.00]	0.00	0.00	Direct matching	Direct matching
Farm producing other GI products	Binary	[0.00;1.00]	0.15	0.35	[0.00;1.00]	0.16	0.37	Covariate	Propensity score
Farm with organic production	Binary	[0.00;0.00]	0.00	0.00	[0.00;0.00]	0.00	0.00	Direct matching	Direct matching
Farm utilized agricultural area	Continuous	[0.42;40.85]	5.56	4.73	[0.25;14.62]	1.94	1.70	Covariate	Propensity score
Individual characteristics of the farmer	Not observable	-	-	-	-	-	-	Estimator structure	Estimator structure
Labor intensity	Continuous	[0.08;4.04]	0.37	0.26	[0.07;3.87]	0.84	0.58	Covariate	Propensity score
Education of the farmer: none	Binary	[0.00;0.00]	0.00	0.00	[0.00;1.00]	0.02	0.14	Covariate	Propensity score
Education of the farmer: primary	Binary	[0.00;1.00]	0.09	0.29	[0.00;1.00]	0.13	0.34	Covariate	Propensity score
Education of the farmer: lower secondary	Binary	[0.00;1.00]	0.42	0.49	[0.00;1.00]	0.41	0.49	Covariate	Propensity score
Education of the farmer: upper secondary	Binary	[0.00;1.00]	0.42	0.49	[0.00;1.00]	0.42	0.49	Covariate	Propensity score
Education of the farmer: university	Binary	[0.00;1.00]	0.07	0.25	[0.00;1.00]	0.01	0.10	Covariate	Propensity score
Type of GI product	Categorical	-	-	-	-	-	-	Control group	Control group
Year of observation	Categorical	-	-	-	-	-	-	Estimator structure	Estimator structure

[1]Summary statistics were omitted, in addition to the not observable variable, for the type of product, because it is unique in the samples (either apple or olive oil) and for the year of observation, because the balanced structure of the panels that makes each level (year) equally represented.

Table 3. TWFE results for Mela Val di Non PDO and Riviera Ligure PDO.

Variable	Mela Val di Non PDO		Riviera Ligure PDO	
	Basic	Covariates	Basic	Covariates
GI	-0.35** (0.09)	0.02 (0.10)	0.15 (0.13)	0.31** (0.14)
UAA	-	0.00 (0.02)	-	-0.12 (0.13)
Age	-	-0.11** (0.02)	-	-0.01 (0.01)
Education (primary)	-	2.64** (0.65)	-	1.39 (0.161)
Education (lower secondary)	-	-	-	1.59 (1.10)
Education (upper secondary or university)	-	-	-	0.00 (0.56)
Other GI	-	0.21 (0.18)	-	-0.23* (0.13)
Labor/ha	-	0.17 (0.14)	-	0.24* (0.15)

Note: Asterisk (*) and double asterisks (**) denote group-time ATTs significant at 10% and 5% respectively.

17 farms that never use the GI certification in the observed period. Farms in the Riviera Ligure PDO sample are observed continuously for 5 years (from 2008 to 2012). Only one treated group is present (farms that start to certify in 2010), which consists of 17 units. The control sample is larger, including 91 farms.

The results of the impact analysis performed using the TWFE for the basic models (without covariates) and for the models with independent variables are reported in Table 3. In two of the four models, the GI certification has no statistically significant effect on the outcome variable. However, the GI certification has a negative impact on the crop gross margin per hectare in the Mela Val di Non model without covariates, while the GI effect is positive for Riviera Ligure olive oil when independent variables are included. In both cases, the parameters associated to the treatment variable are statistically significant at the usual 5% level.

In Table 4, we report the CSA group-time ATT estimates, which are also displayed graphically in Figures 3- 6, along with their 95% confidence intervals. According to the CSA estimator definition, groups refer to individuals that receive the treatment (i.e., adopt the GI certification) for the first time in year *g*. On the other hand, the *Year* column in Table 4 indicates the time at which the effect is estimated. In Figures 3-6 the estimates in red (*post* = 0 in the figures boxes) refer to pre-treatment ATTs and can be used to validate the extended parallel trend assumption. In all samples, the pre-treatment ATTs do not statistically differ from zero, therefore the assumption is not rejected. The standard errors were computed using the CSA bootstrap procedure. Referring to the same level of

Table 4. CSA group-time results for Mela Val di Non PDO (without covariates) and Riviera Ligure PDO (with covariates).

Mela Val di Non PDO				Riviera Ligure PDO			
Group[1]	Year	ATT (basic)	ATT (covariates)	Group[1]	Year	ATT (basic)	ATT (covariates)
2009	2009	-0.17* (0.09)	-0.29* (0.17)	2010	2009	0.15 (0.18)	0.37 (0.20)
2009	2010	-0.10 (0.11)	-0.15 (0.16)	2010	2010	0.33** (0.17)	0.37** (0.19)
2009	2011	-0.21 (0.16)	-0.33 (0.24)	2010	2011	0.06 (0.19)	0.07 (0.20)
2009	2012	0.49** (0.17)	0.78* (0.46)	2010	2012	-0.09 (0.16)	-0.08 (0.18)
2009	2013	0.07 (0.12)	0.28 (0.26)				
2009	2014	0.54** (0.25)	1.23** (0.44)				
2010	2009	-0.17 (0.12)	-0.17 (0.12)				
2010	2010	-0.20* (0.12)	-0.23 (0.17)				
2010	2011	-0.66** (0.21)	-0.69** (0.20)				
2010	2012	-0.01 (0.21)	-0.20 (0.25)				
2010	2013	-0.21 (0.21)	-0.31 (0.20)				
2010	2014	-0.25 (0.35)	-0.59* (0.32)				

[1]The column *Group* identifies farmers that enter the GI scheme in a specific year *g*. In the Mela Val di Non sample some farmers adopt the certification in 2009 and others in 2010. Conversely, all farmers in the Riviera Ligure PDO sample start certifying in 2010, therefore only one group is present.
Note: Asterisk (*) and double asterisks (**) denote group-time ATTs significant at 10% and 5% respectively.

statistical significance (5%), we note that all samples are characterized by few significant estimates, while the majority of the group-time ATTs are not statistically significant. The differences between the basic models and the models where covariates were included are minor. The effect of the certification, in the Mela Val di Non case, is positive and statistically significant at the 5% level, for the group first treated in 2009, in 2012 and 2014 (only in 2014 when covariates are considered). Conversely, in the same sample, the effect is negative, for the group first treated in 2010, in 2011. In the other sample, the only significant estimate (ATT(2010,2010)) shows a positive sign.

Figure 3. Group-time ATTs estimates (basic model) – Mela Val di Non PDO sample.

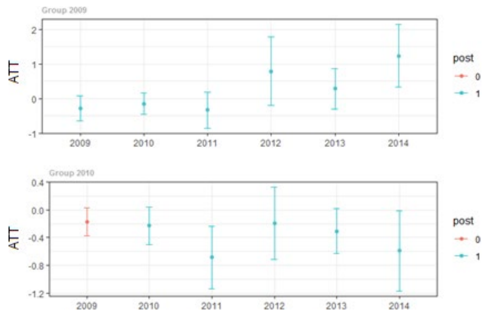


Figure 4. Group-time ATTs estimates (covariates model) – Mela Val di Non PDO sample.

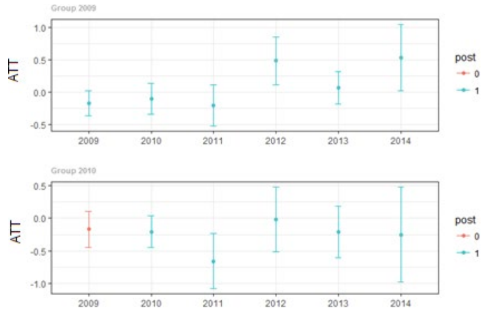


Figure 5. Group-time ATTs estimates (basic model) – Riviera Ligure PDO sample.

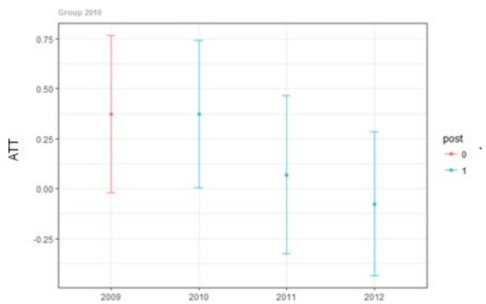
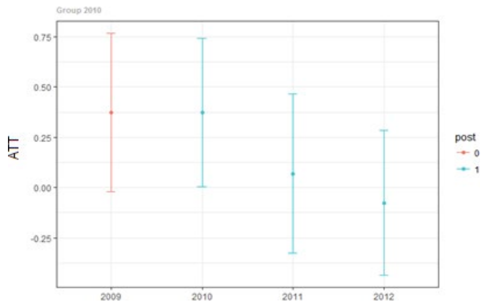


Figure 6. Group-time ATTs estimates (covariates model) – Riviera Ligure PDO sample.



Finally, in Table 5, we report the CSA summary measures. Similarly to what observed for the group-time ATTs, with the exception of the *Selective treatment timing* for the Mela Val di Non sample, the significance levels of the basic models estimate are similar to those of the models where covariates are considered. Because of the presence of only one group of treated units in the Riviera Ligure PDO sample, all the summary measures for this sample converge to the *Weighted average*. The *Weighted average* is the CSA counterpart of the TWFE impact estimate, and therefore the one in which we are most interested in for the comparison of the two estimators. In all samples this summary measure is not statistically different from zero. While this results are in line with the TWFE estimates for two models (Mela Val di Non PDO covariates model and Riviera Ligure PDO basic model), for the other two models the evidence is in contrast to what obtained from the TWFE estimation.

With respect to the other parameters, that can be estimated only in the Mela Val di Non PDO sample, the first-level measures that are statistically significant are usually dynamic or calendar effects but, for the covariates model, selective timing too. We must consider that both dynamic and calendar measures are obtained aggregating two group-time ATTs. In this way, each ATT has a considerable power in shaping the aggregated measure. With respect to the second-level of aggregation measures, none of them are sta-

Table 5. CSA summary measures for Mela Val di Non PDO and Riviera Ligure PDO.

Mela Val di Non PDO[1]											
Weighted average			Selective treatment timing			Dynamic treatment effects			Calendar time effects		
Summary measure	Basic	Covariates	Summary measure	Basic	Covariates	Summary measure	Basic	Covariates	Summary measure	Basic	Covariates
θ	-0.05 (0.13)	-0.02 (0.14)	$\theta_S(2009)$	0.10 (0.09)	0.25** (0.18)	$\theta_D(1)$	-0.18** (0.08)	-0.26** (0.12)	$\theta_C(2009)$	-0.17 (0.11)	-0.29 (0.18)
			$\theta_S(2010)$	-0.27 (0.18)	-0.40** (0.16)	$\theta_D(2)$	-0.36** (0.14)	-0.40** (0.13)	$\theta_C(2010)$	-0.15* (0.09)	-0.16 (0.11)
			θ_S	-0.07 (0.13)	-0.05 (0.14)	$\theta_D(3)$	-0.12 (0.13)	-0.27 (0.19)	$\theta_C(2011)$	-0.42** (0.14)	-0.50** (0.17)
						$\theta_D(4)$	0.16 (0.15)	0.28 (0.23)	$\theta_C(2012)$	0.25 (0.17)	-0.33 (0.28)
						$\theta_D(5)$	-0.08 (0.16)	-0.12 (0.21)	$\theta_C(2013)$	-0.06 (0.13)	0.01 (0.19)
						$\theta_D(6)$	0.54* (0.27)	1.23** (0.47)	$\theta_C(2014)$	0.17 (0.27)	0.39 (0.30)
						θ_D	-0.01 (0.11)	0.08 (0.19)	θ_C	-0.06 (0.10)	-0.04 (0.16)
Riviera Ligure PDO											
Weighted average			Selective treatment timing			Dynamic treatment timing			Calendar time effects		
Summary measure	Basic	Covariates	Summary measure	Basic	Covariates	Summary measure	Basic	Covariates	Summary measure	Basic	Covariates
θ	0.16 (0.13)	-0.03 (0.21)	-	-	-	-	-	-	-	-	-

[1] For the definition of each summary measure reported in this table refer to Table 1.
Note: Asterisk (*) and double asterisks (**) denote group-time ATTs significant at 10% and 5% respectively.

tistically significant, indicating that there is no trend of the effect due to selective, dynamic or calendar effects.

5. Discussion

The results of our analysis show that, in a European agricultural policy framework characterized by event study characteristics, the TWFE, the parametric technique that has been commonly used in literature to estimate the ATT in these contexts, might provide different estimates than a novel non-parametric estimator that accounts for treatment effect heterogeneity. The main concern we observed is not the discrepancy in the magnitude of the estimated effects, which could be traced back to a cumbersome interpretation of the TWFE estimate (Imai and Kim, 2019; Athey and Imbens, 2018; Goodman-Bacon, 2018). Rather, in some samples, there is a substantial difference in the significance levels of the two estimates. Technical literature warns about the possibility that this eventuality may occur in contexts characterized by a differed administration of the treatment and by the continuation of the treatment over multiple periods, and attributes this fact to the possible occurrence of negative weights in the construction of the TWFE estimate (Abraham and Sun, 2018; Borusyak and Jaravel, 2017; de Chaisemartin and D'Haultfoeuille, 2019) when treatment effect heterogeneity is at stake. In two of our samples, evidences of group-time effect heterogeneity emerged. In the Mela Val di Non samples, the aggregate measures show that the effect varies over time. We must use caution in relying heavily on these measures, because of the few number of groups in the sample. Therefore, despite we found some hints of time heterogeneity, it is difficult to clearly attribute it to dynamic rather than to calendar effects. A stronger evidence of the presence of effect heterogeneity is provided by the single group-time ATT estimates, whose variability is observed in all samples used in the analysis. The presence of time heterogeneity is reliable given the structure of the GI policy. Especially under a *calendar* point of view, the economic effect of this policy may well depend on factors that varies over time (e.g. prices, level of production, demand). This variability might translate into an inter-annual effect variability. In light of this, the issue of negative weights pointed out by the literature, which may cause the TWFE estimator to be biased, may be relevant when estimating economic impacts in the GI context. Since the CSA estimator is specifically built to address the issue of negative weights when aggregating the single group-time ATTs, our results cast doubts about the reliability of the TWFE estimates in this policy context.

It should be noted, however, that our results are valid just for our scale of analysis, i.e. the farm level, and should not be extended to contexts where the analysis is performed at different scales or with a continuous treatment variable. For example, among the studies we referred to in the introduction, Raimondi et al. (2019) study the trade effects of the number of GIs in a given product line using decomposed bilateral trade flows at the HS 6-digit level as their units of analysis. In cases like this the CSA estimator simply cannot be computed in the current specification. In addition, a characterization of calendar and group effects when the treatment is continuous has not been developed yet.

A possible limitation of our study derives from the fact that we dropped several units from the samples we used in the analysis. This was done to balance the panels as well as to perform direct matching on some covariates. On the one hand, dropping observations increases the variance of the estimates (Caliendo and Kopeinig, 2008; Faries et al., 2020). On the other hand, similarly to what happens when trimming observations that lay out of the common support in matching studies, the reference population change (Yang et al., 2016). Especially the latter issue would be a relevant concern if the aim of the study was to provide a rigorous impact assessment of the GI policy, because results would not be externally valid. However, since our aim is to compare the two estimators using a real policy setting, these concerns are not relevant.

6. Conclusions

In this article, we explored the relevance and the possible effects of group-time treatment effect heterogeneity in impact analysis in the context of the European GI policy. As highlighted by a recent strand of literature, this kind of heterogeneity creates some problems for the estimation of the impact with traditional techniques. In line with these concerns, we observed that the standard parametric way to estimate the effect of the certification, the two-way fixed effects regression, provides different results from a recently developed estimator that accounts explicitly for group-time effect heterogeneity and its negative effects on the estimate unbiasedness. While these results are in line with the evidences reported in technical literature, our study represents, to our knowledge, a first application of a method that takes into account group-time treatment effect heterogeneity in the European agricultural economics context. Moreover, our results showed that this kind of heterogeneity might have important practical implications when measuring the impact of policies where the treatment is administered on a voluntary basis and whose effect may depend on factors that changes over time. In the case that we analyzed, i.e. the GI policy, the estimation through the two-way fixed effects estimator not only masks the underlying time effect heterogeneity, but also fails in providing an unbiased estimate of the average GI effect. Therefore, estimating the effect of this policy through the TWFE might provide biased results and wrong conclusions. Notably, time, but also group effects are particularly relevant for agricultural productions which are dependent on weather vagaries and related biotic factors which in turn impact on market equilibrium and resulting prices. Since we worked on logarithms of gross margin, wide changes in the level of prices for the baseline (i.e the conventional) product are likely to impact on the percentage premium of the GI counterpart.

This issue is particularly relevant because of the tendency of agricultural economists, so far, to estimate the impacts of this type of policies through the classical TWFE estimator. It is important to note that the use of the standard parametric estimator does not automatically lead to biased results, because both the presence and the extent of the bias depend on the structure of the weights associated to the single group-time ATTs. However, using an estimator that does not consider the possibility that the effect of these policies may vary over time and/or across groups of units can lead to misleading conclusions. This is particularly important whenever the outcome of a policy is affected by market conditions, in which case calendar effects are likely to arise.

The focus of our study was the European GI certification system, but several other policies can be found in the European agricultural body of legislation where treatment effect heterogeneity may be at stake, such as the Rural Development Programs and their measures that are developed in each CAP programming period, or other types of voluntary certifications (e.g., organic certification). In addition, in the EU political context, the assessment of the policies' performances, especially in the agricultural sector, is acquiring a leading position, which makes the concern of group-time treatment effect heterogeneity even more pressing. The evidence-based policy making course, undertaken in the current CAP programming period and confirmed and strengthened for the next one, needs, in fact, reliable evidence to show out its usefulness in building new policies or in improving old ones. The methodological accuracy of impact evaluation studies becomes thus fundamental to avoid inappropriate policy actions guided by misinterpreted evidence.

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Full Research Article

The impact of food price shocks on poverty and vulnerability of urban households in Iran

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Abstract. The aim of this paper is to assess the welfare effects of food price changes on urban households' poverty and vulnerability. This is achieved by using Hicksian price Compensating Variation (CV) and compensated price elasticities, based on Quadratic Almost Ideal Demand System (QAIDS). The study includes in total eight food groups (cereals, meats, dairy, cooking oil, sugar, fruits, vegetables, and tea and coffee) and encompasses 18852 urban households. The results showed that the welfare index for food groups was 20 USD (2.52% of the monthly average income of urban households). After increasing food prices, based on the poverty line, 41% of urban households were observed to be below the poverty line and the number of poor households increased by 10.63%. To enable food security and to execute food safety goals, the Iranian government should compensate for the welfare losses by supportive policies such as direct subsidy payments to vulnerable households.

Keywords. Compensating Variation (CV), Quadratic Almost Ideal Demand System (QAIDS), welfare effect, vulnerability, food price shocks.

JEL Codes. I32, N95, Q18.

1. Introduction

The level of the Iranian food consumption is expected to increase significantly in next years. There are two main reasons for this issue: First, the Iranian population of currently approximately 82 million is estimated to grow by around 1 million people annually in the next 5 years. The expected short-term population growth will increase demand and consumption of food products in Iran. Second, an increasing part of the Iranian population is moving from rural into urban areas. The growing urbanization decreases the amount of wholly or partly self-sufficient people in Iran. Instead, they become consumers in the urbans contributing to a growing food demand (ISC, 2016).

The GDP-growth in Iran has increased from 0.9 % in 2015 to 4.6 % in 2016. The Economist Intelligence Unit predicts that the Iranian GDP will increase further, reach-

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ing 5.4 % in 2017 and 5.9 % in 2018. This positive development in Iranian economy is expected to contribute to a general increase in food consumption and demand, as it is likely to increase the living standard for the growing middle class in Iran, raise purchasing power and consumers' confidence. This will raise the demand for more expensive and specialized food products. The demand for basic food products is also expected to increase, as the current consumption of food products in Iran is relatively low by regional standards. This especially concerns sugar, corn, meat, and vegetable oils. During the sanctions period, real disposable incomes for most consumers were falling, due to high inflation rates not matching by salary increases. As a consequence, the consumption per capita of some of the more expensive food products like red meat, cheese and milk declined. With increasing economic growth, the repressed food demand is expected resume and continue to grow. Traditional grocery and other stores accounts for more than 80% of retail sales in Iran. However, recently hyper- and supermarkets are growing in importance thereby stimulating the demand for more advanced products. A larger product variety is expected to lead to a growing demand (IMAJ, 2016). Therefore, Iran is expected to be faced with increasing food prices, which leads to increased adverse impacts on poverty and food security. In this regard, it is of utmost importance to know how changes in food prices affect the welfare of households. Hence, understanding the effects of price increases of food especially on vulnerable households could have significant implications for the design of supporting policies (Fallahi *et al.*, 2016) and to help decrease the negative impacts of increasing prices towards achieving the goal of food security.

In the case of Iran, over the course of the last 15 years (2001-2015), the average annual imports of eight main food groups, namely meat, cereals, dairy products, oils and fats, sugar, fruits, vegetables and tea and coffee, has reached a level of 12430 million tons, which has shown an increase of 54 percent over 15 years, and around 5.21 percent increase, annually. To provide an example, Iran is the major importer of oilseeds and about 90 percent of the country's oil needs to be provided through imports. Also, in the year 2018, nearly 20 percent of meat and more than 40 percent of cereals supplied in the Iranian market have been provided through imports (FAO, 2016). This significant rise in the level of imports, hence, brought about an increase in the prices of many products. Being vulnerable to the rising food prices in the world due to high level of imports in food products and increasing global food prices also carry major implications for both the economic and social welfare of Iranian households, which has been subject of increasing concern. In this context, urban households, which constitute around 75 percent of the total number of households in Iran, and whose budget composition is directly impacted by the inflated food purchases, are hit ineluctably (Ravallion and Chen, 2007; Robles and Keefe, 2011). In this study, our aim is to estimate the effects of the 2000–2016 food price surges on urban households' expenditure and food poverty. Our methodological approach follows Azzam and Rettab (2012) and Rodriguez-Takeuchi and Imai (2013) to take into account the impacts of food price changes on households' vulnerability and poverty. The rest of the paper is structured as follows: The next section provides the background of the importance of studying the behavior of consumers. We, then introduce the methodology of the Quadratic Almost Ideal Demand System (QAIDS) model and the Vulnerability Index and Data. Own- and cross-price elasticities, welfare and poverty effects of food price changes are presented in the results section, and also, the final section offers concluding remarks and policy discussion.

1.1 Measuring economic welfare

Measuring the economic welfare and poverty effects of different policies among societies have always been one of the most important economic issues of public policies. Countries often use policy interventions to dampen the impacts of international food price spikes on domestic markets and lessen the burden of these especially on vulnerable population groups. Besides, understanding the causes of the food price shocks and addressing its significant effects on developing countries have been critical in order to analyze the efficiency and adequacy of policies in addition to be able to propose policy options. The impact of these shocks on welfare depends on a variety of factors, including but not limited to the nature of the shock, initial household, or community conditions and also policy responses by the government (UNICEF, 2009). In addition to such macro impacts, micro impacts are mainly experienced in the form of reduced household income, due to lower wages and employment or limited access to credit and reduced real income in the face of higher food prices, and decreased access to public services, as a result of reduced service delivery on the part of the government (UNICEF, 2009). Meanwhile, the extent to which households are affected by these shocks will depend on the change in relative prices, substitution of commodities and response of households to all these factors (Osei-Asare and Eghan, 2013).

Towards this end, numerous studies worked on the relative prices and substitution relation among commodities by estimating elasticities of demand functions based on Translog or "Almost Ideal Demand System" (AIDS) forms. Some of the examples include Deaton and Mulbaer (1980), studying the case of Great Britain, Blanciforti and Green (1983), and Hayes *et al.* (1990), of United States; Fulponi (1989), of France; Abdulai *et al.* (1999), of India; Tefera (2012), of Ethiopia and Suharno (2010) of Indonesia. Meanwhile, other studies have used the AIDS model, which has assumed a linear Engel curve (Tefera, 2012), while Banks *et al.* (1997) proposed a Generalized Quadratic Almost Ideal Demand System (QAIDS) that permits a non-linear Engel curve. Matsuda (2006) also applied QAIDS to estimate food demand in Japan. On the other hand, Arabatzis and Klonaris (2009) studied on cases, in which QAIDS has been applied for wood product imports in Greece. Furthermore, Layani and Esmaeili (2015) also used QAIDS and a welfare index such as Hicksian compensating variation (CV) to analyze food demand in order to assess the welfare effects of increasing food prices for households in Iran.

The significant welfare impacts of price shocks have prompted studies to evaluate recent price shocks on household poverty in developing countries (e.g., De Janvry and Sadoulet, 2010; Leyaro *et al.*, 2010; Coleman, 2012; Ivanic *et al.*, 2012; Fujii, 2013; Layani and Bakhshoodeh, 2016). In recent studies of the economic welfare effects of food price changes, Azzam and Rettab (2012) have focused on the vulnerability of households in the United Arab Emirates (UAE) as a result of increasing prices for imported food products; while, Rodriguez-Takeuchi and Imai (2013) and Fujii (2013) have first calculated the poverty line and then analyzed the effects of increasing food prices on household expenditure and the poverty line. In this study, in addition to discussing the welfare effects of food rising prices in the face of highly elastic poverty lines to relative food prices, the poverty line changes in urban households are also addressed to understand the extent of Iranian consumers' vulnerability to food price increases and food supply shocks. Measuring the welfare changes caused by increasing food prices is crucial to provide a compensatory support system. Our methodological approach follows Azzam and Rettab (2012) to determine the impacts of food price changes on Iranian urban households' expenditure and poverty line.

Within this context, the objectives of this paper are: (1) To determine the price and income elasticity for food groups by using Quadratic Almost Ideal Demand System (QAIDS); (2) To explore welfare impacts of increasing world food prices using Compensated Variation (CV); and (3) To calculate the consumer vulnerability index and poverty effects of food price shocks.

2. Methodology

2.1 Poverty Line and the Vulnerability Index

Poverty measurement is based on a comparison of resources to need (World Bank, 2000). A person or family is identified as poor if their resources fall short of the poverty threshold. Meanwhile, poverty is defined by using a poverty line; when a household falls below this line, it is considered to be poor. For instance, the World Bank considers a household to be poor if it survives on less than 1.90 USD per day. In this study, food poverty has been considered. In order to measure the poverty line based on the relative concept, poverty line can be determined by the percentage of average household expenditure. By following the work of Khodadad Kashi *et al.* (2005) and Arshadi and Karimi (2013), we take 66 percent of the average household food expenditure as a threshold for determining the relative poverty line:

$$\text{Poverty Line} = 66 \text{ percent} \times (\text{average food expenditure}) \tag{1}$$

Therefore, the relative poverty line is calculated before the change in food prices by (1). After computing the poverty line, we can divide urban households into two groups: The households that have a food expenditure higher than poverty line (above the poverty line), and the households that have a food expenditure lower than poverty line (below the poverty line). The reason for this is because poverty lines are highly elastic to relative food prices and changes in food prices result in variations of poverty prevalence. Furthermore, we then compute a new poverty line, after accounting for the rise in food prices (Rodriguez-Takeuchi and Imai, 2013):

$$\text{Secondary Poverty Line} = \text{Poverty Line} + \text{Welfare Index} \tag{2}$$

In addition, we compute the Vulnerability Index following Azzam and Rettab (2012):

$$\text{Households Vulnerability} = \text{total welfare loss relative to income} = WI/AI \tag{3}$$

In the equation, WI is the total welfare effects of rising food prices and AI is the average income of urban households.

2.2 Welfare Index with price changes

In general, in the welfare literature, there are various indexes for measuring the welfare changes due to implementation of different policies (Gohin, 2005). By changing economic conditions, such as price changes, consumers' utility rates may increase or decrease. To determine how and how much of the consumer utility changes due to changing economic conditions, some criteria are used such as Consumers Surplus (CS), Compensated Variation (CV) and Equivalent Variation (EV). In our context of rising food prices, CV is the minimum amount, the Iranian consumers are willing to accept (WTA) to tolerate higher food prices; and EV is the maximum amount they are willing to pay (WTP) to avoid higher food prices. The focus of CV is on the welfare level prior to the increase in prices, while the focus of EV is on the subsequent welfare level after the increase in prices (Azzam and Rettab, 2012). Hence, we use the CV in our study, based on the studies of Azzam and Rettab (2012), Tefera (2012) and Cranfield (2007).

The starting point of the CV model with price changes is the consumer problem of minimizing expenditures on N food commodities subject to a utility level U^0. Substitution of the resulting optimal Hicksian quantities into the expenditure equation yields the minimized expenditure function (Azzam and Rettab, 2012):

$$\begin{aligned} E = E(P_1, P_2, \dots, P_3, U^0) &= p_1 q_1^H(P_1, P_2, \dots, P_3, U^0) + p_2 q_2^H(P_1, P_2, \dots, P_3, U^0) \\ &\quad + \dots + p_N q_N^H(P_1, P_2, \dots, P_3, U^0) \end{aligned} \tag{4}$$

Where Pi for i = 1, 2, . . ., N are the respective prices of the N commodities, and the superscript H stands for Hicksian. Denoting the initial and the subsequent periods by superscripts "0" and "1", respectively, consumer WTA to tolerate higher prices is given by:

$$CV = E(p_1^1, p_2^1, \dots, p_{\mathrm{N}}^1, U^0) - E(p_1^0, p_2^0, \dots, p_N^0, U^0) \tag{5}$$

Using (4), we can expand (5) as follows:

$$\begin{aligned} CV &= p_1^1 q_1^H(p_1^1, p_2^1, \dots, p_N^1, U^0) - p_1^0 q_1^0 + p_2^1 q_2^H(p_1^1, p_2^1, \dots, p_N^1, U^0) - p_2^0 q_2^0 + \dots \\ &\quad + p_N^1 q_N^H(p_1^1, p_2^1, \dots, p_N^1, U^0) - p_N^0 q_N^0 \end{aligned} \tag{6}$$

Direct measurement of CV using (6) is not possible because the Hicksian demand functions $q_i^H(.)$ for i = 1, 2, . . ., N depend on the utility level U0, which is unobservable. However, as shown by Huang (1993), if the respective changes in prices and Hicksian quantities are defined as (Azzam and Rettab, 2012):

$$\begin{aligned} dp_{\mathrm{i}} &= p_i^1 - p_i^0 \; for \; i = 1,2, \dots, N \\ dq_i^H &= q_i^H - q_i^0 \; for \; i = 1,2, \dots, N \end{aligned} \tag{7}$$

and substituted into (6), CV can be approximated by:

$$CV = p_1^0 q_1^0 \left(\frac{dp_1}{p_1^0} + \frac{dq_1^H}{q_1^0} + \frac{dp_1}{p_1^0}\frac{dq_1^H}{q_1^0}\right) + p_2^0 q_2^0 \left(\frac{dp_2}{p_2^0} + \frac{dq_2^H}{q_2^0} + \frac{dp_2}{p_2^0}\frac{dq_2^H}{q_2^0}\right) + \cdots + p_N^0 q_N^0 \left(\frac{dp_N}{p_N^0} + \frac{dq_N^H}{q_N^0} + \frac{dp_N}{p_N^0}\frac{dq_N^H}{q_N^0}\right) \quad (8)$$

The percentage change in Hicksian quantities is not observed. However, an approximation of the change is obtained through the total differential of the Hicksian demand functions $q_i^H(.)$. For example for i = 1, 2, . . ., N:

$$\begin{aligned}
\frac{dq_1^H}{q_1^0} &= \epsilon_{11}^H \frac{dp_1}{p_1} + \epsilon_{12}^H \frac{dp_2}{p_2} + \cdots + \epsilon_{1N}^H \frac{dp_N}{p_N} \\
\frac{dq_2^H}{q_2^0} &= \epsilon_{21}^H \frac{dp_1}{p_1} + \epsilon_{22}^H \frac{dp_2}{p_2} + \cdots + \epsilon_{2N}^H \frac{dp_N}{p_N} \\
&\;\;\vdots \\
\frac{dq_N^H}{q_N^0} &= \epsilon_{N1}^H \frac{dp_1}{p_1} + \epsilon_{N2}^H \frac{dp_2}{p_2} + \cdots + \epsilon_{NN}^H \frac{dp_N}{p_N}
\end{aligned} \quad (9)$$

where ϵ_{ij}^H is the Hicksian price elasticity for i = 1, 2, . . ., N and j = 1,2, . . ., N.

2.3 Quadratic Almost Ideal Demand System

To estimate the Hicksian price elasticities as shown in (9), we estimate a Quadratic Almost Ideal Demand System (QAIDS) model for N commodities by imposing the usual restrictions: Adding-up, homogeneity, and symmetry. The QAIDS model developed by Banks *et al.* (1997), which has budget shares that are quadratic in log total expenditure, is an example of the empirical demand systems that have been developed to allow this expenditure nonlinearity. The QAIDS not only retains the desirable properties of the popular AIDS of Deaton and Muellbauer (1980) nested within it, but also has the additional advantage of being versatile in modelling consumer expenditure patterns. Quadratic in the logarithm of total expenditure, the QAIDS allows such situations where the increase in the expenditure would change a luxury to necessity (Arabatzis and Klonaris, 2009).

The QAIDS model is (Gorman, 1981; Jing et al, 2001):

$$S_i = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} log p_j + \beta_i log\left[\frac{M}{f(p)}\right] + \frac{\lambda_i}{g(p)}\left\{log\left[\frac{M}{f(p)}\right]\right\}^2 \quad (10)$$

Where S_i is the share of food group i in total expenditure on the N food groups, for i=1,2,..,N; and p_j is a vector of prices; M is total expenditure. Also, *f(p)* is the Stone Price Index defined by $logf(p)^* = \sum_i si\ logp_i$.

The restrictions are:

$$\sum_{i=1}^{n} \alpha_i = 1, \sum_{i=1}^{n} \gamma_{ij} = 0, \sum_{i=1}^{n} \beta_i = 0 \quad , \gamma_{ij} = \gamma_{ji} \tag{11}$$
$i,j = 1,2,\ldots,N$

The respective formulas for computing the Hicksian Price elasticities for N groups are:

$$e_{ij}^{h} = \left(\frac{u_{ij}}{s_i} - \delta_{ij}\right) + (1 + \frac{u_i}{s_i})s_j \tag{12}$$

$$u_i = \frac{\partial s_i}{\partial lnm} = \beta_i + \frac{2\lambda_i}{g(p)}\left[log\left[\frac{M}{f(p)}\right]\right]$$

$$u_{ij} = \frac{\partial s_i}{\partial lnp_j} = \gamma_{ij} - \left(\beta_i + \frac{2\lambda_i}{g(p)}\left[log\left[\frac{M}{f(p)}\right]\right]\right)(\alpha_j + \sum_{i=1}^{k} \gamma_{ji} logp_i) - \frac{\lambda_i \beta_i}{g(p)}\left[log\left(\frac{M}{f(p)}\right)\right]^2 \tag{13}$$

Where δ_{ij} is the Kronecker delta taking the value $\delta_{ij} = -1$ if i = j and $\delta_{ij} = 0$ if i ≠ 0. In terms of the u_i, the formula for Income elasticities can be written as:

$$e_i = 1 + \frac{u_i}{s_i} \tag{14}$$

Negative cross-price elasticities indicate a complementarity relationship and the positive values for cross-price elasticities indicate substitutability. Also, the positive (negative) values for expenditure elasticity indicated non-inferior (inferior). In the former case when $\varepsilon_i \geq 1$ the goods are regarded as luxury. Specifically, so-called normal necessities have an income elasticity of between 0 and 1.

But one of the problems with working with these kind of models is the phenomenon of zero consumption of a commodity or the zero budget share, which is due to the division of food groups into a large number of groups and the use of cross-sectional data at the household level. In other words, some households report a zero consumption, and some others spend a non-zero share. Therefore, the variable is censored. In order to solve this problem, based on the Bakhshoodeh (2010) study, we use the following equation instead of equation (10).

$$s_i = \varphi(z_i^h \tau_i)\left[\alpha_i + \sum_{j=1}^{k\sum\left[\frac{m}{f(p)}\right]\frac{\lambda_i}{g(p)}\left\{log\left[\frac{m}{f(p)}\right]\right\}^2} \gamma_{ij} \log p_j\right] \tag{15}$$

Where $\phi(0)$ and $\varphi(0)$ are Cumulative Distribution Function (CDF) and Probability Distribution Function (PDF) for each household

The system of Eq. (15) is estimated using iterative seemingly unrelated regression (SURE) to calculate elasticities for eight food groups (cereals, meats, dairy, oil, sugar, fruits, vegetables, and tea and coffee).

3. Data and information

This study is based on urban household's income-expenditure survey (2012) of the Iranian Statistics Center (18852 urban households) for computing price and income elasticities. We collected data on food imports to Iran during the years of 2000 to 2016. Then the average annual growth of imported food prices is defined as a price shock scenario. By referring to Ivanic *et al.* (2012), we assume that the global food price shocks transferred completely to the domestic market in Iran. Finally, welfare effects and changes in food poverty are determined.

Mean and standard deviations of expenditure share and average monthly expenditures for eight food groups including cereals, meats, dairy, cooking oil, sugar, fruits, vegetables, and tea and coffee are presented in Table 1. Generally, the share of food and beverage expenditures in total household budget is equal to 23.5%. The share of food expenditures is in the second-placed after the share of buying/renting house budget (ISC, 2016). Among eight food groups, the maximum and the minimum average expenditure shares related to cereals were 26.21 percent (monthly 43.69 USD) and 2.9 percent for tea and coffee (about 4.69 USD) respectively.

Table 1. Average expenditure shares of different food groups.

Group	Average expenditure share	Coefficient of variation	Standard deviation	Average monthly food expenditure
Cereals	26.21	0.45	0.11	43.69
Meats	22.87	0.47	0.10	41.01
Dairy	12.16	0.51	0.06	18.68
Oil cooking	5.42	0.71	0.03	8.84
Sugar	4.60	0.81	0.03	8.13
Fruits	12.29	0.63	0.07	22.38
Vegetables	13.55	0.45	0.06	21.76
Tea and coffee	2.90	1.07	0.03	4.69

Source: Iranian Statistics Center, 2016.

4. Result and discussion

According to the price elasticities of the QAIDS[1] model, all own-price elasticities are negative. In terms of absolute values, the highest own-price elasticity is related to tea and coffee (2.19 percent) and the lowest own-price elasticity is related to fruits (0.05%). It means that, demand for tea and coffee is highly responsive to any change in the price. The estimated own price elasticities for vegetables (-0.74%) and for sugar (-0.82%) are close to one. In fact, demand for these two groups has large response to changes in their relative prices. The estimated own-price elasticity is low for others. We concluded that demand for cereals, meat, dairy and oil cooking are stable to price changes, meaning that these food groups are essential in household consumption patterns.

[1] QAIDS estimation is reported in the Annex.

Cross-price elasticities show competitive or complementary relations among products. Positive cross-price elasticities indicate competitive relations, while negative cross-price elasticities indicate complementary relations. The Cross-price elasticities presented in Table 2 also show that most of the selected goods have complementary relationship with each other. In addition, in terms of the absolute value of the elasticity, the complementary relationship can also be stronger than the substitution relation. The cross-elasticity of other commodities with cereals and meats suggest a substitution relationship between them, but the relationship between cereals and meat with other commodities is mostly complementary. This pattern of relationships can indicate the importance of consumption of cereals and meat in the consumer food pattern. By illustration, consumers prefer to add other commodities as a complement to their consumption patterns after the inclusion of cereals and meat, while these two products will be the substitution to other commodities. The patterns of household consumption, and especially the high per capita consumption of cereals such as rice and wheat, can also confirm these results.

The estimated total income elasticities presented in Table 2 have the expected positive signs in all eight commodities. The values for cooking oil (e=1.76), fruits (e=1.38), meat (e=1.22) and cereals (e=1.18) are much higher than others. This implies a fairly large response of demand for these food groups to changes in total food expenditure. Actually, the demand for cooking oil, fruits, meat and cereals are elastic with respect to total food expenditure. The estimated income elasticities of dairy, sugar, vegetables and tea and coffee are less than unity, so these goods are fairly inelastic with respect to total food expenditure.

After obtaining compensated own and cross price elasticities in this section we examine the welfare impacts of the changes in selected food items' prices. Following some recent literature, we estimate the change in consumer welfare by using the compensating variation (CV). The compensating variation is the amount needed to compensate a household for a price increase, in order for the household to remain at the same utility level after a price change. We define price shock scenarios based on average annual changes in world food prices presented by FAO (2016) for period of 2000-2014. Prices of cereals, meat, dairy, oils, sugar, fruits, vegetables and tea and coffee have increased by 9.80, 8.35, 7.72, 8.06, 8.78, 3.16, 15.70 and 4.68 percent, respectively.

We present the average compensating variation values in Table 3. Results show that the welfare losses from the price increases in cereals, meats, dairy, oils, sugar, fruits, vegetables and tea and coffee amount to 20 USD. In other words, on average, Iranian urban households need to be compensated with approximately 11.82 percent of their 2016 total household expenditure on food in order to accommodate the adverse impact of food price changes they faced between 2000 and 2014. The highest amount of CV as a result of the increase of prices is obtained for fruits. The amount of CV for fruits is estimated at 4.90 USD, which is equivalent to 2.42 percent of the average food expenditures in 2016. Also, the CV index of cereals is estimated to be 3.56 USD, which is equivalent to 2.11 percent of the average food expenditure in 2016. Thus, with an increase of 9.80 percent in the price of cereals (considering the simultaneous price change), urban household expenditures increase and their welfare decreases. The CV for meat, dairy and vegetables are 2.86 (equivalent to 1.69 percent of the average food expenditure), 3.46 (equivalent to 2.05 percent of average food expenditure) and 3.03 USD (equivalent to 1.79 percent of average food expenditure), respectively. Finally, the last column of Table 3 shows the weight of the calculated CV index for each food group

Table 2. Hicksian (Compensated) Price and income elasticities for different food groups.

	Cereals	Meats	Dairy	Oil cooking	Sugar	Fruits	Vegetables	Tea and coffee
Cereals	-0.22 (-7.51) *	-0.01 (-12.98)	0.31 (11.63)	0.17 (15.01)	0.61 (9.82)	-0.24 (-5.25)	0.02 (7.96)	1.01
Meats	0.05 (12.98)	-0.27 (-11.09)	0.15 (10.44)	0.26 (9.10)	0.25 (2.34)	-0.01 (-2.34)	0.09 (2.34)	0.23
Dairy	-0.06 (-11.63)	-0.19 (-10.44)	-0.22 (-8.04)	-0.56 (-7.26)	0.78 (6.37)	-0.01 (-4.13)	1.35 (10.51)	0.61
Oil cooking	0.13 (15.01)	0.12 (9.10)	0.14 (7.26)	-0.24 (-5.54)	0.10 (10.43)	0.12 (5.14)	-0.04 (-6.02)	0.39
Sugar	0.01 (9.82)	-0.13 (-2.34)	0.48 (6.37)	-0.60 (-10.43)	-0.82 (-7.07)	-0.25 (-8.23)	0.94 (7.05)	0.71
Fruits	-0.07 (-5.25)	-0.00 (-2.34)	0.32 (4.13)	0.25 (5.14)	0.02 (8.23)	-0.05 (-8.66)	0.25 (6.15)	-0.26
Vegetables	-0.04 (-7.96)	-0.01 (-2.34)	0.40 (10.51)	-0.21 (-6.02)	0.51 (7.05)	0.01 (6.15)	-0.74 (-7.04)	-0.07
Tea and coffee	0.28 (10.01)	0.48 (6.21)	-0.84 (-7.33)	1.36 (9.07)	-0.58 (-7.58)	0.34 (5.98)	-1.02 (-4.56)	-2.19 (-8.43)
Income Elasticities	1.18	1.22	0.23	1.76	0.39	1.38	0.58	0.14

Source: Authors' calculations
* Indicates significance at the 5% level, t-ratios are in parentheses.

from the total welfare index. According to the results, the amount of CV for fruits, cereals and dairy constitutes the highest share of the total CV index, respectively equal to 20.45 percent, 17.80 percent, and 17.30 percent of the total CV, respectively.

Table 4 shows the average monthly food expenditure of the 8 food groups, total CV, average monthly income for households, and the welfare measure of the vulnerability index (total CV relative to income). Given that the average monthly income of Iranian urban households is 792.66 USD, the total welfare loss due to rising food prices is equivalent to 2.52 percent of an average household income, which is an indicator of the vulnerability of urban households as a result of the increase in global prices. This index can be used as an effective tool as part of efforts towards enforcing supportive policies. In more detail, policymakers determine the rate of increase in employees' wage annually, based on economic indicators such as inflation. Specifying the vulnerability index would be a suitable measure to balance the wages and inflation in the society.

Finally, we examine the effect of rising food prices on poverty in urban households in Table 5. According to the average total food expenditures, the initial poverty line is computed as 111.66 USD; and after rising food prices, the secondary poverty line is computed to be 131.66 USD. In the initial setting, 30.13 percent of urban households have a monthly food expenditure below the poverty line (about 5680 households).

Table 3. Welfare effect of price changes(The average compensating variation values).

Group	Proportion of CV (%)	Compensated Variation (%)	Compensated Variation (USD)	Price Change (%)	Average monthly food expenditure (USD)
Cereals	17.80	2.11	3.56	9.80	43.69
Meats	14.29	1.69	2.86	8.35	41.01
Dairy	17.30	2.05	3.46	7.72	18.68
Oil cooking	5.59	0.66	1.12	8.06	8.84
Sugar	6.56	0.78	1.31	8.78	8.13
Fruits	20.45	2.42	4.09	3.16	22.38
Vegetables	15.15	1.79	3.03	15.70	21.76
Tea and coffee	2.84	0.34	0.57	4.68	4.69
Total	100	11.82	20	-	169.18

Source: Authors' calculations.

Table 4. Vulnerability index.

Average Monthly Urban Household Income (USD)	792.66
Total Welfare Index (USD)	20
Average Monthly Food Expenditure (USD)	169.18
Household vulnerability	2.52

Source: Authors' calculations.

Table 5. The effect of rising food prices on poverty in urban households (Poverty line for urban households).

Poverty line	Household	Percent	First poverty line (USD)
Upper	13172	69.87	111.66
Lower	5680	30.13	
Total	18852	100	

Source: Authors' calculations.

Based on what was explained, the total share of poor households in urban areas increases to 40.76 percent (Table 6). We find that 10.63 percent of households, which were above the poverty line before the food price increase, become poor after the price shock. Consequently, the overall share of poor households increases from 0.30 to 2.05 percent in urban areas. For instance, in the case of a 9.80 percent price increase for cereals, the CV is 3.56 USD and the poverty line is 115.52 USD. Our results suggest that an additional 1.79

Table 6. The impact of rising food prices on the poverty.

Group	CV (USD)	Secondary poverty line (USD)	Households (%) Poverty line		Change in household poverty	
			Upper	Lower	(Number)	%
Cereals	3.56	115.22	68.08	31.92	338	1.79
Meats	2.86	114.52	68.48	31.52	262	1.39
Dairy	3.46	115.12	68.16	31.84	323	1.71
Oil cooking	1.12	112.78	69.37	30.63	95	0.50
Sugar	1.31	115.75	69.26	30.74	116	0.62
Fruits	4.09	114.69	67.82	32.18	386	2.05
Vegetables	3.03	112.97	68.39	31.61	280	1.49
Tea and coffee	0.57	112.23	69.57	30.43	57	0.30
Total	20	131.66	59.24	40.76	2004	10.63

Source: Authors' calculations

percent of urban households (about 338 households) drop below the poverty line after a 9.80 percent price increase.

5. Policy implications

In Iran, goods and services subsidy policy has been one of the most important consumer supportive policies over the past 40 years. The main goals of this policy include controlling and stabilizing prices, supporting vulnerable groups, reducing poverty, and distributing equitable income. Although this policy instrument may help improve food security, it has been subject to increasing critiques in recent years. In fact, some local actors claim that, apart from the budget constraint, the use of goods and services subsidy policy in Iran dates to the early 1970s, however, poverty index is still high, standard welfare is not achieved for households yet, and food safety and food security for poor and vulnerable households are still major concerns. As such, this instrument is seen as inefficient given its high budget costs, as a potential source of market distortions, and benefitting some groups who do not need to be supported (e.g. target groups are not identified and households receive the same subsidy) (Azzam and Rettab, 2012; Bakhshoodeh, 2010; Tefra, 2012).

The subsidy payments by 11 USD per month for each person has been constant without considering inflation over the last two decades. These untargeted subsidy payments to the households, regardless of considering their vulnerability and their income level, in addition to being costly for the government, does not improve welfare indicators at the national level. Identification of vulnerable households and determining the amount of subsidy payment to the target groups is one of the most important challenges that policymakers in Iran are facing. Assessing the effects of simultaneous price changes on household expenditures would be one of the tools to identify target groups in receiving subsidies. In other words, determining the share of household expenditure changes (with different socio-economic characteristics) in their income show households that are more vulnerable and in need of government support. Also, the government can use the effect of total price increases on household expenditures to determine the optimal subsidy payment. Finally, implementing this supportive policy by identifying target groups could reduce poverty and increase social justice and keep households with low-income above the food poverty line.

6. Conclusion

We employed Iranian urban households' price elasticities of eight food groups (cereals, meats, dairy, oils, fruits, vegetables, sugar and tea and coffee) to evaluate the welfare effect of food price changes. For this aim, the Compensated Variation (CV) has been utilized, based on the changes in global food prices between 2000 and 2016. Meanwhile, Iranian food demand has been estimated by using the Quadratic Almost Ideal Demand System (QAIDS). This model used to explore how increasing food prices affect Iranian urban consumer welfare and the poverty line. Substitution effects among food items are estimated by including own and cross price elasticities obtained through the estimation of a demand system, QAIDS. According to the demand theory, all the estimated price and expenditure elasticities are acceptable (negative for own elasticities and positive for expenditure elasticities).

Increasing food price leads to urban Iranian household welfare losses and a decrease in the purchasing power. Also, the results of CV suggest that on average, Iranian urban households need to be compensated with approximately 11.82 percent of their 2016 total household expenditure on food in order to accommodate the adverse impact of food price changes they faced between 2000 and 2014. Although the food price changes have had differential effects for each of the food groups, price changes for the majority of households, have brought severe hardship for them to access food. The food price changes drive 2004 urban households below the food poverty line and causes a 10.63 percent increase in the number of poor urban households.

Our findings, hence, underline the negative impacts of price shocks on households' welfare, especially those that are more vulnerable than others. Being informed about the extent of these impacts, by the use of the vulnerability index, hence carries a crucial significance in the context of efforts towards achieving food security in developing countries, and towards supportive policy making targeted at especially vulnerable households. In a similar manner, in order to contribute to food security efforts and to execute food safety goals, the Iranian government should compensate the welfare loses that are incurred by vulnerable households by putting in place supportive policies including but not limited to raising wages or subsidizing vulnerable households.

The strengths of this study compared to other research include: (i) using Quadratic system of the equation which is more flexible than other demand functions, (ii) calculating welfare changes simultaneously with food price changes, (iii) calculating vulnerability index, (iv) calculating second poverty line due to simultaneous changes in food prices and (v) assessing the increase of food prices simultaneously on food poverty of rural households.

There are, however, some limitations of our study that could be addressed in order to add more precision to our results. This paper has focused on the vulnerability index of aggregate eight food groups rather than individual food items. Further research can also focus on individual food items as well as major expenditure groups such as clothing, housing services and health for urban households. Meanwhile, the compensated elasticities can also be calculated for each household in order to identify the social characteristics of households that fall in the category of vulnerable households. Moreover, in this study, all the simulations were carried out by cross-sectional data. Future research would need to use panel data and explore poverty dynamics to test how food price shock affects poverty over time by taking into account the household livelihood strategies. Last but not least, we assume that the global food price shocks transferred completely to the domestic market in Iran. Future work would benefit substantially using accurate quantities of food price transfer in welfare calculations.

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Appendix

The QAIDS for eight food groups reported below:

$$s_1 = \varphi_1(z_i^h\tau_i)\begin{bmatrix}\alpha_1 + \gamma_{11}\log p_1 + \gamma_{12}\log p_2 + \gamma_{13}\log p_3 + \gamma_{14}\log p_4 + \gamma_{15}\log p_5 + \gamma_{16}\log p_6 + \gamma_{17}\log p_7 + \gamma_{18}\log p_8 \\ +\beta_1\left[\frac{m}{f(p)}\right] + \frac{\lambda_1}{g(p)}\left\{\log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} + \mu_{11}z_{1_i} + \mu_{12}z_{2i} + \mu_{13}z_{3i} + \theta\phi_1(z_i^h\tau_i)$$

$$s_2 = \varphi_2(z_i^h\tau_i)\begin{bmatrix}\alpha_2 + \gamma_{21}\log p_1 + \gamma_{22}\log p_2 + \gamma_{23}\log p_3 + \gamma_{24}\log p_4 + \gamma_{25}\log p_5 + \gamma_{26}\log p_6 + \gamma_{27}\log p_7 + \gamma_{28}\log p_8 \\ +\beta_2\left[\frac{m}{f(p)}\right] + \frac{\lambda_2}{g(p)}\left\{\log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} + \mu_{21}z_{1_i} + \mu_{22}z_{2i} + \mu_{23}z_{3i} + \theta\phi_2(z_i^h\tau_i)$$

$$s_3 = \varphi_3(z_i^h\tau_i)\begin{bmatrix}\alpha_3 + \gamma_{31}\log p_1 + \gamma_{32}\log p_2 + \gamma_{33}\log p_3 + \gamma_{34}\log p_4 + \gamma_{35}\log p_5 + \gamma_{36}\log p_6 + \gamma_{37}\log p_7 + \gamma_{38}\log p_8 \\ +\beta_3\left[\frac{m}{f(p)}\right] + \frac{\lambda_3}{g(p)}\left\{\log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} + \mu_{31}z_{1_i} + \mu_{32}z_{2i} + \mu_{313}z_{3i} + \theta\phi_3(z_i^h\tau_i)$$

$$s_4 = \varphi_4(z_i^h\tau_i)\begin{bmatrix}\alpha_4 + \gamma_{41}\log p_1 + \gamma_{42}\log p_2 + \gamma_{43}\log p_3 + \gamma_{44}\log p_4 + \gamma_{45}\log p_5 + \gamma_{46}\log p_6 + \gamma_{47}\log p_7 + \gamma_{48}\log p_8 \\ +\beta_4\left[\frac{m}{f(p)}\right] + \frac{\lambda_4}{g(p)}\left\{\log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} + \mu_{41}z_{1_i} + \mu_{42}z_{2i} + \mu_{43}z_{3i} + \theta\phi_1(z_i^h\tau_i)$$

$$s_5 = \varphi_5(z_i^h\tau_i)\begin{bmatrix}\alpha_5 + \gamma_{51}\log p_1 + \gamma_{52}\log p_2 + \gamma_{53}\log p_3 + \gamma_{54}\log p_4 + \gamma_{55}\log p_5 + \gamma_{56}\log p_6 + \gamma_{57}\log p_7 + \gamma_{58}\log p_8 \\ +\beta_5\left[\frac{m}{f(p)}\right] + \frac{\lambda_5}{g(p)}\left\{\log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} + \mu_{51}z_{1_i} + \mu_{52}z_{2i} + \mu_{53}z_{3i} + \theta\phi_5(z_i^h\tau_i)$$

$$s_6 =$$

$$\varphi_6(z_i^h \tau_i)\begin{bmatrix}\alpha_6 + \gamma_{61}\, log\, p_1 + \gamma_{62}\, log\, p_2 + \gamma_{63}\, log\, p_3 + \gamma_{64}\, log\, p_4 + \gamma_{65}\, log\, p_5 + \gamma_{66}\, log\, p_6 + \gamma_{67}\, log\, p_7 + \gamma_{68}\, log\, p_8 \\ +\beta_6\left[\frac{m}{f(p)}\right] + \frac{\lambda_6}{g(p)}\left\{log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} +$$

$$\mu_{61} z_{1_i} + \mu_{62} z_{2i} + \mu_{63} z_{3i} + \theta\phi_6(z_i^h \tau_i)$$

$$s_7 =$$

$$\varphi_7(z_i^h \tau_i)\begin{bmatrix}\alpha_7 + \gamma_{71}\, log\, p_1 + \gamma_{72}\, log\, p_2 + \gamma_{73}\, log\, p_3 + \gamma_{74}\, log\, p_4 + \gamma_{75}\, log\, p_5 + \gamma_{76}\, log\, p_6 + \gamma_{77}\, log\, p_7 + \gamma_{78}\, log\, p_8 \\ +\beta_7\left[\frac{m}{f(p)}\right] + \frac{\lambda}{g(p)}\left\{log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} +$$

$$\mu_{71} z_{1_i} + \mu_{72} z_{2i} + \mu_{73} z_{3i} + \theta\phi_7(z_i^h \tau_i)$$

$$s_8 =$$

$$\varphi_8(z_i^h \tau_i)\begin{bmatrix}\alpha_8 + \gamma_{81}\, log\, p_1 + \gamma_{82}\, log\, p_2 + \gamma_{83}\, log\, p_3 + \gamma_{84}\, log\, p_4 + \gamma_{85}\, log\, p_5 + \gamma_{86}\, log\, p_6 + \gamma_{87}\, log\, p_7 + \gamma_{88}\, log\, p_8 \\ +\beta_8\left[\frac{m}{f(p)}\right] + \frac{\lambda_8}{g(p)}\left\{log\left[\frac{m}{f(p)}\right]\right\}^2\end{bmatrix} +$$

$$\mu_{81} z_{1_i} + \mu_{82} z_{2i} + \mu_{83} z_{3i} + \theta\phi_8(z_i^h \tau_i)$$

The results of QAIDS model represented in Table A.

Table A. Estimated parameters for the QAIDS model.

	α_i	γ_{1j}	γ_{2j}	γ_{3j}	γ_{4j}	γ_{5j}	γ_{6j}	γ_{7j}	γ_{8j}	β_i	λ_i
Cereals	0.312	0.142	-0.053	-0.014	0.001	0.004	-0.079	-0.021	0.021	0.095	-0.009
	(0.072*	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.02)	(0.03)	(0.00)
Meats	-0.121		0.089	0.002	-0.001	-0.001	-0.038	-0.003	0.005	0.131	-0.021
	(0.06)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.02)	(0.03)	(0.00)
Dairy	0.730			-0.021	0.019	-0.021	0.028	0.017	-0.011	-0.171	0.016
	(0.04)			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.02)	(0.02)	(0.00)
Oil cooking	-0.055				-0.033	6×10^{-4}	0.001	-0.001	0.014	0.099	-0.012
	(0.03)				(0.00)	(0.00)	(0.00)	(0.00)	(-0.01)	(0.01)	(0.00)
Fruits	0.475					0.021	-0.017	0.013	0.002	-0.142	0.021
	(0.04)					(0.00)	(0.00)	(0.00)	(-0.01)	(0.02)	(0.00)
Vegetables	0.108						0.109	0.005	-0.010	0.086	-0.007
	(0.04)						(0.00)	(0.00)	(-0.02)	(0.02)	(0.00)
Sugar	0.202							1×10^{-4}	-0.01	-0.056	0.008
	(0.02)							(0.00)	(-0.01)	(0.01)	(0.00)
Tea and coffee	-0.651								-0.011	-0.042	0.003
	(0.13)								(0.15)	(-0.15)	(0.00)

*The numbers in parenthesis are standard deviation.
Source: Authors' calculations from Eviews 9.

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