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Causal inference on the impact of nutrition policies using observational data

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Abstract. We discuss the state-of-the-art in the application of quasi-experimental methods to estimate the impact of nutrition policies based on observational data. This field of application is less mature compared to other settings, especially labour and health policy, as food economists have started to implement widely counterfactual methods only over the last decade. We review the underlying assumptions behind the most prominent methods, when they can be regarded as credible and if/when they can be tested. We especially focus on the problem of dealing with unobserved confounding factors, emphasizing recent evidence on the limitations of propensity score methods, and the hard task of convincing reviewers about the quality of instrumental variables. We discuss the application of Difference-in-Difference, with an emphasis on its potential in consumer panel data applications, and how results from Regression Discontinuity Design studies should be interpreted. Finally, we cover the estimation of counterfactual outcomes using structural methods and provide an overview of recent developments and current gaps.

Keywords: quasi-experimental methods, policy evaluation, nutrition policy, assumptions.
JEL codes: C54, C21, Q18, I18.

1. INTRODUCTION

The call for evidence-based policy decision has generated an exponential growth in food policy evaluations over the last decade. Table 1 shows the counts obtained from a Google Scholar search for relevant keywords over the last three decades. Between 2011 and 2020 the number of hits for the generic term “Food Policy” is 4.8 times the baseline period, about 229,000 documents compared to 47,400 over the decade 1991-2000. Adding the keyword “impact evaluation” highlights a much faster trend. The increase in the number of Google Scholar hits is almost 25-fold. The proportion of papers with these keywords in relation to the simple “food policy” search results was only 0.63% in the 1990s, and rose to 3.24% in the 2010s. This pattern is confirmed by more specific keyword searches. For example, the additional keyword “causal identification” returns a 67-fold rise over two decades, and when looking for a specific method like “difference-in-difference”, hits grew from almost zero to 2,160, a 108-fold increase.

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Table 1. Food policy and evaluations in Google Scholar keywords searches over three decades.

	(a)		(b)		(c)		(c)/(a)	(c)/(b)
	1991-2000	%	2001-2010	%	2011-2020	%		
"Food policy"	47.4		178		229		4.83	1.29
"Food policy" and "impact evaluation"	0.3	0.63	1.89	1.06	7.43	3.24	24.77	3.93
"Food policy" and "randomized experiment"	0.02	0.04	0.46	0.26	1.86	0.81	93.00	4.04
"Food policy" and "counterfactual"	0.37	0.78	1.86	1.04	5.64	2.46	15.24	3.03
"Food policy" and "quasi-experimental methods"	0.006	0.01	0.07	0.04	0.36	0.16	60.00	5.14
"Food policy" and "causal identification"	0.003	0.01	0.009	0.01	0.2	0.09	66.67	22.22
"Food policy" and "difference-in-difference"	0.02	0.04	0.48	0.27	2.16	0.94	108.00	4.50

Source: Our search, Google Scholar accessed on 16/5/2022.

While this trend is similar in other areas of applied economics like health economics or energy economics, it has brought a small revolution in the agricultural economics field. In the year 2000, the journal Food Policy was 123th by impact factor within a population of 166 economics journal. In 2019 the journal ranked 28th out of 373 economics journals, and has been regularly the highest ranked agricultural economics journal since 2008. In 2010 the Agricultural and Applied Economics Association, formerly known as the American Agricultural Economics Association (same acronym, AAEA) decided to rebrand its second-ranked journal, and the Review of Agricultural Economics became Applied Economics Perspectives and Policy (AEPP). In terms of impact factor, the AEPP journal is now the second best in the field of agricultural economics after Food Policy, ahead of the leading AAEA journal, the American Journal of Agricultural Economics.

In short, (agricultural and food) policy analysis has become a best seller, and demand and supply of rigorous policy evaluations have grown very rapidly. From an era of paucity of quantitative evaluations, we have moved to abundance. Beyond societal interest, this trend has been driven by the amazing progress in data availability, and the evolution in user-friendly econometric software has been equally rapid.

As readily available data and software fertilize policy evaluation studies, the academic community needs to set higher methodological standards to defend the credibility and robustness of the findings. Without claiming the authority to define those standards, this manuscript has the objective to review the main quantitative methods currently employed in food policy evaluation, more specifically those targeting the causal identification of policies, and explicit the key assumptions they rest on. We restrict our range of applications to the analysis of policies targeting nutrition outcomes. There are not many comprehensive work on impact evaluation methods that are specific to nutrition policies (Babu *et al.*, 2016), and not many reviews of the policy evidence consider the credibility of causal inference methods (see e.g. Capacci *et al.*, 2012; Mazzocchi, 2017)

More specifically, the focus of this article is on the application of quasi-experimental methods when secondary data are used for ex-post assessment of food policies. While these "counterfactual" approaches are relatively young within this research field, they are rapidly becoming a minimum standard for causal inference in absence of randomization studies. The 2021 Nobel prize in economics has been awarded to David Card, Joshua Angrist, and Guido Imbens, three key contributors to methodological and empirical research on causal inference with observational data[1]. As it happens with most social science research objectives, economic policy analysis faces relevant challenges in drawing causal inference from randomized experiments[2]. Even in the less frequent situations where experimental evidence can be collected, the findings can be hardly generalized to be useful in other contexts. Thus, economists have historically relied on observational data in their evaluations of public policies, hence the need to address biases from the lack of randomization.

The article is structured as follows. We first discuss the opportunities and limitations in the data avail-

[1] See the document on the scientific background for the Nobel Prize, "Answering causal questions using observational data", https://www.nobelprize.org/uploads/2021/10/advanced-economicsciencesprize2021.pdf

[2] Still, the application of the experimental approach to economic problems has also generated important results. As one anonymous reviewer points out, the 2019 Nobel Prize was awarded to Esther Duflo, Abhijit Banerjee et Michael Kremer also in recognition of their application of the experimental approach "to alleviate global poverty".

able to researchers, especially in relation to the choice of adequate outcome variables to evaluate nutrition policies (Section 2). Then, we provide a short overview of the main quasi-experimental approaches to identify the causal effect of policies, with an emphasis on the assumptions they rest on, and whether and how they can be tested, as well as some approaches to demonstrate the robustness and validity of the causal findings (Section 3). Finally, we draw some take-home messages and suggest directions for future research.

2. DATA AND MEASUREMENT

What is the goal of nutrition policy? Such question is only apparently trivial, if one thinks what "improving nutrition" means. It is rather obvious that the ultimate aim of the policy is to improve human health, thus evaluations should rely on health outcomes. Unfortunately, the cause-effect path between improved nutrition and health outcomes is not immediate, and subject to major uncertainties. Hence, it is not surprising that most empirical evaluations of nutrition policies look at their short- to medium-term effects on intermediate outcomes, such as food choices or diet quality indicators, which in turn are health predictors[3]. The definition of these intermediate outcomes, however, is also subject to a variety of measurement-related issues.

Food choices not only vary across individuals, but also within individuals. Our Christmas food choices are likely to differ from those preceding the summer season, we may want to compensate on Mondays our week-end eating and drinking choices, and after a heavy lunch we may opt for a light dinner. Thus, a first question refers to the time interval which matters to define our baseline outcome indicator.

In nutrition science, the gold standard is the dietary record approach (Thompson and Byers 1994), the amount of food and beverages intake is recorded through a diary kept over a period of few days, normally no more than 7 consecutive days. This minimizes the memory bias, but may generate a fatigue effect (too much effort to keep the diary), and a behavioural bias associated with a "learning-by-doing" effect, as participants become aware of their eating patterns as they record them, and may alter their diets accordingly. An alternative approach rests on 24-hour recalls, which requires the respondent to recall and report all the food and beverages consumed during the previous day. While the task is not particularly burdensome and potentially more accurate, it fails to capture variation between days. This issue may be mitigated by appropriate sampling designs, assuming that heterogeneity across individuals belonging to a specific population group and interviewed at different times reflect – at least on aggregate – the average choices and intertemporal substitutions of individuals in the same group. A third nutrition-focused alternative is the Food Frequency Questionnaire (FFQ), which records the "usual" frequency of consumption of a list of food items. FFQs can be acceptable to measure average individual behaviours, but they are usually less accurate in quantifying intakes. Despite this, they are cheap and simple, and place a low burden for participants, which made them a commonly used dietary assessment tool (Thomson et al. 2003). Key food security indicators (e.g. the Food Consumption Score by the World Food Program) are based on FFQs.

Although this type of data has become relatively more common in food policy analysis, especially in development studies, economists remain concerned about the quality of measurement tools which depend on some form of self-assessment and have a component of social desirability bias (Grimm 2010). For example, Lissner (2002) shows that selective underreporting by obese individuals occurs with almost all methods of dietary assessments which rest on self-reports. Furthermore, nutrition survey data have a limited coverage of key food policy covariates, often failing to record the prices faced by individuals, their incomes, and consumption of non-food items.

This is why purchase data remain the preferred source of outcome indicators for economic studies, especially in the scanner data era. These large data sets not only allow to monitor individual daily transactions by individual household over several years, but they also have been augmented to provide detailed nutrient information at the level of unique product codes, as well as detailed data on purchase outlets, and household characteristics (Muth *et al.*, 2020; Biondi *et al.*, 2022). In household budget surveys, households record purchases through one- or two-week diaries, and data suffer by the aforementioned potential biases, although the lack of an explicit nutrition focus should mitigate social desirability biases. In consumer panels based on home scanners, participants scan universal product codes of all products taken home after each shopping trip. Point-of-sale scanner data are another rich source and provide measurements of sales volumes and prices, but cannot be related to individual consumer characteristics.

[3] When data allow to do so, causal mediation analysis is a powerful approach which supports the identification of causal chains, i.e. a causal estimate which goes beyond the total effect of the treatment on the outcome, and also identify the indirect effect that occurs due to one or more mediating variables. For a comprehensive overview, see Celli (2022).

Obviously, purchases are only a proxy of actual intakes, and the fact that these measures are at the household level is one serious shortcoming. Still, an underused opportunity of large scanner data-set is the possibility to monitor the transaction of one-member households over several years. While this is clearly a selected sample of the overall population, a time series of thousands of high-frequency data for the same individuals could be a unique setting for causal identification for policy evaluations.

To show the implications of using different outcome measures and ignoring self-reporting biases, we report in Table 2 some aggregate figures on attitudes towards fruit and vegetable consumption, self-assessed intakes and purchase-based intakes in the UK since the start of the 2003 national Five-a-Day campaign. The data come from nationally representative surveys and were not collected specifically to evaluate the campaign.

The first row captures the awareness impact of the information policy. During the first year of the policy, the average perception of what constitutes an optimal consumption was 4.4 portion per day. Over time, the campaign has been successful in increasing this target towards the "5-a-day" objective. The second row displays self-assessed intakes and is a clear demonstration of what social desirability means. While in 2003 participants were reporting an intake below the optimal target, in 2007 they were declaring an (average) consumption well above the ultimate policy objective. Unfortunately, when assessing intakes based on more objective purchase data, we find that the increase has been quite modest, and well below the perceived optimal intake. Clearly, the assessment of the policy effectiveness heavily depends on which outcome we choose to focus on.

There is no such thing as the perfect outcome variable and the quality of data is very heterogeneous. Rather than an excuse to discard quantitative policy evaluations, this should push researchers to discuss their data sources in great detail, acknowledge any limitation and adopt appropriate countermeasures and robustness checks.

Table 2. Knowledge, self-assessed consumption purchases of fruit and vegetables in the UK, number of portions per person per day (years 2003, 2006, 2007).

	2003	2006	2007
Optimal intake (reported)	4.4	4.6	4.8
Self-assessed intake	3.4	5.2	5.6
Assessed intake from purchases	3.7	4	3.9

Source: Our processing on data from UK Consumer Attitude Survey and Expenditure and Food Survey (various years).

A list of secondary data sources potentially relevant for nutrition policy evaluation is provided in Table 3. While individually these sources suffer from a variety of shortcomings, some may be addressed by adopting methods which integrate data from different sources, even if they do not pertain to the same subjects. Various techniques enable to combine two or more dataset. For example, Blundell *et al.* (2008) match consumer expenditure data from repeated cross-sectional consumer surveys with longitudinal data providing accurate information on incomes. Other techniques exist to combine information from different surveys (see the review in Lohr and Raghunathan, 2017). Furthermore, data collected as repeated cross-sections – as is the case for most of national household budget surveys – can be restructured into pseudo-panels by aggregating individual observations into homogeneous groups (e.g. same age group, same gender, same income bracket, etc.) which become the panel unit (Deaton 1985).

3. METHODS FOR CAUSAL INFERENCE

How do we know that it is rain that leads people to open their umbrella, and not open umbrellas that cause rain? If we had a spreadsheet showing (cross-sectional) data on the presence of rain and open umbrellas, statistics could definitely confirm that the two things are connected, and bring evidence that it is much less likely to find open umbrellas on sunny days. However, without some manipulation, statistics without prior theoretical knowledge is unable to infer causality from mere observational data. One way out in economics (and in life), is the assumption that what happens earlier is more likely to be the cause than the effect, but this reasonable simplification is often useless[4]. Suppose the government lowers VAT on healthy foods in year t, and in year $t+1$ people consume less healthy foods. Using again our common sense and theoretical knowledge, we know that lowering VAT cannot cause lower consumption, but previous trends or other confounding factors (e.g. prices going up) are messing up with our attempt at causal inference.

[4] Indeed, estimates from correctly specified structural models drawing from validated economic theories can return good causal estimates. Once we know that rain causes open umbrella, and we have enough information to correctly specify our model (e.g. weekday, time of the day, ecc.), we can estimate the relationship between the amount of rain and the density of umbrella, and check that our estimator meets the desired economic properties. Our focus is in the (frequent) situation where theory provides insufficient guidance, or lack of information leads to biased estimates. As discussed later in the article, quasi-experimental methods can be a powerful complement to structural models. We are grateful to an anonymous reviewer for soliciting this clarification.

Table 3. Secondary data sources relevant for nutrition policy evaluation.

Type of survey	Description
Nutrition surveys	Specifically aimed at monitoring people diet, usually through dietary records, recall or FFQ. They usually collect data on key individual characteristics, mostly demographics, but sometimes also on health status and attitudes.
Health surveys	Based on interviewing/questionnaires and objective measurements (e.g. blood tests, urine samples, etc.), health surveys record information on people subjective and objective health status. Other information often collected: health related behavior, demographic characteristics, lifestyle topics such as smoking habits or dietary habits.
Household budget surveys	Their scope is to collect information on household purchases over a period of one or two weeks, based on expenditure diaries and face-to-face interviews. They normally include detailed information on food purchases (at the food item level) and demographic information on the household. In most countries they are run every year. When purchased quantities are provided along with expenditures, it is possible to estimate average prices.
Scanner data	This type of data records expenditure, paid prices and purchased quantities at the most detailed product level (brand and pack size). Data are collected either at the point-of-sale through cash registers (retail panels) or at home by household panels equipped with a barcode scanning device (consumer panels). These data are collected by private companies, and in some cases combined with product label information, including nutrition information. Households may remain in consumer panels for several years, allowing for longitudinal analyses.
Opinion/omnibus/ attitude surveys	These surveys collect information for multiple purposes, often including measurement of opinions, beliefs, self-reported habits, attitudes, stated preferences, perceived health, lifestyle factors, etc. They may contain self-reported information about eating behaviours and knowledge, and sometimes anthropometric measures.
Food composition databases	Food composition tables contain information on the average nutrient content of raw and processed food items available in one country. They are useful in combination with other data-sets to associate food items with their nutrient content.
Audience measurement data	These data are normally used to monitor media consumption (radio, television, newspaper, magazines, websites, social networks). They are conducted by private market research companies, and when combined with purchase data can be useful to explore the exposure to advertising and the impact of advertising regulations.
Epidemiological studies	They provide information on the prevalence and incidence of diseases, morbidity, mortality and related risk factors. They are useful to predict and simulate the ultimate health outcome of a policy based on the estimated impact. They are population-specific and are very heterogeneous in terms of sample sizes and duration.
Administrative data	These data are collected for administrative purposes, but some may be useful for evaluation, e.g. population registers of births, deaths, tax records as well as information on household access to subsidies and financial support. Administrative sources may also help quantifying the policy cost.

This short account does not do justice to centuries of questions about how science should look at cause-effect relationships, since Francis Bacon, and the logic provided by John Stuart Mills in 1843 to frame scientific experiments. But the key elements that matter to our treatment are randomization and the potential outcome framework, first formalized by Fisher in 1925 and Neyman in 1923, respectively (see Boring, 1954). Interestingly, while these two essential elements behind randomized experimental designs have developed almost simultaneously, their combination to support causal inference with observational data took another half century, until the key contribution of Donald Rubin (see Imbens and Rubin, 2015). The rationale behind randomized assignment was that "the validity of the test of significance may be guaranteed against corruption by the causes of disturbance which have not been eliminated'' (Fisher, 1935, p. 19). In other words, randomization as an insurance against confounding factors. Meanwhile, Neyman had introduced the concept of potential outcomes: "Let *x* denote a possible outcome of the experiment consisting of drawing one ball from the *i*-th urn" (Splawa-Neyman *et al.*, 1990). Basically, before the draw, an undrawn ball can take any number, just like the health status of Schrödinger's cat is unknown before opening the box.

How these philosophical wanderings matter to policy evaluation becomes clearer when one considers the "fundamental problem of causal inference", also referred to as the Neyman-Rubin causal model (Holland 1986). Before any scientific (randomized) or natural (non-randomized) experiments, subjects may expect one of two "future" outcomes, either under treatment or in a non-treatment ("control") situation. For example, before the government approved the budget law in October 2021, an Italian shopper could envisage for the first week of January 2022 one level of sugar-sweetened beverage (SSB) purchases "under the soda tax", and another level of SSB purchases “without the soda tax”. For the policy analyst, the perfect evaluation would require to observe both outcomes on the same subject. The outcome difference would be the impact of the SSB tax on that specific individual consumer, and repeating the analysis on many shoppers would return the full distribution of impacts. In absence of parallel words, we have to settle with observing a single outcome. The Italian government decided to postpone the introduction of the soda tax for the second consecutive year, and in January 2022 only the “no tax” outcome was observable.

3.1 Randomized experiments

In experiments, a Fisher-style randomized study is the solution to this fundamental problem. The difference between average outcomes from two random samples drawn from the same population, where only one of the two sample is treated, returns an average effect of the treatment. As a matter of facts, in absence of the treatment, two random samples from the same population return average outcomes from the same outcome distribution, and there is no reason why the difference in average outcomes should be significantly different from zero.

The above trick works very well with scientific experiments, but several complications emerge when the subjects of the experiment are humans. Even in medical randomized controlled trials, external validity of treatment effect estimates is all but granted. Designs of experiment for social and policy evaluation studies are even harder to be set up in a meaningful way, for example ensure real randomization, avoid compliance issues, control for a multitude of confounding factors that may act differently between the two groups during the experiment.

One key dimension to be considered is what sort of randomization drives the experiment. Random assignment to the treatment or control group is the prerequisite of randomized controlled trials. However, this only ensures that the two samples come from the same population, which is not necessarily the actual population of interest and may be self-selected, especially if participation is voluntary. It is hard to think about ethically acceptable trials where participation is compulsory. Thus, even a perfect RCT may return an estimate of the treatment effect which is affected by a selection bias, when the overall sample of participants is not representative of the target population.

An excellent review of the potential limitations of RCTs – especially for causal inference in economics – is provided in Deaton and Cartwright (2018). Randomized (food) policy experiments are quite rare. Some notable exceptions are the US Healthy Incentives program (Olsho et al. 2016), or the income support Progresa program in Mexico, where the government – not having enough budget to target all low-income families – randomized the villages where the policy was implemented (Gertler 2004).

Meeting all conditions that make a randomized experiment on food policy able to deliver a reliable estimate of the treatment effect is not a trivial task. Thus, it should not be maintained (as it is often the case in public health studies) that randomized experiments are the gold standard, and observational studies are a second-best options to learn about policy effectiveness. However, randomization might be the best route (and possibly the only one) when the objective is not the ex-post quantification of the policy impact, but rather an ex-ante assessment or the ranking of alternative policy instruments addressing the same policy objective. Even in cases where the estimate of overall effect sizes cannot be fully trusted, it is possible that the ranking of policy instruments in terms of their cost-effectiveness has an acceptable external validity. See, for example, the randomized experiment on food/voucher/cash transfer in Northern Ecuador (Hidrobo et al. 2014).

3.2 Quasi-experimental methods

We now go back to the goal of this article, and discuss how observational non-randomized data can provide ex-post evidence on the impact of a policy. To introduce this class of methods, it may be useful to recall some very standard and light notation.

Let y_{it} be the potential outcome for unit *i* if exposed to the policy, and y_{ic} the potential outcome for the same unit when not exposed to the policy. Suppose that in our target population some units are eventually “treated” and exposed to the policy and other units are not, but assignment to treatment is not necessarily random. This situation where the treated and control group are not the consequence of an explicit randomized design is commonly referred to as a “natural” experiment[5]. For

[5] There is no consistent definition of “natural experiment” in the literature, beyond the common consensus on the lack of explicit randomization. Some restrict the definition to those situations where randomization occurs “naturally”, i.e. assignment to treatment is “as if random”, even without the explicit intervention by the researcher. For our discussion, we consider a broader case where the assignment mechanism is unknown and unknowable by the researcher, but there is some external event which allows to regard such mechanism as probabilistic (for a detailed discussion see Titiniuk, 2019).

example, one may compare soft-drink consumption in a country exposed to a SSB tax (France) with a neighbouring country without the tax (Italy), or school fruit schemes where participation of schools to the program is voluntary. We use a binary indicator D_i to capture exposure to the policy, where D_i=1 when units are treated and 0 otherwise. At this stage, we consider a situation where we only have a cross-section of units observed in a single time period after the policy implementation, but we can extend later the notation to consider methods that rely on multiple time periods.

Consider the following identity, where the left-hand term is the average outcome difference between the treated and the control group:

$$E(y_{it}|D_i=1)-E(y_{ic}|D_i=0)=[E(y_{it}|D_i=1)-E(y_{ic}|D_i=1)]+[E(y_{ic}|D_i=1)-E(y_{ic}|D_i=0)] \quad (1)$$

This equation decomposes the difference in means in two parts, the actual average treatment effect on the treated population (ATT) and the selection bias (SB). On the right-hand side of the equation, the first square bracket $[E(y_{it}|D_i=1)-E(y_{ic}|D_i=1)]$ is the ATT, since it compares the average potential outcome under treatment and the average potential control outcome for the same population of individuals, those that are actually treated. Thus, the ATT is the objective of the evaluation, and indicates how much the policy changes the outcome of those that have been exposed to the policy.

The second square bracket is the selection bias $[E(y_{ic}|D_i=1)-E(y_{ic}|D_i=0)]$, which is the difference in the average potential control (i.e. without policy) outcome between the treated population and the control population. Under perfect randomization, there would be no reason for this difference to be significantly different from zero, as the two samples (treated and controls) would be extracted from the same population. Here, however, we deal with observational data. It is hard to think that even without the French SSB tax, France would report the same average soft drink consumption level as Italy. Thus, in order to get the ATT it is necessary to purge the outcome difference from our data from a "baseline difference", intended as the difference between the two groups in absence of the policy.

In order to estimate the ATT, a counterfactual estimate is necessary. One way is to try and estimate $E(y_{ic}|D_i=1)$, which is the outcome we would have observed on the treated group had the policy not been implemented. This would allow to obtain the ATT directly from the left-hand side of (1). A symmetric route is to try and estimate the SB, and the same counterfactual estimate is needed for this purpose.

A first operational step in that direction is the identification of the drivers of the SB. Why are the outcomes in the two groups expected to be different in the two group in absence of the policy? Why is the French consumption of soft drinks expected to be different from the Italian one, even without the SSB tax? We can start by listing those characteristics – other than the tax – that influence soft drink consumption, the many "confounding factors" which are balanced between the two groups when a randomized assignment is possible. The list is long, prices (of soft drinks and substitutes), incomes, levels of advertising, culture and tastes, temperatures and seasonality… Having good information on all potential confounders is a very lucky situation, possibly unreal. In many policy situations where subjects may self-select into treatment, namely in voluntary schemes, psychological drivers can play a major role and they are hardly measured in secondary surveys. Thus, we complete our notation by defining a vector of subject characteristics $\mathbf{x}$, which is composed by a set of observed variables (or *observables*) $\mathbf{x_O}$ and a set of unobserved variables (*unobservables*) $\mathbf{x_U}$. Whether a variable ends up in the former or latter set depends on the contents of our dataset.

In a randomized setting, the policy impact could be obtained by a very simple regression model, corresponding to a mean comparison test:

$$y_i=\alpha+\beta D_i+\varepsilon_i \quad (2)$$

Since we have no reason to think that there are other differences than the policy between the two groups, β is a consistent estimate of the ATT, and the variance of the 0-mean random error captures the variability in outcomes. Randomization is expected to balance both $\mathbf{x_O}$ and $\mathbf{x_U}$ between the two groups, but the researcher may want to test how well it worked, and test for significant differences in $\mathbf{x_O}$. A successful randomization should ensure that none exists.

Without randomization, we ideally want to control for any confounding factors. Thus, the policy model for observational data becomes

$$y_i=\alpha+\beta D_i+\gamma\mathbf{x_O}+\delta\mathbf{x_U}+\varepsilon_i \quad (3)$$

Which still returns a consistent estimate of the ATT through β. Unfortunately, we do not have information on $\mathbf{x_U}$, which leads to an omitted variable problem. Quasi-experimental methods try to sort out the issue.

3.2.1 Propensity score matching

The class of methods based on propensity score matching (PSM) has been popular in health sciences, but it is hardly useful for causal inference without combining it with other quasi-experimental methods[6]. The reason is simple, the key assumption behind PSM (called unconfoundedness) is that there are no variables in $\mathbf{x_U}$. Any variable which matters to the outcome and is unevenly distributed between those exposed to the policy and those not treated must be either known or highly correlated with a known variable. In other words, an effective matching requires full knowledge of the structural model determining outcomes, or full information about the selection process. In such especially desirable situation, even OLS estimates of the model in equation (3) would provide a consistent estimate, even more efficient than PSM provided that the linearity assumption holds and there are no heterogeneous treatment effects. Not only, but authoritative recent studies have emphasized that improper application of PSM could lead to the opposite (and highly undesirable) result of increasing unbalances in unobservables, and lead to larger biases (King and Nielsen 2019).

Nevertheless, PSM is widely used, probably because it is effective in reducing dimensionality, it is an intuitive and relatively easy to teach method, and statistical packages offer fast implementation algorithms. Without indulging in technical details that are much better described elsewhere (see Caliendo and Kopeinig, 2008), PSM aims at balancing the distribution – or at least the means – of observables between the treated and the control samples. It does so by working on the control sample, by dropping observations, or by applying weights. For example, an observation in the treatment group can be matched with a single observation in the control group, or with a weighted average of observations from the control group. How this matching is accomplished depends on the matching algorithm, and there are many variants: nearest neighbour, radius, kernel and stratification matching being those most commonly implemented. The idea is that rather than matching on the full set of variables $\mathbf{x_O}$, a synthetic function of these variables is used, the propensity score. A propensity score is the probability of a unit to end up in the treatment group given its observed characteristic $\mathbf{x_O}$, and can be easily estimated via a probit or logit model. Matching on the probabilities estimated through these models is easier and more feasible than attempting to match all individual characteristics.

The key assumption to exploit PSM for causal inference is unconfoundedness, which requires that no relevant unobservable variable exists. Can this assumption be tested? Not directly, but propensity scores are based on the estimation of a binary dependent variable model, and goodness-of-fit measures for that model, e.g. the Pseudo-R^2 or the rate of correct predictions, provide some feedback. Even if we find that most of the covariates are relevant (significant) in explaining the assignment-to-treatment process, low goodness-of-fit diagnostics signal that our observables are not enough, and the unconfoundeness assumption is not credible, unless one accepts that unexplained variability only depends on random factors, quite a strong requirement. More sophisticated testing strategies exist, as the Rosenbaum bounds or IV-based tests (see DiPrete and Gangl, 2004), but one should be wary of any PSM study that does not provide strong evidence that the unconfoundedness assumption is met, as ATT estimates may otherwise be affected by large biases.

Beyond this, PSM requires overlapping of the propensity scores ranges between the treatment and control group. In a non-random setting we are likely to find higher propensity scores in the target group, and some of them might be too high to find the right match in the control group. In that case, unmatchable observations are dropped from the target group, which means that the estimated ATT does not refer to the original treated sample, but to the reduced one. This might become a major limitation for the ATT estimate. Imagine that in a voluntary food assistance the poorest individuals are very likely to participate, hence have very high propensity scores, but they are not accounted in the ATT estimate because no adequate match is found. Then, the ATT will measure the impact of the policy on a population which excludes those who benefit the most.

Relative to other methods, PSM evaluations are less popular in nutrition policy analysis, but several applications can be found in the literature. Clark and Fox (2009) apply matching methods to investigate the impact of the US School Breakfast and National School Lunch Programs on vitamin, mineral and sodium intakes. The method seems to be more popular among development economists, for example Abebaw *et al.* (2010) use PSM to estimate the effects of a food security program in Northwestern Ethiopia.

3.2.2 Instrumental Variables

Provided that one or more "good" instruments are available, IV estimators of the ATT work on the same

[6] As pointed out by an anonymous reviewer, propensity scores estimates remain a useful tool to reduce dimensionality, and/or as a complement to other methods. Also, PSM has advantages when dealing with heterogeneous treatment effects.

data structure of PSM, and allow to control for selection effects driven by both observables – through direct inclusion in the estimation equation – and unobservables, the latter through instrumenting. We discuss later the fuzzy concept of "good instrument", and how authors, reviewers and journal editors tend to diverge in their opinion about the validity of instruments. The interpretation of IV models is straightforward, as it suffices to consider model (3). In absence of information on $\mathbf{x}_U$, we face the econometrics textbook problem of omitted variables, so that all coefficient estimates are biased and inconsistent. Under an economics viewpoint, a parallel interpretation is that the selection variable D_i is endogenous, as the probability of being exposed to the policy depends on the outcome level. For example, schools located in high income and education areas where fruit consumption is high, are more likely to participate in school fruit schemes.

Provided we have one or more adequate instruments $\mathbf{w}$ to instrument D_i, we can control for the selection bias and obtain consistent ATT estimates, at the cost of giving up some efficiency. Statistical packages routinely provide IV-2SLS estimators where the first stage regression is again a binary dependent variable model, a probit or a logit. Note that the structural policy model (3) still accounts for unbalances in observables , which enter directly the model as they are expected to influence the outcome. Instead, instruments should be variables that we would not use as direct explanatory variables for the outcome, and should be exogenous. If we have access to such type of variables, the first stage binary regression would be the same used to estimate propensity scores, with $\mathbf{x}_O$ as explanatory variables, plus the instruments $\mathbf{w}$ which do not belong to $\mathbf{x}_O$ and do not enter (3).

Since IV encompasses PSM[7] and accounts for selection on unobservables, why don't researchers just rely on IV estimation? The problem is likely to be a familiar one for the experienced reader. First, we struggle to find reasonable instruments in the dataset. Second, we struggle to convince reviewers that our instrument choice is a good one. Unfortunately, there is no definitive test on the validity of instruments that can convince all actors in the publication process. The issue is a Catch-22 one. In order to show that an instrument is exogenous, it must be independent from the residuals of the structural (second stage) equation. However, this test is theoretically impossible, as we only obtain unbiased estimates of the residuals when we have an exogenous instrument. The empirical solution is to use several instruments, leave one out, estimate the structural equation residuals through the other instruments, then check the correlation between the excluded instrument and the estimated residuals. One can then repeat the procedure leaving out a different instrument each time. While such a strategy may provide some support to the instrument validity claims, it is an empirical one, and it is still grounded on the assumption that the included instrument are exogenous and the residual estimates are unbiased. If many of our instruments are endogenous, the procedure is useless. Thus, we still need to be convinced and convince others that the instruments make sense under an economic perspective.

The other interesting element is the trade-off between consistency and efficiency. If the instrument are reasonable, exogenous, and obviously significant in the first stage equation, then we can place some trust in the consistency of the ATT estimate in the second stage equation. However, the ATT will have a larger standard error, as we rely on predictions of the D_i variable in the second stage, a sort of propensity score augmented by the instruments. How much larger the standard error depends again on the goodness-of-fit of the first stage probit or logit equation. This time, however, a poor fit does not lead to systematic biases, it just inflates the standard errors, and with large data-sets this is not usually a problem.

A list of instruments used in the food policy literature is beyond the scopes of this article, although it would be an interesting reading. For example, Hofferth and Curtin (2005) investigate the effect of school lunch programs on the BMI of students. Participation to the lunch programs is voluntary for schools, and students need to have specific characteristics to be eligible for a free meal. These policy elements are clearly a source of endogenous selection. Public school attendance is used as an instrument, as it does not affect BMI directly, but it is strongly associated with the school program participation, since public schools are more likely to be part of lunch programs.

An alternative strategy resting on the use of instruments is the control function approach. This approach involves a first stage to model the exposure to the program, and a second stage where the individual probability of exposure is included as an additional variable on the right-hand side of the outcome model, to correct for the selection bias. The Heckman two-step estimator is the most widely used control function approach. For example, Butler and Raymond (1996) explore the impact

[7] A caveat is necessary. Just like in OLS, unbiased estimation through a regression model still requires that the linear specification is appropriate and treatment effects are homogeneous, whereas PSM is more flexible. However, there is extensive research to extend IV to deal with heterogeneous treatment effects (see e.g. Klein, 2010 and references therein), and propensity score matching can be used in combination with IV estimates, which is why we refer to encompassing here.

of household participation in US Food Stamp program on nutrient intakes of the elderly, using a variety of instruments, including household assets and distance to a food stamp office.

3.2.3 Regression Discontinuity Designs

For some specific policies, eligibility depends on the threshold value for a single continuous variable. Typical examples are policies designed around an administrative eligibility criterion based on age or income thresholds to allow access to food assistance programs or other subsidies. When such a sharp classification exists and the variable is known, the division between target and control units is straightforward. As this variable is most likely to be a key determinant for the outcome of interest, this also implies that there is no overlapping and two sub-population are hardly comparable.

In these cases, restricting the analysis to those units that are just below or just above the threshold is a potential solution. With a very large sample, the researcher might have a sufficient number of observations even after restricting the data-set. For example, if a policy is targeting subjects aged below 30, and we have a large data set including individuals within 6 months from their 30th birthday, the resulting sample is relatively homogeneous in terms of age, and splitting the sample in two groups through the date of birth is similar to randomizing assignment, and one should not expect major selection biases. A mere mean comparison test between the average outcomes could be a quite good estimate of the ATT.

However, one major caveat accompanies this estimate of the treatment effect, which is certainly valid in the selected neighbourhood of the cut-off point, but not necessarily for data points further away. In our example, we may get good and reliable estimates of the ATT for those aged 30, but we can say little about the policy effects on those that are aged 20 or 25 relative to those aged 35 or 40. Thus, ATTs estimated through RDD are characterized by limited external validity.

Furthermore, this threshold analysis commonly runs into two major issues: (1) the number of available observations around the cut-off value is not large; (2) the cut-off point may be associated with a number of confounding events creating discontinuities. For example, if the age cut-off is also the retirement age (e.g. 65), one may think that such an event creates relevant disparities between the target and control groups in variables that may in turn affect the outcome variable.

The first problem is addressed by relying on the functional relationship between the outcome and the assignment (running) variable. When such function is identifiable, it can be exploited to expand the sample of interest. To do that, we need to assume continuity, which means that without the policy the outcome would just follow the identified functional relationship with the running variable. The most basic functional form is a simple bivariate linear regression, and the policy impact would be captured by a sharp shift in the intercept as the running variable reaches the cut-off point. By exploiting this linear relationship, one is able to expand the sample and consider units that are further away from the threshold. This brings in a second assumption, linearity, which requires that the linear relationship is valid within the expanded neighbourhood of the cut-off point. Although few relationships between the outcome and the running variable are indeed linear, when the neighbourhood under consideration is still relatively small, then the linear approximation performs well and the ATT estimate becomes more credible (and efficient) for the sample of interest. In other words, its internal validity is higher. Clearly this introduces a trade-off between internal validity and efficiency. If we consider a large neighbourhood, we have more observations and a more efficient estimate of the ATT. However, observations become more heterogeneous, the linearity assumption becomes more influential, and there is less internal validity.

RDD deals well with unobservables when these are unlikely to differ substantially between the two groups within a small neighbourhood of the cut-off point. However, the crucial continuity assumption implies that there are no other major “jumps” in relevant outcome determinants at the same cut-off point. There are cases when this assumption is clearly challenged, for example when the cut-off value is one with administrative and legal relevance. For example, age cut-offs at 18 and 65 are common to several economic and health policy measures, or some income eligibility threshold levels can be similar across different policies in the same country, which complicates the attribution of the causal effect to a specific policy. In such situations, the only viable solution seems to be the inclusion in the model of covariates which help to control the confounding effects (Frölich and Huber 2019). More generally, one should test whether the continuity assumption holds simply by applying the same RDD model to relevant confounding factors, and the expectation is not to find significant discontinuities. The continuity assumption fails to hold when subjects have some control on the assignment variable. For example, one might delay some revenue (job offer) to maintain eligibility for a program based on income thresholds. If these behaviours (“bunching”) are possible, then the continuity assumption is challenged and RDD becomes less credible[8].

Since the estimation of causal effects through RDD depends on assumptions on the neighbourhood size and the shape of the relationship between the outcome and the running variable, a number of extensions and variants in the estimation procedures exist. First, the optimal size of the window around the cut-off point (the bandwidth) may be also an output of the estimation algorithm. Second, non-parametric regressions allow to relax the assumption of a linear relationship, and place different weights on observations depending on how far they are from the cut-off point. Third, when the running variable does not determine a sharp cut-off (i.e. all individuals meeting the rule are treated), but only creates a shift in the probability to be treated, then fuzzy RDD better serves for the purpose. This is the case of voluntary policies, where not all eligible individuals are exposed, and/or when there are exceptions allowing participation of subjects that do not meet the cut-off eligibility requirement.

Including covariates, changing the bandwidth, allowing for non-linear relationships, or opting for a fuzzy design are all choices that may potentially lead to different results, which is why convincing robustness checks are not an optional feature in RDD studies. On the one hand, one may want to show that the estimate of the causal effect is relatively consistent across different choices. On the other hand, falsification tests add credibility to the identification strategy. For example, one may want to show that different cut-off points other than the one relevant to the analysis are not associated with discontinuities.

Although the range of policies that are suitable to this method is limited, and the aforementioned external validity caveat applies, RDD is considered a relatively powerful causal identification method. Sometime researchers have expanded the scope of RDD by considering time as the assignment variable with panel or time series data (see e.g. Aguilar *et al.*, 2021). In these exercises, the idea is that comparing outcome just before and after the time of the policy implementation, while exploiting some outcome-time relationship, may lead to the identification of the policy causal effect. However, this also leads to major differences in the requirements for successful identification relative to the standard RDD method, an issue which deserves careful consideration before one chooses "time" RDD over simpler event study models (Hausman and Rapson 2018).

[8] Interestingly, this opens the way to relevant behavioural evaluations and estimation which exploit the possibility to identify manipulation (see Kleven, 2016).

Examples of RDD application to nutrition policies include the income-eligibility rule for the US School Lunch Program (Schanzenbach 2009), the removal of vending machines from secondary schools in France (Capacci *et al.*, 2018), the impact on nutrition and well-being of a new refugee assistance program in Kenya (MacPherson and Sterck 2021), and the effects of micro-credit on children nutrition in China (You 2013).

3.2.4 Difference-in-differences

Difference-in-differences (DID) has clearly become the most popular and widely applied quasi-experimental method for investigating the causal effects of nutrition policies. The rationale of the method is well known, and it allows to control for selection biases driven by unobserved factors when data from natural experiments are available before and after the policy, provided the appropriate assumptions hold.

The DID approach follows from the extension of equation (1) to account for multiple time periods. Consider its most basic formulation with two time periods, one before (period 0) and one after the policy implementation (period 1). In period 1, by reworking equation (1), one may obtain the ATT by subtracting the SB from the difference in means:

$$ATT=[E(y^1_{it}|D_i=1)-E(y^1_{ic}|D_i=0)]-[E(y^1_{ic}|D_i=1)-E(y^1_{\mathrm{ic}}|D_i=0)] \quad (4)$$

Where the superscript of the outcome variable indicates the time period. Assuming that the selection bias does not change between period 0 and period 1, the pre-policy data can be exploited to estimate the selection bias and the ATT can be rewritten as:

$$ATT=[E(y^1_{it}|D_i=1)-E(y^1_{ic}|D_i=0)]-[E(y^0_{ic}|D_i=1)-E(y^0_{\mathrm{ic}}|D_i=0)] \quad (5)$$

Now all terms on the right hand-side of the equation are observable. Since there is no policy in period 0 we observe the control outcomes for both the treatment and the control groups. The assumption of constant selection bias is usually referred to as the parallel (or common) trend requirement, since it implies that in without the policy the outcomes evolve at the same pace over time, and could be represented graphically as two parallel lines. Such assumption can (and must) be tested when data are available for multiple periods before the policy implementation.

One nice feature of the DID model is that the ATT can be estimated through a standard regression model on the outcomes, which also allows to control for all observed covariates $\mathbf{x_O}$:

$$y_i=\alpha+\beta D_i+\gamma T_i+\delta P_i+\vartheta\mathbf{x_O}+\varepsilon_i \tag{6}$$

Where T_i is a binary variable which is 1 in time periods after the policy implementation and 0 otherwise, and $P_i=D_iT_i$ is another binary variable which is 1 when observation i belongs to the treatment group (D_i=1) and is observed after the policy implementation (T_i=1). The coefficient estimate δ is the ATT.

If equation (6) is based on repeated cross-sections over multiple time periods ($t=1,\ldots,K$), one could test the parallel trend assumption by allowing (conditional) outcomes to evolve linearly over time before the policy implementation:

$$y_{it}=\alpha+\beta D_{it}+\gamma t+\theta(D_{it}\times t)+\vartheta\mathbf{x_{O\mathit{it}}}+\varepsilon_{it} \qquad \forall t\in\{T_{it}=0\} \tag{7}$$

When θ=0, there are no differential trends between the treated and control groups. When $\theta\neq0$ one might still estimate a DID model augmenting (6) to allow for divergent linear trends, but such an extension should be supported by credible graphical evidence of a linear evolution of the conditional outcomes.

More informative (and efficient) estimates are derived from panel data, where the same units are observed over multiple time periods. There are several advantages in the generalized DID model for panel data (a two-way fixed effects panel regression), as (a) the inclusion of cross-sectional fixed effects further controls for constant unobserved heterogeneity across units; (b) the inclusion of time fixed effects allows to control for non-linear heterogeneity across time periods, and extensions to control for differential linear or even non-linear trends are possible; (c) it is possible to allow for different levels of policy intensity (e.g. differential tax rates). Consider, for example, the following model:

$$y_{it}=\alpha_i+\mu_t+\Sigma^N_{r=1}\beta_r(R_{ir}\times t)+\delta P_{it}+\vartheta\mathbf{x_{O\mathit{it}}}+u_{it} \tag{8}$$

where the subjects belong to N different groups which may exhibit different linear trends, for example there are N regions or states, and R_{ir}=1 when the subject belongs to region r and is 0 otherwise. In this model P_{it} is not necessarily a binary variable, for example it might be a continuous variable between 0 (no policy) and 1 (full policy implementation). In this case, δ estimates the effect of full implementation.

With adequate panel data, it is theoretically possible to allow for non-linear differential trends:

$$y_{it}=\alpha_i+\mu_t+(\tau_t\times D_{it})+\delta P_{it}+\vartheta\mathbf{x_{O\mathit{it}}}+u_{it} \tag{9}$$

The above specification allows for differential time fixed effects between treated and control subjects, but identification becomes quite challenging, and even impossible if the policy is implemented at the same time for all treatment units. An alternative is to omit δP_{it} and explore the evolution of the differential time fixed effects $\tau_t\times D_{it}$ over time, expecting that they change abruptly relative to their previous pattern for time periods following an effective policy.

Whatever the specification of the DID model, a thorough exploration of pre-existing trends when panel data allow to do so is a necessary but not so trivial task. Pre-testing may be affected by low power, and conditioning on pre-existing trends may lead to biases. An interesting review of these issues and a survey of recent papers in leading economics journals is provided in Roth (2022). Another important note of caution is needed for the estimation of two-way fixed effects panel DID models when the policy effects are heterogeneous across groups or time periods, as causal estimates of average treatment effects may be misleading. Alternative estimators have been proposed to address the issue (see e.g. de Chaisemartin and D'Haultfœuille, 2020).

The growing availability of panel data, especially commercial consumer panels with a high level of geographical details, has generated an exponential growth of DID models applied to the evaluation of the impact of fiscal policies on nutrition outcomes. For example, there is a high number of studies on national, state-level or even city-level taxes on sugar-sweetened beverage (see the review in Cawley *et al.*, 2019, or the report by Griffith *et al.* 2019). Beyond taxation, the DID approach has been applied to a variety of nutrition policies, including nutritional label regulations (Variyam 2008), calorie labelling in restaurant menus (Vadiveloo, Dixon, and Elbel 2011), school-based policies (Bhattacharya *et al.*, 2006), targeted subsidies (Griffith *et al.*, 2018), food assistance programs (Rahman 2016), information campaigns (Asirvatham *et al.*, 2017) advertising regulations (Dhar and Baylis 2011). The latter reference contains an example of how DID can be reinterpreted in applications lacking the time dimension, and even extended to the situation where multiple control groups can be considered. In Dhar and Baylis (2011) the impact on fast-food purchases of an advertising ban to children programs applied to TV channels in French-speaking Ontario is estimated through a Triple DID model using post-policy data only. The identification strategy rests on different target-control classifications, as both household without children and household with children in the near English-speaking Ontario region constitute potential control groups for household with children in Quebec, the target group.

3.2.5 Strategies based on structural models

An alternative approach is needed in situations where there is no natural counterfactual, for instance when a policy potentially acts on the whole population, as in a nationwide a public information campaign. As information policies may be expected to generate behavioural effects beyond the mere change of the average outcome, an option is to generate model-based counterfactual estimates. This approach is especially interesting when the behaviour of interest is well captured by a consolidated economic specification, and it is conveniently applicable when the pre-policy and post-policy data come from different (repeated) cross-sectional samples from the same population[9]. One may then express the outcome as the function of its determinants in each period:

$$y^0_i = f^0(\mathbf{x}^0_{iO}) + \varepsilon^0_i$$

and

$$y^1_i = f^1(\mathbf{x}^1_{iO}) + \varepsilon^1_i$$

The functions f^0 and f^1 have the same structural specification, but are characterized by different parameters. For example, f might be a demand function and the parameters represent price and income elasticities. As implied by the Lucas critique, a policy is likely to go beyond changing the average level of consumption, and also lead to a change in elasticities, hence the change from f^0 to f^1.

If the policy has no direct impact on the covariates $\mathbf{x}_{iO}$, then the two set of estimates allow to evaluate the counterfactual outcome, which is estimated as $y^1_i = f^0(\mathbf{x}^1_{iO})$. In in our example this is the level of consumption that would have been observed in period 1 had the population maintained the preference structure of period 0. The ATT is $f^1(\mathbf{x}^1_{iO}) - f^0(\mathbf{x}^1_{iO})$. The approach can be modified to include constraints on behavioural parameters, for example one might require that some of them remain constant between the two time periods. Also, if there are variables in $\mathbf{x}^1_{iO}$ that are significantly affected by the policy, and it is possible to disentangle such effect (e.g. an estimate of the change in public advertising expenditure, or of the price change associated with a tax), one might estimate the counterfactual through $f^0(\mathbf{x}^1_{iO})$ where the relevant variables in $\mathbf{x}^1_{iO}$ are purged from the policy effect.

When data are organized as panels or relatively long time series, alternative approaches based on structural models may rely on switching and time-varying parameter regressions, intervention or event study analyses. All of these models allow one or more parameters to change in response to the policy. The most basic formulation aims at estimating a sharp step (i.e. an intercept shift as in event studies) at the time of the policy implementation[10]. When data allow to do so, any parameter in the structural model can potentially change and evolve, either with a pre-determined shape (as in intervention analysis or switching regression) or through random shocks (as in time-varying parameters models).

An example of nutrition policy evaluation where the counterfactual is based on a structural model is provided in Capacci and Mazzocchi (2011), who explore the effects of the 5-a-day information campaign in the UK through a demand system. Attanasio *et al.* (2012) exploit randomisation in the Mexican program Progresa to discuss how structural models can improve program evaluations even in cases where evidence from experiments is available. Kim *et al.* (2001) estimate a switching regression model to capture the effect of the Nutrition Labelling and Education Act on diet quality in the US.

4. CONCLUDING REMARKS, EXTENSIONS AND PERSPECTIVES

This article aims to provide a critical overview of the current state-of-the-art in the field of nutrition policy evaluation using quasi-experimental data. It is not comprehensive in terms of the range of counterfactual methods potentially available to researchers, and by the time it will be published and read it might even be "not-so-current". However, until the recent past, nutrition policy evaluation has relied on a much more outdated toolbox relative to other fields, especially compared to labour and health policy analyses.

A ranking or a direct comparison of the different methods would not be a wise exercise, as the choice and credibility of quasi-experimental methods is heavily dependent on the plausibility of the underlying assumptions, and the quality and detail of the available data. Inevitably, empirical diagnostics on the quality of "counterfactual" causal inference must depend on observed

[9] Furthermore, structural models and theoretical knowledge are always a valuable complement in the estimation of regression-based quasi-experimental models, as the DID, RDD and IV approaches can follow a structural specification.

[10] The analogy with regression discontinuity design is considered in Section 3.2.3.

variables, which can be outcomes, covariates, or instruments. Still, the crucial assumptions refer to unobserved and unobservable variables, and in most cases no conclusive test is available, as discussed in this article.

Despite this necessary disclaimer, we believe that consolidated and emerging methods will need to deal with the key elements we emphasize. The central and obvious one is that the success of any causal identification depends on the validity of its underlying assumptions. Under a technical point of view, this requires validation of findings through appropriate tests for these assumptions – even when they are only suggestive and not conclusive -, together with robustness and falsification checks, and comparisons with alternative identification strategies and possibly even different data.

There are several variants of quasi-experimental methods that may improve causal inference. For example, when pre-policy data cover multiple periods and multiple non-treated groups (e.g. regions), the synthetic control method (SCM) is a popular option (Abadie *et al.*, 2015). Consider a situation where only one region is treated, and there are n non-treated regions. The principle is relatively straightforward, instead of using the n controls separately, they are artificially combined into a single control group as a weighted average. The weights are obtained through an optimization algorithm which minimizes – in each time period before the policy – the distance between the outcomes and the observed covariates measured in the target group and those obtained as the weighted average of the n values measured in the multiple control groups. In other words, the SCM allows not only to ensure the common trend between the treated region and the artificial control group, but also balances the covariates. Then, the weights can be applied in the post-policy period to obtain the counterfactual outcomes.

Other extensions allow to provide better insights on the impact of a policy by going beyond the average effect and considering characteristics of the ATT distribution. For example, the difference-in-difference method can be implemented through (panel) quantile regressions, as in the study on the effect of the India public distribution system on nutrient intakes (Chakrabarti *et al.*, 2018). Recent developments exploit evaluation techniques based on machine learning methods and LASSO estimators (Belloni *et al.*, 2017).

The growing availability of micro-data has brought more emphasis on the identification of heterogenous policy impacts, which poses serious challenges to the interpretation of the average treatment effect (whether ATE or ATT), to the point that in some cases it is not possible to estimate credible average effects. One of these situations is the potential non-compliance to the policy measure by treated subjects, as non-compliers become a third selected group whose members may be systematically different from both treated-compliers and non-treated subjects. A typical example is a policy where compliance is correlated with the treatment effect, for example adherence to nutrition guidelines is likely to depend on the distance between the current diet and the recommended one. One solution might be simply to ignore the compliance issue, consider all those exposed to the policy as the target group, then apply the appropriate method. Hence, the resulting estimate will not reflect the actual effect of the treatment, but rather to the average impact on those that are exposed even if they do not "take" the treatment, which is referred to as the average intention-to-treat (ITT) effect. Alternatively, one may want to consider only those subjects that are exposed and comply with the policy, obviously controlling for the additional selection effect between compliers and non-compliers. The latter approach aims to estimate local average treatment-effects (LATE), generally through an IV estimator (Imbens and Wooldridge 2009). More generally, it is not infrequent that the impact of a program varies across subjects just because of the nature of the intervention, for example personalized nutrition actions, hence effectiveness depends on individual subject characteristics. The recent methodological developments are directed at tackling this challenge and capture heterogeneous effects across population subgroups, typically by letting the treatment effect depend on subject characteristics. The developments in data availability and machine learning techniques are especially important to address treatment effects heterogeneity (Athey and Imbens 2017).

Under a broader economic evaluation perspective, as researchers we unfortunately face a trade-off between the econometric rigour of the identification strategy and the policy relevance of the findings. A typical example is the focus on immediate (and easier to measure) outcomes which may be distant from the ultimate goal of the policy. Do sugar taxes work? Typing this question into Google Scholar returns a little less than 300,000 references at the date we are writing, but we challenge readers to find studies with robust causal inference about their effect on morbidity or mortality. This does not mean that "reasonable" assessments and simulations of the health impact of sugar taxes do not exist, nor that the scarcity of ATT estimates for health outcomes depends on gaps in the quantitative evaluation toolbox. Obviously, the problem lies in the lack of adequate data. The desired effects of many nutrition policies only emerge in the medium-to-long term, and would require prospective cohort studies following people from the cradle to the grave. To the best of our knowledge, no

European country is running nutrition studies of this type, and probably the only good example is the cohort study which monitors cardiovascular disease, diet, physical activity on the population of Framingham in Massachusetts since 1948, now on the third generation of participants (Andersson *et al*., 2019). Public investments on more broadly representative and durable prospective cohort studies would generate more knowledge on policy effects than what a century of studies on causal inference has allowed us to do.

Under this perspective, the "big data" challenge for causal inference, the hot topic in data-rich environments, is less urgent for nutrition policy analysts. Instead, we believe that another big methodological challenge of the coming years will become especially relevant to nutrition policy, i.e. the ability to make adequate causal inference from observational data when multiple policies coexist over the data support window. The international history of policy failures in trying to improve diets and reduce obesity, together with a lack of conclusive evidence on longer term outcomes, has favoured the adoption of a "trial and error" policy approach, with a variety of overlapping policies. The coexistence of multiple interventions is clearly an obstacle for the causal inference approaches discussed in this review.

On the other hand, a key contribution to nutrition policy evaluation from economists and researchers is related to improving the specification of structural (behavioural) models of food choice. Just to mention the most apparent challenge, few evaluation studies succeed in properly modelling dynamic behaviours when using secondary data, which is a requirement to consider habits, intertemporal compensations, discounting, stockpiling. In our discussion, we have underlined that structural models and the proper consideration of prior theoretical knowledge make them an ideal complement rather than an alternative to quasi-experimental methods.

Finally, causal inference techniques might bring major benefits to the policy evidence-base when combined with other decision support tools that are becoming increasingly popular in nutrition, stochastic microsimulation methods (see e.g. Emmert-Fees *et al*., 2021). Robust evidence on proximal outcomes from quasi-experimental methods could be valued in combination with simulation methods able to account for longer term effects, dynamic behaviours and heterogeneous impacts.

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Italian farms during the COVID-19 pandemic: main problems and future perspectives. A direct analysis through the italian FADN

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Abstract. The spread of the COVID-19 virus in Italy during the first phasis of the pandemic (February-May 2020) has caused a large-scale crisis, with an almost immediate decrease of industrial production and a consequent contraction in domestic consumption and external trade. However, the issue of food security was immediately recognized as one of the most sensitive, so that the Government has decreed the priority role of the food system, which has been included among those considered fundamental services and economically essential, allowing the related activities to be carried out during the lockdown. Agricultural production activities transformation, and commercialization remained fully operative during the lockdown; nevertheless, the sector has faced many difficulties related to the contraction of some of the marketing channels (restaurants, on farm sales, agritourism, problems with the logistics and many other ones). To better understand the effects of the initial phasis of the pandemic on the Italian agricultural sector and provide useful information to the government and decision makers, a survey was carried out with a CAWI (Computer Assisted Web Interviewing) sent to over 10,000 farmers belonging to the sample of the Farm Accountancy Data Network (FADN). The number of respondents has been of 733 farms, which represents around 7% of the Italian FADN sample. The results of the questionnaire have been matched with FADN data on the structure and the economic performance of farms, allowing a more precise evaluation of the condition and effects of the pandemic. The results highlight a relevant effect of the COVID-19 pandemic emergency on the agricultural sector: 37% of the interviewed farmers declared a significant liquidity crisis, while 60% predicted a contraction in turnover. These effects are more relevant for the wine, olives, and horticulture types of farming and more frequent in medium/large farms. A better situation has been found for farms which usually outsource processing and/or marketing/sale of the products.

Keywords: COVID-19, farms, farm income, Italy, FADN.
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1. INTRODUCTION

The COVID-19 pandemic in Italy started to become dramatic in February/March 2020, a bit earlier than other European Countries, and is still ongoing, albeit with reduced diffusion. The initial pandemic diffusion led to a severe lockdown in all the Country, causing a severe stress not only to the health system, but also to the financial, economic, and social situation of the population. To curb the spread of the infections, the national and regional authorities adopted severe restrictive measures, closing a lot of economic activities and dramatically limiting the social life of people. The crisis triggered by COVID-19 caused a significant slowdown in production activity, a sharp contraction in internal demand for some types of goods and services, and a reduction in commercial and trade activities. Consequently, in the first quarter of 2020 National Gross Domestic Production (GDP) decreased by 5.3% compared to the previous quarter (ISTAT, 2020a) and data for the year 2020 show a global reduction equal to -9,2% (Banca d'Italia, 2021; ISTAT, 2020b), pushing the country towards the most dramatic crisis faced since the post second war period.

In this situation of emergency, the issue of food security was recognized as one of the most sensitive, so that the Government has decreed the priority role of the food system, which has been included among those considered fundamental services and economically essential, allowing the related activities to be carried out during the lockdown (art. 1, co. 4, DPCM 11/03/2020). However, the authorization to maintain the operation of agricultural production, trade of agricultural products, and marketing activities (except for the Hotel, Restoration and Catering, Ho.Re.Ca.) did not prevent several difficulties related to the lockdown, which effects have been depending on the positioning of each company on the supply chain, the range of activities carried out, the geographical area, the organization, and the management of the production activities.

Available statistics show that just in the first quarter of 2020 an important reduction of the agricultural activity has been registered, with a reduction (with respect to the last quarter of 2019) of -1.9% in the added value and -1.8% of the work units (CREA, 2020a). These reductions are mainly due to the scarcity of temporary workers, lack of liquidity, reduction/lack of other gainful activities together with the impossibility non-postponement of necessary operations (seedling, cure of livestock, veterinary visits, crop's phytosanitary treatments, and fertilization, etc.). During the year, difficulties became more evident as showed by ISTAT (2021), which estimated the reductions of the sectoral value added higher than -6% and of the work unit equal to -2,3%, mainly due to a smaller use of employees. This result seems related principally to the trend of vegetal productions (notably olive oil), to the reduction suffered by agricultural services (-4,1%), and mostly to the dramatic fall of secondary activities (-20,3%), mainly driven by the restrictions enforced for the agritourism services (Buonaccorsi, 2020). These trends are confirmed by a FAO report (FAO, 2020) which states that in Italy "lockdown measures and border closure disrupted the usual organization of work and flow of labour, causing risks of seasonal workers shortages for the spring harvest. Rural tourism was impacted due to the cancellation of all farms' stay accommodations".

Therefore, needs and problems of farms have different relevance, according to the type of farming, the specialization in different productions and activities, the organizational and managerial schemes adopted (use of family labor, presence of permanent workers vs. seasonal/foreigner workers, outsourcing services), commercial channels utilized, and final markets of the products. The relevance of the structural and organizational characteristics in managing the responses to the post pandemic crisis has been put in evidence in many other countries, as emerges from the literatures published in the months following the spread of the COVID-19 (Aday and Aday, 2020; Gruère and Brooks, 2021; Marusak et al., 2021; Weersink et al., 2021).

At the same time, food industry has faced the challenge to quickly reorganize working spaces and shifts, for ensuring the safety of employees and granting the regular delivery of processed food to the distribution companies, in addition to the necessity to retrieve all required raw materials, often of foreign origin (CREA, 2020c; Ecovia Intelligence, 2020; ISMEA, 2020a e 2020b). In this case, the index of industrial production has showed a more significant decline (about -4%) in comparison with same period of 2019 (March), and the negative trend has been confirmed in the following month, with a further reduction of -2% (CREA, 2020a). In addition, within the phase of the industrial processing, the sector of beverages has suffered the highest reduction; in particular, the index of alcoholic products has showed a dramatic reduction (less 39% in March and -74% in April). These trends are summarized in a decrease of the added value of the food industry, estimated by ISTAT equal to -1,8% (2021) and in a severe reduction of employment (-6,7%).

The performance of the retail sector has been different, thanks to the role played by Large Scale Retail Trade and food and beverage distribution in replacing the market spaces of the Ho.Re.Ca. (FIPE, 2020), to ensure the compliance of the lockdown rules[1]. So, the value of sales has showed a positive trend (+10%) in March and also traditional retailers and specialized and small shops have increased the sales in the lockdown period (CREA, 2020a). Other distribution channels, such as proximity stores, short supply chains, home deliveries and online or digital sales, have acquired a strategic relevance, because they have been able to provide specific types of services or sales conditions more suited to the new and unexpected circumstances (ISMEA, 2020b). Given this general framework, the agricultural sector deserves a special attention and analysis, because its activities may be only partially and slowly adjusted to the situation deriving from a lockdown. Often, the main difficulties suffered by farms regarded the availability of specific production factors. Particularly critical has been the availability and health protection of workers, in particular foreign ones, whose movements were heavily reduced by restrictions of mobility and by anti-contagion rules (e.g., the reduction of international connections and the obligation of quarantine) (ILO, 2020; ISMEA, 2020a and 2020b, Macrì, 2020). In other cases, the undesirable effects of the crisis affected the organization of production activities, caused by the weakness of some essential services, including the structural lack of infrastructure and technological equipment in agriculture. In addition, some specific sectors have more severely hindered the negative impact of the economic slowdown, suffering a quite total stop of important market channels (as in the case of the floriculture or wine sector) (ILO, 2020; Mediobanca, 2020).

Furthermore, the slowdown of the agricultural activities has generated serious damages in terms of food waste (as well as a related environmental damage), due to the loose of edible products remained not harvested and/or unsold (ILO, 2020).

The scope of this work is to provide a picture, albeit partial, of the main difficulties that have affected the management of agricultural production activities and the financial situation of Italian farms in the short term (during the lockdown of spring 2020), as well as the expectations expressed by farms for policy actions considered necessary to mitigate the difficulties arising from unpredictable and global event, such as the recent pandemic. The aim is to identify the areas of most significant weakness that can reduce the organizational and economic capacity of farms, threatening their functionality. Knowledge about these aspects is of great importance for the programming of the CAP 2023-2027 and other support actions aimed at overcoming some of the critical issues come to light.

The paper is organised as following: the next section describes the rationale of the questionnaire and the methodology adopted for its submission to a sample of Italian farms belonging to the Farm Accountancy Data Network. The third section presents the results of the analysis, matching the responses of the questionnaire and the structural, economic and financial data of the FADN dataset. The fourth section focuses on the main measures taken in the short term to respond, both at EU and national level, to the emergencies triggered by COVID-19 pandemic, also offering useful directions in the medium-term aimed at stemming future crises. In the conclusions some implications are discussed, for the next future, offered by the results of the analysis.

2. MATERIALS AND METHOD

During the first phasis of the emergency attention was focused on aspects related to availability, distribution, and consumption of food and agricultural products, while analysis on the effects of pandemic on agricultural production and farms have been relatively scarce.

However, the need to investigate the problems faced by Italian agricultural farms and related solutions has been highlighted by many institutional and non-institutional actors, such as government authorities, professional organizations, and associations. Indeed, to define possible actions to support farms and prevent the risks of other emergencies, it is crucial to have a deeper understanding of the effects of the covid pandemic and related policy actions on the agricultural sector and the farmers behaviors.

Currently, these issues are widely documented mainly through journalistic investigations or experts-based research methods, while there is a lack of direct information from the farmers. To contribute to cover this lack of information this work is based on a direct survey collecting data and information from farms.

The asked research questions are the following:

Following the COVID-19 emergency and the measures adopted to contain the pandemic, which kind of difficulties did the farms face in relation to the conduct of their activities?

- Which actions did the farms put in place to face the pandemic situation and the lockdown?
- Do the size, farm structure, production sector, marketing or other specificities have resulted in significant differences in terms of problems and adopted solutions?

[1] With the exception of those actors (bar, restaurant, catering) which have rapidly reorganized the supply towards the home delivery or take away services.

- What were the forecasts of farms with respect to the immediate future, in terms of both difficulties/solutions and economic results?
- Did farmers expect a change in the total production of their farm? In what percentage?

The hypothesis is that, although the restrictive lockdown measures regarded most of the other productive sectors but not directly the agricultural production, the effects of the COVID-19 emergency have largely affected agriculture, although to diverse extents and in different ways.

To carry out the survey quickly and reach enough farmers, the CAWI (Computer Assisted Web Interviewing) methodology was used (via web), also ensuring compliance with public health and safety regulations. Despite this methodology reaches only those who have access to Internet and does not allow statistically representative sampling, it guarantees a remarkable speed in the collection of information and the CAWI is rather easy to be filled by the respondents.

The questionnaire was structured in 5 sections aimed at collecting information on: the difficulties faced by Italian farms due to the COVID-19 emergency; the actions taken to deal with them; the public support granted for supporting farms; the forecasts for the future, in terms of possible difficulties / solutions; and the expected change in the farm's output. Each section was organized in a set of closed-ended answers (with the possibility of multiple choice), in which also an open-ended answer was included, to collect additional unexpected input.

To overcome the representativeness problems associated with CAWI method, the questionnaire was sent to over 10,000 farmers belonging to the sample of the Farm Accountancy Data Network (FADN), distributed throughout the national territory. In this way it has been possible to match the data and information collected with the questionnaire to all the individual farm data already available in the FADN dataset (Total Output, production, costs, income, structural information on the farm, etc.).

The questionnaire was available online for 14 days (April-May 2020); 733 farms, operating in all the Italian regions and covering all productions, filled out it with a response rate covering over 7% of the FADN sample (Tab. 1).

The data from the questionnaire were analyzed to estimate the impact of pandemic on some relevant farm indicators, using the economic results of farms recorded in the Italian FADN survey in the 2016-2018 period as baseline. The matching of the farmer to which the questionnaire was sent with the farm code registered in the FADN database made it possible to link the responses of the questionnaire to the technical and accounting information found in the FADN survey.

The baseline consists of 30,374 observations and includes the farms recorded in 3 consecutive accounting years. The annual sample, of about 10,100 units, is statistically representative of the universe (field of observation) of Italian farms. However, based on the European FADN regulations, only a part of the farms is considered in the field of observation, i.e., those having a Standard Production (SP) greater than 8,000 euro. The field of observation of Italian FADN represents only 50% of the farms estimated by the Farm Structure Survey (FSS) but more than 96% of the Standard Production and almost 90% of the agricultural area used in Italy, guaranteeing an almost total coverage of the Italian agricultural production.

Being the FADN sample designed using a rigorous methodology, it is statistically representative and it is therefore possible to extend its results to the entire field of observation of the survey with a good statistical precision at level of administrative Region, Type of farming, and economic size class. In addition, the estimates can also refer to structural elements of farms, such as the use of family and wage labour.

In synthesis, among FADN variables, the following economic variables have been identified and used for the analysis:

(1) *Total Output*; (2) *Specific Costs*; (3) *Value Added;* (4) *Agricultural Working Unit*.

To facilitate the reading of the economic results between the various typological classes of farms, the selected economic variables were also analyzed as working unit indices. To exclude anomalous values (outliers) within the layers considered, the dataset has been subject to statistical treatment.

Table 1. Structure of questionnaire and number of respondents.

Survey Sections	Number of answers
A. Kind of difficulties faced by farms due to the COVID-19 emergency	733
B. Actions taken to deal with different difficulties	535
C. Priority support actions by State and Regions	528
D. Difficulties expected by farms during the following months	600
E. Expected change in Total Output following the COVID-19 emergency	639

Source: own elaboration on collected data.

The 10 types of farming (TF-10) used in the analysis represent the most representative TF (in term of Standard Output) at national and regional level. In term of economic size, we aggregated the farms based on 3 classes of economic dimension (*Small*, *Medium*, *Large*) to allow an easier representation of the stratification of the sample.

To eliminate annual variation of economic figures, three-year average values were used in the analysis.

The Added Value (AV), in absolute or index form, constitutes the most appropriate FADN indicator for this type of analysis. For a better understanding of the results, it needs to be considered that there is a strong relationship between the economic size of the farm and the average levels of income produced, productivity, and profitability indexes. In every TF, smaller farms are characterized by lower income and productivity (per Work unit) with respect to larger ones.

Figure 1 describes the similarities and differences between the FADN sample and the subsample of respondent to the questionnaire.

Respondents are proportionally less than the FADN sample in southern regions and insulas (Sardinia and Sicily) while they are more than the FADN sample (as proportion) in North-West, North-East and Central regions.

Considering the gender and age of respondents, no relevant differences appear between the subsample of respondent and the FADN sample, similarly for the organic/conventional classification of farms. Indeed, a relevant difference can be seen in the variable describing the diversification of farm activities: the proportion of diversified farms (agritourism, educational farms, etc.) is almost double in the subsample of respondent with respect to the FADN sample. One possible explanation for that could be the fact that these farms have a greater propensity to use social networks and participate in surveys. In addition, they are more sensible to the effects of the lockdown because their activities have been almost completely cancelled during the pandemic, so they are more interested to communicate it (ISMEA, 2020c)

The Farm Type (FT) and Size differences between the subsample of respondent and the FADN sample are less relevant but still interesting. Regarding the FT, Figure 2 shows on its left part that the respondents are pro-

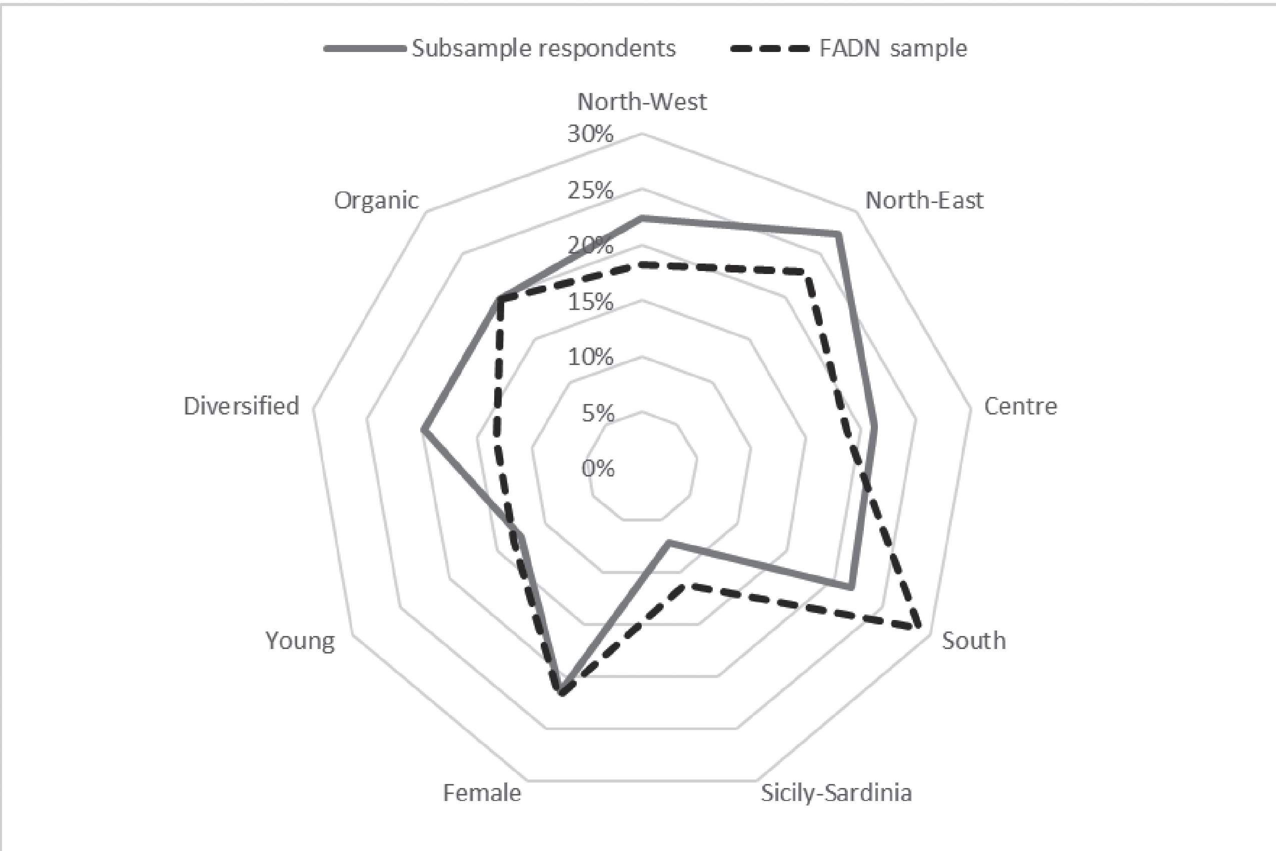

Figure 1. Comparison of FADN sample and subsample of respondents. Source: own elaboration on FADN and collected data.

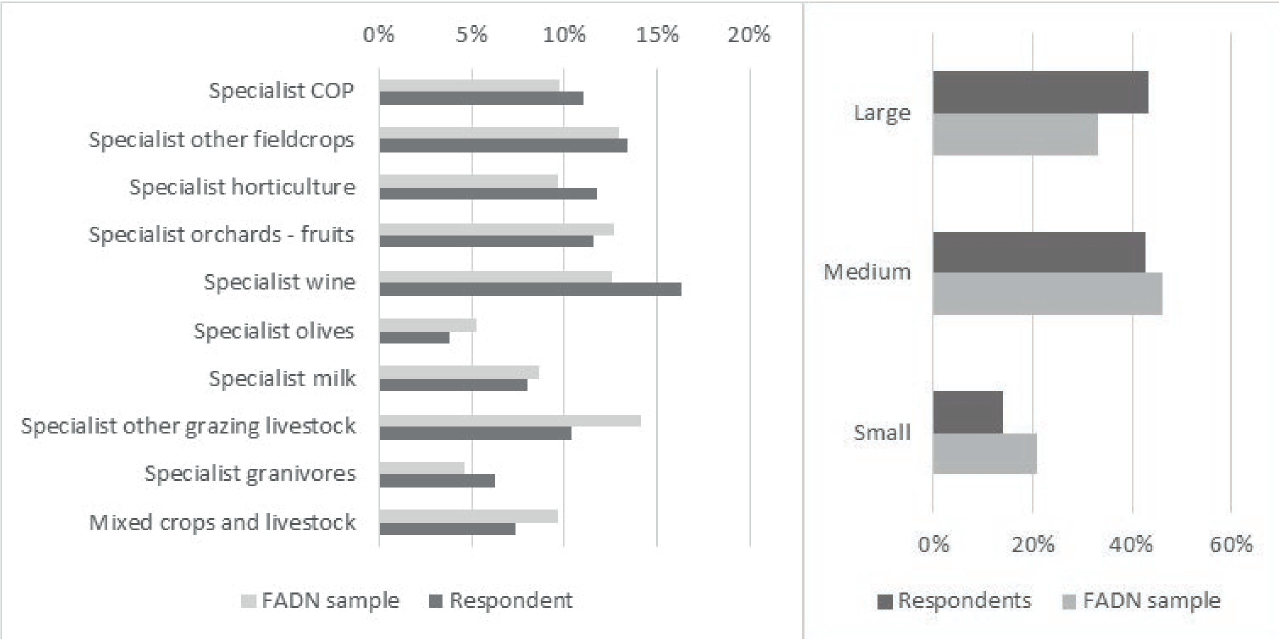

Figure 2. Comparison of FADN sample and subsample of respondents per FT and FS. Source: own elaboration on FADN and collected data.

portionally more numerous in the FTs "specialist wine" and "specialist horticulture" while farms specialized in livestock production (milk and grazing) are less frequent in the subsample of respondents, Regarding the Farm Size (FS) there is clear evidence that large farms are more represented in the subsample of respondent than in the FADN sample. Overall, we can assume that farmers who forecast major losses as an effect of the pandemic are more propense to answer the questionnaire, as clearly demonstrated by the results of the analysis of the questionnaire.

This framework shows differences according to various issues covered by the questionnaire, as described in the following paragraph.

3. MAIN RESULTS AND PRELIMINARY EVALUATIONS

The answers given by the 733 farms of the FADN sample who accepted to fill the questionnaire show some elements of great interest.

The answers reporting a reduction in the Farm Total Output (FTO) are prevalent, with over 60% of the responding sample expecting a decrease in the FTO (for 13% of respondent the reduction is estimated to be higher than 50%). In all types of farming, estimates of negative changes in FTO are prevalent, so that the distribution in the first three quartiles and the median are always below zero; this highlights the respondents' expectation of marked contractions and significative FTO decreases. This is particularly evident for some TF such as wine, olive, and horticultural ones, in which most of the observations are positioned on reductions that reach even 50%, with contractions in FTO that in the last quartile reach almost 100% (Fig. 1). The relatively more negative forecasts regarding the FTO recorded for the wine, oil, and vegetable sectors mainly depend on the closure of the Ho.Re.Ca. channels, which also affected the reduction in exports, the contraction in tourism and, in the case of horticultural products, by the penalization suffered in general by perishable products compared to those preserved or frozen and by fears about the availability of foreign labour for harvesting activities (Coluccia *et al.*, 2021).

The distribution of the responses received is shown in the box plot chart below (Fig. 3), with the expected changes in FTO in relation to the types of farming.

However, some of the respondents also expect an increase in agricultural revenues, albeit with variations among the TF. With reference to wine and horticultural farms, a quarter of the responses expected positive variation of the revenues even higher than 50%. Positive changes in revenues, but more sporadic, are found for the fruit, granivorous, and arable crops (including cereals).

To better understand the situation, the information on the expectation in term of Farm Total Output

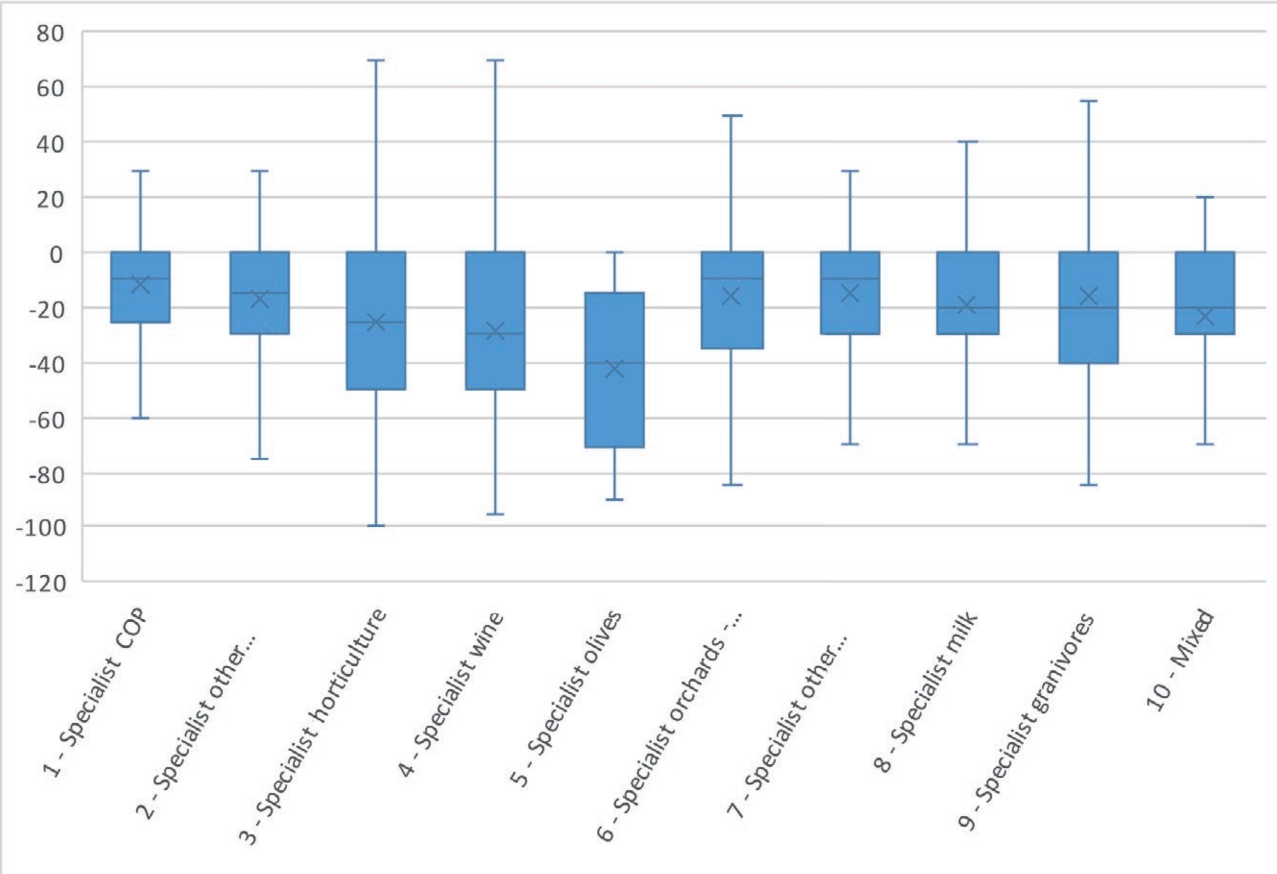

Figure 3. Expected changes in farm Total Output in relation to the different Types of Farming. Source: own elaboration on collected data.

resumed from the questionnaire has been coupled with the sales channels adopted by respondent farms (derived from the FADN database).

As shown in Table 2, the expectations for a reduction in TO are significantly different for each sales channel.

The most significant prospects for a reduction in FTO regard farms with agritourism (75%), with direct sale in the farm or by vending machines. These farms declare to expect the revenue in the next future to close to zero. On the other hand, the least negative expectations are found in farms selling a part or the entire production, including a part of transformed products, to cooperatives or transformation industries. It is therefore evident that the higher importance of the direct sale of products and services will make these farms more sensitive to current and future market difficulties.

However, it should be recalled that the questionnaire was submitted to farmers in the very first phase of the lockdown, when there was still uncertainty on the duration of the epidemic and the possible schedule of reopening of markets was unknown by farmers.

The availability of adequate financial liquidity was one of the difficulties most reported by the respondent farms: as shown in Fig. 4, 42% of respondents declared this issue as relevant, preceded only by the difficulties of repairing equipment, machineries, and buildings during this emergency period (49% of the participants). The difficulties in accessing advisory services and technical assistance services, or in finding technical means are also reported by a significant number of respondents (approximately 1/3 of the total), followed shortly after by the complications linked to the marketing of the products and the signing of new sale contracts.

Farmers declare they intend to cope with financial difficulties in this emergency period by resorting above all to their own savings and/or forms of corporate self-financing and, more rarely, by accessing financing and emergency instruments put in place by the Government or bank credit. This last option probably has been evaluated by farmers as less timely and less effective in responding to contingent needs. However, it should be remembered that the questionnaire was submitted in the

Table 2. Expected changes in Total Output by sales channel for the surveyed farms.

	Negative >75	Negative 50-75	Negative 25-50	Negative 0-25	None	Positive	Total
Wholesales, large-scale distribution, exporters	7%	7%	26%	27%	26%	9%	100%
Industry	5%	6%	27%	27%	25%	10%	100%
Retailers	7%	9%	26%	22%	22%	13%	100%
Other farms	5%	5%	23%	31%	27%	9%	100%
Direct sale in farm and automatic distribution	13%	14%	25%	22%	22%	5%	100%
Agritourism	25%	22%	19%	8%	17%	8%	100%
Cooperatives	1%	7%	21%	26%	32%	12%	100%
Others	3%	8%	23%	28%	29%	8%	100%
Undetermined	7%	7%	25%	23%	28%	10%	100%
Total	6%	7%	24%	25%	27%	10%	100%

Source: own elaboration on collected data.

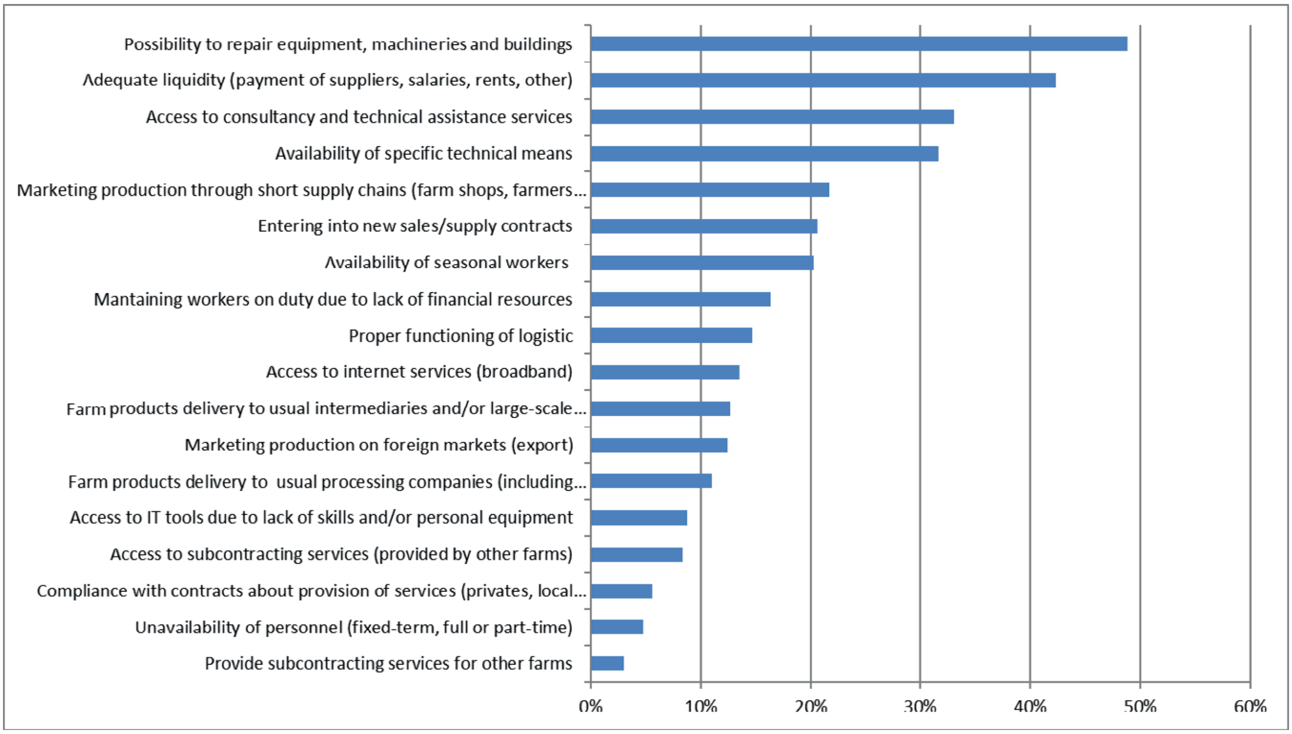

Figure 4. Difficulties faced by surveyed farms during the lockdown (%). Source: own elaboration on collected data.

first phase of the lockdown, when some measures had not yet been implemented and/or not adequately known.

It is interesting to note that respondents who declared problems of financial liquidity are not homogenously distribute per geographic area and specialization: farms located in central and southern Italy are more affected by liquidity problems/concerns, while no relevant differences are registered in term of age and gender of the farmers. At the same time diversified and organic farms are more affected by liquidity problems than the average of respondent.

For other relevant questions of the questionnaire, like the problem of repairing machinery and equipment similar differences are less relevant.

The main results from the survey conducted on the FADN farms have been considered for the formulation of simulations on the impacts on farm income, by interfering the subsample of respondents with the FADN

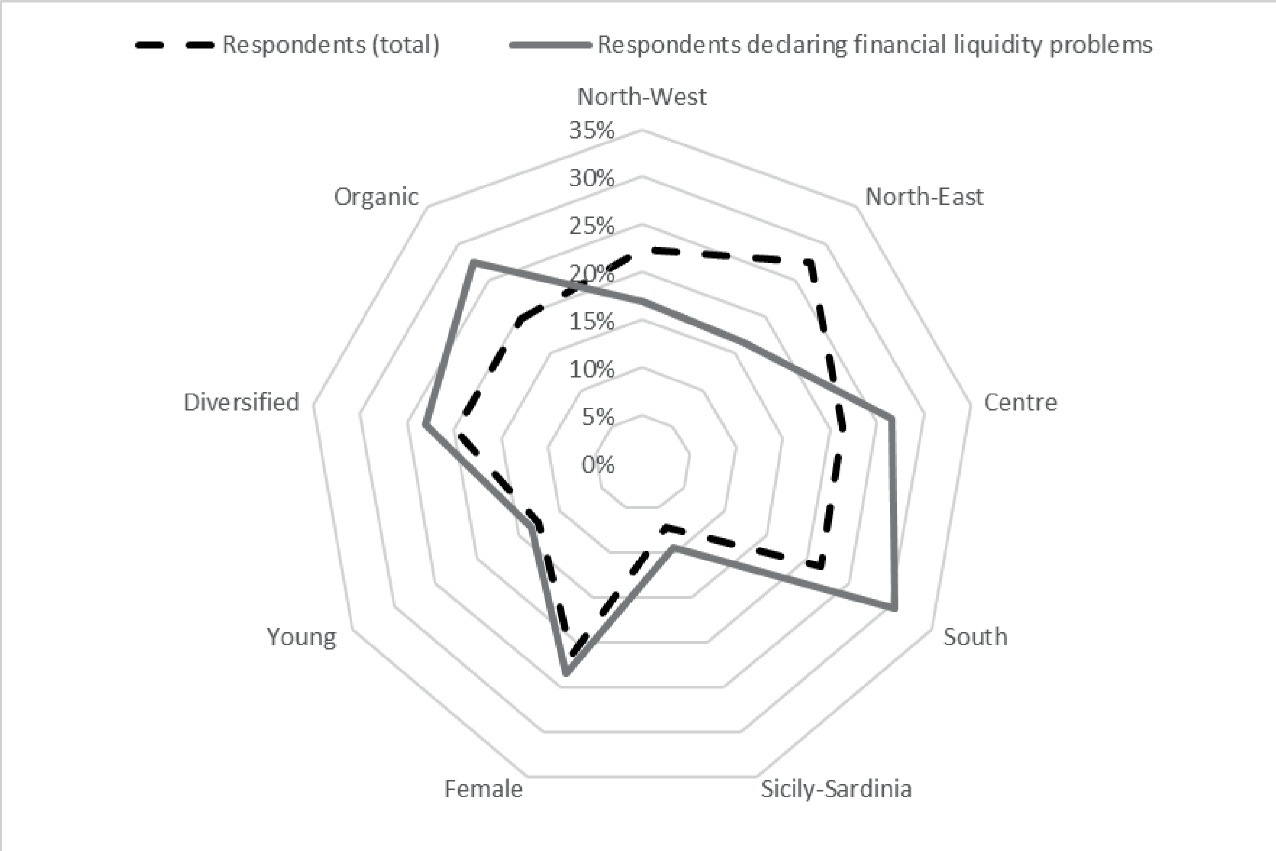

Figure 5. Focus on financial liquidity problems. Source: own elaboration on collected data.

database. More precisely, the contraction of Total Farm Revenues (TFR) has been calculated in the three-year average 2016-2018, considering the median value of the responses, stratified according to the three classes of economic size of farms. In addition, starting from FADN data, the incidence of current costs on revenues was calculated, obtaining the farm added value (AV) as difference between farm Total Output and current costs; the AV was then ratioed to farm Agricultural Working Units (AWU) (Fig. 6).

It is important to emphasize that the high incidence of current costs amplifies the effect of the contraction of revenues in the more intensive farm types, such as horticulture, viticulture, and granivores, causing a significant reduction in productivity per unit of work, expressed by the AV/AWU index, much larger than the expected contraction in farm revenues.

The assessment of the real economic effects deriving from the current health emergency should therefore consider not only the organizational structure of the farm and the prevalent type of production, which evidently influences farmers' expectations, but also the different cost structures characterizing the farm typologies. Therefore, for the same reduction in revenues, the effects on farm income can also be significantly different.

Finally, examining the future expectations of the farms interviewed, financial liquidity remains the most felt concern, also for the future, given that almost 2/3 of the survey participants identify it as the main problem to be faced in the next few months (Fig. 7). It seems to emerge in the farms that participated in the survey a deep concern about their ability to meet the needs of current expenses necessary for carrying out production activities in the next future, probably cause of a reduced consistency of monetary liquidity.

In this regard, farms of medium and large economic sizes express, to a greater extent, their concern for a possible unavailability of financial resources in the coming months, expressed by almost 2/3 of the respondents, against a steady expectation recorded for small farms. The latter, however, are characterized by a profile that is hardly identifiable with a professional management of the agricultural activity and closer to a connotation of non-professional farms, or farms that are characterised

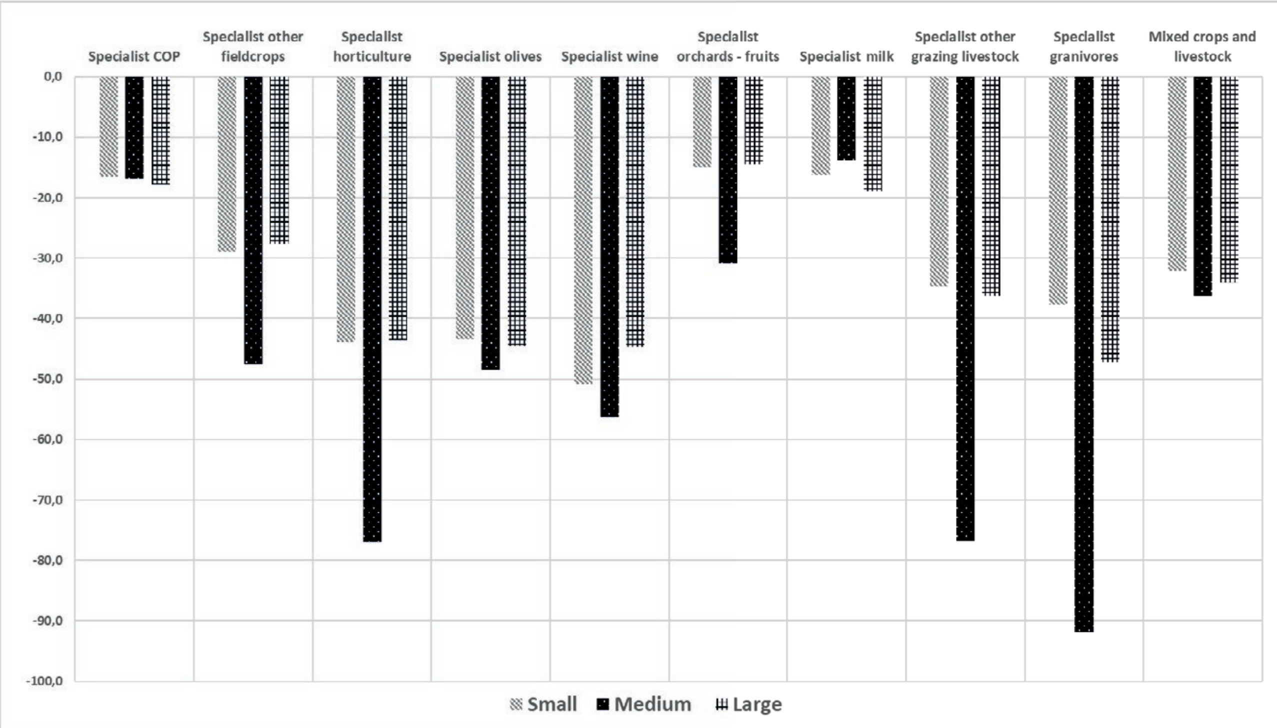

Figure 6. Changes in the ratio AV/AWU based on the estimated variations of Total Farm Revenues. Source: own elaboration on collected data.

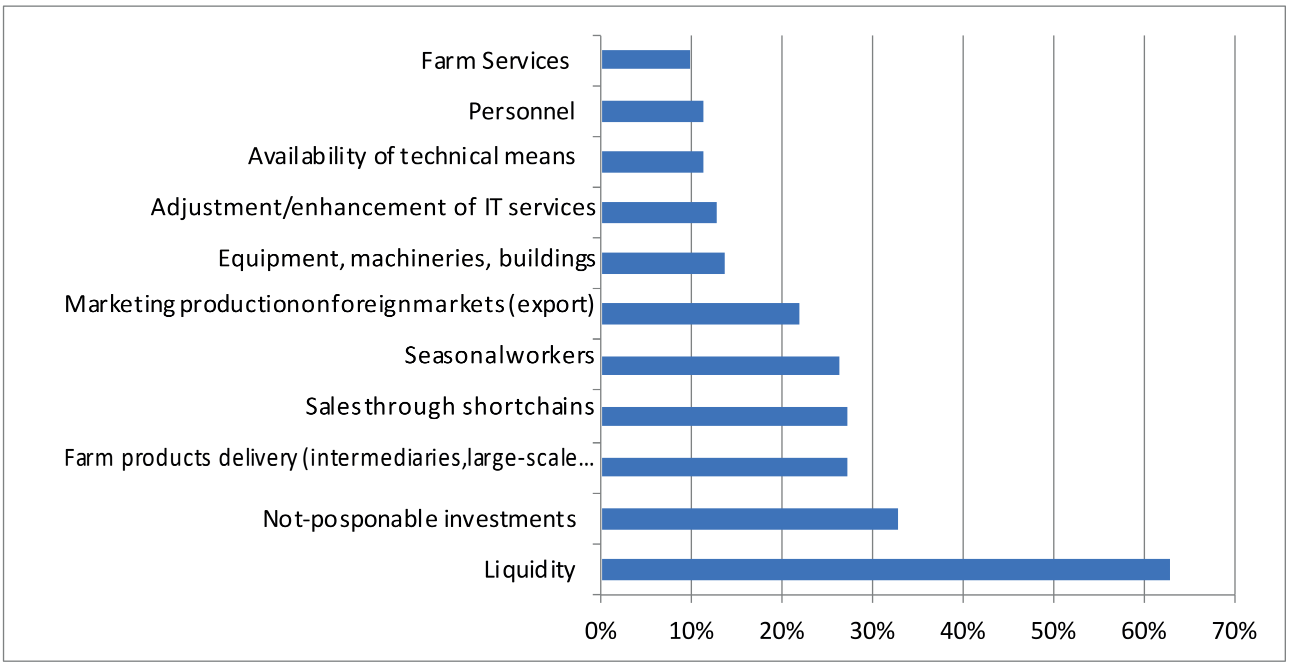

Figure 7. Difficulties expected by surveyed farms in the months following the lockdown. Source: own elaboration on collected data.

by the integration of other income. This peculiar condition may have affected the assessments expressed regarding the adequacy of future financial resources.

4. FROM EMERGENCIES TO RESPONSES: EXPECTED MEASURES AND POLICY IMPLICATIONS

After the first lockdown in March 2020, some buffer measures at EU and national level, through State Aids and a more extensive use of CAP resources, were activated to mitigate the liquidity crisis faced by the Italian farms during the phase of more severe restrictions and afterwards (CREA, 2020d), also detected through the survey addressed to FADN farms of May 2020.

At EU level, this was mainly implemented by the European Commission through the introduction of "Measure 21" in the framework of RDPs. The new measure was activated by almost all the Italian Regions (17 out of 21), allocating a maximum of 2% of the financial resources of the RDPs in favor of agritourism, educational farms, social farming and the sectors considered most exposed to the pandemic effects by each Region. Therefore, a non-repayable grant of up to seven thousand euros per farmer and 50 thousand for processing and marketing Small and Medium Enterprises (SMEs) was arranged. Furthermore, the advance on CAP contributions was raised from 50% to 70%.

As in numerous other EU Member States, different schemes have been activated through the mechanisms of State Aids to support agriculture, animal husbandry, forestry, and related sectors with different measures (e.g. renegotiation of mortgages, issue of zero-rate mortgages, establishment of the "Fund for the development and support of agricultural, fishing and aquaculture chains", favorable tax regimes, exemption from the payment of social security and welfare contributions by employers, for farms belonging to agricultural supply chains, intervention by the Guarantee Fund also in favor of agricultural SMEs). Other measures were aimed at simplifying some procedures that the COVID-19 emergency would have hindered (e.g., suspension of visits to the farms by certification bodies to issue the certificate of suitability, suspension of certificates of qualification for sale, consultancy and purchase and use of plant protection products and extension of existing ones, extension of terms and derogations from agricultural sector legislation).

Regarding agricultural labour, the survey of the FADN farms highlighted two problems: 1) keeping it on the farm, avoiding dismissal; 2) ensure the availability of seasonal workers, especially foreign ones (about 300,000 units). To facilitate agricultural enterprises, therefore, on the one hand, the extraordinary exemption or the suspension of the payment of social security and welfare contributions of workers by employers and the wage supplement for agricultural workers, for example, have been introduced. In the case of seasonal workers, on the other hand, the duration of residence permits was extended until the end of July 2021 and agricultural professional organizations were authorized to set up databases to recruit people to be hired temporarily on farms, a tool that minimally resolved the problem (Contignani *et al.*, 2020). Nevertheless, the regularization of agricultural workers was unsuccessful (Legislative Decree no. 34/2020), with only about 2,000 units regularized (May 2021; Bettini and Coderoni, 2021). Furthermore, in Italy the green corridors, aimed at facilitating the entry of seasonal workers, have not yet been activated, with the exception of the Autonomous Provinces of Trento and Bolzano, because the active quarantine protocols have not been officially recognized by the State. Therefore, the solution to the seasonal labour problem has been left mainly to the private initiative (Bettini and Coderoni, 2021).

Also, the difficulties of marketing farms' products in Italy and abroad, due to the closure of the Ho.Re.Ca. channels and canteens, both public (especially school) and private, or due to the contraction of tourist flows and of the reduction in the subscription of new sales contracts, have been faced by public authorities with extraordinary campaigns of purchases financed by European and national extra funds. These measures were aimed at readdressing a more sensitive group of unsold products - such as, fresh milk, typical cheeses (Pecorino Romano, Parmigiano Reggiano, Grana Padano, Fontina etc.), extra-virgin olive oil, cured meats and so on – and supporting the increasing share of citizen affected by economic deprivation. However, in a medium-term perspective, the only remedies appear to be the restoring of traditional markets, mainly thanks to the results of vaccination campaign, still in progress, and the gradual reopening of the activities. About marketing, it is worth highlighting once again the results reported from farms involved in cooperative's system. Indeed, data confirm the relevance of the implementation of measures for strengthening networks or cooperatives, especially for those sectors in which this type of organization is weaker, such us proposed also in the framework of the CAP 2023-2027.

Other critical issues highlighted by the survey addressed to the FADN farms (difficulties in maintaining / repairing machineries, equipment and buildings, finding technical means, access to consultancy and technical assistance services, making non-deferrable investments, marketing of production via short supply chain), on the other hand, currently appear less serious than one year ago, as the supply of goods and services upstream and downstream of farms has been reorganized to comply with safety standards and operators have adapted to work in adverse conditions, thanks to the widespread use of protection systems and the gradual results of the vaccination campaign. However, these problems can recur with the recurrence of situations similar to the COVID-19 pandemic, their evolution, or due to "catastrophic" natural events.

As resulted by the survey, one of the main challenges of new policies in favor of the agricultural sector should be to prevent the negative impact of new possible global crises, health and non-health, through structural interventions, promoting resilience of farms. In the long run, the resilience of farms is fundamentally affected by the availability of liquidity, inputs, including labour, and services. Farms, therefore, between now and 2030, should reorganize their production processes to reduce their dependence on the outside and the production costs with the support of the public sector, which should provide them with a range of services, positively also influencing the availability of liquidity.

In particular, the latter problem could be mitigated by expanding to pandemic risk the mission of the EU toolkit for risk management in agriculture (insurances, mutual funds, and income stabilization tools), currently mainly addressed to mitigate the effects of climatic and health emergencies (epizootic and plant diseases, parasitic infestations) and sectoral income losses (durum wheat, fruit and vegetables, etc.). These measures should be better promoted, also favoring greater synergies among them, in addition with the adoption of strategies differentiated for business model, as well as their financial reinforcement in the next CAP programming period, for reaching a wider range of farms, currently still too limited (Capitanio, Adinolfi, 2013; Trestini et al., 2017; Severini et al., 2018; Capitanio and De Pin, 2018). In China, for example, agricultural insurance has been activated, on the one hand, to stabilize the incomes of farmers who produce fruit and vegetables, reducing their risk in agricultural production and operation during the COVID-19 pandemic, and, on the other, to guarantee a constant supply of these products to consumers in urban areas (Gu and Wang, 2020).

With reference to other emerging issues highlighted by the survey, it must be emphasized the relevance of the opportunities offered by the recent policy documents and financial instruments launched by EU, ranging from the *European Green Deal* (European Commission, 2019) and the *Farm to Fork Strategy* (European Commission, 2020c), up to massive amount of resources offered by the *Next Generation EU* (NGEU) (European Commission, 2020d) and the new programming period of the CAP, that will enter in force in 2023 (De Castro et al., 2021). Programming differentiated proposals for intervention according to specific needs should be effective not only to reduce current difficulties, but also for avoiding similar situation that could occur in the future. In this view, many are the future interventions that could positively affect the resilience of the farms, territories, and the environment, giving impulse to an ecological and digital transition, in line with the Next Generation EU strategy (European Council, 2020).

The European *Green Deal* aims to promote the efficient use of resources by moving to a clean and circular economy, restoring biodiversity and reducing environmental pollution. It also promotes a fair and inclusive transition transforming climate issues and environmental challenges into growth opportunities for all sectors. The challenge of producing more with fewer resources, dissociating the growth of output from a more intensive use of factors, strongly involves and affects the agri-food sector. The objectives for the agri-food sector are defined in the *Farm to Fork* Strategy, whose ambitions are to protect the health and well-being of European citizens, to increase the EU's competitiveness and resilience, to make the EU food system a standard for sustainability at a global level. The Strategy identifies the strengthening the sustainability of food systems, both by reducing their environmental footprint and improving energy efficiency, and by increasing the availability and affordability of healthy and sustainable food options, as the set path, also functional in making farms less sensitive to various adverse conditions, similar to those detected due to the COVID-19.

In this view, EU regions could play an important role in the implementation of differentiated strategies, managing as much as possible the resources of the new CAP in favor of those areas and sectors with greater difficulties or more negative outlook, but which play a strategic socio-environmental role at local level (Frascarelli, 2021). This strategy should be accompanied by actions for supporting the development of the short chain, including local markets, which could allow SMEs farms to improve their economic results and consumers to continuously have local food at lower prices, in line with the *Farm to Fork Strategy* (European Commission, 2020c). These measures should also be accompanied by information and education actions on sustainability aimed at increasing the community awareness about its contribution to the maintenance of farms in the territory and on the mutual benefits of a closer relationship between producers and consumers, as it has happened in this emergency period. Indeed, some studies highlight the importance of awareness campaigns addressed to farmers and consumers and initiatives aimed at public procurement of local products for canteens (Reis, 2019).

The issue of digitalization, including the infrastructure of the rural areas, is among the core area of interventions identified by the Italian National Recovery and Resilience Plan (NRRP; Presidenza del Consiglio dei Ministri, 2021), approved by UE within the NGEU. The NRRP provides for the implementation of structural and training interventions in favor of businesses, especially small and medium-sized enterprises (SMEs), public administration, health and tourism operators, citizens. The first step in the NRRP is the coverage of the whole territory with ultra-broadband networks (FTTH fiber, FWA and 5G), then to address resources for supporting the adoption of digital technologies by companies, so as to improve their logistics, marketing, and the efficiency of production processes. Furthermore, precision agriculture, aimed at rationalizing the use of technical means and improving the quality of products, constitutes one of the three areas of intervention of the NRRP in favor of the agricultural sector and one of the farming systems promoted by the *Farm to Fork Strategy* (EC, 2020c), together with agroecology, organic farming, carbon farming, and agroforestry, all agricultural production systems also aimed at reducing or eliminating synthetic chemical inputs. In relation to the difficulties in the supply of technical means encountered by farms and detected through the survey, the expected impact should make farms more competitive and self-sufficient, even SMEs located in the most marginal rural areas, facilitating their activities especially in times of unforeseen crisis.

Finally, the survey shows that difficulties in accessing extension services during the emergency period were reported by a third of farms interviewed. These services should be considered as fundamental policy tools in supporting farms and accelerating change towards food sustainability; however, in recent years they suffered a sharp downsizing due to the decrease of awareness about their relevance and the consequent reduction of resources allocated in their favor by public policy. Nevertheless, research, advisory services, and education have a key role in socio-economic and technical development as demonstrated in work of several authors, some of which highlighted the importance of producing tailor-made innovations analyzing the farmers' problems/opportunities (Sewell et al., 2017) and the need to enhance the interactions among different actors (Klerks et al., 2012; Hermans et al., 2015) in order to introduce innovation and promote rural development.

In the current programming period, specific interventions are foreseen to provide efficient knowledge and innovation systems (AKIS). Advisory, farmers' and advisors' training, demonstration, exchange and dissemination of knowledge, information are foreseen in the EU regulation proposal. It is a question not of new types of intervention compared to the current programming period, but of a more flexible and organized way to use them (Van Oost and Vagnozzi, 2020), to reach the aim of building a more sustainable, competitive, and inclusive Europe. Their effectiveness will largely depend on the capability to grant a better link between the new forthcoming measures and both the new policy objectives and the different characteristics of the farms.

5. CONCLUSIONS

The direct survey carried out during the first first phasis of the COVID-19 pandemic, combined with FADN data, allowed obtaining a very detailed information and thorough results, otherwise difficult to achieve using a single questionnaire submitted to a random sample of farms. The number of farms reached also offered the possibility of having a significant overview of the situation, in terms of different types of farming, referred to an exceptional period, characterized by uncertainty and a lack of data based on scientific evidence. The one presented in this study is, in fact, the largest Italian survey in the COVID-19 period which reached such many farms (and in general of subjects within a specific sector) using a consolidated methodology and being compliant with the sanitary emergency.

The analysis of the results has showed that the COVID-19 emergency produced severe consequences on the agricultural sector, both in relation to the development of cultivation / breeding activities and marketing. In addition, farmers' forecasts for the medium term indicated a growing concern about a possible worsening of the situation, with a significant part of interviewed which expressed uncertainty about the performance in the remaining part of 2020, forecasting negative impacts on agricultural incomes, especially in some sectors and for some types of farms. Final official data about the yearly trend have effectively showed an important reduction suffered by a large part of Italian agriculture.

But the survey has also put in evidence the presence of a large variety of situations and farms' characteristics which can give an important contribution in the mitigation of the negative impact caused by unexpected situation of general crisis. The organization of the supply chain, for example, seems to play a significant role, as it is witnessed by the less negative expectations on the economic performance predicted by farms marketing their products towards cooperative structures. As well as smaller farms, often considered less significant within the sector, have showed expectations of a substantial balance. For these farms, with a smaller quantity of marketable production, in comparison with the medium-large ones, look promising the opportunities of development towards alternative distribution models, such as home deliveries, particularly suitable for farms located near the urban areas and / or in areas with more efficient roadway systems.

Considering the differences related to the farm size, the structural and production characteristics and the position within the supply chain, it is possible to highlight how differentiated policy measures, able to respond to specific problems of individual sectors or activities, could produce more durable effects. Then, it could be useful to deepen the analysis with a further step. A second survey could be repeated using the same FADN sample to obtain more accurate estimates on the effects of the pandemic and on the "mitigation" measures implemented by the EU and national Government.

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The Role of Energy on the Price Volatility of Fruits and Vegetables: Evidence from Turkey

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Abstract. In agricultural economics, fluctuations in food prices and the factors affecting these fluctuations have always been an important research topic. From production to delivery to consumers, the supply chain of agricultural products has a dynamic structure with continuous changes. In this dynamic process, analyzing the intensive use of energy at each stage has gained more importance with its deepening effects in comparison to the past. This study will empirically explore the volatility spillovers between energy price index and fruit-vegetables price index in the period of 2007-2020 in Turkey using the Kanas and Diebold-Yilmaz approaches. According to the results obtained from the Kanas approach in the study, it has been observed that there is a statistically significant volatility spillover from the energy price index to the vegetable price index, whereas there is no statistically significant volatility spillover to the fruit price index. This finding was supported by the results obtained from the Diebold-Yilmaz approach showing that there is a volatility spillover of 13.52% to the vegetable price index and 0.86% to the fruit price index from the energy price index.

Keywords: volatility spillover, energy, agricultural prices, EGARCH, agricultural markets.
JEL codes: Q11, Q18, Q41, Q47, C32.

1. INTRODUCTION

Volatility in food prices and the reasons behind this volatility have recently become a trending topic of discussions throughout the world, while they are often discussed in literature as well. In this regard, pricing process of sub-product groups must also be analyzed in addition to general food prices. Indeed, due to the difficulties in storing these products for a long period, changing vegetable and fruit prices might well cause producers and consumers to be deeply affected by price volatility. On the other hand, it is also highly important to examine the reasons that may affect the price fluctuations of these products.

Fresh fruit and vegetables sector is considered one of the most essential sectors in the agricultural industry as it is vital for sustaining human life. In this context, the United Nations declared the year of 2021 as the "International Year of Fruits and Vegetables", highlighting the importance of fruits and vegetables in nourishment, the problems experienced in the process from production to consumption, food wastes and losses, the importance of farming in the fight against famine and small family businesses generating incomes. Thus, the factors that underlie price changes in agricultural markets is currently a hot topic. Prices in agricultural markets have recently been affected by macroeconomic factors such as exchange rate, inflation (Algieri, 2016), interest rates, energy prices and demand for biofuels, monetary policies, financial investments and speculations, sudden trade restrictions or lack of information, transaction costs, agricultural policies and international prices (Kalkuhl et al., 2016; Algieri, 2016; Kornher and Kalkuhl, 2013).

This study will focus on Turkey from an empirical perspective within its scope. While the country stands out in fruit and vegetable production across the world, Turkey is experiencing frequent price volatility at recent times. According to the World Food Organization's 2019 statistics, Turkey is the 4th largest producer of fresh vegetables in the world (Statista, 2021a). In addition, it is the 6th largest producer of fresh fruits in the world (Statista, 2021b). Therefore, Turkey is one of the most important agricultural producers in the world. However, Turkey's currency is one with the highest volatility among emerging market markets and this causes fluctuations in the fruit and vegetable price indices. Besides, fluctuations in energy prices due to the volatility of the exchange rate and global markets has become significant as energy is an input item in production processes. Considering upward fluctuations in particular, the practices for direct sale points and mediators in the supply chain have been heavily discussed in recent years. In the same vein, the fluctuations in food prices have been the hot topic in Turkey too due to the recent global crises, the climate change and foreign-source dependency on energy. It is stated that the reason behind these fluctuations in agricultural product prices is the increasing production input prices by farmers. Besides seasonal effects on the price fluctuations in agricultural commodities, it can be observed that increasing energy prices have a direct or indirect aggravating effect on the costs of agricultural inputs such as fertilizers, chemicals, irrigation, production, storage and transportation (Fasanya and Akinbowale, 2019; Tadasse et al., 2016; Algieri, 2016). Moreover, the use of modern technology applications in agriculture also increases energy consumption. The use of agricultural machinery and pesticides requires the consumption of fossil fuels, and indeed, intense energy consumption is particularly observed in the field of pesticide production (Öztürk et al., 2010). Besides, price volatility in the categories of electricity, coal, petroleum products and natural gas has an extremely deep negative impact on the economic performance of Turkey, as an energy importer. As a matter of fact, oil and natural gas reserves are limited in Turkey leading to foreign-source dependence in the field of energy. Thus, it is observed that Turkey has been the country with the fastest increase in energy demand among the Organization for Economic Cooperation and Development (OECD) countries in the past 20 years. Within this framework, Turkey ranks second in the world after China in the increase in electricity and natural gas demands. Existing energy sources cannot unfortunately meet Turkey's increasing energy needs and thus, the country meets nearly 74% of its energy needs via imported sources (MFA, 2020). Considering that Turkey is a country dependent on imports of oil in its consumption, there is an urging need to address the effects of changing energy prices on the performance of several sectors and industries (Algan et al., 2017). On the other hand, the increase in energy prices in recent years is one of the most crucial cost items threatening agricultural production (Yıldırım, 2020). Hence, the fluctuations in these costs reflect on product prices and cause difficulties in production plans (Fasanya and Akinbowale, 2019: 186; Tadasse et al., 2016: 63; Algieri, 2016: 210).

For the reasons mentioned above, this study aims to investigate the effects of changes in energy prices on other price indices for Turkey. In this regard, we analyzed the volatility spillover between the Energy Price Index (EPI), the Fruit Price Index (FPI) and the Vegetable Price Index (VPI) using monthly data sets from January 2007 to December 2019 by two different methods: The Kanas (1998) Approach for volatility spillover effect and the Diebold-Yilmaz (2009, 2012) spillover index, analyzed respectively. As for the content of the study, the second section consists of an extensive literature review. This part is followed by a detailed description of the methodology. The fourth section summarizes the data set used in the study. In the fifth part, empirical results of the analyses are given in two subsections. Finally, the last section covers comments, discussions and policy recommendations based on the study results.

2. BACKGROUND AND LITERATURE REVIEW

Energy consumption is one of the main determinants of the socio-economic development of countries. More specifically, oil and its derivatives are considered one of the main production factors in an economy. They are used in the energy supply of various sectors including agriculture, transportation, industry and households, in addition to their extensive use as raw materials in the production of other energy products like electricity and petrochemistry. Thus, oil and its derivatives have a vast impact on other commodities (Sarwar et al., 2020; Taghizadeh-Hasery et al., 2019).

At recent times, agricultural products and energy markets have been growingly intertwined (Koirala et al, 2015: 431). From this perspective, energy consumption in agriculture can be evaluated in two categories: (1) Direct energy use: Energy inputs such as electricity, fuel, oil, coal, petroleum products, natural gas, biomass can be used in agricultural activities. (2) Indirect energy use: The amount of energy consumed in human and animal labor, agricultural tools or machineries, fertilizers, pesticides, irrigation or seed production. In this regard, energy prices affect the costs of inputs necessary for faming including inorganic fertilizers and fuel for agricultural machinery. Moreover, it is commonly observed that energy prices increase transportation costs and therefore, affect food transportation and distribution costs. The primary energy products directly consumed in agricultural production include fuels such as coal, petroleum products, natural gas and biomass. Also, electricity is widely used as power carrier in farming and particularly irrigation operations. It is a source commonly benefited in the agricultural industry (Akder et al., 2020: 9; Radmehr and Henneberry, 2020: 2; Sarwar, 2020: 1; Öztürk et al., 2010: 2; Mawejje, 2016: 2; Nwoko et al., 2016: 2; Gilbert and Mugera 2014: 201).

Yet, the history is marked by many crises related to food supply and demand. In this vein, it can be observed that the recent price volatility in food has had a destructive effect. The increased volatility in prices in this field can be associated with the transition from the labor-intensive to a more capital-intensive agricultural production in recent years as well as the regional and national differences in terms of farming. The use of energy is naturally essential in agricultural production. Today's technology enables growing even tropical products in cold regions thanks to the heat provided by energy sources. Hence, technology allows countries that are rich in energy sources to produce fruits and vegetables despite their cold climate. On the other hand, especially developing countries that import energy seem to have hardship in their agricultural operations due to the high energy prices increasing the costs of inputs. This leads to an intricate relationship between energy and prices of agricultural products. From this perspective, various studies analyze the effects of oil and other energy prices on agricultural product prices. For example, Hau et al. (2020) and Koirala et al. (2015) discuss the relations between oil and agricultural prices in terms of futures. Sarwar et al. (2020), Hesary et al. (2019), Alghalith (2010) and Zhang et al. (2010) examine the effects of the changing crude oil prices on agricultural products. On the other hand, Radmehr and Henneberry (2020), Balcılar and Bekun (2019) and Huchet-Bourdon (2011) scrutinize the effects of energy and exchange rates on agricultural products' prices. Mawejje (2016) further dwells upon the importance of energy and climate shocks in the case of Uganda and the food prices in this country.

In their study, Volpe et al (2013) also investigate how fuel prices in the USA affect the prices of wholesale products and their transportation costs. Since agricultural products themselves have been used for energy production at recent times, Baffes (2011) examines the relations between oil, biofuel and prices of agricultural products.

The literature in this field contains many other similar studies analyzing the volatility in the prices of energy and agricultural product using the econometric techniques that are also benefited in this study. Table 1 summarizes these studies in detail:

3. METHODOLOGY

3.1 The Kanas approach for the volatility spillover effect

Engle (1982) developed a new method to measure the volatility in a time series by modeling conditional variance. He revealed that the conditional variance is a function of the lagged values of the error term squares and modeled the change of the error term squares with respect to time using the ARCH process. Thanks to the introduction of the GARCH model in the literature, many other conditional variance models started to be widely used (Bollerslev, 1986). Although the standard GARCH model captures various features of financial series such as excess kurtosis and volatility clustering, they are not successful in capturing the leverage effect of financial time series. Standard GARCH models tend to ignore the negative correlation between current return and future return volatility. Further, the constraints on parameters to ensure the stationarity of the GARCH process can make parameter estimation difficult. Lastly, another difficulty is to interpret whether shocks persist on the conditional variance in the standard GARCH model. An alternative model developed by Nelson (1991) is the EGARCH model that removes these defects in the standard GARCH modeling of the financial time series, prevents the model from giving symmetrical responses in cases of positive and nega-

Table 1. Summary Literature Review.

Authors	Goal	Methodology	Industry	Region	Results
Hau et al. (2020)	To explore the volatility between global crude oil and China's agricultural futures.	- Time-dependent parameter stochastic volatility - Conditional volatility	Agriculture, Energy, Futures and Options Market	China	There is a heterogeneous dependence between the volatility of agricultural futures and the volatility of crude oil. While crude oil volatility does not affect agricultural volatility in the normal mode of the crude oil market, oil volatility at high or low amounts has been found to have an extremely significant effect.
Tiwari et al. (2020)	To analyze the progression-regression relationship between the price indices of energy fuels and food, industrial inputs, agricultural raw materials, metals, and beverages (lead-lag relation) in the time-frequency domain.	- Wavelet coherence and phase differences, - Diebold & Yilmaz (2012) and Barunik & Krehlik (2017) volatility spillover indices	Food &Energy	Global	The results revealed significant relationships between fuel and food prices, fuel and industry prices, and fuel and metal prices. The results also showed that there are phase relationships between these paired prices. The volatility spillover results showed that the agricultural industry was the most affected industry by shocks from other markets.
Balcılar and Bekun (2019)	To examine the structure of the interconnectedness between the returns of oil and foreign exchange prices with selected agricultural commodity prices.	- Diebold & Yilmaz (2012) volatility spillover index	Food, Energy & Finance	Nigeria	Analyses demonstrate that banana, cocoa, peanut, corn, soybean, and wheat are net transmitters of spillover. Moreover, there is weak spillover between the variables of rice and sorghum, in addition to price inflation, nominal effective exchange rate, and oil prices.
Fasanya and Akinbowale (2019)	To analyze the returns and volatility of crude oil and food prices.	- Diebold & Yilmaz (2012) volatility spillover index	Food &Energy	Nigeria	Evidence of the interconnectedness between crude oil and food prices was found based on spillover indices.
Adrangi et al. (2017)	To examine the daily volatility spillovers between crude oil prices and a selected group of basic agricultural products.	- Johansen-Juselius cointegration test, - Dynamic conditional correlations, - Spectral and cross spectral analyses, - The Bivariate EGARCH model and Granger causality tests.	Food &Energy	USA	The Johansen-Juselius cointegration test reveals that the long-run equilibrium relationships between crude oil prices and the commodities in question have disappeared. The dynamic conditional correlations show that the relationship between agricultural products and crude oil changes over time. The spectral and cross-spectral analyses confirm that volatility in crude oil prices is associated with volatility in agricultural products given in the sample. The Bivariate EGARCH model and Granger causality tests confirm this relationship. Analyses also confirm that the fluctuations in crude oil prices are related with the volatility of agricultural products given in the sample.
Judith et al. (2017)	To investigate the cause of increased food price volatility.	- Descriptive statistics - Correlation analysis	Food	USA	The results show that the main source of food price volatility is mainly the oil price shock.

Authors	Goal	Methodology	Industry	Region	Results
Cabrera and Schulz (2016)	To investigate the risk of price and volatility arising from the correlation between energy and agricultural commodity prices and to examine their changing dynamics over time.	- The asymmetric dynamic conditional correlation GARCH model, - The multivariate multiplicative volatility model	Food &Energy	Germany	It is revealed that prices move together in the long run and both rapeseed and biodiesel prices react to deviations from the equilibrium. In the short run, biodiesel prices do not affect rapeseed and crude oil price levels, but rather react to price changes in the other two markets. Moreover, the volatility of biodiesel is related to the volatility of crude oil and rapeseed, while the correlation between the fluctuation of rapeseed and crude oil has been increasing in recent years.
Lucotte (2016)	To analyze the dynamics of co-movements in crude oil and food prices.	- Correlations of VAR estimation errors (variance decompositions)	Food &Energy	Global	Empirical results manifest that after the spikes in the commodity prices, strong positive co-movements were observed between the crude oil price and food price indices, while significant correlation coefficients were not observed in the period before the spikes in the commodity prices.
Nwoko et al. (2016)	To examine the long-run and short-run relationships between oil price and food price volatility and the causality relationships between them.	- Johansen and Juselius co-integration test, - The vector error correction model, - Granger causality test	Food &Energy	Nigeria	Analyses reveal that there is a long-run relationship between oil price and local food price volatility and that causality is one-way from oil price volatility to food price volatility.
Gilbert and Mugera (2014)	To investigate the role of biofuels in explaining the increased volatility in food products.	- The multivariate GARCH model - The Dynamic Conditional Correlation model	Food &Energy	USA	Analyzing a sample between 2000 and 2011, the study found increases in the correlation and joint movements between grain and crude oil prices after 2006 and especially in 2008 when crude oil prices were high. Researchers concluded that the increased volatility in grains during the 2008-2009 increase was largely due to shocks transferred from crude oil to grains, particularly corn, wheat, and soybean prices.
Tadesse et al. (2014)	To search for empirical evidence on the quantitative significance of supply, demand, and market shocks for price changes in international food commodity markets. To explore the main drivers of food price spikes and volatility for wheat, corn, and soybeans and show how these factors triggered the crisis in extreme price swings.	- The price spike model by differentiated regression - The volatility model by panel regression - The prediction of extreme volatility by quantile regression	Food	Global	They concluded that oil prices are a statistically significant factor in explaining the increases and volatility in food prices.

Authors	Goal		Methodology	Industry	Region	Results
Gardebroek and Hernandez (2013)	To examine the volatility spillovers in oil, ethanol, and corn prices.	-	Multivariate GARCH models	Food &Energy	USA	In the study, significant volatility spillover is observed only from corn and not vice versa. Also, researchers do not detect cross-volatility effects from oil to corn markets. The results do not provide any evidence that volatility in energy markets has a significant effect on price volatility in the US corn market.
Nazlıoğlu et al. (2013)	To examine the volatility transmission between oil and selected agricultural commodity prices which are wheat, corn, soybean, and sugar.	-	The variance causality test	Food &Energy	Global	Data are analyzed in two periods as the pre-crisis period (January 1986 - December 2005) and the post-crisis period (January 2006-March 2011) to determine the impact of the food price crisis. The results showed that although there was no risk of spillover between oil and agricultural commodity markets in the pre-crisis period, there was actual oil market volatility spillover to agricultural markets - excluding sugar - in the post-crisis period.
Serra (2011)	To investigate price relations between crude oil, ethanol and sugar	-	a semiparametric GARCH model	Food &Energy	Brazil	The results reveal that in the long run, ethanol prices increase along with the increase in both crude oil and sugar prices.

tive shocks in volatility, and thus is more convenient for modeling conditional variance. In this model, the logarithmic conditional variance depends on both the size and the sign of the residuals (Nelson, 1991; Bollerslev et al., 1994). EGARCH (p, q) is:

$$\ln(\sigma^2_t)=\omega+\Sigma^p_{i=1}[\alpha_i z_{t-i}+(\gamma_i|z_{t-i}|-E[|z_{t-i}|])]+\Sigma^q_{i=1}\beta_i\ln(\sigma^2_{t-i}) \quad (1)$$

where $z_t=\varepsilon_t/\sigma_t$ and the coefficient α_i captures the sign effect and γ_i captures the size effect. So, the EGARCH (1, 1) model can be expressed as follows

$$\ln(\sigma^2_t)=\omega+\alpha_1 z_{t-i}+(\gamma_i|z_{t-i}|-E[|z_{t-i}|])]+\beta_1\ln(\sigma^2_{t-i}) \quad (2)$$

where γ_i is also referred to as the asymmetry coefficient and β_1 indicates volatility persistence. It can be said that there is a leverage effect on the conditional variance when has a value other than 0.

In this study, the Kanas (1998) approach is taken as basis in determining the volatility spillover. Before volatility modeling, it is first necessary to determine the most convenient Autoregressive Moving Average (ARMA) models for the conditional mean process. By testing the ARCH effect on the residuals obtained from these models, the most convenient EGARCH (1, 1) model is determined according to the information criteria and likelihood value. The assumed distributions for EGARCH models are Normal Distribution (norm), Skewed-Normal Distribution (snorm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Generalized Error Distribution (ged), Skewed-Generalized Error Distribution (sged), Normal Inverse Gaussian Distribution (nig) and Johnson's SU Distribution (jsu). EGARCH (1,1) models with different distributions are compared according to Akaike Information Criteria (AIC), Bayes Information Criteria (BIC), Shibata Information Criteria (SIC), Hannan-Quinn Information Criteria (HQIC) and likelihood values.

Kanas (1998) defines the residual squares of other variables obtained from the conditional variance model as exogenous variables and made parameter estimates in order to determine the volatility spillover. Accordingly, the EGARCH (1,1) model to be estimated is as follows:

$$\ln(\sigma^2_t)=\omega+\alpha_1 z_{t-i}+(\gamma_i|z_{t-i}|-E[|z_{t-i}|])]+\beta_1\ln(\sigma^2_{t-i})+\tau_1\ln(u^2_{t-i}) \quad (3)$$

In the above equation, u_t is the residuals obtained from the conditional variance model, and τ_1 is the coefficient showing the volatility spillover. If the coefficient τ_1 is statistically significant, it is concluded that there is a volatility spillover.

3.2 The Diebold-Yilmaz approach for the volatility spillover effect

Diebold and Yilmaz (2009) describe the return and volatility spillover on the basis of the Vector Autoregressive (VAR) model. Here, the total spillover index is measured based on the Cholesky decomposition. Nevertheless, Diebold and Yilmaz (2012) developed a methodology in a later study to evaluate directional spillover in a generalized VAR framework. This VAR framework approach offers variance decomposition that is invariant to the order of variables after that of Koop et al. (1996) and Pesaran and Shin (1998). In the N-component standard *VAR* model, each entity *xi* with = 1,…, *N* is expressed as follows:

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{4}$$

where y_t is $Nx1$ matrix of dependent variables and φ_i are NxN matrix of coefficients. ε_t is the vector of independently and identically distributed innovations (iid) and follows $\varepsilon_t \sim N(0,\Sigma)$ where Σ is variance-covariance matrix. The moving average representation of the *VAR* model is as follows:

$$y_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i} \tag{5}$$

where A_i are NxN matrix of moving average coefficients and $A_i=\varphi 1A_{i-1}+\varphi_2 A_{i-2}+\ldots+\varphi_p A_{i-p}$. Then, given the VAR framework, H-step-forecast error-variance decompositions are defined as follows:

$$\theta_{ij}^{g} = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} \left(\Delta_i^T A_h \Sigma \Delta_j\right)^2}{\sum_{h=0}^{H-1} (\Delta_i^T A_h \Sigma A_h^T \Delta_i)} \tag{6}$$

where σ_{ij} represents the standard deviation of the error term, Σ is variance-covariance matrix and Δ_i is the selection vector of which i^{th} element is equal to 1 and the other elements are 0. If each element of the decomposition matrix is divided by row sums, each forecasting error decomposition variance will be normalized, thus using the available information in the decomposition matrix to compute the spillover effects as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)=N$.

In the light of the above definitions and equations from 4.4 to 47, Diebold and Yilmaz (2012) defined total, directional and net spillovers as described below:

The total volatility spillovers index based on h-step-ahead forecasts with the following equation:

$$TS^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} x100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} x100 \tag{8}$$

Directional volatility spillovers to i market from other *j* markets:

$$DS_{j\to i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} x100 \tag{9}$$

Directional volatility spillovers from market *i* to other *j* markets:

$$DS_{i\to j}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} x100 \tag{10}$$

The net spillover index is obtained using Equations 4.9 and 4.10 as follows

$$NS_{i}^{g}(H) = DS_{i\to j}^{g}(H) - DS_{j\to i}^{g}(H) \tag{11}$$

4. DATA ANALYSIS

As signified in the introduction, this study aimed to analyze the relationship between the fruit and vegetable price volatility and the energy price volatility in Turkey. Both energy and product prices consist of the data sets obtained from Eurostat within the scope of the Harmonized Index of Consumer Prices (HICP). The scope of energy index includes "electricity, gas and other fuels". The energy price index is a variable with broader content than the crude oil price, which is widely cited in the literature. It is considered noteworthy to refer to this energy price index in this analysis.

The monthly data set obtained from Eurostat consists of the Energy Price Index (EPI), the Fruit Price Index (FPI) and the Vegetable Price Index (VPI) between January 2007 and December 2020. Appendix-A, Table-A1 and Table-A2 demonstrate the descriptive statistics and Augmented Dickey-Fuller Unit Root Test results for the data set of these indexes and their loga-

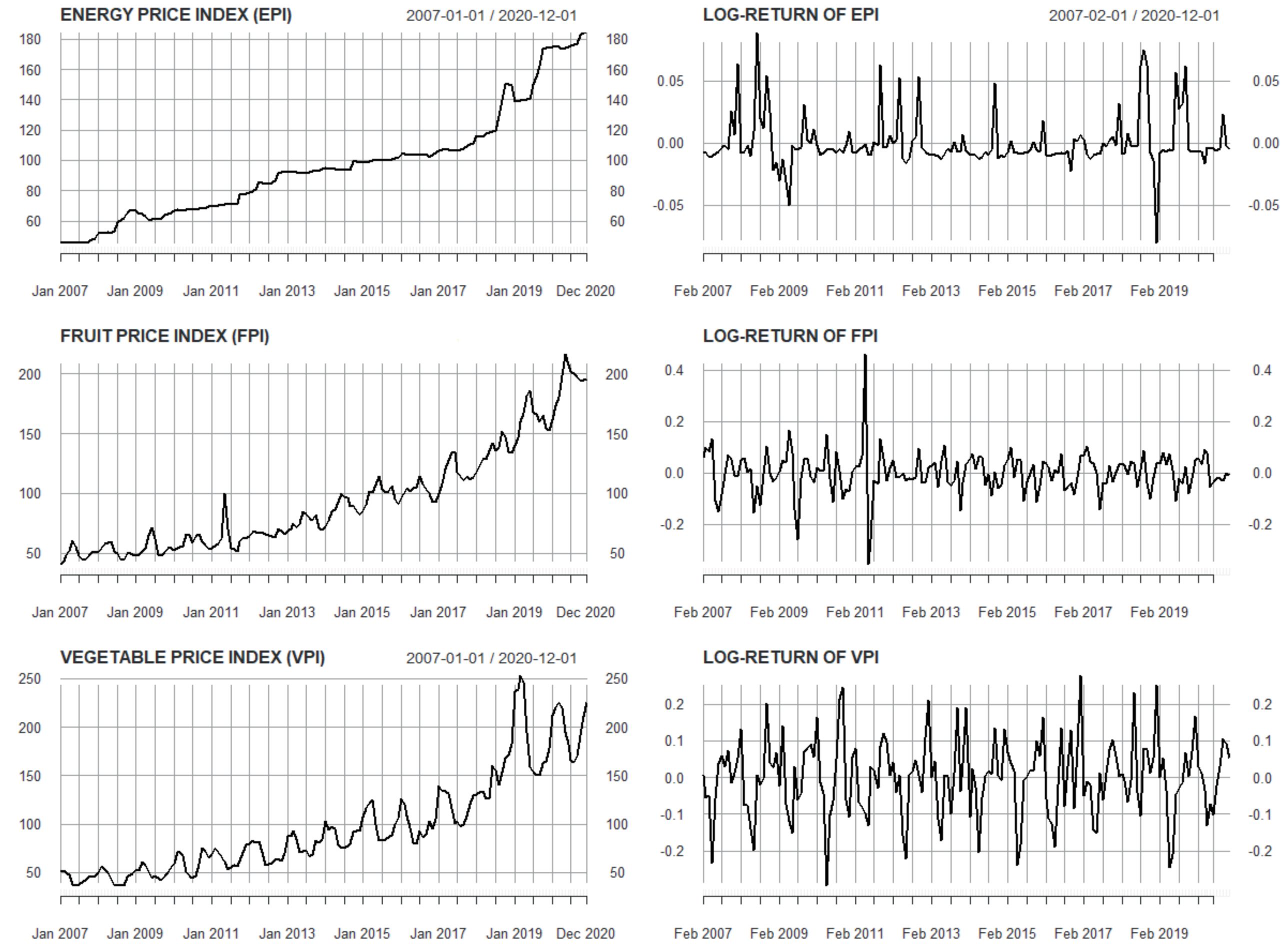

Figure 1. Time-series Plot of Indexes and Log-returns.

rithmic returns. Figure 1 shows the time-series plot of the variables.

5. EMPIRICAL RESULTS

5.1 Empirical results for Kanas Approach

The convenient conditional mean models for EPI, FPI, and VPI were found to be AR (1), ARMA (2,2), and MA (1), respectively. The output of conditional mean models and ARCH test results are given in Table A3 in Appendix-A. The evaluation of the volatility models is given in Table 2.

The results[1] in Table 2 manifest that the most adequate models are as follows: Sged-EGARCH (1,1) for EPI; std-EGARCH (1,1) for FPI and norm-EGARCH (1,1) models for VPI. Table A2 points out to the parameter estimation results and diagnostic test results of the models.

It is evident in all three models that all parameters are statistically significant. According to the diagnostic test results, the results of Ljung-Box (LB) and Langrange-Multiplier (LM) tests indicate that there are no autocorrelation problems in the residuals and heteroscedasticity problem in the residual squares. The Nyblom Stability Test (NST) results show that there is no structural break according to the NST critical value of 1.49 at 10% confidence level. As in NST, common statistical values calculated for Sign Bias Test (SBT) are given and according to these test statistics, there is no functional error in the conditional volatility model. Looking at the results of the Pearson Goodness of Fit (GoF) test, it can be understood that the empirical distribution of standard residuals and the theoretical distribution are aligned.

[1] EGARCH-type volatility models were estimated using "rugarch" R package developed by Ghalanos (2020a, 2020b).

Table 2. EGARCH(1,1) Model Evaluation depending on Information Criteria and Likelihood Values.

dist	EPI					FPI					VPI				
	AIC	BIC	SIC	HQIC	L	AIC	BIC	SIC	HQIC	L	AIC	BIC	SIC	HQIC	L
norm	-5.18	-5.10	-5.18	-5.15	436.5	-2.54	-2.44	-2.54	-2.50	216.9	**-1.91**	**-1.81**	**-1.91**	**-1.87**	**164.2**
snorm	-5.33	-5.23	-5.33	-5.29	449.8	-2.56	-2.45	-2.56	-2.52	219.9	-1.90	-1.78	-1.90	-1.85	164.3
std	-5.63	-5.53	-5.63	-5.59	474.7	**-2.71**	**-2.59**	**-2.71**	**-2.66**	**232.0**	-1.87	-1.76	-1.87	-1.83	162.3
sstd	-5.63	-5.53	-5.63	-5.59	474.7	-2.71	-2.59	-2.71	-2.66	232.0	-1.87	-1.76	-1.87	-1.83	162.3
ged	-5.54	-5.44	-5.54	-5.50	467.3	-2.62	-2.51	-2.62	-2.57	224.7	-1.90	-1.79	-1.90	-1.86	164.9
sged	**-6.17**	**-6.06**	**-6.17**	**-6.13**	**521.2**	-2.65	-2.52	-2.66	-2.60	228.6	-1.88	-1.75	-1.89	-1.83	164.2
nig	-6.14	-6.03	-6.15	-6.10	519.0	-2.68	-2.55	-2.68	-2.63	230.8	-1.88	-1.75	-1.88	-1.83	163.9
jsu	-6.16	-6.04	-6.16	-6.11	520.1	-2.69	-2.56	-2.70	-2.64	232.0	-1.87	-1.74	-1.88	-1.82	163.5

Normal Distribution (norm), Skewed-Normal Distribution (snorm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Generalized Error Distribution (ged), Skewed-Generalized Error Distribution (sged), Normal Inverse Gaussian Distribution (nig) and Johnson's SU Distribution (jsu), Akaike Information Criteria (AIC), Bayes Information Criteria (BIC), Shibata Information Criteria (SIC), Hannan-Quinn Information Criteria (HQIC), Llikelihood (L).

Table 3. The Parameter Estimation of EGARCH(1,1) Models for Price Indices.

Parameters	sged-EGARCH(1,1) for EPI				std-EGARCH(1,1) for FPI				norm-EGARCH(1,1) for VPI			
	est	Std.Err	t-stat	sig	est	Std.Err	t-stat	sig	est	Std.Err	t-stat	sig
omega	-1.49	0.01	-194.71	0.00	-2.47	1.14	-2.16	0.03	-0.33	0.00	-3793.40	0.00
alpha1	0.35	0.03	11.90	0.00	0.12	0.11	1.05	0.29	0.26	0.00	2136.50	0.00
beta1	0.81	0.00	1176.69	0.00	0.56	0.21	2.71	0.01	0.93	0.00	4454.40	0.00
gamma1	-0.08	0.00	-16.82	0.00	0.39	0.15	2.63	0.01	-0.30	0.00	-2522.70	0.00
shape	0.47	0.01	76.08	0.00	5.69	1.84	3.08	0.00				
skew	1.44	0.01	163.05	0.00								
		stat	sig			stat	sig			stat	sig	
LB on SR		1.48	0.75			3.71	0.29			0.25	0.82	
LB on SSR		1.19	0.82			0.13	1.00			3.59	0.31	
ARCH LM		1.15	0.69			0.10	0.99			2.04	0.46	
SBT Joint		0.12	0.99			3.26	0.35			0.60	0.90	
Perason GoF		47.67	0.53			42.88	0.72			35.10	0.93	
NST Joint		2.41				1.57				1.48		
Persistence		0.81				0.56				0.94		
Half-life		3.36				1.19				9.94		

LB: Ljung-Box SR: Standardized Residuals SSR: Standardized Squared Residuals LM: Langrange Multiplier SBT: Sign Bias Test NST: Nyblom Stability Test GoF: Goodness-of-Fit. "omega" is the constant term. "alpha1"is the the ARCH coefficient that is a measure of sign effect. "beta1" is the the ARCH coefficient that is a measure of volatility persistence "gamma1" is the asymmetry coefficient that is a measure of leverage effect. "Normal Distribution (norm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Skewed-Generalized Error Distribution (sged).

Negative values for EPI and VPI can be found by analyzing the values of "gamma1" parameters that show the leverage effect. In this case, it can be concluded that the effect of bad news on EPI and VPI volatility is higher the effect of good news and increases the volatility persistence. The persistent values indicate that the volatility persistence is high for EPI and VPI variables. It is also found that the half-life of persistence in VPI was 9.94 days. Thus, the effect of good news on the volatility is higher for FPI, while the volatility persistence and half-life are lower. This is an indication that good news has a less impact than bad news in the leverage effect. The time-series graph of the volatilities obtained from the models is as described in Figure 2.

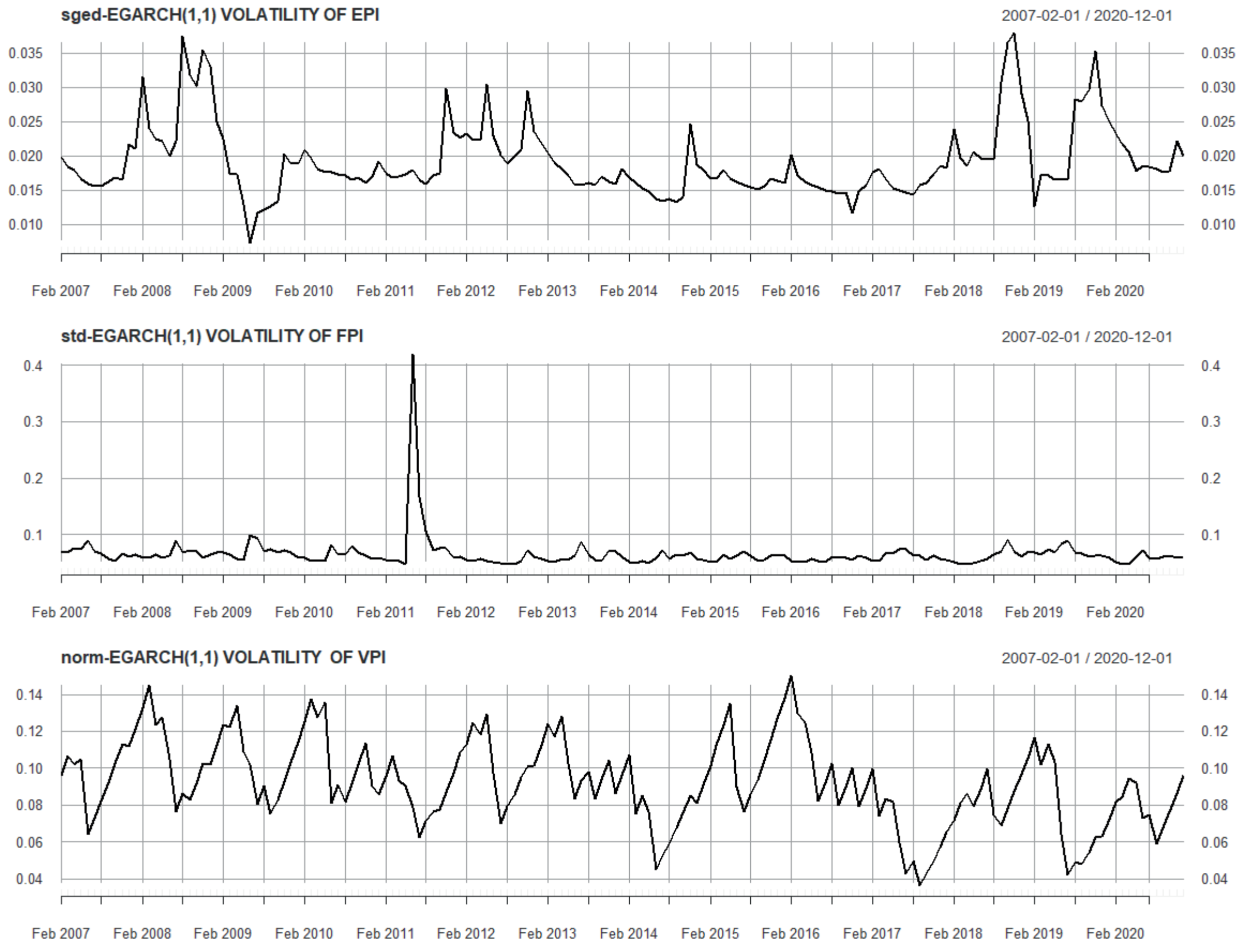

Figure 2. Time-Series Plot of Volatilities Obtained from EGARCH Processes.

It can be said that there was a fluctuation in FPI volatility in May 2011 similar to a big shock effect. In this regard, the Iterative Cumulative Sum of Squares (ICSS) introduced by Inclan and Tiao (1994) was applied to all three indexes to locate any structural break in the variance. However, the results showed no break in the variance. To test the volatility spillover of EPI on other variables in this study, the residual squares obtained from the sged-EGARCH (1, 1) model (given in Table 3) were added as an exogenous variable to the volatility models. This step was followed by the parameter estimation. The results are given in Table 4.

The diagnostic test results in Table 4 indicate that the models support the hypotheses. According to the results of FPI parameter estimation, it is understood that the "tau1" coefficient (which shows the volatility spillover from EPI to FBI) is not statistically significant, and therefore there is no volatility spillover from EPI to FBI. On the other hand, according to the VPI parameter estimations, the "tau1" coefficient is found to be statistically significant leading to the understanding that there is a volatility spillover from EPI to VPI. Hence, it can be concluded that the volatility in the EPI negatively affects the VPI volatility.

4.2 Empirical Results for the Diebold-Yilmaz Approach

Table 3 demonstrates the most suitable volatility models determined for EPI, FPI and VPI indexes. Derived from volatility data obtained from these models, the lag value of the VAR model was found to be 1. In addition to this calculation, the VAR (1) model parameter was estimated. The results of the model estimated by the lag value of selection criteria are respectively presented in Appendix-B, Table B1 and Table B2. The Die-

Table 4. The Parameter Estimation of EGARCH(1,1) Models for Spillover from EPI to FPI and VPI with Diagnostics Tests.

Parameters	std-EGARCH(1,1) for FPI				norm-EGARCH(1,1) for VPI			
	est	Std.Err	t-stat	sig	est	Std.Err	t-stat	sig
omega	-2.52	1.08	-2.33	0.02	-0.28	0.00	-7553.23	0.00
alpha1	0.13	0.11	1.11	0.27	0.28	0.00	5849.33	0.00
beta1	0.56	0.19	2.90	0.00	0.94	0.00	7751.43	0.00
gamma1	0.38	0.15	2.57	0.01	-0.28	0.00	-10783.22	0.00
shape	5.74	1.85	3.10	0.00				
tau1 (EPI spillover)	14.36	115.70	0.73	0.47	-7.75	0.01	-686.85	0.00
		stat	sig			stat	sig	
LB on SR		9.76	0.01			3.54	0.32	
LB on SSR		3.21	0.37			0.12	1.00	
ARCH LM		1.87	0.50			0.08	0.99	
SBT Joint		0.40	0.94			3.17	0.37	
Perason GoF		48.87	0.48			36.89	0.90	
NST Joint		1.60				1.53		
Persistence		0.56				0.94		
Halflife		1.19				11.68		

LB: Ljung-Box SR: Standardized Residuals SSR: Standardized Squared Residuals LM: Langrange Multiplier SBT: Sign Bias Test NST: Nyblom Stability Test GoF: Goodness-of-Fit. "omega" is the constant term. "alpha1"is the the ARCH coefficient that is a measure of sign effect. "beta1" is the the GARCH coefficient that is a measure of volatility persistence "gamma1" is the asymmetry coefficient that is a measure of leverage effect. "tau1" is the coefficient showing the volatility spillover Normal Distribution (norm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Skewed-Generalized Error Distribution (sged).

bold-Yilmaz approach results[2] obtained on the basis of the VAR model can be seen in Table 5.

Before moving on to the results, it is worth reiterating that the spillover index shows how much of the total variance that occurs in the variables themselves is caused by other variables. In other words, the Diebold-Yilmaz spillover index demonstrates the contribution of the volatility in price indices to the forecasting error variance. Thus, the results of the total volatility spillovers index are based on a 10-step-ahead approach.

As these results suggest, it is observed that the volatility spillover from EPI index to other indexes is higher than the others. Furthermore, the VPI is the index that is exposed to the highest volatility transfers. The total spillover from EPI to the other indexes is 14.38% and 13.52% of this value belongs to the VPI and the rest belongs to the FPI index. This case points out to shocks in energy prices exhibiting a higher possibility to affect the pattern of other prices in the investigated area. Here, the EPI can be defined as a volatility transmitter. It can be deduced that the risk that the FPI index is exposed to from the outside is low. Indeed, only 2.68% of its current volatility results

Table 5. Diebold-Yilmaz Generalized Directional Spillover Output.

	EPI	FPI	VPI	Contribution from others
EPI	91.80	0.27	7.92	8.20
FPI	0.86	97.32	1.82	2.68
VPI	13.52	4.45	82.03	17.97
Contribution to others (spillover)	14.38	4.72	9.75	9.62
Contribution to others including own	106.18	102.04	91.78	300.00
Net Spillover	6.18	2.04	-8.22	
Total Spillover Index	9.62%			

from other indexes. On the other hand, it is seen in the VPI index that the externally exposed volatility spillover is 17.97%, and 75.23% of it (13.52%) is due to the EPI. These results also support the outputs obtained from the Kanas (1998) approach. The fact that the total spillover index value is 9.62% points out to a low connectedness between these indexes. Nevertheless, it can be seen that the risk in energy prices is transferred to vegetable prices. Due to the high energy prices in Turkey, for instance, people can only heat their greenhouses only to protect them from frost rather than proper

[2] Diebold-Yılmaz analysis was performed using "Spillover" R package developed by Urbina (2020).

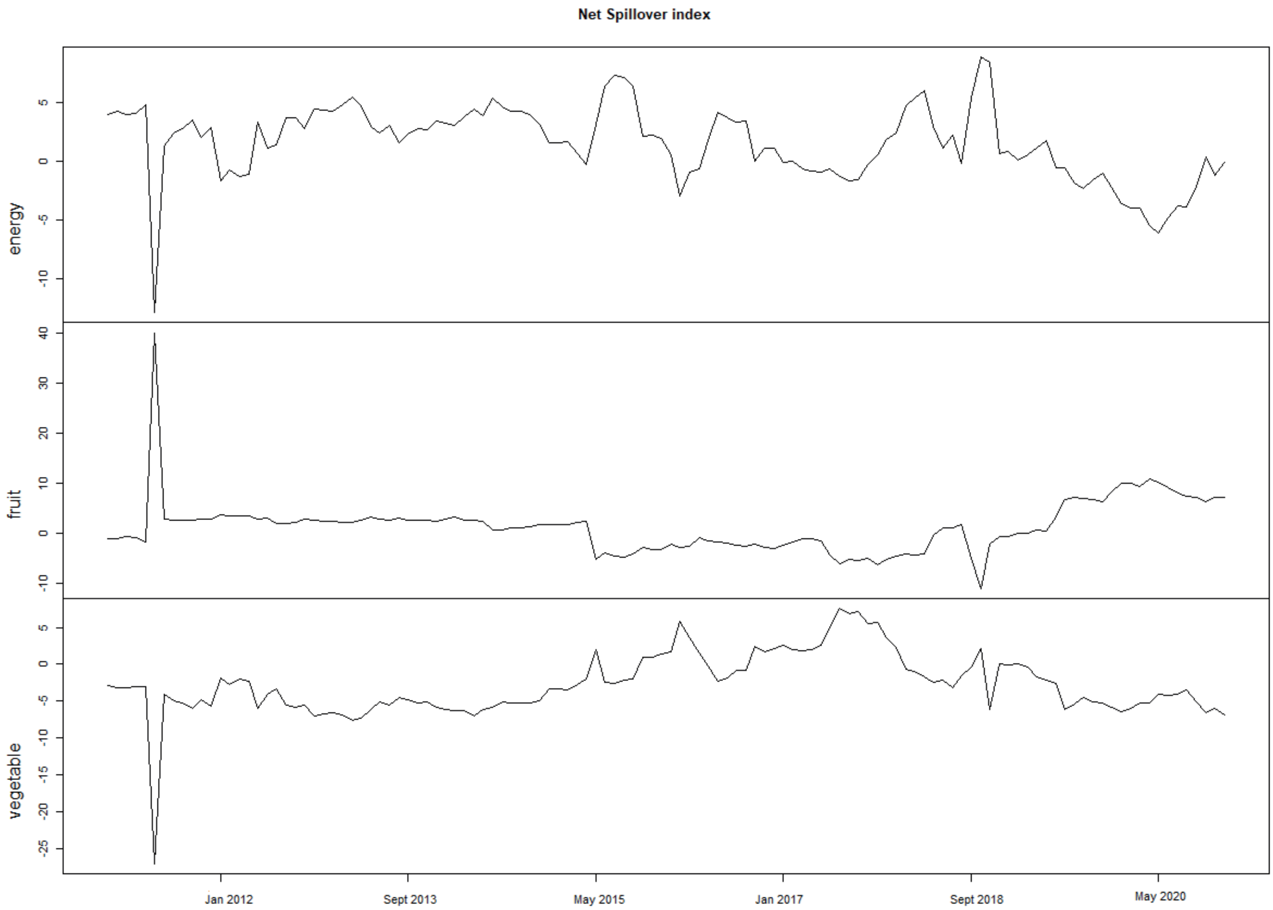

Figure 3. The Top-Down Rolling Net Spillovers Indexes for EPI, FPI and VPI.

heating. Despite this widespread use of limited energy, volatility in energy prices affects greenhouse costs. 31 million tons of vegetables were produced in Turkey in 2019 as the world's 4th largest producer of fresh vegetables. 23.2 million tons of these crops were grown in agricultural or open areas, and 7.8 million tons were produced in greenhouses. As a matter of fact, around 0.6 million tons of fruits are produced in greenhouses (MAF, 2021). According to the results of the analysis, this explains the reason why the vegetable price index is subject to volatility from the spillover of the fluctuating energy prices.

Within this framework, the average spillover effects over the full sampling period are obtained by generalized spillover analysis. Diebold and Yilmaz (2009, 2012) stated that full sample spillover measurements cannot clearly reflect the important sustained and cyclical movement in spillovers. Thus, they developed a rolling window framework that allows time-varying spillover indices to overcome their shortcomings in the spillover index, using a 48-month subsample. In this line, the following graphs show the estimation of the dynamic net and total spillover indexes. These rolling windows were obtained using the 10-step-ahead forecasting spillovers.

The date that stands out at first glance in the rolling net spillover index is May 2011, when consumer prices increased by 2.42% and annual inflation rose to 7.17 %. Coupled with the base effect, the high increases in fresh fruit prices due to seasonal transitions marked the rationale behind this rise. In this period, fresh fruit prices increased by 76.12% on a monthly basis, well above the average of the previous period (TCBM, 2011). Therefore, the FPI became the volatility transmitter in May 2011 and created a net volatility spillover of 40.05% on the forecasting error variances of other indices. Thus, the total spillover index was estimated as 44.33%.

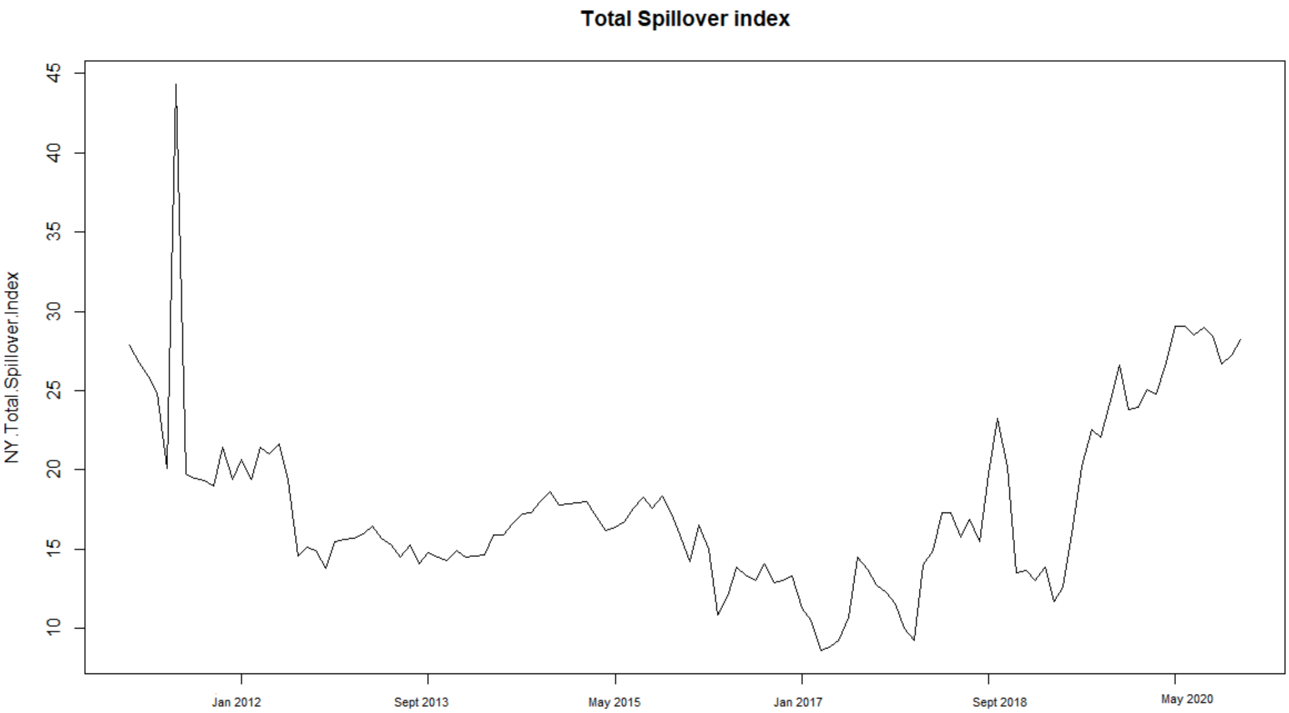

Figure 4. The Rolling Total Spillovers Index.

6. CONCLUSION

Input costs have a significant share in setting the prices of agricultural products and ensuring sustainable production. Increases especially in energy prices may have an effect on many items from production to delivery of products to final consumers. These items include but are not limited to fertilizers, chemicals, irrigation, production, storage and transportation costs. In this context, stable pricing in the field of energy is essential for the price stability of agricultural products. However, energy prices are not reflected on every agricultural product at the same level. Thus, this study analyzed the prices of fruits and vegetables as the category containing the highest price fluctuations compared to other agricultural products.

Two different analysis methods, Kanas (1998) and Diebold-Yilmaz (2012), were used in the study and it is concluded that the results obtained from both methods support each other. After the parameter estimation of the relevant ARMA models for logarithmic changes of energy, fruit and vegetable price indices, the ARCH effect was determined in the residuals of conditional mean models. To identify the residuals of conditional mean models, volatility modelling was performed through the EGARCH conditional variance model introduced to the literature by Nelson (1991). Parameter estimations were made for the EGARCH models by assuming eight different conditional probability distributions. In this regard, sged-EGARCH, std-EGARCH and norm-EGARCH were found to be the most compatible models for EPI, FPI and VPI, respectively. Considering the outputs of these models indicating the leverage effect, it can be seen that the volatility of energy and vegetable price indexes is more affected by bad news in the market. On the other hand, the volatility of fruit price index appears to be mostly affected by good news. At the same time, it can be understood that the volatility persistence and half-life of energy and vegetable price indexes are higher according to the fruit price index. As an exogenous variable in other variables' volatility modelling, we used the residual squares obtained from the volatility model estimated for the energy price index on the basis of the Kanas (1998) approach. Consequently, it is concluded that there is a statistically significant volatility spillover from the energy to the vegetable price index, while not from the energy index to the fruit price index. This clarifies that the fluctuations in energy prices increase the risk and uncertainty in vegetable prices. In the Diebold-Yilmaz (2012) approach, the volatility spillover index results were obtained by using the VAR model for the volatilities attained from the EGARCH models, which were found to be most compatible for the indexes. Accordingly, it is understood that the volatility spillovers from the energy to the vegetable price index and the fruit price index are 13.52% and 0.86%, respectively. In addition, these calculations show that the risk that the fruit price index is exposed to from the outside is rather low, and only 2.68% of the current volatility are due to other indexes. In the case of the vegetable price index, however, it is found that 75.23% of the net volatility index is from energy prices. These results are well overlapping with the results obtained by applying the Kanas (1998) approach. The fact that the total spillover index value is 9.62% points out to a low connectedness between these indexes. As we mentioned in the findings section, the share of greenhouse cultivation in vegetable production is considerably higher than in fruit production. At the same time, vegetable production is higher than fruit production in Turkey. In this case, the amount of energy input needed in vegetable production is naturally higher than fruit production. In addition to these, Turkey's dependence on foreign energy, increases in the exchange rate, and price increases in the global energy market are other factors to be considered. Thus, it is an expected result that the spillover effect of the energy price index volatility on the vegetable price index is greater than the fruit price index.

Another production input that has an indirect effect on energy prices (which, in turn, affect vegetable and fruit prices) is the price of fertilizers used in farming. Indeed, it may well be observed that fertilizer production is decreasing due to the increasing costs of natural gas and electricity all over the world. This is the indirect factor that causes the upward volatility trend of fruit and vegetable price indices in Turkey. In other words, the volatility of energy prices is quite high in the country.

Elaborated in this study from a scientific perspective, the increasing energy prices can be associated with expensive foods due to the increasing costs of processing, transportation, and distribution of agricultural products. In addition, the effect of energy prices on food prices also varies depending on the distance traveled by road.

Largely focusing on the fluctuating energy prices and their impact on agricultural products, the results of this study provide important implications for policymakers. In this sense, policymakers should urgently do make improvements in their exchange rate policies and the oil reserve system in order to reduce the negative impact of fluctuations in oil prices on the agricultural sector in Turkey, which is an oil importer country. They should also pay as much attention as possible to the global oil markets and their impact on transportation costs. In parallel with the developments in the energy industry, there is also a need to design preventive/protective regulations to mitigate the agricultural price risks and stabilize the market. In addition, policymakers should take measures to prevent speculative behaviors in the markets in an attempt to prevent price increases of food. In addition to these measures and regulations, governments must support farmers so that they maintain their resilience, while also protecting consumers against price changes. On the other hand, it is necessary to expand the use of alternative energy sources such as biofuels, wind, and solar energy in order to reduce Turkey's dependence on foreign-sourced oil consumption.

Similar to the rest of the world, Turkey can grow fruits for a much longer time period than vegetables. According to the results obtained from our study, the time-wise conclusion is that that energy prices have a greater effect on agricultural products grown in a shorter time. Also, the study results are reasonable in the sense that vegetable production in greenhouses is often in greater amounts than fruit production, while requiring a high amount of energy consumption.

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APPENDIX-A

Table A1. Summary Statistics.

Variable	Mean	Median	Min	Max	Std. Dev.	Skewness	Ex. kurtosis	5% Perc.	95% Perc.	IQrange
energy	96.50	93.68	45.33	184.46	36.02	0.82	0.07	45.75	175.00	39.66
fruit	94.05	82.58	40.38	217.00	43.83	0.98	0.06	47.88	194.70	56.74
vegetable	96.89	82.71	36.15	253.72	51.55	1.15	0.63	41.24	216.29	68.24
logret(energy)	0.00	-0.01	-0.08	0.09	0.02	1.60	5.25	-0.02	0.06	0.01
logret(fruit)	0.00	0.00	-0.36	0.46	0.08	0.16	7.82	-0.14	0.10	0.08
logret(vegetable)	0.00	0.01	-0.30	0.28	0.10	-0.06	0.42	-0.19	0.19	0.12

Table A2. Augmented Dickey-Fuller Unit Root Test Results.

		energy	fruit	vegetable	logret(energy)	logret(fruit)	logret(vegetable)
With Constant	t-Statistic	1.39	5.28	1.02	-9.08	-6.10	-8.42
	Prob.	1.00	1.00	1.00	0.00	0.00***	0.00***
With Constant & Trend	t-Statistic	-0.49	2.15	-1.31	-9.05	-6.98	-8.46
	Prob.	0.98	1.00	0.88	0.00	0.00***	0.00***
Without Constant & Trend	t-Statistic	3.64	6.46	2.80	-9.11	-6.09	-8.43
	Prob.	1.00	1.00	1.00	0.00	0.00***	0.00***

*** indicates that log-returns of EPI, FPI and VPI has no unit root.

Table A3. ARMA Model Outputs for EPI, FPI and VPI.

Coefficients	AR(1) for EPI		ARMA(2,2) for FPI		MA(1) for VPI	
	est	sig	est	sig	est	sig
const	−3.99718e-05	0.99	−0.000537185	0.71	0.00	0.99
phi_1	0.33	0.00	1.55	0.00		
phi_2			−0.795506	0.00		
theta_1			−1.76350	0.00	0.41	0.00
theta_2			0.83	0.00		
Mean dependent var	0.00		−1.91e-17		0.00	
Mean of innovations	0.00		0.00		−0.000061	
R-squared	0.11		0.27		0.13	
Log-likelihood	417.55		206.90		154.05	
Schwarz criterion	−819.7365		−383.0893		−292.7434	
S.D. dependent var	0.02		0.08		0.10	
S.D. of innovations	0.02		0.07		0.10	
Adjusted R-squared	0.11		0.26		0.13	
Akaike criterion	−829.0905		−401.7972		−302.0974	
Hannan-Quinn	−825.2939		−394.2041		−298.3008	
ARCH LM test	56.00 (9.65e-10)***		51.3 (7.91e-09)***		15.33 (3.20e-02)**	

** and *** indicate that there is an ARCH effect on residuals.

APPENDIX-B

Table B1. VAR Lag Selection.

lags	loglik	p(LR)	AIC	BIC	HQC
1	1484.04		-18.51*	-18.28*	-18.42*
2	1485.41	0.97	-18.42	-18.01	-18.26
3	1487.78	0.86	-18.34	-17.76	-18.10
4	1494.17	0.17	-18.30	-17.55	-18.00
5	1499.96	0.24	-18.26	-17.34	-17.89
6	1508.76	0.04	-18.26	-17.16	-17.81
7	1521.01	0.00	-18.30	-17.03	-17.78
8	1526.37	0.30	-18.26	-16.81	-17.67

*The most convenient VAR Lag is selected 1.

Table B1. VAR(1) Model Output.

Dependent Var	Energy Volatility (evol)		Fruit Volatility (fvol)		VegetableVolatility (vvol)	
	est	sig	est	sig	est	sig
const	0.01	0.00	0.05	0.00	0.01	0.07
evol[-1]	0.77	0.00	−0.381	0.35	0.44	0.03
fvol[-1]	−0.0063	0.49	0.30	0.00	−0.0383	0.29
vvol[-1]	−0.0263	0.02	−0.0193	0.83	0.82	0.00
Mean dependent var	0.02		0.06		0.06	
Sum squared resid	0.00		0.13		0.13	
R-squared	0.60		0.10		0.10	
F(3, 162)	82.29		5.79		5.79	
rho	−0.021		−0.004		−0.004	
S.D. dependent var	0.01		0.03		0.03	
S.E. of regression	0.00		0.03		0.03	
Adjusted R-squared	0.60		0.08		0.08	
sig(F)	0.00		0.00		0.00	
Durbin-Watson	2.04		2.01		2.01	
All lags of evol F(1, 162)	241.41	[0.0000]	0.86818	[0.3528]	5.0403	[0.0261]**
All lags of fvol F(1, 162)	0.4696	[0.4942]	15.226	[0.0001]	1.1422	[0.2868]
All lags of vvol F(1, 162)	5.6895	[0.0182]	0.044003	[0.8341]	354.2	[0.0000]

**The test statistics of all lags of evol in vvol model indicates that evol Granger causes vvol.

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Impacts of fertilizer subsidy reform options in Iran: an assessment using a Regional Crop Programming model

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Abstract. The aim of this paper is to assess the potential impacts of different fertilizer subsidy reform options on the performance of the Iranian crops production sector. This is achieved using a Regional Crop Programming (RCP) model, based on Positive Mathematical Programming, which includes in total 14 crop activities and encompasses 31 administrative regions. The RCP model is a collection of micro-economic models, working with exogenous prices, each representing the optimal crop allocation at the regional level. The model is calibrated against observed data on crop acreage, yield responses to nitrogen application, and exogenous supply elasticities. Simulation results show that a total removal of nitrogen fertilizer subsidies would affect the competitiveness of crops with the highest nitrogen application rates and lead to a slight reduction of national agricultural income, at approximately 1%. This effect, which is more pronounced at the regional level, is driven by area reallocation rather than land productivity. The reallocation of nitrogen fertilizer subsidy to only strategic crops boost their production and income but increase disparity among regions and affects negatively welfare compared to the current universal fertilizer program. The transfer efficiency analysis shows that both target and universal simulated options are inefficient with an efficiency score below one.

Keywords: agricultural policy, fertilizer subsidy, land use effect, Regional Crop Model, Positive Mathematical Programing (PMP), Iran.
JEL codes: Q18, C13, C61.

1. INTRODUCTION

Iran is a country in Western Asia with 82 million inhabitants, standing at the world's 18th most populous country. Its territory spans 1,648,195 km2, making it the second largest country in the Middle east. In 2016, the Gross Domestic Product (GDP) was 1797 billion IRR, while the per capita GDP was about 219 million IRR, and the country is ranked as an upper-middle income economy by the World Bank (ICB, 2016). The agricultural sector plays an important role in the Iranian economy. In 2016, agriculture contributed up to 9.64 % of the GDP, provided up to 87% of the food supply, occupied around 10% of the land, and employed 19% of the labor force (IRICA, 2016; ICB, 2016; SCI, 2016). Smallholder farms with less than 25 acres (10 hectares) largely dominate the Iranian agricultural sector. They represent more than 70% of the country's agricultural producers and occupy more than 55 % of cropland (CSI, 2014). They are basically family-based and family-managed farms with an average size of 3 hectares, with 2 hectares under cultivation (IRNAGRIC, 2015). The crop sector is the most significant agricultural subsector in the country with 65.7% of agricultural' value added and 2.5 million agriculture production units. Field crops, mainly cereals, constitute the bulk of Iranian's crop production. In 2016, wheat makes up 50.39% of total cultivated land, followed by barley 14.95%, rice 5.07%, and corn 1.35%. However, in spite of input and output support policies, the yields of these crops remain below the world average (WB, 2016; IMAJ, 2016).

To boost productivity and foster national food security and agricultural self-reliance, Iran has deployed a multi-pronged program of subsidies. This includes guaranteed price floors for more than twenty crops, and which often results in producer prices that are well above world prices. In addition to this price floor, the Iranian Government provides support to farmers in the form of subsidized prices for fertilizer, pesticides, and improved seeds, as well as for equipment and basic inputs like water and energy (Hosseini and Shahnabati, 2015; Pakravan et al., 2016; Hosseini et al., 2017). Fertilizer subsidy is the most important of these subsidy programs. It started in the 1970s, but it focuses mostly on export crops and on training farmers in the proper use of fertilizers. However, as food security became a top priority with the explosion of population, fertilizer subsidy it was extended to staple crops (IC, 2016).

In 2016, mineral fertilizer subsidy represented around 10% of the public expenditure in agriculture. The subsidy was paid to the Iranian Petro-chemical industry, to permit it to sell fertilizers at reduced prices. Subsidized fertilizers were universally available to all farmers, regardless their specialization, size, geographical location, etc. (i.e., universal fertilizer program). However, due to the government's limited budget, not all farmers have access to subsidized fertilizer. In addition, given that subsidized fertilizers are often traded by intermediate dealers, they were sometimes sold to farmers at inflated prices or even smuggled out of the country. To address this issue, the "Agricultural Support Services Company (ASSC)", responsible for providing and distributing mineral fertilizers, has recently implemented a Smart Agricultural Input Distribution System (SAIDS) (SITO, 2016) that records detailed farmer information and monitors the transportation of fertilizer from petrochemical companies to the different regions (ASSC, 2016).

Although the introduction of fertilizer subsidy may contribute to enhancing food availability and food security, it has been subject to increasing criticism in recent years from both national and international players. In fact, several local experts argued that the use of input subsidies in Iran dates to the early 1970's, however agricultural productivity is still low, self-sufficiency is not achieved yet, and food safety and food security are still major concerns. As such, this instrument is seen as inefficient, given its high budget costs, and source of market distortions since it benefits only specific groups of farmers (e.g., farmers with ease access to input market). To this, one can add the new pressure coming from the World Trade Organization (WTO). In fact, the Iranian government is expecting to become member of WTO and such kind of subsidies are not allowed by this organization (Najafi and Dehghan, 2010; Alijani et al., 2012; Barikani and Shahbazi, 2016).

The debate on the 'efficiency' of fertilizer subsidy program is not new and not specific to Iran. According to the literature there are two types of subsidy programs depending on whether these are universally applied or targeted to a specific crop, category of farmers or region. Targeted subsidy programs include, for example, the five recent programs implemented in East and Southern Africa: Kenya, Malawi, Rwanda, Tanzania, and Zambia. These programs have in common their large scale in terms of number of beneficiaries (e.g., 2.5 million in Kenya), time frame (e.g., 10 years in Zambia), coverage (nation-wide), and implementation arrangements (voucher-based system). On the opposite, other countries such as Iran, India, and west African countries (Burkina Faso, Ghana, Mali, Nigeria, and Senegal) have adopted fertilizer subsidy programs, which seem to revert to universal (untargeted) price subsidies (Dorward, 2009; Praveen et al., 2017).

Both targeted and universal subsidies are highly discussed in the literature and two opposing views are generally identified. Those who sustain their effectiveness in bringing about green revolution (Gardner, 1992; Wright, 1995; Denning et al., 2009; Javdani, 2012) and those who considers them expensive, mainly benefit the wrong people, and distort agricultural markets (Holden and Tostensen, 2011; Chibwana et al., 2014).

The main objective of this paper is to contribute to this debate by assessing the economic effects of the fertilizer subsidy program currently implemented in Iran and to compare its performance with an alternative program based on targeting strategic crops. This is achieved using a Regional Crop Programming (RCP) model designed to simulate farms' responses to policy and market changes.

The paper is structured as follows: Section 2 describes the Regional Crop Programming (RCP) model and its major features. Section 3 presents and discusses the results of model simulation. Finally, section 4 draws the main conclusions and policy implications.

2. THE REGIONAL CROP PROGRAMMING (RCP) MODEL

2.1 Model features

RCP is a comparative static, regional, positive mathematical programming model, which includes in total 14 crop activities and encompasses 31 administrative regions. Positive means that the model aim to reproduces the real conditions as accurately as possible and to simulate "what is likely" to happen to this situation when changing external conditions (Howitt, 1995; Janssen and Van Ittersum, 2007). Regional signifies that the model operates at regional level and considers each region as one farm, as is often done in regional programming models (CAPRI (Britz and Witzke, 2014); REAP (Johansson, 2007); TASM (Eruygur and Cakman, 2008)). This implies that all farms within the region are assumed to be homogenous, have the same behavior and can perfectly exchange production factors. The use of a regional approach is motivated by the relative homogeneity[1] of arable farms in Iran as well as by the limited access to micro-data (i.e., farm data) for confidentiality reason.

Builds on regional data from the Iranian Agriculture Ministry-Jihad (IMAJ, 2016), the RCP model is a collection of 31 non-linear regional programming models, working with exogenous prices, each representing the optimal crop allocation at regional level. After being solved, the regional results of the regional models are aggregated to national level.

RCP is calibrated using positive mathematical programming (PMP) (Howitt, 1995) [2]. PMP is a methodology developed to exact calibrate programming models against observed economic behavior without the use of artificial flexibility constraints, while requiring minimal data. The PMP method is often preferred to linear mathematical programming as it avoids over specialization in crop production and yields smooth responses to policy changes. Because of these desirable characteristics, models calibrated using the PMP approach and its variants are popular in agricultural and environmental policy analysis. Existing agricultural supply models that rely on PMP principles include, among others, the European Common Agricultural Policy Regionalized Impact (CAPRI) modelling system (Britz and Witzke, 2014), the US Regional Environment and Agriculture Programming (REAP) model (Johansson et al., 2007), the Canadian Regionalized Agricultural Model (CRAM) (Horner et al., 1992), the Turkish Agricultural Sector Model (TASM) (Eruygur and Cakman, 2008), and the Dutch Regionalized Agricultural Model (DRAM) (Helming, 2005).

Over time, the literature on PMP has evolved and several variants have been developed to accurately calibrate programming models[3]. The more recent literature has focused on using supply elasticities and/or shadow prices for resources to reduce the under-determinacy of the model and increase the robustness of the parameter specification (Heckelei and Wolff, 2003; Mérel and Bucaram, 2010; Jansson and Heckelei, 2011; Mérel et al., 2011, Mérel et al., 2013; Britz and Witzke, 2014; Louhichi and Gomez y Paloma, 2014; Garnache et al., 2017; Louhichi et al., 2018; Henry de Frahan et al., 2019).

The PMP method used in this study builds upon this strand. It follows the variant proposed by Louhichi et al., (2018), which use cross-sectional data and prior information on supply elasticities and on dual values of land constraints, to calibrate the model to the base year condition. Supply elasticities are taken from the literature (Sabohi and Azadegan, 2014; Garshasbi et al., 2014; Jafari Lisar et al., 2017), while prior information on dual values of land constraints is derived from the Iranian Agriculture Ministry- Jihad (IMAJ) database.

RCP model relies on profit maximizing behavior and search for the optimal land allocation among production activities in each region taking into account land constraints. The regional profit (i.e., agricultural income) is defined as the sum of gross margin minus a nonlinear quadratic cost function for specific activity. The gross margin is equal to the total revenue from the sales of agricultural products plus fertilizer subsidies minus the accounting variable cost of production activities. The accounting costs include cost of seed, fertilizer,

[1] If we exclude large-scale farms which represent less than 0.2% of agricultural holding (SCI, 2014), arable farms within the same region tend to be relatively homogeneous because the majority have small farm size and most of them are sharing the same technology and equipment (Ansari et al., 2020).

[2] Other methods have been developed to calibrate optimization models to observed allocations, although not perfectly. The well-known ones are the risk (Hazell and Norton, 1986) and the multi-attribute utility theory (Keeney and Raiffa, 1993) based methods.

[3] For a review of PMP models, see Heckelei et al., (2012) and Henry de Frahan (2019).

pesticides, hired labor, and water. The quadratic activity-specific function is a behavioral function introduced to calibrate the model to the observed land allocation of the base year, as is usually done in positive programming models. This function allows capturing the effects of factors that are not explicitly included in the model, such as capital and labor constraints, price expectations, risk-adverse behavior, and other unobserved costs (Heckelei and Wolff, 2003).

The crop yields and the nitrogen application rate are endogenously defined in our model to allow their adjustments under market and policy changes. This achieved thanks to a crop-specific quadratic[4] yield response function to nitrogen fertilizer (considered to be the most important nutrient), econometrically estimated and embedded in the model, under the assumption that yield is independent of the acreage planted.

The other fertilizer elements (P and K) are assumed to be applied in fixed proportion to nitrogen fertilizer and the remaining intermediate inputs such as seeds and pesticides are supposed to be independent to fertilizer and employed in fixed rate by hectare of each specific crop[5]. Intermediate inputs are also assumed to be independent on the (unknown) marginal costs that are captured by the quadratic behavioral function (Heckelei and Wolff, 2003).

The general mathematical formulation of profit maximization problem of region r = (1, 2, …, R) is as follows:

$$\max_{x\geq 0} \pi_r = \sum_i (p_{r,i} y_{r,i} x_{r,i} - w_{r,i} n_{r,i} x_{r,i} + s_{r,i} n_i x_{r,i}) - \sum_{i,k} C_{r,i,k} x_{r,i} - \sum_i d_{r,i} x_{r,i} - 0.5 \sum_{i,i'} x_{r,i} Q_{r,i,i'} x_{r,i'} \tag{1}$$

Subject to:

$$\sum_i A_{r,i,m} x_{r,i} \leq b_{r,m} \qquad [\varphi_{r,m}] \tag{2}$$

$$y = \alpha n + \beta n^2 + \gamma \tag{3}$$

$$x \geq 0;\ y \geq 0;\ n \geq 0 \tag{4}$$

Where indices $i,i'=1,2,\ldots,I$ denote the crop activity; $k=1,2,\ldots,K$ the intermediate inputs (i.e., seed, pesticides, hired labor, water, etc.) and $m=1,2,\ldots,M$ the resource constraints (only land is considered here).

π is the objective function value of region r, $x_{r,i}$ is the unknown level (hectares) of crop activity i, $p_{r,i}$ is the crop price (i.e. market price), $y_{r,i}$ is the crop yield, $w_{r,i}$ is the fertilizer price, $n_{r,i}$ (per hectares) is the fertilizer quantity, $s_{r,i}$ is the fertilizer subsidy (per hectares), and $C_{r,i,k}$ are accounting variable costs (per hectares) for each intermediate input k and crop i. $d_{r,i}$ is the linear term of the behavioral activity function and $Q_{r,i,i'}$ is the quadratic term of the behavioral activity function.

$A_{r,i,m}$ are the coefficients of resource (i.e., land) constraints, $b_{r,m}$ is the level of available resources and $\varphi_{r,m}$ are their corresponding shadow prices.

α,β and γ are the coefficients of the yield response function to nitrogen. The coefficients α and β are crop, seed variety, season, and agro-ecological zone specifics to take into account technological, soil and climate heterogeneity. γ is the intercept parameter whose position (value) can be shifted up or down in the calibration step to capture region specification.

By setting α and β at agro-ecological level we assumed that regions within the same agro-ecological zone have a common technology and, therefore, they have the same yield curve shapes but with different starting points (i.e., intercept γ is region specific). Five agro-ecological zones are defined for Iran, based on climatic conditions, soil characteristics and type of crops grown: Mountain Climate, Moist Climate, Hot and Dry Climate, Temperate Climate and Hot and Moist.

2.2 Model calibration

The aim of the calibration process is to ensure that, in each region, the observed crop allocation during the base year period is exactly reproduced by the optimal solution of the programming model, which relies on profit maximization. This implies that two key variables need to be calibrated: the regional crop yield and area. This is performed in two successive steps: first, we calibrate yield response to the applied nitrogen rate and then, the land allocation.

2.2.1 Calibrating yield response to nitrogen fertilizer

Calibrating yield response to nitrogen fertilizer consists of recovering the unknown crop specific nitrogen

[4] We opted for a quadratic functional form because it keeps the model quadratic and simplifies the resolution of the optimization problem. More sophisticated specifications may consider exponential form (Godard et al., 2008; Mérel et al., 2011) or quadratic-plus-plateau form (similar to the conventional quadratic, but a plateau is imposed).

[5] This assumption lacks of rationalization given the strong relationship between fertilizer and other inputs. In fact, one could expect that an increase in fertilizer use would increase the risk of pest infestation (Rossing et al., 1997) and, as a consequence, the amount of pesticides applied (similar effects could be observed in other inputs). However, due to the lack of data to make a reliable estimate of this relationship and in order to avoid additional bias we have adopted this assumption following previous studies by Mérel et al., 2011; Mérel et al., 2013; Graveline and Mérel, 2014, Britz and Witzke, 2014, etc.

fertilizer prices w, the nitrogen response's intercept γ and the nitrogen fertilization rate n that allows reproducing exactly the observed yield y^0 assumed to be at the optimum level.

Mathematically, the above consists of solving the following model where the objective is assumed to be the maximization of the profit by unit of area with respect to nitrogen fertilization use (Godard et al., 2008; Louhichi et al, 2020):

$$\max \pi_{r,i}=p_{r,i}y(n)-w_{r,i}n_{r,i}+s_{r,i}n_{r,i} \quad (5)$$

Subject to:

$$y(n)=\alpha_i n_{r,i}+\beta_i n^2_{r,i}+\gamma_{r,i} \quad (6)$$

$$y(n)=y^0 \quad [\eta_{r,i}] \quad (7)$$

$$\eta_{r,i}\geq 0 \quad [\mu_{r,i}] \quad (8)$$

Where π is profit by unit of area, r is the region, i is the crop activity, y is the crop yield (kg ha^{-1}) and y^0 is its observed level in the base year (assumed to be optimal), p is the crop prices assumed to be known with exactitude, α,β and γ are the coefficients of the regression model, n is the nitrogen fertilizer quantity (kg ha^{-1}), w is the nitrogen fertilizer prices, $s_{r,i}$ is the fertilizer subsidy, η is the Lagrange multiplier related to the constrained yield level and μ is the Lagrange multiplier related to the non-negativity constraints for n,α and β are estimated by agro-ecological zone (more details are available in Louhichi et al., 2020).

2.2.2 Calibrating production activity levels

The calibration of activity levels consists of recovering the set of unknown parameters (d, Q and φ), so that the optimization model as described in equations (1) and (4) replicates exactly the observed activity levels (x^0) of the base year. This is performed using the results of the yield calibration step and a new variant of Positive Mathematical Programming (PMP) approach proposed by Louhichi et al., (2018). This variant relies on prior information on (i) supply elasticities ($\bar{\varepsilon}_{r,i,i}$), and on (ii) dual values of (irrigated and rainfed) land constraints ($\varphi_{r,m}$).

To perform the estimation, we derive the FOCs of the optimization model, equation (1) and (4) and then we apply the HPD method to estimate the unknown parameters $d_{r,i}$,$Q_{r,i,i}$' and $\varphi_{r,m}$.

The HPD model minimizes, in each region, the weighted sum of normalized square deviations of estimated national and agro-ecological zone own price(diagonal) supply elasticities and dual values of constraints from their prior subject to set of data consistency (FOC) constraints.

Following Louhichi et al., 2018, the general formulation of the corresponding HPD problem is the following:

$$\min HPD = \left[\sum_{i,i'}\frac{\left(\varepsilon_{i,i}-\bar{\varepsilon}_{i,i}\right)^2}{\sigma^{\varepsilon}_{i,i'}}+\sum_{z,i,i'}\omega_z\frac{\left(\varepsilon_{z,i,i}-\bar{\varepsilon}_{z,i,i}\right)^2}{\sigma^{\varepsilon}_{z,i,i'}}+ + \sum_{z,r,m}\omega_r\frac{\left(\varphi_{r,m}-\bar{\varphi}_{z,m}\right)^2}{\sigma^{\varphi}_{z,m}}\right] \quad (9)$$

Subject to:

$$gm_{r,i}-d_{r,i}-\sum_{i'}Q_{r,i,i'}x^0{}_{r,i'}-\sum_{m}A_{r,i,m}\varphi_{r,m}=0 \quad (10)$$

$$b_{r,m}-\sum_{i}A_{r,i,m}x^0_{r,i}=0 \quad (11)$$

$$\varepsilon_{r,i,i'}=\left[Q^{-1}_{r,i,i'}-\sum_{m}\left(\sum_{j}A_{r,j,m}Q^{-1}_{r,i,j}\left(\sum_{j,j}A_{r,j,m}Q^{-1}_{r,i,j}A_{r,j',m}\right)^{-1}\sum_{j}A_{r,j,m}Q^{-1}_{r,j,i'}\right)\right]\frac{gm_{r,i}}{x^0_{r,i}} \quad (12)$$

$$\varepsilon_{z,i,i'}=\frac{\sum_r\omega_r x^0_r\varepsilon_{r,i,i'}}{\sum_r\omega_r x^0_{r,i}} \quad (13)$$

$$\varepsilon_{i,i'}=\frac{\sum_z\omega_z x^0_z\varepsilon_{z,i,i'}}{\sum_z\omega_z x^0_{z,i}} \quad (14)$$

$$B_{z,i,i}{}'=\sum_j \mathrm{L}b_{z,i,j}\mathrm{L}b_{z,i',j};\ \mathrm{L}b_{z,i,i}{}'=0 \quad \text{for } i'>i \quad (15)$$

$$Q_{r,i,i'}=\sum_{z}\delta_{r,i}B_{z,i,i'}\delta_{r,i'} \quad (16)$$

$$\sum Q_{r,i,i'}Q^{-1}_{r,i,i\prime}=1 \quad \forall i=i$$
$$\sum_{i} Q_{r,i,i'}Q^{-1}_{r,i,i\prime}=0 \quad \forall i\neq i \quad (17)$$

Where indices j,j'=1,2,…,I (similar to i,i') denote the crop activities; $gm_{r,i}$ is the gross margin for activity i (IRR/ha) with $gm_{r,i}=p_{r,i}y^0{}_{r,i}-w_{r,i}n^0{}_{h,i}+s_{r,i}-\sum_k C_{r,i,k}$. y^0 is the observed yield and w and n^0 are, respectively, the nitrogen fertilization price and quantity estimated in the yield calibration step.

$\bar{\varphi}_{z,m}$ and $\sigma^{\varphi}_{r,m}$ are, respectively, mean and standard deviation of the regional rental prices for irrigated and non-irrigated lands and $\bar{\varepsilon}_{i,i'}$,$\bar{\varepsilon}_{z,i,i'}$, $\sigma^{\varepsilon}_{i,i'}$ and $\sigma^{\varepsilon}_{z,i,i'}$ are mean and standard deviation of own price elasticities of supply at country and agro-ecologic zone levels used as prior (Jansson and Heckelei, 2011) and $\delta_{r,i}$ is a scaling factor with $\delta_{r,i}=\sqrt{1/x^0_{r,i}}$.

The normalized squared deviations of dual values and of agro-ecological zone supply elasticities are weighted (ω) with the inverse number of administrative regions (i.e., 1/31) and the inverse number of agro-ecological zones (i.e., 1/5), respectively, to obtain a comparable weight with the first component of the HPD objective function.

The prior for the own price supply elasticity at agro-ecological zone ($\bar{\varepsilon}_{z,i,i'}$) is defined as the own price supply elasticity at national level time the ratio of average production between agro-ecological zone and national level. This allow agro-ecological zone with low (high) average production to be more (less) elastic to price change compared to the national average.

The endogenous variables of HPD problem defined in equations (9)-(17) are: (i) the dual values of land constraints, $\varphi_{r,m}$, (ii) the own and cross price elasticities of supply at regional ($\varepsilon_{r,i,i}$'), agro-ecological zone ($\varepsilon_{z,i,i}$') and national ($\varepsilon_{i,i}$') levels, (iii) the elements of the lower triangular Cholesky decomposition related to $B_{z,i,i}$' parameters, $Lb_{z,i,i}$', and (iv) the regional-specific behavioral parameters $d_{r,i}$ and $Q_{r,i,i}$' (including the inverse matrix $Q^{-1}_{r,i,i'}$).

Equations (10) and (11) represent the FOC of the optimization model for crop activities and for land constraints, respectively. Equations (12), (13) and (14) compute supply elasticities at regional, agro-ecological zone and national levels, respectively. Equation (15) is the Cholesky decomposition which ensures appropriate curvature properties of the estimated quadratic cost function (i.e., convex in activity levels), Equation (16) calculates the region-specific quadratic parameters $Q_{r,i,i}$' and Equation (17) calculates its inverse $Q^{-1}_{r,i,i'}$.

2.3 Data

The primary data source used to parametrize RCP model are regional data from the Iranian Agriculture Ministry- Jihad (IMAJ, 2016) for the three-years average around 2015 (2014, 2015 and 2016). IMAJ publish annual report on crop area and production in each region obtained from the aggregation of individual farm data collected through face-to-face survey. The Information and Communication Technology Centre of Iranian Agriculture Ministry (ICTC- IMAJ) also use these individual farm data to derive input and output prices and quantities of crops in different regions as Cost Bank System (CBS).

The CBS and IMAJ database provide detailed regional information for the five groups of crops, namely cereals (wheat, barley, corn, and rice), legumes (pea and lentil), vegetables (onion, potato and tomato), fruit (melon and cucumber), and industrial crops (cotton, canola and sugar beet). Table 1 reports the statistical characteristics of the key variables for the 14 selected crops in RCP. These variables include total cultivated areas and total production for each crop as well as their yield, revenue, estimated fertilizer application rates, fertilizer subsidy, production costs (e.g., seed, pesticides, fertilizer, hired labor and water), gross income, estimated implicit costs/revenues and net income per unit of land, average across 31 regions and for the three-year average around 2015.

2.4 Scenarios: layout and implementation

As mentioned previously, apart from the pressure coming from the WTO, there is an intensive ongoing debate about the effectiveness of the input subsidies in Iran given their high, possibly unsustainable costs and the absence of credible empirical evidence on their impacts on agricultural productivity. Therefore, a reduction or a total removal of these subsidies or their reallocation to only specific farm groups or to specific crop sectors are among the reform options that are currently under discussion in the country.

In this regard, the aim of this paper is to simulate the impacts of two policy options: (i) a total removal of nitrogen fertilizer subsidy for all crops and all regions (ABOL scenario) and (ii) a reallocation of nitrogen fertilizer subsidy to only strategic crops (wheat, maize, and rice) while keeping the same subsidy budget (TARG scenario).

We are aware that this drastic scenario of a total removal of fertilizer subsidy is currently to a great extent unrealistic and cannot represent a prospective or even likely development; however, it might contribute to the on-going debate on their relevance and their legitimacy. Keeping the subsidies (or reallocating all of them) for only strategic crops seems to be more realistic due to the high attention given by the government to these crops for political, economic and food security reasons, particularly under the various international sanctions.

Both scenarios are implemented and compared to a baseline scenario representing the business as usual (i.e., the baseline scenario is used for the counterfactual comparison of the simulated scenarios).

3. RESULTS AND DISCUSSION

In this section we examine whether and how the simulated fertilizer subsidy reform options affect land

Table 1. Statistical characteristics of the key variables.

	Crops	Area under cultivation (1000ha)	Production (1000 ton)	Yield (ton)	Revenue (1000 IRR/ ha)	Fertilizer use (kg/ha)	Fertilizer Subsidy (IRR/kg)	Nitrogen use (kg/ha)	Production Cost (IRR/ha)	Gross Income (1000IRR/ha)	Implicit costs/ revenues (1000IRR/ha)	Net Income (1000IRR/ha)
Cereals	Wheat	5894.07	12117.70	2.06	11815.04	302.02	277.76	194.46	20906.21	-8.81	42.73	33.92
	Barley	1739.84	3281.66	1.89	9246.78	171.97	135.86	110.06	19982.51	-10.60	44.43	33.83
	Maize	173.53	1249.70	7.20	73584.91	677.63	506.43	441.84	38678.80	35.41	36.13	71.54
	Rice	332.58	1737.17	5.22	92201.17	1127.29	1076.53	695.03	49732.81	43.54	-26.64	16.90
Legumes	Lentil	134.57	74.71	0.56	27663.63	5.13	2.91	3.36	7968.69	19.70	14.07	33.77
	Peas	492.56	236.67	0.48	7045.33	18.49	20.69	11.45	7924.71	-0.86	55.01	54.15
Vegetables	Tomato	118.76	4878.06	41.08	139039.97	676.35	961.94	427.57	88656.44	51.35	5.88	57.23
	Potato	148.45	4726.75	31.84	175494.44	620.01	794.18	371.17	110089.80	66.20	16.61	82.81
	Onion	50.16	1861.46	37.11	126122.08	1033.77	1853.98	629.38	98891.62	29.08	19.09	48.17
Fruit	Cucumber	46.25	1007.52	21.78	233610.84	307.87	271.12	209.55	73462.27	160.42	-53.94	106.48
	Melon	112.39	3099.80	27.58	100423.7	487.34	841.26	288.78	55581.61	45.68	-0.95	44.73
Industrial crops	Canola	60.01	93.63	1.56	21864.07	425.24	305.52	259.02	12638.04	9.53	24.93	34.47
	Sugar beet	100.66	5278.90	52.44	133050.2	587.20	467.32	350.48	71686.40	61.83	9.54	71.37
	Cotton	72.09	166.30	2.31	65600.89	132.61	86.32	81.20	45810.45	19.88	22.13	42.01
MIN	46.25	74.71	0.48	233610.84	5.13	2.91	3.36	7924.71	-10.60	-53.94	16.90	
MAX	5894.07	12117.70	52.44	7045.33	1127.29	1853.98	695.03	110089.80	160.42	55.01	106.48	
STDEV	1564.68	3248.38	18.14	69273.66	345.43	517.20	211.90	34388.40	43.18	28.70	23.86	

Source: ICTC- IMAJ. Three-years average around 2015 (2014, 2015 and 2016)
*Net income equals to the total revenue from the sales of agricultural products plus fertilizer subsidies minus the accounting variable cost of production activities plus implicit revenues/costs (i.e., PMP terms).

allocation, nitrogen fertilizer application rate, production, agricultural income, and government budget in Iran at both regional and national levels and compare their cost-effectiveness using the transfer efficiency index.

Before presenting simulation results it is important to notice that farmers may respond in three ways to a reduction or a removal of fertilizer subsidy: (i) extensive margin, that is, reallocation of acreage among crops by, for example, substituting more fertilizer-intensive crops with less fertilizer-intensive crops (i.e. acreage effects), (ii) intensive margin, that is, reducing fertilizer intensity per hectare for a given crop (i.e. yield effects), and (iii) land abandonment, that is, putting out of production land (i.e. land abandonment effects).

With our models we tried to capture only the first two adjustments which represent the main opportunities for farmers to respond to shocks. Land abandonment adjustment is excluded because agricultural utilized area is assumed to be fix in our model.

3.1 Acreage, fertilizer intensity and yield effects

3.1.1 ABOL scenario

The implementation of the ABOL scenario, based on a total removal of nitrogen fertilizer subsidy, would lead, as expected, to the reallocation of land from crop groups strongly dependent on fertilizer such as industrial crops, vegetables, and fruit to crop groups less dependent on fertilizer like legumes and cereals. As shown in Table 2, the acreage of industrial crops, vegetables and fruit decreased by -1.72%, -1.47%, and -1.16%, while the acreage of legumes and cereals increases by +0.93 and +0.06%, respectively. These results are also confirmed while looking to individual crops. The acreage of crops strongly dependent on fertilizer such as rice, tomato and maize decreased by -5.75%, -2.54% and -1.46%, respectively, whereas the acreage of crops less dependent on fertilizer such as barley, peas and lentil increase by +9.56%, +1.02% and +0.63%, respectively. This finding is explained by the fact that fertilizer-intensive crops become less competitive with the removal of subsidy and, therefore, lose some of their areas in favor of less fertilizer-intensive crops. Pishbahar and Khodabakhshi (2015) in a study focusing on farmers of Varamin area have found similar results showing a decrease in the acreage of maize and tomato with the removal of input subsidy. Kohansal and Ghorbani (2013) and Shirmahi et al., (2014) have revealed, using estimated price elasticity for nitrate fertilizer, that removing nitrate subsidy would cause a remarkable land reallocation among crops.

From this Table it also appears that all crops experience a reduction in their fertilizer application rates when the nitrogen price increase with the removal of subsidy. The average reduction of fertiliser application rate across all crops is around -9.16%, ranging between -0.7 % and -18%. Legumes are the most responsive to nitrogen price increase, in terms of fertiliser application rate. However, this response is small in absolute terms because legumes have relatively low fertiliser application rate in baseline. In the opposite, the response of fertiliser-intensive crop groups (e.g., industrial crops, vegetables, and fruit) is relatively low (less than 20%) but quite large in absolute terms. While comparing individual fertiliser-intensive crops (e.g., rice, onion, tomato, and maize), we found that their responses to nitrogen price increase are quite similar and close to -2.5%. The exception is maize where the percentage change in application rate seems to be very small (less than 1%), explained by the fact that the observed application rate for maize lies on the flatter proportion of the yield response curve.

Table II also shows that the reduction of nitrogen application causes relatively drastic yield losses in nitrogen-intensive crop groups than in less nitrogen-intensive crop groups. This clearly appears for legumes where a -48% decrease of fertiliser application rate causes a reduction of only -1.92% for yield, while a –1.84% decrease of fertiliser application rate for vegetable causes a reduction of its yield by -0.37%. However, given the relatively high yield of nitrogen-intensive crop groups their yield losses could be significant in absolute terms.

Appendix Table A1 reports the reallocated area in each region as a result of the ABOL scenario. From this Table it clearly appears that all regions seem to be affected by this scenario with different degree depending on their specialization. The largest reallocated area is observed in regions specialised in rice such as Mazandaran, those specialised in industrial crops (mainly canola) like Golestan and those specialised in vegetables (mainly tomato) like Fars. Golestan tend to be more affected because it is the first producer of canola with 14200 thousand hectares (around 25% of total canola area) and the second after Mazandaran in cultivating rice with 59060 thousand hectares (around 10% of total rice land). This result is expected, as these three crops have the highest fertilisation rates and, therefore, a reduction of fertilisation application cause drastic losses in their yields and, thus, in their performances. Regions specialised in maize such as Kurdistan seem to be able to maintain such specialisation although its dependency on fertiliser. This means that maize remains competitive in these regions even with an increase of nitrogen fertiliser price.

Table 2. Fertilizer application rate, acreage, production, yield, and income changes under ABOL and TARG scenarios (% change relative to baseline).

Crop/ group/ Scenario	Fertilization Application Rate		Acreage		Production		Yield		Average Net Income	
	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG
Wheat	-8.32	1.31	-2.38	0.90	-4.18	0.90	-1.94	0.00	-1.67	0.22
Barley	-18.15	3.65	9.56	-2.63	1.37	-1.06	-7.41	1.59	-0.51	-0.01
Maize	-0.72	0.15	-1.46	0.60	-1.73	0.67	-0.28	0.14	-0.39	0.10
Rice	-2.68	0.64	-5.75	0.76	-6.24	0.90	-0.38	0.19	10.51	-1.01
Cereals	**-4.02**	**0.81**	**0.06**	**0.13**	**-3.22**	**0.53**	**-1.34**	**0.31**	**0.49**	**-0.02**
Lentil	-11.61	-12.20	0.63	-0.38	0.26	-0.38	-1.79	0.00	1.27	-0.10
Peas	-58.60	-60.61	1.02	-0.16	-1.37	-2.40	-2.08	-2.08	-0.31	0.05
Legumes	**-47.94**	**-49.63**	**0.93**	**-0.20**	**-0.97**	**-1.92**	**-1.92**	**-0.96**	**0.30**	**-0.01**
Tomato	-1.86	-1.63	-2.54	-1.42	-2.79	-1.75	-0.27	-0.34	-0.47	-0.25
Potato	-0.97	-0.98	-0.71	-0.68	-0.79	-0.73	-0.06	-0.06	0.12	-1.80
Onion	-2.34	-2.33	-1.17	-1.39	-1.93	-2.03	-0.75	-0.65	-2.84	-1.41
Vegetables	**-1.84**	**-1.77**	**-1.47**	**-1.07**	**-1.83**	**-1.37**	**-0.37**	**-0.36**	**-0.90**	**-1.02**
Cucumber	-8.90	-8.72	-0.41	-0.38	-0.58	-0.51	-0.14	-0.09	-0.07	-0.16
Melon	-0.94	-0.95	-1.46	-1.72	-0.96	-1.03	0.51	0.69	8.05	-1.26
Fruit	**-4.29**	**-4.22**	**-1.16**	**-1.33**	**-0.87**	**-0.90**	**0.22**	**0.34**	**2.33**	**-0.49**
Canola	-1.78	-0.66	-3.44	-2.02	-3.69	-1.38	0.00	0.64	0.13	-0.39
Sugar beet	-2.25	-2.27	-0.87	-0.42	-0.85	-0.50	0.02	-0.08	0.39	-0.94
Cotton	-16.26	-14.10	-1.49	-3.19	-1.36	-3.40	0.00	-0.43	0.07	1.85
Industrial crops	**-3.72**	**-3.06**	**-1.72**	**-1.69**	**-0.91**	**-0.60**	**0.02**	**-0.07**	**0.18**	**0.12**
National	**-9.16**	**1.05**	**0.00**	**0.00**	**-2.61**	**-0.12**	**-0.23**	**-0.10**	**-076**	**-0.01**

Source: Model results.

3.1.2 TARG scenario

Paying nitrogen fertilizer subsidy to only strategic crops (“TARG scenario”), namely wheat, maize and rice boosts their areas at the expense of non-target groups. As shown in Table II, the area devoted to cereals group increase by 0.13%, whereas the area dedicated to all other groups’ decline, reaching -1.69% for industrial crops. The percentage increase of strategic crops area is relatively small; however, measured in absolute terms, it is quite significant (about 57 thousand hectares) due to their large initial shares in the total area (Table 1).

Looking at fertilization application rate change under TARG scenario reported in Table II, we can see the same trend as for acreage change: an increase of fertiliser intensity for target crops and a decrease for the other crops. However, the magnitude of changes is quite different: the percentage change of fertiliser application is bigger than the percentage change of acreage, which is not surprising given that a large increase of crop area will be costlier due to rising marginal costs. The yield effect of the TARG scenario seems to be limited which means that reducing fertiliser price for target crops, which are nitrogen-intensive crops, boost only marginally their yield.

As predicted, the reallocation of fertiliser subsidies to only strategic crops stimulate their acreages in all regions (see Table A1). Regions specialised in target crops (i.e., with largest share of target crops) react relatively more rapidly to a nitrogen price decrease triggered by the TARG scenario, in comparison to the other ones. For example, in the East Azerbaijan, Fars and Kurdistan regions, where target crops area in baseline exceeds 70% of total cropland, the percentage increases are larger, in comparison to regions with small initial share (less than 30%). In these regions the land adjustment occurs, mainly at the expense of barley. For instance, in Fars, the acreage of barley declines by -20% under the TARG scenario and its share in total land drop down from 20% (121693 hectares) to 16% (97411 hectares).

3.2 Production effects

Table II shows the production effects of ABOL and TARG scenarios. As can be seen from this Table, the average production effects of ABOL and TARG scenarios are estimated to be around -2.61% and -0.12%, respectively. The main production effects under the ABOL scenario are (i) a decrease of production for nitrogen intensive crop groups (e.g., vegetable decrease by -1.83%, industrial by -0.91%, and fruit by -0.87%) and (ii) an increase of production for less nitrogen intensive crop groups (e.g., legumes). These trends are also confirmed while looking to individual crops. Production of crops less dependent on fertilizer such as barley and lentil increase whereas, whereas production of crops strongly dependent on fertilizer like rice, tomato and maize decrease ranging between -1% and -7%. These results are consistent with Rahmani et al., (2011) who also found that increasing fertilizer price led to a decrease in the production of maize by -1.28% and cotton by -1.62%.

Under the TARG scenario, the large positive effects in production are observed for the targeted crops, namely wheat, maize, and rice, ranging between +0.6% and +0.9%, while negative effects are experienced by less competitive crops such as cotton, tomato, and barley, with a production retraction of -3.4%, -2.4% and -1.06% respectively.

At regional level, Mazandaran by -31 %, Golestan by -26% and Kohkiloyeh by -20% show the highest decrease in production under the ABOL scenario. However, in the TARG scenario production increased in Mazandaran by +4% and Bushehr by +2% (see Table A2). As mentioned before, Mazandaran and Golestan are the most important regions in cultivation rice.

These production effects are driven either by land reallocation (i.e., land substitution between crop groups), land productivity (i.e., yield effect) or both. To better understand the contribution of each driver, we decomposed the production effects into two effects using the Logarithmic Mean DIVISIA Index (LMDI) approach (Ang, 2005): acreage effect (i.e., area) and yield effect (i.e., productivity):

$$production=\left(\frac{Production}{Area}\right)\times Area=Productivity\times Area \tag{18}$$

Where area stands for cultivated area, therefore, production impacts are decomposed into productivity and area effects in an additive form as follows:

$$\Delta production=\Delta productivity+\Delta Area \tag{19}$$

Where $\Delta x=x(scenario)+x(baseline)$. The LMDI approach is used to calculate the above individual contributions. For example, the area effect is calculated as follows:

$$\Delta Area=\frac{prod_{-S}-prod_{-B}}{\ln(prod_{-S})-\ln(prod_{-B})}\times ln\left(\frac{Area_{-S}}{Area_{-B}}\right) \tag{20}$$

Where $prod_{-s}$ and $prod_{-B}$ refer to production (in tons) under ABOL and TARG scenarios and baseline respectively, in stand natural logarithm and $Area_{-s}$ and $Area_{-B}$ denote the cultivated area under ABOL and TARG scenario and baseline, respectively.

Figure 1 reports the decomposition of production effects under ABOL and TARG scenarios. From Figure 1 it clearly appears that the acreage effect explains around 80% of production effect for vegetable, fruit, and industrial groups under both ABOL and TARG scenarios. As an example, the -1.83% decrease of vegetable production under ABOL scenario is assumed to be a combined effect of yield (-0.37%) and area (-1.47%). The acreage effect accounts for 80.33% of the total change in vegetable production, while the remaining 19.67% is attributed to yield effect. Given that the acreage effect explains most of the changes in production under ABOL and TARG scenario for these three crop groups, it is not surprising to observe that their production and acreage effects are strongly correlated. On the other hand, for cereal and legumes groups, production changes under both ABOL and TARG scenarios seem to be mainly driven by yield effect. For example, the 0.53% production increase of cereals is a result of a 75% yield change and 24 % of acreage change.

3.3 Agricultural income effects

The land and production effects presented previously dictate changes in agricultural income reported in Table II. Before interpreting these changes, it is important to notice that agricultural income is equal to the maximized value of the objective function presented in equation (1) and, therefore, it is inclusive of all shadow costs.

The impact of the removal of fertilizer subsidy (ABOL scenario) on agricultural income is rather small when aggregated at national level (less than 1% compared with the baseline), and the reallocation of fertilizer subsidy to only target crops has very limited effect on national agricultural income, compared to baseline. This is to say that due to the relatively low shares of subsided fertilizers in total fertilizer consumption and of fertilizer costs in total production costs, the removal or reallocation of fertilizer subsidy will not engender a large impact on agricultural income at national level. However, while looking deeper at the regional and crop levels the impact could be more pronounced and sometime with opposite sign.

As shown in Appendix Table A3, income change under ABOL scenario is negative for all regions, which

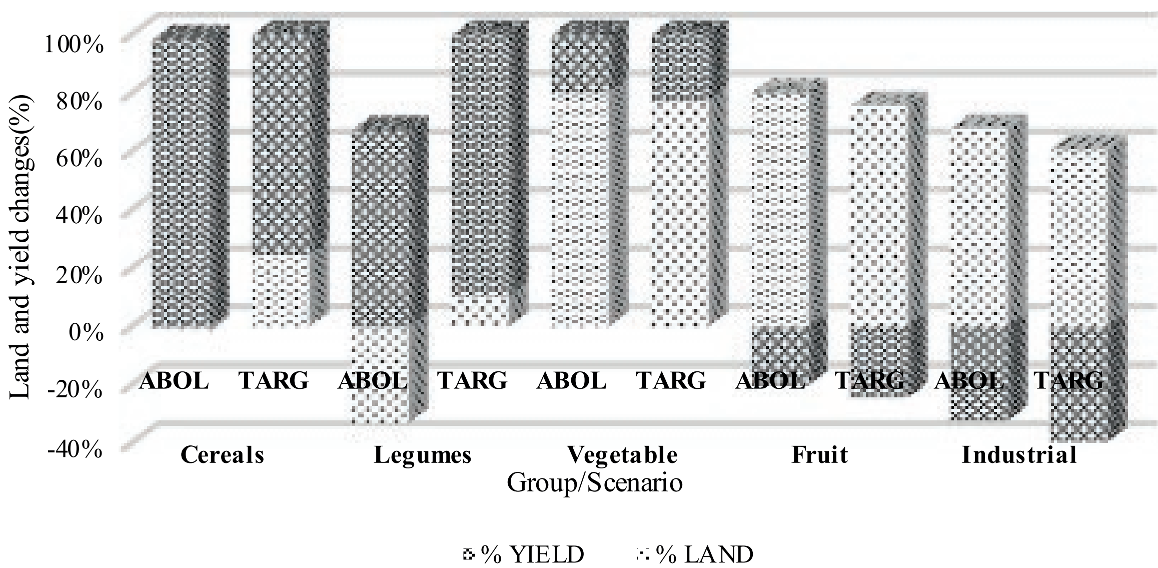

Figure 1. Production change decomposition under ABOL and TARG scenarios.

is not surprising, ranging between -0.35% and 5%. As expected, the most affected ones are those specialized in nitrogen-intensive crops such rice, tomato, and onion. This heterogeneous income effect is probably more noticeable when we go at lower levels such as sub-regional and farm levels.

Under TARG scenario (Table 6), the economic impact remains also small for the majority of the regions, ranging between -3% and 0.64%; nevertheless, there is an opposite effect: some regions loose and some regions gain from the reallocation of subsidy. Regions specialized in target crops (wheat, maize, and rice) such as Golestan gain from the reallocation, while other regions either they lose or almost no change compared to the current situation (i.e., Khorasan and, South Khorasan).

3.4 Policy efficiency

In this section we use the results of the RCP model to compare welfare implications of the two simulated policies: current (i.e., baseline) vs. target (i.e., TARG) fertiliser policies. For doing that, we use the ABOL scenario as counterfactual. In fact, the difference between the baseline and the ABOL scenario provides an estimation of the effect of the current policy (universal subsidies), while the difference between the TARG and the ABOL scenarios gives an estimation of the alternative policy (target subsidies).

From a cost/benefit perspective, the most efficient policy instrument is the one best at achieving the target benefit at lowest cost. Following Brooks et al., (2011), we use the transfer efficiency (TE) index to compare the relative efficiency of both policies. This index is calculated as follow:

$$TE = \left(\frac{increase\ in\ agricultural\ income}{total\ cost\ to\ taxpayers\ and\ consumers}\right) \quad (21)$$

The implementation of the target fertiliser policy (TARG scenario) came at a total cost to taxpayers and consumers of about IRR 2.83 billion and generates an increase of agricultural income of IRR 2.64 billion, which means a TE of 0.93. Whereas the application of the universal fertiliser policy (baseline scenario) came at the total cost to taxpayers and consumers of IRR 2.83 billion and generates an increase of agricultural income of IRR 2.69 billion, which implies a TE of 0.94.

The main conclusion coming out from this comparison is that, first, the two policies are quite similar in terms of welfare implications and, second, both policies seem to be inefficient because their TE are lower than one, knowing that all the administrative costs related to the implementation of this policy are not considered in our analysis. These results are in line with the finding of Karimzadeh et al., (2006), Mosavi et al., (2009), Bakhshi et al., (2010) and Rahmani et al., (2011) who also reported that fertiliser subsidy in Iran has led to an inefficient use of nitrate fertilizer and, therefore, needs to be reviewed.

4. CONCLUSION

This paper presents the results of a comprehensive analysis aiming to assess the economic effects of the fertilizer subsidy programs currently implemented in Iran and to compare its performance with an alternative program based on targeting strategic crops. Two policy scenarios are simulated, and their results are compared to a baseline scenario representing the business as usual: a total removal of fertilizer subsidy "ABOL", and a reallocation of fertilizer subsidy to only strategic crops (wheat, corn, and rice) "TARG".

This analysis is done using a regional economic model which includes in total 14 crop activities and encompasses 31 administrative regions. This model is a collection of micro-economic models, working with exogenous prices, and calibrated against observed data on crop acreage, yields and exogenous supply elasticities.

From a methodological perspective, the novelty of this paper lies in the employ of detailed regional modelling approach that allow for an adjustment of both crop acreage and input intensities and, therefore, to infer the effects of policies that are likely to have effects at the extensive and intensive margins.

From a policy perspective, findings from this study reveal several exciting patterns. First, the effects of fertilizer subsidy removal are rather small at national level (less than 1%), although more pronounced at regional level, implying that a large share of farms do not use or use small quantity of fertilizer and, therefore, additional government efforts are needed to facilitate them access. Second, the reallocation of fertilizer subsidy to only strategic crops under TARG scenario boost their production and income, however, it increases disparity among regions and affects negatively national agricultural income and welfare compared to the current universal fertilizer policy. This imply that targeting strategic crops could not be the best solution and higher efficiency could be achieved by taking into consideration regional and farm heterogeneities. Policymakers may gain from be cognizant of heterogeneity among regions/farms and that one policy may not fit all regions/farms. Third, based on the result of the Transfer Efficiency (TE) analysis, both target and universal simulated options seem to be inefficient, as their TE indexes are lower than one, meaning that one IRR injected in the Iranian's agriculture sector generate less than one IRR. Such results tend to confirm previous studies in the literature showing low productivity of Iranian agriculture (Bakhshi et al., 2010; and Rahmani et al., 2011).

Our findings, however, need to be considered with some caution, on account of the model's assumptions. First, output market prices are assumed to be exogenous. This implies that market feedback (output price changes) is not taken into account in the model. This could be an issue mainly when production change is quite high such as for cereals under ABOL scenario. Accounting for price effects requires extending the supply model into a partial or a general equilibrium model which is clearly beyond the scope of the present paper. A relaxation of this assumption would dampen supply effects and partially offset the negative impacts of subsidy removal (ABOL scenario) given that a production decrease induced by higher fertilizer prices raises output prices which in turn enhances production. Similar trend would be observed for non-target crops under TARG scenario.

Second, due to data limitations the administrative costs related to the implementation of fertilizer policies are not considered. This may lead to an overestimation of the welfare impacts. A third potential caveat to our analysis is that we assume a fixed regional structure, implying that agricultural land extension/retraction (abandonment) in response to the simulated policies is not captured by the model. This may lead to an underestimation of the simulated impacts, mainly under ABOL scenario. A careful analysis of each of these limitations is, therefore, needed when examining simulation results.

Despite these limitations, our paper gives some insights on the potential role of fertilizer subsidy and provides useful recommendations to the policy making process aiming to enhance productivity and sustainability of the farming sector in Iran.

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Appendix Table A1. Regional acreage changes under ABOL and TARG scenarios (% change relative to baseline).

Region/Crop	Cereals		Legumes		Vegetables		Fruit		Industrial crops		Total	
	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG
Alborz	0.05	0.01	-	0.00	-0.55	-0.38	-	0.00	-1.60	0.19	0.00	0.00
Ardabil	0.06	0.03	-0.02	0.00	-0.60	-0.42	-0.20	-0.19	-1.40	-0.11	0.00	0.00
Boshehr	0.01	0.01	-	0.00	-0.68	-0.71	-0.37	-0.39	-	0.00	0.00	0.00
Chaharmahal	0.05	0.03	0.32	-0.10	-0.80	-0.36	-2.97	-0.84	-0.70	-0.06	0.00	0.00
East Azarbaijan	-0.43	0.10	4.86	-0.77	-1.28	-0.56	-14.15	2.13	-2.19	-0.54	0.00	0.00
Elam	0.03	0.01	0.48	-0.06	0.00	0.00	-0.75	-0.06	-1.46	-0.01	0.00	0.00
Esfahan	0.58	0.16	-8.97	-2.13	-2.51	-0.98	-4.42	-0.24	0.70	0.75	0.00	0.00
Fars	-0.70	0.31	29.08	-8.62	0.02	-0.80	1.56	-1.26	2.62	-1.40	0.00	0.00
Gilan	0.01	0.03	0.08	-0.13	-0.20	-0.55	-0.14	-0.26	-	0.00	0.00	0.00
Golestan	0.56	-0.02	-26.25	-4.72	-9.16	1.49	7.58	-2.82	-8.80	0.62	0.00	0.00
Hamedan	0.03	0.05	0.34	-0.04	-0.62	-0.63	-0.59	-0.52	-0.43	-0.16	0.00	0.00
Hormozgan	0.62	1.22	-	0.00	-0.53	-0.72	-0.05	-0.05	11.22	-23.83	0.00	0.00
Kohkiloyeh	0.33	0.02	-5.24	-0.39	-18.87	-0.99	-9.15	-0.60	-	0.00	0.00	0.00
Kerman	0.09	0.01	-1.91	-0.33	-0.60	-0.26	-0.18	-0.40	-1.57	1.02	0.00	0.00
Kordestan	0.09	0.03	-0.45	0.06	-1.21	-1.21	-0.34	-0.31	1.25	-5.49	0.00	0.00
Kermanshah	-0.04	0.08	0.09	0.12	1.57	-5.53	-	0.00	-0.66	0.30	0.00	0.00
Khouzestan	0.11	0.22	1.12	0.97	-0.87	-0.68	-0.51	-0.24	-2.61	-7.64	0.00	0.00
Lorestan	-0.02	0.03	0.14	-0.04	-0.39	-0.33	-0.16	-0.15	-0.41	-0.15	0.00	0.00
Markazi	-	0.01	0.59	-0.20	-0.10	-0.14	-	0.00	-2.81	0.33	0.00	0.00
Mazandaran	0.19	0.00	-	0.00	-1.49	-2.61	-31.24	3.77	-1.83	0.11	0.00	0.00
North Khorasan	0.14	0.12	1.53	0.02	-1.74	-1.75	7.11	-1.14	-4.33	-1.33	0.00	0.00
Qom	-0.01	0.00	-	0.00	-	0.00	-	0.00	0.08	-0.07	0.00	0.00
Qazvin	0.74	0.13	5.69	0.38	-9.34	-1.31	-19.03	-0.93	-12.41	-2.45	0.00	0.00
Razavi Khorasan	0.39	0.94	0.22	-0.42	-1.03	-3.81	-6.58	-9.25	-1.46	-4.72	0.00	0.00
Sistan	0.05	0.12	-0.45	-0.99	-0.40	-0.58	-0.13	-0.32	0.02	-1.07	0.00	0.00
South Khorasan	0.03	0.10	1.76	-8.69	-0.16	0.39	-0.65	-2.08	0.13	0.47	0.00	0.00
Semnan	0.06	0.05	-0.69	-0.32	-0.41	-0.54	-0.12	0.22	-0.04	-0.03	0.00	0.00
Tehran	0.03	0.01	-	0.00	-0.35	-0.16	-0.20	0.00	-	0.00	0.00	0.00
West Azarbaijan	-0.01	0.04	0.30	-0.04	-0.58	-0.51	-0.55	-0.30	-0.36	-0.22	0.00	0.00
Yazd	0.05	0.06	-	0.00	-1.17	-1.27	-0.01	-0.17	-	0.00	0.00	0.00
Zanjan	0.07	0.07	0.78	0.12	-2.10	-1.32	-1.79	-1.11	-3.93	-1.57	0.00	0.00
National	**0.06**	**0.13**	**0.93**	**-0.20**	**-1.47**	**-1.07**	**-1.16**	**-1.33**	**-1.72**	**-1.69**	**0.00**	**0.00**

Source: Model results.

Appendix Table A2. Regional production changes under ABOL and TARG scenarios (% change relative to baseline).

Region/Crop	Cereals		Legumes		Vegetables		Fruit		Industrial crops		Total	
	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG
Alborz	-1.39	0.26	0.00	-	-0.54	-0.40	0.00	-	-2.15	-0.26	-1.23	0.12
Ardabil	-3.38	0.60	0.01	0.01	-0.69	-0.51	-0.29	-0.27	-1.58	-0.21	-1.95	0.04
Boshehr	-9.84	1.94	0.00	-	-0.88	-0.92	-0.41	-0.42	0.00	-	-4.88	0.66
Chaharmahal	-3.21	0.47	-0.06	-0.34	-0.85	-0.40	-3.83	-1.72	-0.98	-0.35	-1.79	-0.06
East Azarbaijan	-6.04	0.79	3.08	-1.88	-1.37	-0.64	-8.76	1.06	-3.45	-1.82	-3.82	0.09
Elam	-3.32	0.55	0.48	-0.06	0.00	-	-0.88	-0.08	-8.94	0.17	-2.56	0.33
Esfahan	-3.76	0.03	-7.95	-2.65	-2.96	-1.22	-5.03	-0.30	-0.05	0.37	-3.16	-0.64
Fars	-2.41	0.25	14.92	-6.21	-0.39	-1.30	1.34	-1.46	1.68	-1.02	-0.56	-0.70
Gilan	-1.09	0.24	0.06	-0.15	-0.20	-0.55	-0.16	-0.26	0.00	-	-0.49	-0.09
Golestan	-3.47	0.75	-26.26	-4.73	-11.63	1.90	7.45	-2.94	-9.91	0.37	-4.91	0.87
Hamedan	-2.55	0.43	-2.51	-2.87	-0.69	-0.70	-0.91	-0.84	-0.57	-0.29	-1.35	-0.27
Hormozgan	-0.54	1.44	0.00	-	-1.15	-1.35	-0.82	-0.82	2.85	-29.57	-1.02	-1.01
Kohkiloyeh	-5.89	0.37	-5.21	-0.44	-19.72	-1.93	-11.91	-0.96	0.00	-	-7.10	0.10
Kerman	-1.79	0.32	-4.01	-1.72	-0.62	-0.28	-0.24	-0.44	-3.00	-0.07	-1.25	0.03
Kordestan	-1.77	0.35	-1.66	-1.20	-1.44	-1.44	-0.43	-0.40	0.36	-0.81	-1.54	-0.26
Kermanshah	-2.57	1.06	-2.14	-1.05	1.36	-6.03	0.00	-	-0.77	0.07	-1.22	-0.91
Khouzestan	-1.85	0.37	1.12	0.97	-1.25	-1.07	-0.63	-0.34	-1.51	-0.48	-1.49	-0.12
Lorestan	-2.73	0.50	-2.50	-2.68	-0.41	-0.35	-0.30	-0.27	-0.50	-0.25	-1.52	-0.05
Markazi	-2.22	0.39	-3.36	-3.87	-0.19	-0.17	0.00		-1.96	-0.17	-1.90	0.26
Mazandaran	-1.83	0.30	0.00	0.00	-5.79	0.13	-31.25	3.76	-1.90	0.04	-2.67	0.38
North Khorasan	-5.40	0.44	0.77	-0.73	-2.00	-2.06	6.79	-1.44	-5.03	-1.38	-4.13	-0.66
Qom	-0.84	0.16	0.00	-	0.00	-	0.00	-	0.09	-0.10	-0.79	0.15
Qazvin	-11.04	-0.73	4.07	-1.15	-8.76	-1.33	-19.09	-1.00	-16.72	-2.02	-10.41	-1.15
Razavi Khorasan	-4.60	1.45	-4.89	-5.55	-1.18	-4.06	-1.98	-4.77	-1.16	-1.46	-2.40	-1.46
Sistan	-5.66	1.19	-1.00	-1.69	-0.50	-0.70	-0.16	-0.36	-1.23	-2.31	-1.54	-0.05
South Khorasan	-3.98	1.23	1.76	-8.69	-6.08	-5.57	-1.06	-1.04	-0.51	-0.18	-2.53	0.16
Semnan	-2.28	0.46	-0.70	-0.32	-0.41	-0.49	-0.13	0.22	-0.31	-0.39	-0.97	-0.06
Tehran	-1.34	0.20	0.00	-	-0.40	-0.21	-0.25	-0.06	0.00	-	-0.91	0.03
West Azarbaijan	-3.47	0.62	-2.74	-3.08	-0.68	-0.62	-0.61	-0.30	-0.43	-0.29	-1.23	-0.13
Yazd	-1.27	0.33	0.00	-	-2.50	-2.57	-0.10	-0.26	0.00	-	-1.37	-0.59
Zanjan	-3.21	0.19	-0.56	-1.29	-2.24	-1.46	-1.85	-1.16	-4.09	-1.74	-2.53	-0.84
National	**-3.22**	**0.53**	**-0.97**	**-1.92**	**-1.83**	**-1.37**	**-0.87**	**-0.90**	**-0.91**	**-0.60**	**-2.61**	**-0.12**

Source: Model results.

Appendix Table A3. Regional agricultural income changes under ABOL and TARG scenarios (% change relative to baseline).

Region/Crop	Cereals		Legumes		Vegetables		Fruit		Industrial crops		Total	
	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG	ABOL	TARG
Alborz	-0.61	0.10	-	-	-12.95	-11.00	-	-	0.14	0.07	-0.60	0.06
Ardabil	-0.27	0.05	-0.03	-	-0.42	-0.40	-0.22	-0.20	-0.27	-0.24	-0.44	-0.02
Boshehr	-1.23	0.33	-	-	-1.01	-0.95	-0.42	-0.34	-	-	-0.29	-0.01
Chaharmahal	-0.30	0.10	-0.27	-0.06	-0.46	-0.38	0.05	0.04	-0.34	-0.25	-0.56	-0.02
East Azarbaijan	-0.12	-0.06	-0.06	-0.02	-0.63	-0.60	0.11	0.11	0.55	0.50	-0.40	-0.01
Elam	-0.34	0.08	-0.08	0.02	-	0.00	-0.22	-0.18	0.07	0.06	-0.49	0.06
Esfahan	5.19	-0.48	-29.76	-2.77	-3.28	-2.00	-1.45	-0.69	-0.68	-0.24	-1.43	-0.09
Fars	14.64	-23.26	-9.76	2.40	-1.69	-1.14	-0.78	-0.47	-0.69	-0.29	-1.57	-0.10
Gilan	-0.59	0.09	-0.55	0.05	-0.13	0.01	-0.75	-0.51	-	-	-0.66	-0.02
Golestan	-30.67	5.72	0.05	-	-0.48	-0.37	0.64	0.54	-2.97	0.64	-4.83	0.64
Hamedan	-0.56	0.07	-0.26	0.02	-0.84	-0.73	-0.40	-0.32	-0.35	-0.26	-0.52	-0.08
Hormozgan	-3.16	-1.78	-	-	-3.73	-3.43	-3.08	-2.67	-1.42	-1.17	-4.15	-3.65
Kohkiloyeh	-3.14	0.32	1.46	0.10	0.42	0.38	10.43	8.14	-	-	-1.58	0.22
Kerman	-0.86	0.16	-	-14.27	-0.53	-0.41	-0.15	-0.11	2.24	0.89	-0.69	0.04
Kordestan	-1.70	0.42	-0.13	0.03	-4.62	-4.03	-0.23	-0.15	-0.41	-0.28	-0.44	0.01
Kermanshah	-0.27	0.08	-0.14	-0.25	-0.46	-0.43	-	0.00	-0.34	-0.28	-0.35	0.02
Khouzestan	-0.53	0.04	-0.30	0.05	-0.75	-0.67	-0.26	-0.21	-0.61	-7.13	-0.67	0.01
Lorestan	-0.46	0.09	-0.11	0.02	-0.39	-0.32	-0.20	-0.14	-0.40	-0.31	-0.29	0.01
Markazi	-0.47	0.09	-0.52	0.05	-117.64	-89.64	-	-	0.11	0.07	-0.62	0.09
Mazandaran	0.37	-0.27	-	-	0.22	0.08	0.16	0.05	-4.00	-0.11	-2.03	0.38
North Khorasan	-0.41	0.18	-0.32	0.06	-2.53	-2.09	-0.40	-0.23	-1.14	-0.62	-0.80	0.02
Qom	-0.49	0.09	-	-	-	-	-	-	2.58	0.89	-0.47	0.07
Qazvin	0.36	0.20	-0.33	-	-1.02	-0.88	-0.32	-0.18	-0.45	-0.30	-1.08	-0.02
Razavi Khorasan	-0.69	-0.04	-0.38	-0.19	-15.75	-14.54	2.26	2.33	-0.93	-0.73	-0.70	-0.08
Sistan	0.70	-0.05	-1.54	-0.52	-1.26	-0.84	-0.45	-0.23	-0.79	-0.28	-1.53	-0.28
South Khorasan	-1.01	-0.05	-22.51	-20.38	-0.31	-0.29	-3.56	-2.27	-0.55	-0.52	-0.90	-0.08
Semnan	-0.83	0.15	-0.28	0.03	-0.52	-0.32	-0.30	-0.12	-0.39	-0.15	-0.85	-0.01
Tehran	-0.71	0.10	-	-	-0.60	-0.41	-0.24	-0.12	-	-	-0.72	0.04
West Azarbaijan	-0.85	0.13	0.51	-0.07	-0.55	-0.52	-0.26	-0.23	-0.23	-0.20	-0.38	-0.03
Yazd	-1.12	0.03	-	-	-3.34	-2.78	-1.19	-0.82	-	-	-1.49	-0.20
Zanjan	-1.94	-0.02	-0.08	0.01	-0.65	-0.60	-0.27	-0.22	-0.34	-0.28	-0.50	-0.03
National	**0.49**	**-0.02**	**0.30**	**-0.01**	**-0.90**	**-1.02**	**2.33**	**-**	**0.18**	**0.12**	**-076**	**-0.01**

Source: Model results.

Appendix Table A4. Regional agricultural cultivated area (1000 ha) and production (1000 T).

Region/Crop	Cereals		Legumes		Vegetables		Fruit		Industrial crops		Total	
	Area	Prod	Area	Prod	Area	Prod	Area	Prod	Area	Prod	Area	Prod
Alborz	18.96	85.65	-	-	0.64	21.30	-	-	0.39	1.06	20.01	108.02
Ardabil	469.41	863.32	33.16	19.42	25.61	840.94	2.48	77.50	7.43	15.70	538.11	1816.90
Boshehr	121.69	125.82	-	-	0.79	18.31	3.14	123.35	-	-	125.64	267.49
Chaharmahal	94.8	173.49	2.78	2.44	6.15	219.08	0.03	1.29	1.2	47.69	104.98	444.02
East Azarbaijan	510.51	828.19	58.51	36.87	19.26	741.71	2.45	47.21	1.97	2.98	592.72	1656.98
Elam	195.78	376.31	9.86	6.48	0	0.00	7.12	190.12	3.55	8.28	216.32	581.20
Esfahan	138.94	466.83	3.18	1.90	18.76	696.11	1.8	52.41	3.9	80.13	166.6	1297.41
Fars	536.92	1706.22	9.51	8.20	29.87	1327.49	18.48	733.72	27.5	620.26	622.31	4395.91
Gilan	16.77	21.08	0.82	0.57	0.05	1.16	1.64	35.66	-	-	19.3	58.48
Golestan	529.17	1583.54	0.78	0.66	12.62	393.84	6.62	49.78	24.1	44.58	573.31	2072.42
Hamedan	490.24	841.32	20.84	10.64	29.25	1110.40	4.41	143.18	8.59	305.26	553.35	2410.82
Hormozgan	18.54	81.69	-	-	24.66	719.85	12.11	250.88	0.18	0.10	55.51	1052.53
Kohkiloyeh	155.67	221.24	6.4	5.68	0.24	4.98	1.44	44.77	-	-	163.78	276.68
Kerman	79.96	325.08	0.88	1.15	3.43	101.87	4.28	122.91	1.74	3.47	90.31	554.50
Kordestan	603.16	831.53	98.28	30.30	11.87	374.73	2.4	45.87	1.57	53.26	717.29	1335.71
Kermanshah	603.46	1264.86	135.54	60.41	11.91	592.79	0	0.00	14.27	549.71	765.19	2467.78
Khouzestan	628.27	1975.09	1.1	0.77	23.52	776.63	21.4	599.42	15.56	263.93	689.87	3615.86
Lorestan	363.75	619.61	110.34	64.58	7.58	227.68	11.33	264.32	6.51	242.27	499.52	1418.47
Markazi	258.48	539.49	8.04	3.61	3.71	104.73	-	-	1.47	26.48	271.71	674.32
Mazandaran	309.01	1418.05	0	0.00	1.92	43.55	1.52	37.15	4.74	6.31	317.21	1505.07
North Khorasan	211.6	354.23	13.98	6.76	6.37	207.13	0.57	8.19	10.04	125.75	242.58	702.09
Qom	31.76	104.67	-	-	-	-	-	-	2.19	5.11	33.95	109.79
Qazvin	200.95	493.04	7.55	3.56	12.56	669.46	1.16	25.01	4.27	99.98	226.51	1291.06
Razavi Khorasan	477.59	1069.87	9.81	3.44	22.8	823.85	15.28	290.13	45.59	994.63	571.1	3181.95
Sistan	105.9	236.45	0.43	0.47	6.73	172.76	22.98	573.91	1.27	1.83	137.32	985.43
South Khorasan	43.17	103.39	0.08	0.02	0.33	5.64	3.71	52.41	9.1	46.74	56.41	208.22
Semnan	56.08	149.93	1.47	0.65	5.1	120.91	2.33	59.94	4.75	119.35	69.75	450.81
Tehran	77.35	310.64	-	-	5.28	200.21	2.04	50.08	0	0.00	84.68	560.94
West Azarbaijan	426.04	739.55	68.44	34.19	9.52	317.49	2.37	65.32	30.4	1873.51	536.79	3030.09
Yazd	20.95	68.39	-	-	0.93	36.57	0.99	27.51	-	-	22.88	132.48
Zanjan	344.96	407.51	25.24	8.50	15.77	594.95	4.4	135.16	0.35	0.33	390.74	1146.48
National	8139.84	18386.08	627.02	311.27	317.23	11466.12	158.48	4107.2	232.63	5539	9475.75	39809.91

Source: ICTC- IMAJ. Three-years average around 2015 (2014, 2015 and 2016).

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Land tenure and property rights, and the impacts on adoption of climate-smart practices among smallholder farmers in selected agro-ecologies in Nigeria

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Abstract. This study investigates the effects of land tenure and property rights (LTPRs) on smallholder farmers' adoption of climate-smart practices (CSPs) among cereal farming households in Nigeria. The data were collected from maize and rice farmers in a Nation-wide Farm Household Survey conducted across the six geopolitical zones in Nigeria. Data collected were analysed within the framework of Multivariate Probit to determine the factors that facilitate and/or impede the adoption of CSPs. The results showed that the adoption of CSPs considered in this study – agroforestry, zero/minimum tillage, farmyard manure, crop rotation and residue retention - were generally low. Empirical analysis showed that farmers with transfer right were more likely to adopt farmyard manure, crop rotation and residue retention while the likelihood of adopting agroforestry reduced with having transfer right. The coefficient of *de jure* secure increased the likelihood of adopting zero/minimum tillage while the coefficient of control right increased the likelihood of adopting agroforestry. Again, we found that the adoption of zero/minimum tillage reduced with control and transfer rights. The study also contributes to the existing literature on adoption by recognizing the interdependence between different climate-smart practices as well as jointly analyse the decision to adopt multiple CSPs. The study therefore, suggests that governments, in whom the responsibility for land use policy reform lies, review the existing framework to ensure a prompt, fair, and efficient land tenure system.

Keywords: climate-smart practices, Land Tenure and property rights, multivariate probit, smallholder farmers, Nigeria.
JEL codes: Q15, Q18.

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1. INTRODUCTION

Agriculture in the world especially sub-Saharan Africa (SSA) is at a crossroads simply because climate change has brought a menace to the agricultural sector, which must be attended to (IPCC, 2014). Nigeria as one of the African countries is not an exemption in this issue. Climate change poses the greatest challenge to smallholder farmers and threatens the progressive efforts towards poverty alleviation, food security, and sustainable agriculture (Lipper *et al*., 2014; Vermeulen, *et al*., 2011). Globally, smallholder farming households are estimated to be between 475-500 million; cultivating less than 2ha of land (Lowder *et al*., 2016). Many of whom are living in abject poverty and on less than $2 a day, hence, experiencing food insecurity (World Bank Group, 2016; Morton, 2007). Usually, smallholder farmers are the main victims of climate change because of their sole dependency on rain-fed agriculture, limited market access, insecure access to land, cultivation of marginal and fragmented land as well as inadequate access to technical and/or economic support which can help them to embrace resilient-farming practices (Donatti *et al*., 2018; Morton, 2007).

The world's climate is changing fast and will continue to do so for the foreseeable future, no matter what measures are now taken. For agriculture, the change will also be significant, as temperatures rise, rainfall patterns change and pests and diseases find new ranges, posing new risks to agriculture and food systems (Cooper *et al*., 2013). The negative impacts of climate change have led to a reduction in agricultural productivity and substantial welfare losses which eventually lead to food and nutrition insecurity in the populace (Tripathi & Mishra, 2017). Shifting to Climate-smart Agriculture (CSA) seems to be the most efficient way for farmers to reduce the negative impacts of climate change on the production, incomes, and well-being of vulnerable smallholder farmers (McCarthy & Brubaker, 2014).

According to the Food and Agricultural Organization of the United Nations (FAO, 2013), CSA is an unconventional approach to manage land in a sustainable manner while increasing agricultural productivity (World Bank, 2011). It is aimed to achieve three key goals - sustainably increasing agricultural productivity and incomes; adapting and building resilience to climate change; reducing and/or removing greenhouse gases emissions, where possible (Braimoh, 2015). Climate-smart Practices (CSPs) include inter-cropping, crop rotation, zero tillage, green manuring, application of farmyard manure, integrated soil fertility management, agroforestry, irrigation, changing planting dates as well as alternate wet and dry lowland rice production systems (Bernier *et al*., 2015).

Despite this potential, adoption of CSPs remains generally low, particularly in SSA, Nigeria inclusive. This may, however, not be unconnected with insecure land tenure and property rights (LTPRs), which is often cited as one of the barriers to the adoption of improved technology and investment in land development in Africa (Shittu *et al*., 2021; Byamugisha, 2013; Liniger *et al*., 2011). It is pertinent to note that without secure property rights, farmers often do not have the emotional attachment to the land they cultivate and would thus, not invest in land improvement that can enhance their productivity in the long run and promote sustainable development (Deininger, 2003).

Empirical evidence from the literature corroborates the earlier assertion that adoption of CSPs are generally low in Nigeria, usually between 15.5% – 40.6% (Shittu *et al*., 2018) while the adoption rate for water harvesting, irrigation, and terraces are 15%, 10%, and 30% respectively (Onyeneke *et al*., 2018). They attributed the low adoption to a very weak agricultural extension service delivery system across various states in Nigeria and also to the need for more capital, lack of technical know-how, low potential for irrigation and most importantly present markets cannot accurately account for the value of the environmental benefits that CSA delivers (Ahiale *et al*., 2020; Shittu *et al*., 2018). Gleaning through the literature, some of the factors driving the adoption of the CSPs among smallholders in Nigeria include education, income, credit, extension services, livestock ownership, farming experience, farm size, distance to market and water resources, gender, land ownership, household size, and mass media exposure among others (Oyawole *et al*., 2020; Amadu *et al*; 2020; Aryal et al., 2018).

Arising from the foregoing, using smallholder farmers in selected rice ecologies of Nigeria as a case study, this paper[1] will build on the recent work of Shittu *et al*., (2018) by assessing the influence of LTPRs on the adoption of CSPs. We used multivariate probit (MVP) regression analysis, which explicitly allows for correlation in the error terms of the adoption equations to control for interdependence in decisions on CSPs' adoption. The paper contributes to the ongoing debates on LTPRs and the adoption of CSPs in Africa's smallholder agriculture in a number of ways. First, technology adoption remains one of the most researched areas in the field of agricultural

[1] An earlier version of this paper, titled 'Land Tenure and Property Rights Impacts on Adoption of Climate Smart Practices among Cereals Farmers in Nigeria', was presented at the 18th Annual National Conference of Nigerian Association of Agricultural Economists, October 16th – 19th, 2017.

Table 1. Kinds of rights and tenure security by mode of land acquisition.

Mode of land acquisition	Use right	Control Right	Transfer right	*De facto* Secure	*De jure* secure
Freehold (Inherited & Purchased	√	√	√	√	×
Communal	√	√	×	√	×
Leasehold	√	√	×	×	×

economics, very few studies have looked at the factors that determine the adoption of CSPs in Nigeria. Second, methods that recognise the interdependence between different climate-smart practices and jointly analyse the decision to adopt multiple CSPs - agroforestry, farmyard manure, crop rotation, zero tillage, and residue retention are used. This study attempts to fill these identified gaps.

In the next section, we describe the theoretical framework underpinning the adoption of CSPs and the econometric approach of multivariate probit. Section three (3) presents the methodology in which we have the study area, research design as well as measurement of land tenure and property rights. In section four, we present and discuss the results, while the final section presents the main conclusions and the policy implications.

1.1 Brief on land tenure and property rights in Nigeria

LTPRs have to do with the rights that individuals, communities, families, firms, and other community structures hold in land and associated natural resources. As noted by Feder and Feeny (1991), the rights on the land are "either *de facto* or *de jure* secure" if they are clearly defined, exclusive, enforceable, transferable, and recognized by relevant authorities. In Nigeria, the land use act made provision for granting two types of land use rights - customary and statutory rights of occupancy - to all categories of land users (Land Use Act [LUA], 2004). Customary right of occupancy is granted under the Act by the local government councils to individuals, firms, and communities while the Statutory right of occupancy is the right to use land in any part of the state and it is granted under the Act by the State Governor (LUA, 2004; Kehinde *et al*., 2021). A certificate of occupancy is issued to a land user as evidence of being granted the statutory right of occupancy on the land by the State Governor, thus making the certificate of occupancy the highest form of land title in Nigeria. Issuance of certificate of occupancy requires that the landowner possesses a purchase receipt, duly stamped deed of transfer, and an approved boundary survey of the land. The customary rights of occupancy are governed by the largely unwritten customary laws in various localities and are also considered *de facto* held by holders of agricultural lands in rural areas that have been under use for agricultural purposes prior to the enactment of the Land Use Act of 1979 (LUA, 2004; Shittu *et al*., 2018).

Shittu *et al*. (2018) show that when the land has not been issued a certificate of occupancy, it is subject to unfair expropriation, though the LUA made everybody an occupant of the land. Landowners that acquired their land through direct inheritance and outright purchase enjoy customary rights on their land even though that title is not officially certificated but they are recognized as having a secure title on their land from the customary point of view. Both the latter and the former will enjoy statutory rights of occupancy when the *de facto*-held land is moved to the highest level of tenure security (*de jure* secure) by getting the land surveyed, registered with the state government, and possibly obtain the certificate of occupancy. It is important to note that freehold land is still susceptible to unfair expropriation if it is not registered with the government. Table 1 shows the different land tenure types, possible types of rights with their level of tenure security.

2. ANALYTICAL FRAMEWORK

2.1 Multivariate Probit Model

Multivariate probit regression framework was used to analyze the factors that facilitate or impede the adoption of CSPs, following Scognamillo and Sitko, (2021), Aryal et al., (2018), Kpadonou *et al*., (2017), Timu *et al*., (2013), and Teklewold *et al*., (2013). The model is an extension of the probit model used for the estimation of several correlated binary choices jointly (Greene, 2003).

Considering several agricultural technologies, there is the possibility that some level of interdependence may exist among the technologies with farmers adopting some of these technologies as substitutes, complements or supplements. A farming household would be adopting one or more of the components of CSPs if and only if the utility expected is higher than otherwise. A positive correlation of the error terms means the technologies are complements while negative correlations of the errors terms imply the technologies are substitutes (Teklewood *et al*., 2013; Belderbos *et al*., 2004).

If a correlation exists, simply estimating the technology adoption equations independently will generate biased and inefficient estimates of the standard errors of the model parameters for each technology (Greene 2008), inducing incorrect inference as to the determinants of technology adoption. Dorfamn (1996) observed that the estimates of separate probit equations (univariate probit) exclude useful economic information contained in interdependence and simultaneous adoption decisions. Hence, when farmers adopt a combination of technologies to deal with land degradation rather than adopting just a single practice or technology, the adoption decision is inherently multivariate. Hence, the MVP estimator corrects for these problems by allowing for non-zero covariance in adoption across technologies.

Thus, the observed outcome of CSPs adoption can be modelled following a random utility-based estimation framework. Consider the i_{th} farm household $i=(1,\ldots,N)$ facing a decision on whether to adopt the available CSPs on plot $p(p=1,\ldots,P)$.

Let U_0 represent the benefits to the farmer from traditional management practices, and let U_k represent the benefit of adopting the k_{th} CSPs: *vis-a-vis*, agroforestry (AG), farmyard manure (FY), crop rotation (CR), zero tillage (ZT), residue retention (RR). The farmer decides to adopt the k_{th} CSPs on plot p if $Y^*_{ipk}=U^*_k-U_0>0$.

The net benefit (Y^*_{ipk}) that the farmer derives from the adoption of k_{th} CSPs is a latent variable determined by observed household, plot (Z_{ip}) and socio-economic characteristics X_i and the error term ε_{ip}:

$$Y^*_{ipk}=Z'_{ip}\delta_k+X'_i\beta_i+\varepsilon_{ip} \quad (k=AF,FY,CR,ZT,RR) \tag{1}$$

Using the indicator function, the unobserved preferences in equation (1) translate into the observed binary outcome equation for each choice as follows:

$$Y_{ipk}=\begin{cases}1\ if\ Y^*_{ipk}>0\\ 0\ otherwise\end{cases} \quad (k=AF,FY,CR,ZT,RR) \tag{2}$$

Equation 1 can be rewritten as a system of equations that can be estimated simultaneously using equation 3;

$$\begin{array}{ll} Y^*_{1pk}=\beta'_1X_{1i}+Z'_{1i}\delta_k+\varepsilon_{1i} & Y_{1pk}=1\ if\ Y^*_{1pk}>0,\ Y_{1pk}=0\ otherwise \\ Y^*_{2pk}=\beta'_2X_{2i}+Z'_{2i}\delta_k+\varepsilon_{2i} & Y_{2pk}=1\ if\ Y^*_{2pk}>0,\ Y_{2pk}=0\ otherwise \\ & \vdots \\ Y^*_{Npk}=\beta'_kX_{ki}+Z'_{ki}\delta_k+\varepsilon_{ki} & Y_{Npk}=1\ if\ Y^*_{Npk}>0,\ Y_{Npk}=0\ otherwise \end{array} \tag{3}$$

In the multivariate model, where the adoption of several CSPs is possible, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters) where ($\mu_{AF},\mu_{FY},\mu_{CR},\mu_{ZT},\mu_{RR}$), MVN $(0,\Omega)$ and the symmetric covariance matrix Ω is given by:

$$\Omega=\begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1k} \\ \rho_{12} & 1 & \rho_{23} & \cdots & \rho_{2k} \\ \rho_{13} & \rho_{23} & 1 & \cdots & \rho_{3k} \\ \vdots & \vdots & \vdots & 1 & \rho_{4k} \\ \rho_{1k} & \rho_{2k} & \rho_{3k} & \cdots & 1 \end{bmatrix} \tag{4}$$

The off-diagonal elements in the covariance matrix represent the unobserved correlation between the stochastic components of the different types of CSPs. This assumption means that equation (2) generates a MVP model that jointly represents decisions to adopt farming practices. This specification with non-zero off-diagonal elements allows for correlation across the error terms of several latent equations, which represent unobserved characteristics that affect the choice of alternative CSPs[2].

The computation of the maximum likelihood function based on a multivariate normal distribution requires multidimensional integration. Different simulation methods were proposed to approximate such a function (Train, 2002). The Geweke–Hajivassiliou–Keane (GHK) simulator is a particularly popular choice in empirical research (Geweke *et al*., 1997). The GHK simulator exploits the fact that a multivariate normal distribution function can be expressed as the product of sequentially conditioned univariate normal distribution functions, which can be accurately evaluated (Cappellari and Jenkins, 2003). The GHK simulator relies on a Cholesky factorization, and to do this, the estimate of the correlation matrix at each iteration must be positive definite.

3. METHODOLOGY

3.1 The study area

The study was conducted in selected farming communities reputed for maize and rice production across the six geopolitical zones, and covering five of the seven Agro-ecological zones (AEZs) of Nigeria, viz; rainforest zone, derived, southern Guinea, northern Guinea, and Sudan savannah zones respectively. Nigeria is situated

[2] The authors acknowledge that the correlation between the error terms in a system of simultaneous equation depend on the correct specification of the model.

in the West African region and lies between longitudes 3° and 14° and latitudes 4° and 14°. It has a landmass of 923,768 sq. km. Nigeria shares a land border with the Republic of Benin in the west, Chad and Cameroon in the east, and Niger in the north. Its coast lies on the Gulf of Guinea in the south and it borders Lake Chad to the northeast (Udo *et al*., 2018).

Administratively, it is made of 36 Federating States and the Federal Capital Territory. The States are commonly grouped into six geopolitical zones: Northeast, Northwest, North-central, Southeast, Southwest, and South-south geopolitical zones and seven Agro-ecological zones - all of which are suitable for maize and rice, among several other crops like cassava, yams, etc.

3.2 The study design

The study was part of the FUNAAB-RAAF-PASAN-AO project implemented by the Federal University of Agriculture, Abeokuta in partnership with the National Cereals Research Institute, Baddegi, and funded by the Economic Community of West African States. The central focus was on Incentivising Adoption of Climate-Smart Agricultural Practices in Cereals Production in Nigeria. The data were collected across selected agro-ecologies in Nigeria, focusing on maize and rice farmers. The respondents were selected in a three-stage sampling process, described as follows:

Stage I: Purposive selection of 15 States that have been the leading rice and maize producers in Nigeria (excluding conflict-prone areas), based on production statistics from (National Bureau of Statistics [NBS], 2016).

Stage II: Purposive selection of three Agricultural Blocks per State per crop from the main rice and maize producing areas of the State, and two Extension Cells per block - that is, six blocks per state, 12 Cells per State and 180 Cells in all.

Stage III: Proportionate stratified random selection of 12 Rice and maize farmers from members of Rice/Maize farmers' association in each of the selected Cells.

This process yielded 2,007 households of maize and rice farmers, from which complete datasets were collected through personal interviews of the farmer and other farming members of their households. Data were collected on a wide range of issues, including the households' socio-economics, climate-smart practices, and LTPRs on farmland cultivated during the 2016/17 farming season.

Table 2. Adoption rates of climate-smart practices.

Variable	Mean	Std. Error	Min	Max
Agroforestry	0.090	0.005	0	1
Farmyard manure	0.240	0.007	0	1
Crop rotation	0.080	0.005	0	1
Zero/Minimum tillage	0.220	0.007	0	1
Residue retention	0.540	0.009	0	1

3.3 Dependent variables

The outcome variables considered in this study are the CSPs. The respondents were asked to recount the type of CSPs practiced on each of their plots - agroforestry, farmyard manure, crop rotation, zero/minimum tillage, and residue retention (Table 2). Agroforestry refers to the intentional integration of trees and shrubs into crop and animal farming systems to create environmental, economic, and social benefits. The intentional nature of agroforestry made many of the sampled farmers fall short in this regard; hence, only 9% of the respondents practiced agroforestry on their farms.

Farmyard manure, on the other hand, refers to the application of a decomposed mixture of livestock waste on the farming plot. It is a major component of nutrient management with potential benefits of soil fertility maintenance as well as supply of major nutrients such as Nitrogen, Phosphates, and Potash. Out of the total plots, about 24% of these plots received manure.

Crop rotation involves growing different crops sequentially on the same plot of land to optimize nutrients and reduces the incidence of weeds, pests, and diseases (Bockel *et al*., 2013). In our case, any farmer that plants different crops following a particular sequence and includes a leguminous crop in the rotation was considered as having practiced crop rotation. Based on this concept, only a few of the farmers (8%) practiced crop rotation on their farms.

Zero/minimum tillage is part of CSPs that promotes minimum soil disturbance and allows crop residue to remain on the ground with the accompanying benefits of better soil aeration and improved soil fertility. Minimum soil disturbance requires less traction power and fewer carbon emissions from the soil (Delgado *et al*., 2011). In our case, zero/minimum tillage practice entails reduced tillage with a single plough and/or the use of traditional farm tools such as hoe and cutlass. Zero/minimum tillage was practiced on 22% of the plots.

The use of residue retention is another option of CSPs that provides an opportunity for the farmers to retain crop residues as an alternative to biomass burning and/or exporting the residues from the farm to feed livestock (Bockel *et al*., 2013; Abrol *et al*., 2017). Residue retention was practiced on about 54% of the plots during the cropping season considered for this analysis.

3.4 Independent variables

The description and the summary statistics of the variables are given in Table 3. Specifically, the models include socio-demographic characteristics such as age, sex, year of schooling, household size, extension contact, farmers' association among others.

3.4.1 Socio-demographic characteristics

With respect to socio-demographic characteristics, Table 3 shows that the average age of the smallholder farmers across the six geopolitical zones is 45 years. This implies that the majority of the respondents were still in their active years implying significant participation in the farming activities. This result, however, contradicts the findings of Eze *et al*., (2011) who did a similar study and obtained the mean age of his respondent to be 59 years. Only 12% of the respondents were female indicating that the majority of the sampled smallholder farmers were male. The mean year of schooling is 8 years while those that had access to extension services and belong to one farmers' association or the other were 63% and 94% respectively.

As shown in Table 3, about two-thirds (60.0%) of the respondents have the right to control their land while about 58.0% have the right to transfer their parcels permanently to the third party across the study locations. Table 3 further shows that about half (52.0%) of the parcels were held as inheritance across the study locations, however, this result is much less than the findings of Bamire (2010) who found that 84.0% of farmland was acquired through inheritance in the dry savannah part of Nigeria. On the contrary, about 14.0% of the parcels were purchased by the farm households, 24.0% on leasehold while 10.0% were communal land while only 4.0% of the farmland were titled, i.e., registered with the land registry in the study area. This implies that only a few out of the sampled farmers had legal tenure security while the majority had insecure tenure (*de jure*) which can lead to eviction from their

Table 3. Definitions and Summary Statistics of the Variables Used in the Analysis.

Variable	Description	Mean	SEM
Socio-economic characteristics			
Age	Age of the farmers in years	44.58	0.21
Sex	1 = if the sex of the farmer is female, 0 otherwise	0.12	0.01
Schooling year	Farmers' education level in years	7.74	0.10
Household size	Number of persons in the household	9.25	0.11
Extension Contact	1 = Extension Contact during the last planting season	0.63	0.01
Amount Borrowed	Amount of money borrowed in naira.	99633	11200
Farmers' association	1 = belong to farmers' association, otherwise 0	0.94	0.02
TLU	Tropical livestock unit (Livestock wealth)[1]	3.28	0.23
Plot-level characteristics			
Control right	1 = has control right, 0 otherwise	0.60	0.008
Transfer right	1 = has transfer right, 0 otherwise	0.58	0.008
De jure secure	1 = if registered with the state, 0 otherwise	0.02	0.002
Inherited	1 = cultivates land acquisition by inheritance, 0 otherwise	0.52	0.008
Purchased	1 = land acquisition by purchase, 0 otherwise	0.14	0.01
Leasehold	1 = Land acquisition by leasehold, 0 otherwise	0.24	0.01
Communal	1 = Land acquisition by communal means, 0 otherwise	0.10	0.01
Boundary survey	1 = Has boundary survey, 0 otherwise	0.18	0.007
Farm size (ha)	Cultivated farmland in ha	1.60	0.04
Lowland	1 = cultivates lowland, otherwise 0	0.42	0.01
Extent of farm fragmentation	The extent of land fragmentation computed using Simpson index	0.35	0.01

Note: SEM (Standard error of mean).
[1] TLU conversion factor according to Beyene and Muche (2010): 1 head of cattle = 0.7 TLU, 0.1 TLU for 1 sheep or goat or pigs and 0.01 TLU for poultry.

farmland and regular harassment by land grabbers. A plausible reason for this is that the process of titling land is inexplicably tedious and expensive. Thus, given that most farmers in Nigeria are smallholders and resource poor, they may not allocate their scarce financial resources to land titling. The mean size of household landholdings was 1.60ha portraying the respondents as smallholders. The average farmland that is fragmented is 35% implying that about one-third of the cultivated farmland in Nigeria is not completely consolidated.

3.4.2 LTPRs' measurement

Two indicators were employed in assessing the LTPRs of farmers in this study. They include:

i. Rights Type: This was measured on a nominal scale using three dummy variables – Use, Control, and Transfer rights. Use right refers to the right to access the resource, withdraw from a resource or exploit a resource for economic benefit. Control right on the other hand refers to the ability to make decisions on how the land should be used including deciding what crops should be planted, and who benefits financially from the sale of crops, etc. while Transfer right refers to the ability to transfer land (permanently through sale). Each of the types of rights takes the value of one if the farmer has the right to use, control, and transfer the parcel of land. Otherwise, the dummy variables were assigned a zero. Meanwhile, the use right was dropped as the reference rights-type variable.
ii. *De jure* secure: A tenure was classified as *de jure* secure if the parcel has been surveyed and duly registered with the land registry; otherwise it was classified as insecure. This variable was meant to determine the importance of title registration.

4. RESULTS AND DISCUSSION

4.1 Determinants of adoption of climate-smart agricultural practices

The estimates of the determinants of the probability of adoption of climate-smart agricultural practices are presented in Table 4. The Wald test ($\chi2$ (70) = 404.66; Prob > $\chi2$ = 0.0000) of the hypothesis that regression coefficients in all the equations were jointly equal to zero was rejected at 1% indicating that the model fits the data reasonably well.

The coefficient of transfer right is positive and significant at 1%, 5%, and 10% levels respectively for the adoption of farmyard manure, crop rotation, and residue retention. Hence, transfer right has positive impact on the adoption of farmyard manure, crop rotation, and residue retention, suggesting that farmers are more likely to adopt these CSPs on owned plots. This is in line with the Marshallian inefficiency hypothesis where input use by the tenant on rented or borrowed land is lower or less efficient than on owned land (Gray and Kevane, 2001). This finding may also be due to tenure insecurity, as an insecure tenure status leads to poor agricultural practices (Gray and Kevane, 2001). The long-term dimension of the return on investment in land-enhancing practices such as farmyard manure may discourage land-insecure farmers to adopt them as they may not control the land long enough to reap the benefits of their investments.

Similarly, the coefficient of control right is positive and significant at 10% level for agroforestry, implying that the likelihood of adopting agroforestry rises with farmers' having control right. On the contrary, the coefficient of transfer right is negative and significant at 10% for agroforestry. This implies that having transfer rights reduce significantly the likelihood of agroforestry in the study area. The possible explanation for this might be that farmers are not interested in agroforestry because of its upfront investment that does not yield any immediate returns; they possibly prefer to dispose of the land in the nearest future at a higher price. The result is contrary to the findings of Patanayak *et al*., (2003) who found that landowners are more likely to adopt agroforestry than tenants are because the latter may be prevented from planting trees, as it is less likely that agroforestry will be adopted on insecure land.

Again, we found that the coefficients of control and transfer right significantly and negatively influence the adoption of zero/minimum tillage at 1% level. Security of land tenure, (*de jure* secure), positively and significantly affects the adoption of zero/minimum tillage implying that the probability of adoption of zero/minimum tillage is higher when ownership on land is secure. This flows from the fact that rationally, a farmer may not be willing to adopt any CSPs on land that he/she does not have secure rights to in the long run. As Arthur Young succinctly puts it in his 1792 treatise, "Give a man the secure possession of a bleak rock, and he will turn it into a garden; give him a nine years' lease of a garden, and he will convert it into a desert". This gives credence to the findings of Owombo *et al*., (2015) that secure land tenure significantly influences farmers' adoption of agricultural technology in Ondo State, Nigeria.

The coefficient of farm size is negative and significant at a 1% level for agroforestry. This means that additional hectares of land by the smallholder farmers reduced significantly the possibility of adopting agroforestry; this is simply because the target population for this study is smallholders with an average farm size of 1.60ha. It is also good to note that fragmented farmland does not reduce the adoption of zero tillage in the study area.

The level of education of the cereal farmers has a significant positive relationship with the adoption of crop rotation. This suggests that farmers with higher levels of education are more likely to adopt crop rotation. This finding is consistent with that of Langyintuo and Mekuria (2005) who assert that educated farmers are better able to process information that can enhance production and productivity in agriculture (Ali and Abdulai, 2010). On the contrary, female-headed households are less likely to adopt crop rotation when compared to their male counterparts; this might be because of the level of skill/expertise involved in planting different crops sequentially on the same plot. It is important to note that gender differentiation has no impact on the adoption of any other CSPs. The coefficient for household size is negative and significant at 5% levels for the adoption of crop rotation, suggesting that larger household size is associated with a lower probability to adopt crop rotation. This is consistent with the finding of Bekele and Drake (2003) who find the family size to have a significantly negative relation with certain adoption choices.

The coefficient of farmer's age is positive and significant at a 1% level for the adoption of zero/minimum tillage in Nigeria. This might be because of their farm experience which makes the older farmers be in a better position to adopt new agricultural practices due to their comparative advantage in terms of capital accumulated, frequency of extension contacts/visits, and creditworthiness among others (Langyintuo and Mekuria, 2003). Hence, an experienced farmer is more conscious of the benefits of soil conservation and he would go for adopting the minimum tillage technology. This finding, however, contradicts that of Adesina and Zinnah (1993) who noted that younger farmers are more amenable to change old practices than older farmers because they tend to be more aware and knowledgeable about new technologies. On the other hand, an inverse relationship exists between age and the decision to adopt residue retention among cereals farmers in Nigeria. This can be because the younger farmers are usually more willing to take risks and are likely to perceive increased profits from adoption in terms of accommodating the relative labour-intensive nature that comes with adopting residue retention as against other CSPs (Soule et al., 2000; Aryal et al., 2018; Ekboir, 2003). Hence, the greater willingness to adopt the new agricultural practices.

Meanwhile, the level of education of the cereal farmers has a significant positive relationship with the adoption of zero/minimum tillage, suggesting that farmers with higher levels of education are more likely to adopt zero/minimum tillage. This finding is consistent with that of Shiyani *et al*., (2000) who asserted that education has a positive impact on the adoption of new technology. The role of education enlightens the farming community with the importance of minimum disturbance of the soil in particular.

The adoption of zero/minimum tillage is usually known to reduce the labour required on the farm, hence for larger families where labour is sufficiently available, adoption may not bring many benefit. Hence, the *a priori* expectation is that a larger family size will be inversely related to the adoption of zero/minimum tillage.

Our finding (Table 4) shows a negative relationship between the household size and adoption of zero tillage among the cereal farmers in the study area, indicating that the more the household size, the less likely the adoption of zero/minimum tillage. This is in line with the findings of La Rovere *et al*., (2010) and Laxmi and Mishra (2007).

4.2 Adoption decisions of climate-smart agricultural practices

The MVP model is estimated using the maximum likelihood method on plot-level observations. Table 5 shows the likelihood ratio test [chi square (10) = 161.736, p = 0.000)] of the null hypothesis that the covariance of the error terms across equations is not correlated is rejected. These findings confirm the interdependence between the adoption decisions of CSPs, which may be due to complementarity or substitutability in farming practices, but also potentially, to omitted factors that affect all adoption decisions. Consequently, farmers do not decide upon a single practice to adopt; instead, the probability of adopting a practice is conditional on whether other practices have already been adopted.

The estimated correlation coefficients are statistically significant in seven of the ten pair cases, where five coefficients have negative signs and the remaining two have positive signs. The result shows that farmyard manure is complementary with crop rotation while agroforestry complements residue retention. The complementarity between manure and crop rotation contradicts the finding of Teklewold *et al*., (2013) where they found substitutability. The correlation between adoption of zero/minimum tillage and residue retention is the highest (19.64%) while that of farmyard manure and agroforestry is the least (5.32%). The negative strong correlation between residue retention, zero/minimum tillage,

Table 4. Influence of LTPRs on adoption of climate-smart practices among smallholder farmers: multivariate probit estimates.

	Agroforestry		Farmyard manure		Crop rotation		Zero tillage		Residue retention	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Control right	0.1277*	0.0738	0.0207	0.0576	-0.0134	0.0765	-0.3654***	0.0583	-0.0507	0.0521
Transfer right	-0.1220*	0.0723	0.1839***	0.0573	0.1532**	0.0765	-0.5192***	0.0583	0.0991*	0.0516
Dejure secure	-0.0729	0.2186	-0.2341	0.1780	-0.3115	0.2709	0.3153*	0.1636	0.1504	0.1523
Age	-0.0005	0.0026	0.0014	0.0021	0.0019	0.0028	0.0065***	0.0021	-0.0051***	0.0018
Sex	-0.0517	0.0967	-0.1080	0.0771	-0.2045*	0.1134	0.0817	0.0778	-0.0025	0.0682
Schooling year	-0.0062	0.0053	-0.0075*	0.0041	0.0119**	0.0056	0.0075*	0.0044	-0.0038	0.0038
Household size	-0.0036	0.0048	0.0046	0.0036	-0.0130**	0.0055	-0.0247***	0.0044	0.0045	0.0034
Amount borrowed	-3.39E-08	8.31E-08	-4.84E-08	5.39E-08	3.23E-08	4.73E-08	2.31E-08	5.05E-08	2.88E-08	4.15E-08
Farmers association	0.0111	0.0214	0.0223	0.0166	0.0086	0.0223	-0.0016	0.0182	0.0018	0.0154
Extension contact	-0.0391	0.0638	0.0457	0.0506	0.0071	0.0681	-0.1776***	0.0526	0.0408	0.0456
TLU	-0.0039	0.0046	0.0004	0.0021	0.0037	0.0023	-0.0039	0.0030	-0.0022	0.0020
Farm size	-0.0118***	0.0045	-8.2E-05	0.0027	0.0005	0.0036	-0.0024	0.0029	-0.0017	0.0025
Extent of land fragmentation	-0.0218	0.1085	-0.1780**	0.0834	0.1681	0.1123	0.4113***	0.0885	0.0070	0.0755
Lowland	-0.0147	0.0636	0.0705	0.0496	0.0465	0.0671	-0.0177	0.0528	0.1260***	0.0451
Constant	-1.1136*	0.1594	-0.8917***	0.1250	-1.6749***	0.1722	-0.4639***	0.1298	0.2095*	0.1126
Wald chi-square (70)	404.66		404.66		404.66		404.66	0.0583	404.66	
Log-likelihood	-7452.52		-7452.52		-7452.52		-7452.52		-7452.52	
Prob > chi2	0		0		0		0		0	
Number of obs.	3,311		3,311		3,311		3,311		3,311	

Table 5. Results of the Wald Test of Simultaneity of the decisions to adopt CSPs.

Error correlation[1]	Coefficient	p - value
rho21 (Farmyard manure & Agroforestry)	-0.0532	0.064
rho31 (Crop rotation & Agroforestry)	0.0015	0.969
rho41 (Zero/minimum tillage & Agroforestry)	-0.0747	0.011
rho51 (Residue retention & Agroforestry)	0.1694	0
rho32 (Crop rotation & Farmyard manure)	0.0814	0.047
rho42 (Zero/minimum tillage & Farmyard manure)	-0.1897	0
rho52 (Residue retention & Farmyard manure)	-0.0922	0.001
rho43 (Zero/minimum tillage & Crop rotation)	0.0493	0.192
rho53 (Residue retention & Crop rotation)	0.0346	0.307
rho54 (Residue retention & Zero/minimum tillage)	-0.1964	0

1 Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 =rho43 = rho53 = rho54 = 0.00
Chi-square (10) = 161.736
Prob > chi square = 0

and farmyard manure is logical as the use of one CSP can discourage the adoption of the other one. These findings suggest that using ordinary probit or logit regression to assess the determinants of CSPs adoption among smallholder farmers in Nigeria will yield inefficient estimates. We, however, estimated the model by a set of probit regression (Appendix 1), the result of which shows that the evidence from our study are robust to estimation methods. Though, one will expect that separate probit regression analysis will yield large standard error but we found that the coefficients (βs) and standard errors resulting from each probit regression analysis are the same or nearly the same as that of the multivariate probit estimate. Hence, we conclude that using ordinary probit to assess the determinants of CSPs adoption among smallholder farmers is consistent and asymptotically efficient with large sample (3,311).

5. CONCLUSIONS AND POLICY IMPLICATIONS

This study was carried out to assess the effects of LTPRs on farmers' adoption of climate-smart practices among smallholder farmers in Nigeria. A multi-stage sampling procedure was used to sample 2,007 farm households across 180 farming communities in Nigeria, and data collected were analysed within the framework of Multivariate Probit regression. The results showed that the adoption of CSPs considered in this study – agroforestry, zero/minimum tillage, farmyard manure, crop rotation, and residue retention – were generally low. Policymakers thus need to target practices with lower adoption rates and provide farmers with further incentives towards the intensification of their use.

Another major highlight of this paper is the apparent existence of complementarities between different CSPs such as the use of farmyard manure and crop rotation, use of residue retention, and agroforestry. A potential strategy could be to promote agricultural practices that show some degree of complementarity as a package rather than independently. This may reduce the time required between when the farmer adopts the first technology and the subsequent adoption of other technologies and hence realising the full and extensive benefits of CSPs as a package.

The effects of transfer right on the adoption of farmyard manure, crop rotation, and residue retention are crucial in targeting those farmers that have appropriate socio-cultural characteristics that favour the adoption of the CSPs in question. Secondly, awareness and promotional strategies should be tailored depending on whether the target farmers resemble factors for/against adoption. Our findings confirm that tenure security will increase the likelihood that farmers will reap the returns from the long-term investments such as zero/minimum tillage without unfair expropriation. Therefore, policy measures that will focus on a more effective and efficient land title registration system should be established by the government. This holds important implications for environmental sustainability and climate change adaptation, as farmers will concurrently invest less and try to extract maximum value from land resources if they are unsure about the security of their tenure. As Shittu *et al*., (2018) argue, LTPRs on agricultural lands in Nigeria are mostly informally defined and prone to unfair expropriation, in view of the overriding powers of the State Governor and local governments, as well as the corrupt network of land grabbers. The study suggests that governments, in whom the responsibility for land use policy reform lies, review the existing framework to ensure a prompt, fair, and efficient land tenure system.

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Appendix 1. Influence of LTPRs on Adoption of Climate-smart Practices among Smallholder Farmers: Probit Estimates.

	Agroforestry		Farmyard manure		Crop rotation		Zero Tillage		Residue retention	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Control right	0.1273*	0.0738	0.0183	0.0575	-0.0164	0.0767	-0.3746***	0.0581	-0.0447	0.0522
Transfer right	-0.1214*	0.0722	0.1814***	0.0571	0.1539**	0.0768	-0.5192***	0.0582	0.1010*	0.0517
De jure secure	-0.0747	0.2188	-0.2198	0.1762	-0.2998	0.2688	0.3200*	0.1638	0.1406	0.1522
Age	-0.0005	0.0026	0.0015	0.0020	0.0019	0.0028	0.0066***	0.0021	-0.0051***	0.0018
Sex	-0.0519	0.0967	-0.1080	0.0771	-0.2030*	0.1134	0.0817	0.0778	-0.0069	0.0683
Schooling year	-0.0062	0.0053	-0.0075*	0.0041	0.0120**	0.0056	0.0072	0.0044	-0.0040	0.0038
Household size	-0.0036	0.0048	0.0044	0.0036	-0.0128**	0.0055	-0.0254***	0.0044	0.0044	0.0034
Amount borrowed	-3.18E-08	8.24E-08	-4.71E-08	5.31E-08	3.36E-08	4.72E-08	2.07E-08	5.07E-08	2.97E-08	4.12E-08
Farmers association	0.0114	0.0214	0.0228	0.0166	0.0091	0.0223	-0.0022	0.0182	0.0009	0.0153
Extension contact	-0.0390	0.0638	0.0463	0.0506	0.0085	0.0681	-0.1763***	0.0527	0.0411	0.0457
TLU	-0.0038	0.0045	0.0004	0.0021	0.0037	0.0023	-0.0035	0.0029	-0.0022	0.0020
Farm size (ha)	-0.0119***	0.0045	-0.0001	0.0027	0.0005	0.0036	-0.0024	0.0029	-0.0016	0.0025
Extent of land fragmentation	-0.0208	0.1085	-0.1746**	0.0833	0.1647	0.1125	0.4287***	0.0885	0.0079	0.0756
Lowland	-0.0144	0.0636	0.0715	0.0495	0.0458	0.0671	-0.0202	0.0529	0.1260***	0.0452
Constant	-1.1144***	0.1593	-0.8915***	0.1248	-1.6746***	0.1725	-0.4679***	0.1298	0.2074*	0.1129
LR chi-square (14)	18.35		39.46		32.03		340.93		26.16	
Prob > chi 2	0.1911		0.0003		0.004		0		0.0247	
Log-likelihood	-1004.07		-1789.02		-872.688		-1568.52		-2272.86	
Pseudo R2	0.0091		0.0109		0.018		0.098		0.0057	
Number of obs.	3,311		3,311		3,311		3,311		3,311	

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