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# Potential impacts of the Income Stabilisation Tool on farmers' income and crop diversity: a French case study

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## Abstract

This paper analyses the potential impacts of a hypothetical implementation of the Income Stabilisation Tool in France for the field crops sector. The IST is a risk management tool proposed within the CAP 2014-2020 to support farmers facing a severe drop in their incomes. This analysis was conducted using a farm-level model relying on expected utility theory and based on positive mathematical programming with risk. The model was applied to a sample of 1375 field crop farms in metropolitan France derived from FADN data. Simulation results show that the uptake rate of the tool is relatively low, less than 37% in all scenarios. It strongly depends on the CAP public support, the loss threshold triggering entitlement to the aid and the amount of premium paid by farmers. The highest rates are observed in large farms and farms located in regions highly exposed to climatic risks. Model results also show that the IST boost adopters' income. However, its impacts on crop diversity, measured by Shannon index, are negatives.

**Keywords:** Agricultural risk management, Income Stabilisation Tool, Mutual Fund, Crop diversity, Farm-level Model, Common Agricultural Policy, France

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# 1 Introduction

Agriculture by nature is a risky business. It is exposed to a wide variety of events that can negatively affect farming activities such as the extreme weather conditions, pests and diseases, financial and market uncertainties, and political and institutional setting. These events are expected to be more frequent and intense in the coming years as climate change worsens and market instability intensifies. Several instruments have been proposed in the literature to cope with agricultural risk. They are ranged from on-farm risk instruments, such as production and income diversification, climate-smart agricultural practices and own savings, to off-farm instruments, namely private market tools (e.g. insurance), shared tools (e.g. mutual funds) and public support (e.g. subsidies). These instruments aim at preventing risks and limiting their potential adverse impacts ([Holzmann and Jørgensen, 2001](#); [OECD, 2009](#); [PARM, 2017](#)).

In the European Union (EU), at present, there is no common agricultural risk management instrument<sup>1</sup>. Up to 2007, risk is managed through nationally funded schemes implemented by some Member States (MS) to compensate farmers in case of exceptional events that cause damages to farming operations and to support crop insurance or alternative programs ([García Azcárate et al., 2016](#)). However, given that these programs became quite expensive for national budgets, the CAP has offered MS, during the reform of sectoral Regulations in 2007, the opportunity to co-fund under Pillar I crop insurance schemes or mutual funds to compensate production loss in the operational programmes for fruits, vegetables and wine sectors. In 2008, the CAP Health Check reform extended this opportunity for all sectors through the use up to 10% of their national ceilings devoted to the single payment scheme (Article 68 of the EU Regulation 73/2009<sup>2</sup>). France has used this opportunity to provide a subsidy from the 1st pillar amounting to 65% of insurance premiums ([Enjolras and Santeramo, 2016](#)).

The CAP reform of 2013 goes a step further in supporting the development and implementation of risk management tools. It gave EU Member States the possibility to fund, under Pillar II, three risk management instruments : insurance schemes, mutual funds and income stabilisation tool (IST). It also granted them the use, in the insurance scheme, of indices with biological or climatic bases to determine the losses of each individual farmer in a given year, as well as

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<sup>1</sup>In this study direct payments are not considered as a risk management tool, although they may contribute to stabilise farm income and increase farm resilience, because they are not directly designed for such purpose.

<sup>2</sup>Regulation (EU) no. 73/2009 of the Council with regard to the application of direct payments to farmers in the year 2013 ([OJ L 30,31.1.2009](#)).

the inclusion, in the mutual funds, of coverage against adverse climatic events ([García Azcárate et al., 2016](#)).

The income stabilisation tool, object of this paper, is a new risk management tool introduced to support farmers facing a severe drop in their incomes, regardless of the cause of this drop. Similar to revenue-based programs in the USA (Average Crop Revenue Election Program) and Canada (AgriStability program), the IST provides a whole farm protection where the total farm income is insured rather than separate components of this income such as the yield or the revenue of a particular activity ([Turvey, 2012](#)). It differs from traditional tools for risk management by the fact it compensates farmers for income losses rather than production losses. Also, it targets the individual income situations compared to other tools which are based on aggregate indicator or index such as revenue or yield at the regional or national level ([Pigeon et al., 2014](#)).

The proposed IST is based on a private-public partnership where public financial contribution is limited to 65% of paid indemnities, equally shared between the European Agricultural Fund for Rural Development and national funding. Farmers' compensation can be triggered only for income losses higher than 30% of a historical income<sup>3</sup> (triennial or 'Olympic' averages), with a maximum compensation of up to 70% of lost income (EU Regulation 1305/2013<sup>4</sup>).

The IST is seen to be particularly innovative, not so much by its formula, but by the fact that it covers systemic risks that are not covered by purely commercial insurances (e.g. market risks), combines all farm's insurable risks into a single contract, complies with the WTO green-box requirements and accounts for the correlations between prices, yields and profits of different farm activities ([El Benni et al., 2016](#); [Severini et al., 2019b](#); [Pigeon et al., 2014](#)). Despite these potentials, IST is still largely underutilised and under-explored. Only three out of twenty-eight EU Member States, have planned to implement this tool, namely Italy, Hungary and Spain (Castilla y León region).

To foster the uptake of this tool, an EU Omnibus Regulation (EU Regulation 2393/2017<sup>5</sup>), adopted on the 13th December 2017, has reduced the threshold of income loss from 30% to 20%, increased the maximum percentage of public support from 65% to 70% and allowed for

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<sup>3</sup>Income is defined as 'the sum of revenues the farmer receives from the market, including any form of public support, deducting input costs' (Regulation EU 2393/2017).

<sup>4</sup>Regulation (EU) no 1305/2013 of the European Parliament and of the Council on support for rural development ([OJ L 347,20.12.2013](#)).

<sup>5</sup>Regulation (EU) no 2393/2017 of the European Parliament and of the Council of 13 December 2017 amending Regulations (EU) No 1305/2013 ([OJ L 350,29.12.2017](#)).

the possibility of a sectorial income stabilisation tool. In addition, the Regulation permitted the subsidising of ‘administrative costs of setting up the mutual funds’ and ‘the amounts paid by the mutual funds as financial compensation to farmers’. However, it is still uncertain how much these incentives will facilitate the development of IST given that up to date from the whole EU-MS only Italy has designed and implemented two sector-specific ISTs: one for the apple sector and one for the dairy sector ([Rippo and Cerroni, 2022](#)).

This paper investigates, based on literature, the barriers and levers that influence the implementation of this tool by EU-MS and ex-ante assess its potential impacts in France for field crops, one of the more risky sectors with winegrowers and vegetables. This is conducted using a behavioural optimisation model applied to a representative sample of 1375 field crop farms in metropolitan France derived from the French FADN (Farm Accountancy Data Network) database. It aims at examining whether (or not) farmers will adopt this tool once deployed and if so what would be the percent of potential adopters, their main features and the economic effects of such adoption. A particular focus will also be put on the effects of IST on crop diversity, as the uptake of the IST may discourage farmers to diversify their cropping systems given that they now have an instrument dealing with risks ([Di Falco and Perrings, 2005](#); [Yu and Sumner, 2018](#)). To the best of our knowledge, this is one of the few studies which attempts to simulate the uptake of the income stabilisation tool, taking into account its feedback effect on farmers’ crop choice, mutual fund costs and crop diversity.

The paper is structured as follows. Section 2 reviews the main strands of literature related to risk management tool. Section 3 provides a description of the economic model and the data. Section 4 presents and discusses the results. The final section draws the main conclusions, discusses the policy implications of the findings, and explains the main limitations of the study.

## 2 Literature review on the IST

Income stabilisation tool and its potential implications have been largely debated in literature. Although most of these studies were conducted in Italy, Switzerland and Spain, their results are promising and provide relevant insight to other EU-MS that are considering the introduction of this tool. A large strand of literature has focused on the effects of the IST in terms of risk reduction and income stabilisation ([Capitanio et al., 2016](#); [Castañeda-Vera and Colmenero,](#)

2017; Trestini et al., 2018; Severini et al., 2019a). As such, Severini et al. (2019a) shown, using a FADN panel data set of 3421 farms, that the introduction of the IST would lead to a significant reduction of income variability in Italian agriculture. Castañeda-Vera and Colmenero (2017) found by the application of the certainty equivalence approach to a representative arable farm in Castilla y León, the only Spanish region which has proposed to support IST, that direct payments and crop diversification are more effective for decreasing income variability, while crop insurance and IST are more powerful for improving farm resilience to income variability and limiting public expenditure.

Other studies have investigated the role of IST in reducing income inequality among farmers (Finger and El Benni, 2014; El Benni et al., 2016; Severini et al., 2019b). For instance, Severini et al. (2019b) revealed, through a rich panel of 2777 farms, that a nationwide IST not only stabilises farm income but also enhances its level and reduces income inequality in Italian agriculture. They also showed from a Gini decomposition that IST is more effective in reducing income inequality when farmers contributions to mutual funds are proportional to their income compared to the case of flat rate contributions.

Other works have focused on farmers' acceptability of the IST scheme and the drivers towards its potential implementation. Giampietri et al. (2020) showed, through a stated preference survey in the Veneto region (Italy), that farmer confidence plays an important role in the intention to uptake IST. Severini et al. (2021) reported, based on the expected utility approach, that participation depends on the level of farmers' contributions to mutual funds and their degree of risk aversion. They suggested that farmers' contributions should be differentiated among regions because they face different levels of income risk. Rippo and Cerroni (2022) found, using a three-year panel data set of 3268 farms representative of the apple sector in the Province of Trento (Italy), that prior experience with mutual funds as well as higher crop production specialisation, associated with greater risk exposure, promote participation in the IST.

Other studies have investigated whether the level and probability of indemnification are linked to farms' characteristics. El Benni et al. (2016) conducted an analysis considering a set of sector-specific IST to be implemented in Switzerland. They found that older farmers are less likely to face a severe income reduction, while farms located in the valleys receive higher indemnities compared to farms in upland areas. Trestini et al. (2018), focusing on the potential implementation of IST schemes for the dairy sector in two Italian regions (Veneto and

Lombardy), showed that younger farmers and farms located in upland areas would be more likely to experience a severe income reduction that triggers indemnification. They also reported that farm size does not have a significant effect on the probability of indemnification, while farms' structural changes significantly affect IST indemnities and need to be considered in calculating the reference income. [Pigeon et al. \(2014\)](#) estimated by means of a skew normal linear mixed model the probability and the cost of activation of a typical regional mutual fund in the Walloon Region of Belgium and, in that case, the expected amount of each farm's indemnities.

Others have addressed the question of the better geographical dimension for the establishment of an IST. By comparing the hypothesis of a national IST with five different macro-regional funds, [Trestini and Giampietri \(2018\)](#) have demonstrated that a national IST provides sufficient resources for the compensation of farm losses, in case of insolvency, whereas a macro-regional funds can guarantee more tailored fees for farmers (specific for different geographical areas and level of riskiness). This study was carried out on a constant sample of 325 farms specialised in viticulture over the period of 2011-2014 coming from the Italian FADN database.

Finally, some other literatures have focused on the potential lock-ins and barriers that have prevented the implementation of IST in some EU-MS. According to these studies: (i) in Italy, the main obstacles would be the difficulties in monitoring the historical farmers' income due to loose accounting rules for Italian farmers, (ii) in Spain and in Hungary, the lack of experience within the EU and the absence of guidelines to design IST schemes are the main reasons for their non-implementation, and (iii) in France, the Ministry of Agriculture has decided not to implement the IST, at least in the short term, due to the perception that the instruments<sup>6</sup> in place sufficiently cover risks. Other obstacles have been cited in the literature, such as the reluctance of farmers to adhere to risk management programs in general, their distrust on the financial robustness of mutual funds that cover systemic risks, the relatively high information asymmetry (adverse selection and moral hazard) and transaction costs associated with the implementation

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<sup>6</sup>The issue of risk management is clearly present in the objectives of agricultural policies in France. Particular emphasis is placed on the management of climate, health and environmental risks as a structuring economic measure. From 2015-2022, risk management scheme is placed under the CAP Pillar II and implemented through a specific national programme, the National Risk Management and Technical Assistance Programme (PNGRAT). Co-financed by the European Agricultural Fund for Rural Development (EAFRD), this programme is based on two types of support: (i) support for multi-perils crop insurance (in 2020, more than 30% of agricultural land was covered against climate risks via crop insurance), and (ii) support for health and environmental mutual funds, completed by a guarantee against natural catastrophes funded from national budgets. Since 2023, these supports are implemented under the national strategic plan and funded through EAFRD credits ([MAAE, 2023](#)).

of the IST, the lack of evidence on IST potential effects, the risk of fraud through a modification of accounting records, etc. (Meuwissen et al., 2013; Cordier, 2014; Vera and Colmenero, 2017; Cordier and Santeramo, 2020; Boháčiková and Bencová, 2021; Rippo and Cerroni, 2022).

Whilst all these studies are extremely important, they remain country-specific and can not easily be generalised to other EU-MS. They also do not provide information on the feature of IST's potential adopters and how they will behave when they are given such opportunity. Moreover, none of these studies have discussed the likely environmental impacts of this tool. The implementation of the IST scheme can, indeed, negatively impact crop diversity and, thus, contradict the objective of the CAP greening, as the more agricultural risks are controlled, the more likely farmers will less diversify their crops (Di Falco and Perrings, 2005). We will try to fill this gap through a case study in France for the field crop farms. The objective is to determine, using a farm-level model, the proportion and profile of farmers willing to adopt this tool once implemented by the French government and to assess its economic and crop diversity effects.

## 3 Methodology

### 3.1 The Economic Model

We use a micro-simulation model to assess the potential impacts of the Income stabilisation Tool on farmers' income and crop diversity in France for the field crop sector. It is a farm-level model designed to inform decision-making on how changes in market, policy and climate conditions might affect the viability of heterogeneous sets of farms that characterise the French agricultural sector. It is a constrained optimisation model that relies on expected utility framework to explain and predict farmers behaviours under risk. It assumes that farmers maximise their expected utility at given yields, prices and CAP subsidies, subject to a set of resource and policy constraints. Farmers' expected utility is approximated through a mean-variance (E-V) approach with a constant relative risk aversion (CRRA) specification (Markowitz, 2014). Under this specification, farmers' expected utility is defined as the tradeoff between the expected income and its variance due to price and yield variability. It can be represented as follows:

$$E[U(\pi)] = E[\pi] - 0.5 \frac{\varphi}{\omega^0} V(\pi) \quad (1)$$



where  $U(.)$  is the utility function on income  $\pi$ ,  $E[U(\pi)]$  is the expected utility,  $E[\pi]$  is the expected income,  $\varphi$  is the relative risk aversion coefficient,  $\omega^0$  is the initial farm wealth, and  $V(.)$  is the variance of income.

Farmer's expected income, is defined as the sum of expected gross margin, plus the difference between the premium paid and the indemnities received for IST subscribers, minus a non-linear (quadratic) activity-specific function. The gross margin is the total revenue from sales of agricultural products and direct (both coupled and decoupled) payments minus the accounting variable costs of production activities. The quadratic activity-specific function is a behavioural function introduced to calibrate the farm model to an observed base-year situation, as usually done in positive programming models (Heckeley and Wolff, 2003).

Regarding income variance, most of the models in the literature incorporate uncertainty in gross margin or in revenue per unit of activity. The former models assume that prices, yields and costs are stochastic, while the latter consider costs either non-random, because they are known when decisions are made, or less stochastic than revenues and, therefore, the variance in the gross margin can be approximated by the variance in revenue. In our model, we opted for the second approach, considering uncertainty only in prices and yields (i.e. revenues) without differentiating between sources of uncertainty (Louhichi et al., 2018; Arribas et al., 2020).

The general mathematical formulation of the utility maximisation problem for each farm  $f$  (index omitted for clarity) is as follows:

$$\begin{aligned} \max_{x \geq 0} E[U(\pi)] = & \frac{1}{N} \sum_n [GM_n + z(Ind_n - Prem_n)] \\ & - \sum_i d_i x_i - 0.5 \sum_{i,i'} x_i Q_{i,i'} x_{i'} \\ & - 0.5 \frac{\varphi}{\omega^0} \sum_{i,i'} x_i \Sigma_{i,i'} x_{i'} \end{aligned} \quad (2)$$

$$s.t. \quad \sum_i A_{i,m} x_i \leq b_m \quad [\rho_m] \quad (3)$$

where indices  $i, i' = 1, 2, \dots, I$  denote the crop activities and products<sup>7</sup>,  $n = 1, 2, \dots, N$  the state of nature and  $m = 1, 2, \dots, M$  the resource constraints.  $E[U(\pi)]$  is the expected utility to

<sup>7</sup>To simplify the mathematical notation, we assume one product per activity so that the indices for activity and product are identical.

be maximised,  $GM_n$  is the farm level gross margin under state of nature  $n$ ,  $Ind$  is the mutual fund (MF) indemnification to farmer (i.e. indemnities paid by the MF to the farmer when his/her income falls below a certain proportion of the average historical income),  $Prem$  is the premium paid by the farmer to the MF for contracting the IST (i.e. farmer's contribution to the MF) and  $z$  is a dummy variable with values 1 if the farmer participates in the IST and 0 if he/she does not participate.  $x_i$  is the non-negative level (i.e. hectares) of activity  $i$ ,  $d_i$  is the linear term of the behavioural activity function and  $Q_{i,i}$  is the quadratic term of the behavioural activity function.  $\varphi$  is the farmer's constant relative risk aversion (CRRA) coefficient,  $\Sigma_{i,i'}$  is the variance-covariance matrix of per hectare crop revenues, and  $\omega^0$  is the farm initial wealth represented by the observed value of farm assets, such as farm buildings, machinery, breeding livestock, forest and agricultural land (Basnet et al., 2021).  $A_{i,m}$  are the coefficients of resource constraints,  $b_m$  is the level of available resources and  $\rho_m$  are their corresponding shadow prices.

The farm level gross margin under state of nature  $n$ ,  $GM_n$  is calculated as follows:

$$GM_n = \sum_i (p_{i,n}y_{i,n} + s_i)x_i - \sum_{i,k} C_{i,k}x_i + \bar{e}l \quad (4)$$

where  $p_{i,n}$  and  $y_{i,n}$  are the price and the yield for crop activity  $i$  under state of nature  $n$ ,  $s_i$  is the per hectare coupled payments, and  $C_{i,k}$  are the accounting variable costs for intermediate input  $k$  (i.e. fertilizer, seeds, crop protection, etc.) and crop activity  $i$ ,  $\bar{e}$  is the rate of decoupled payments per hectare, and  $l$  is the eligible area for decoupled payments<sup>8</sup>. Note that no uncertainty is assumed around  $C$ ,  $s$ ,  $\bar{e}$ ,  $l$ ,  $A$ ,  $b$ ,  $d$ , and  $Q$ . All uncertainty are associated to  $p$  and  $y$ .

The MF indemnification to farmer is calculated as follows:

$$Ind_n = \begin{cases} \alpha(\beta\overline{GM} - GM_n), & \text{if } GM_n < \beta\overline{GM} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where  $\alpha$  is the maximum relative level of indemnification of the losses allowed by the EU Regulation (i.e. it is set to 0.7),  $\overline{GM}$  is the triennial average historical income, and  $\beta$  is the payment trigger level as a proportion of the historical income. Farmer gets a payment only when

<sup>8</sup>The eligible area in MS implementing the SPS is equal to the amount of the farm's entitlements, whereas, in MS that implement the SAPS, it is equal to the total agricultural area.

his/her income (i.e. gross margin) declines by more than  $(1-\beta)$  of  $\overline{GM}$ .

Contracting the IST implies paying a premium ( $Prem$ ) calculated as follows:

$$Prem_{f,n} = \mu_f \sum_{f'} (1 - \delta) Ind_{f',n} z_{f'} w_{f'} (1 + \Delta) \quad (6)$$

where  $f, f' = 1, 2, \dots, F$  indexes farms,  $Ind_n$  is the MF indemnification to farm  $f$ ,  $\delta$  is the share of public financial contribution to the MF,  $\Delta$  is the administrative costs of setting up the MF (estimated to 20% of indemnification) and  $\mu_f$  is a factor reflecting how the private financial contribution to the MF is shared among IST subscribers, which can be defined in two ways, among others:

- Flat rate contribution

$$\mu_f = \frac{1}{\sum_{f'} z_{f'} w_{f'}} \quad (7)$$

- Income-based contribution

$$\mu_f = \frac{\overline{GM}_f}{\sum_{f'} \overline{GM}_{f'} z_{f'} w_{f'}} \quad (8)$$

where  $w_f$  is the farm weighting factor reflecting the number of farms in the population that is represented by farm  $f$ ,  $z_f$  is a dummy variable with values 1 if the farmer participates in the IST and 0 if he/she does not participate and  $\overline{GM}_f$  is the farmer's triennial average historical income.

The model is calibrated against crop acreage of a single year (2020), considered as the reference point in our simulation, given that it is more realistic and less diversified than the one of an average year. However, for the estimation of the unknown parameters of the behavioural and risk functions we used data for the three-year average around 2018 (2018, 2019 and 2020). This makes our estimates less sensitive to year-specific fluctuations in price and yield, which can be especially high when using individual farm-level data. A detailed description of the model calibration method is provided in the Appendix. The model programming code<sup>9</sup> is available from the authors upon request.

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<sup>9</sup>The model is programmed in GAMS (General Algebraic Modelling System) and solved using CONOPT and DICOPT for nonlinear mixed-integer programming.

## 3.2 Data

The primary data source used to parameterise the model are individual farm-level data from the French FADN database, complemented by other data sources such as Agreste<sup>10</sup> and Eurostat for variables not available in FADN. However, most of these external data are not directly used in the model, but only serve as input in the estimations. For each farm, the following variables are derived from FADN data: crop acreage (hectares), mean and standard deviation of crop prices and crop yields, coupled and decoupled payments, matrix of coefficients, available farmland (arable and grassland) and land rents. The accounting unit costs are estimated using a Bayesian Highest Posterior Density (HPD) estimator (Heckeleei et al., 2008). The prices and yields under state of nature are independent random numbers generated using a normal distribution function based on the mean and the standard deviation of prices and yields.

The unknown parameters  $d$ ,  $Q$ ,  $\rho$ ,  $\varphi$  and  $\Sigma$  are estimated simultaneously in each region and farm type using a 3-year (2018-2020) data set. It consists of using the HPD estimator so that the first-order conditions (FOCs) of the considered farm model are satisfied at the historical average crop acreage (Louhichi et al., 2018). This is performed using available information on output prices, input unit costs and production quantities during these three years as well as prior information on farm-type crop supply elasticities<sup>11</sup>, land rents and farm-type variance-covariance matrix of crop revenues. Data on labour and capital costs are not included; they are implicitly captured by the behavioural activity function.

The model is applied to a constant sample of 1375 FADN farms for the period 2018-2020. These farms are specialised in COP (Cereals, Oilseeds and Proteins) crops (OTEX<sup>12</sup> 15) and in other field crops (e.g. potatoes, pulses and sugar beet) (OTEX 16). They are sorted, based on standard output (SO), into three economic classes: small (25-100K€), medium (100-250K€), large (over than 250K€). Table 1 presents some key characteristics of the farm constant sample by farm specialisation and economic size. In order to guarantee the highest possible representativeness of the sector and to capture the full heterogeneity across farms, each farm is individually modelled. Results are afterward aggregated at different scales, by farm specialisation, economic size, region and sector.

<sup>10</sup>Agreste is the statistical service of the French Ministry of Agriculture.

<sup>11</sup>Farm-type crop supply elasticities are obtained from a disaggregation of regional crop supply elasticities using information on acreage allocation, following the methodology by Garnache and Mérel (2015).

<sup>12</sup>OTEX: Technical orientation

Table 1: Sample characteristics

Specialisation	Specialist COP				Specialist other field crops				Average
	25 < SO ≤100 (2)	100 < SO ≤250 (3)	250 < SO (4)	Average (5)	25 < SO ≤100 (6)	100 < SO ≤250 (7)	250 < SO (8)	Average (9)	
Farm sample	248	469	194	911	67	178	219	464	1375
Number of represented farms	23475	25566	8520	57562	3623	7818	7674	19116	76677
Number of Agricultural Work Unit	1.08	1.34	1.89	1.32	1.63	1.79	2.98	2.24	2.01
Usable Agricultural Area (ha)	64.34	142.64	274.07	130.16	41.44	93.47	182.29	119.27	127.45
Decoupled payment (€)	14660	29770	55250	27380	10880	21220	38640	26250	27110
Coupled payment (€)	580	1100	2260	1060	260	1400	1090	1060	1060
Rural development (€)	1040	1920	3310	1760	980	2110	960	1430	1690
Land use (% of UAA)									
Cereals	54.3	60.5	60.3	59.2	47.9	49.7	49.5	49.5	56.9
Oilseeds	18.8	18.2	20.2	18.9	8.7	9.5	8.6	8.9	16.6
Protein crops	2.7	3.7	3.2	3.4	1.3	3.2	1.7	2.2	3.1
Other field crops	0.5	1.7	2.5	1.7	11.3	12.7	19.3	16.7	5.2
Other arable crops	4.4	3.2	4.3	3.8	12.6	15.7	14.4	14.6	6.3
Fallow	6.2	4.0	2.9	4.1	3.8	3.0	1.8	2.3	3.7
Grassland	13.1	8.7	6.6	8.9	14.4	6.2	4.7	5.8	8.2

Source: FADN/RICA (2020) - Authors' calculations

Note: COP: Cereals, Oilseeds and Protein crops; SO: Standard output

### 3.3 Model assumptions and scenarios

We investigate four contrasted scenarios which are compared to a Business As Usual (*BAU*) scenario (see Table 2). The first two scenarios represent the initial IST scheme as proposed by the CAP 2014-2020 under the EU Regulation 1305/2013 and the last two reflect the adjusted IST scheme as specified in the EU Omnibus Regulation 2393/2017 of December 13, 2017. Given that the two Regulations do not specify how farmer’s contribution (i.e. premium) to MF must be computed, we have simulated two forms of contribution: regional flat rate (i.e. all IST subscribers within a NUTS2 region pay the same amount defined as the total indemnification augmented by administrative costs<sup>13</sup> divided by the number of subscribers) and proportional rate, depending on farmer’s reference income (i.e. the higher the reference income, the greater the contribution to MF is).

Moreover, since the management of the rural development (Pillar 2) is often decentralised at the regional level and also to account for the heterogeneity among regions in terms of risk exposure, we assumed a regional implementation of the income stabilisation tool. Although regional based mutual funds may lead to high indemnifications in some regions, as stated by [Severini et al. \(2021\)](#), it is easy to implement, less costly to administer and reflect better the levels of risks in each region. In addition, as pointed by [Trestini et al. \(2018\)](#) mutual funds restricted to farmers belonging to same sector and/or region may have the advantage to reduce moral hazard problems due to a relatively less asymmetric distribution of information.

The *BAU* scenario assumes a continuation of the CAP 2014-2020 without IST and without any changes in terms of technological, structural and market development. There is no interaction between farms, neither farm exit/entry nor substitution between different land types.

Table 2: Scenario description

Scenarios	CAP 2014-2020		Omnibus Regulation	
	CAP2014-S1	CAP2014-S2	Omnibus-S1	Omnibus-S2
Income loss (%)	30	30	20	20
CAP public support (%)	65	65	70	70
Premium setting method	Flat rate	Income-based	Flat rate	Income-based

Source: Authors’ elaboration

<sup>13</sup>Following [Severini et al. \(2019b\)](#), administrative costs for setting up the IST are assumed to be 20% of farmers’ contributions.

## 4 Results

In this section, we estimate the proportion of farmers that would adopt the IST under each simulated scenario and examine whether and how this would impact their gross income, expected utility and crop diversity. Results are reported at both national and regional levels, by farm specialisation, economic size and for the full distribution across the farm population.

### 4.1 Percentage and profile of potential IST adopters

Simulation results show that the average adoption rate, at sector level, remains relatively low in all scenarios and would not exceed 37% (see column 10 of Table 3). The highest rates are observed under Omnibus scenarios, particularly when farmers' participations to MF are proportional to their reference income (i.e. 36.4% under *Omnibus-S2*), whereas the lowest rate is registered under the *CAP14-S1* scenario. This finding, which contrasts with many other studies, including the one by [Severini et al. \(2019a\)](#), reveals that the IST schemes proposed under both Regulations are still not attractive for large numbers of farmers.

Results also indicate that the incentives proposed under the CAP 2014-2020 are not sufficiently high to boost the uptake of the IST and the introduction of the Omnibus Regulation would be helpful in this regard. Indeed, the reduction of the threshold of income loss from 30% to 20% and the increase of public support from 65% to 70% provided by this Regulation raise the uptake rate by around 13 percent points (see differences between first and third rows and between second and fourth rows in column 10 of Table 3). Moreover, the way how farmers' contribution to MF would be set-up seems to play a critical role. As such, a contribution proportional to reference farm income would enhance the participation rate by almost 10 percent points (see differences between first and second rows and between third and fourth rows in column 10 of Table 3). This implies that certain farmers are willing to participate in this program if their financial contribution remains reasonable (i.e. takes into account their reference income) and fair (i.e. farmers with more income contribute more to MF).

Findings revealed at sector level remain valid by farm specialisation (see columns 5 and 9 of Table 3): for both specialisations, the highest participation rate is reached under *Omnibus-S2* scenario, while the lowest one is recorded under *CAP2014-S1* scenario. In all scenarios, farms specialised in COP crops register a relatively low uptake rate, compared to farms specialised in

other field crops. This could be explained by the fact that the latter produce risky crops such as pulses and potatoes and, thus, they are more likely to engage in this kind of program. Another possible explanation is that the total number of COP crop farms is much higher (three times the numbers of farms specialised in other field crops as shown in the second row of columns 5 and 9 in Table 1), generating a relative small rate.

Results by economic size show that the relationship between adoption rate and farm economic size is mixed and depends on farmers' contribution forms. For most scenarios, this relationship is direct when farmer's contribution is flat rate (i.e. *CAP2014-S1* and *Omnibus-S1*) and indirect, or inverse, when farmer's contribution is income based (i.e. *CAP2014-S2* and *Omnibus-S2*). This is particularly true for farms specialised in COP crops, regardless of scenarios. This finding first confirms the importance of the contribution form on the uptake of the IST. It promotes its adoption by large farms when contribution to MF is flat rate. In contrast, when contribution to MF is proportional to reference income, it stimulates its uptakes by small farmers. Second, it underscores that farm economic size is less important in explaining the demand for IST, given that both small and large farms desire engaging in this program: the former in fear of farm failure and the latter due to lower costs per insured hectare and also because they are often more specialised and, therefore, can not easily use crop diversification as a risk mitigation strategy.

It is also interesting to note that the new incentives introduced by the Omnibus Regulation would boost more large farms' adoption (see differences between first and third rows and between second and fourth rows of Table 3). The decrease of the loss threshold from 30% to 20% and the increase in the support rate from 65% to 70% raise the subscription rate in this group by more than 13.5 percent points, regardless of scenarios and farm specialisation.

Our results also show that previous experience with insurance (more than 70% of IST adopters have already subscribed a crop insurance), trust on insurance company to cover damages (more than 54% of IST adopters have experienced substantial damages and received pay-outs from crop insurance) and higher crop production specialisation favours participation in the IST. This finding is in line with previous literature by [Rippo and Cerroni \(2022\)](#); [Di Falco et al. \(2014\)](#); [Finger and Lehmann \(2012\)](#).

In terms of area coverage, the effect of the simulated scenarios remains fairly limited. Although the introduction of the Omnibus Regulation would increase the land share covered by



Table 3: Adoption rate by farm specialisation and economic size (%)

Specialisation	Specialist COP				Specialist other field crops				Average
Economic size (1000€)	25 < SO ≤ 100 (2)	100 < SO ≤ 250 (3)	250 < SO (4)	Aver- age (5)	25 < SO ≤ 100 (6)	100 < SO ≤ 250 (7)	250 < SO (8)	Aver- age (9)	(10)
CAP2014-S1	08.3	13.8	17.1	12.1	11.1	12.8	27.7	18.4	13.7
CAP2014-S2	24.3	21.1	15.4	21.5	27.8	19.6	39.9	29.3	23.5
Omnibus-S1	14.6	33.0	36.0	25.9	17.5	23.5	48.8	32.5	27.6
Omnibus-S2	35.1	36.1	28.2	34.7	36.0	31.9	53.5	41.3	36.4

Source: Model results

the IST, its level will not exceed 36% in all scenarios (see Table 4). This finding is consistent with current estimate of crop insurance coverage in France which is around 31.6% (Koenig et al., 2022), very low compared to the US, where around 80% of crops are covered by insurance (Shields, 2015).

Table 4: Area covered by IST (%)

Scenarios	CAP 2014-2020		Omnibus Regulation	
	CAP2014-S1	CAP2014-S2	Omnibus-S1	Omnibus-S2
France	15.72	21.42	33.50	35.42

Source: Model results

At regional level, the effect of the simulated scenarios on adoption rate is quite heterogeneous. As expected, the highest rates are observed in the southern regions of France that are more exposed to climatic variations (i.e. yield variations) such as Rhône-Alpes, Haute-Normandie, Languedoc-Roussillon and Midi-Pyrénées (see Table 5).

Table 5: Adoption rate by region (%)

Scenarios	Adoption rate (%)			
	CAP2014-S1	CAP2014-S2	Omnibus-S1	Omnibus-S2
Ile de France	05.83	14.52	02.24	31.23
Champagne-Ardenne	04.38	06.95	36.62	24.60
Picardie	01.26	18.43	26.18	31.82
Haute-Normandie	39.00	42.46	60.13	60.13
Centre	13.10	24.94	27.80	37.65
Basse-Normandie	20.34	20.34	20.34	20.34
Bourgogne	7.59	10.71	15.31	22.37
Nord-Pas de Calais	01.45	18.53	01.45	27.92
Lorraine	18.49	16.61	37.56	34.39
Alsace	00.00	04.07	00.38	10.22
Franche-Comté	19.37	17.10	33.94	19.37
Pays de la Loire	05.28	05.28	05.28	09.02
Bretagne	26.88	32.70	28.32	32.70
Poitou-Charentes	19.25	28.56	25.49	44.82
Aquitaine	07.24	46.89	20.53	52.80
Midi-Pyrénées	19.83	29.53	27.28	54.13
Rhône-Alpes	46.41	49.58	55.93	55.00
Auvergne	16.10	20.79	19.24	30.62
Languedoc-Roussillon	40.14	54.16	49.67	59.20
Provence-Alpes-Côte d'azur	20.31	22.63	22.88	37.77
France	13.66	23.48	27.58	36.39

Source: Model results

## 4.2 Economic effects of IST adoption

The results reported in column 10 of Tables 6 and 7 reveal that the simulated scenarios would have positive economic impacts. They would increase adopters' average gross income and utility by around 14% and 1%, respectively. This is, however, not surprising and is supported by previous studies that found similar results (Finger and El Benni, 2014; Severini et al., 2019b; Boháčiková and Bencová, 2021).

The increase in average gross income is projected to be between 11% and 19%, depending on scenarios. The largest income increments are registered under *CAP2014* scenarios; i.e. where farm contribution to MF are income-based. They are mainly driven by the improvement of economic performance of small farms. These farms are, in fact, more exposed to climate and market risks, and, therefore, they are expected to gain by participating in the IST, especially when their contribution to MF are income-based.

This relatively large increase in average expected gross income is, nevertheless, partially offset

by a raise in the implicit costs and in the variance of revenue, leading to a small increase in average expected utility, lower than 1.5%. The gain in expected utility seems to be negatively correlated with the adoption rates. The scenarios with the lowest adoption rate (*CAP2014* scenarios) register the highest utility rise. This implies that, first, for several adopters, the utility effect is positive but not significant and, second, the expansion in number of IST subscribers might increase the amount of premiums paid by farmers to the MF and, therefore, reduce the average utility gain.

Results by farm specialisation presented in columns 5 and 9 of Tables 6 and 7 show that the increase in farm income and expected utility is relatively low for farms specialising in COP crops, in comparison to those of farms specialised in other field crops. These results could be explained by the fact the latter produce risky crops such as pulses and potatoes and, therefore, would benefit the most from IST.

Results by farm specialisation and economic size show that the highest percentage changes in expected utility are registered for small farms. This implies that lower income farmers, who may not have the skills and the knowledge to deal with market uncertainty and price fluctuations, would benefit the most from the IST.

The other important result is that the Omnibus scenarios, in comparison with the CAP 2014–2020 scenarios, would further improve the economic situation of farms regardless of their economic size and specialisation. These results confirm that the threshold for triggering the funds and the public support play an important role in stabilising farm income for all farms.

Table 6: Gross income effects (% change relative to baseline)

<b>Specialisation</b>	<b>Specialist COP</b>				<b>Specialist other field crops</b>				<b>Average</b>
<b>Economic size (1000€)</b>	25 < SO ≤ 100 <b>(2)</b>	100 < SO ≤ 250 <b>(3)</b>	250 < SO <b>(4)</b>	Aver- age <b>(5)</b>	25 < SO ≤ 100 <b>(6)</b>	100 < SO ≤ 250 <b>(7)</b>	250 < SO <b>(8)</b>	Aver- age <b>(9)</b>	<b>(10)</b>
CAP2014-S1	18.8	4.1	5.9	6.9	99.8	48.8	21.2	26.7	18.6
CAP2014-S2	12.8	4.9	7.5	7.3	12.9	38.0	16.9	20.3	15.0
Omnibus-S1	19.0	4.9	0.5	4.8	54.0	36.5	13.2	18.2	11.3
Omnibus-S2	11.0	5.3	4.0	6.1	20.4	28.8	12.6	16.1	11.5

Source: Model results

To assess the income distributional effects of the simulated scenarios, we use the Gini coefficient. The Gini coefficient measures the level of inequality in the distribution of income or

Table 7: Utility effects (% change relative to baseline)

Specialisation	Specialist COP				Specialist other field crops				Average
Economic size (1000€)	25 < SO ≤ 100 (2)	100 < SO ≤ 250 (3)	250 < SO (4)	Aver- age (5)	25 < SO ≤ 100 (6)	100 < SO ≤ 250 (7)	250 < SO (8)	Aver- age (9)	(10)
CAP2014-S1	10.9	0.4	1.1	0.9	9.4	0.6	1.5	1.2	1.1
CAP2014-S2	6.4	0.7	1.3	1.3	11.6	0.7	1.7	1.3	1.3
Omnibus-S1	8.6	0.2	0.1	0.3	12.4	0.5	2.1	1.2	0.6
Omnibus-S2	6.4	0.4	0.3	0.5	13.7	0.6	2.3	1.5	1.0

Source: Model results

wealth within a population. It ranges between 0 and 1, where 0 means perfect equality (everyone has the same income or wealth) and 1 means perfect inequality (one person has all the income or wealth).

As shown in Table 8, farm income are unequally distributed among field crop farms in France under the Baseline, indicated by a relatively high Gini coefficient of 0.636. The introduction of the IST would reduce income disparity among adopters as well as for the entire population, shown by a decrease in Gini coefficient in all scenarios. This finding is consistent with [Finger and El Benni \(2014\)](#) who also showed that IST reduce income inequalities, with a reduction in both Gini and Theil indices in Switzerland. This would be explained by the fact that higher-income farms are less likely to receive indemnifications, as they have a lower income risk profile.

The inequality reduction is more pronounced under *CAP2014-S2* and *Omnibus-S2* scenarios, where contributions to MF are based on reference income. These results are in line with [Severini et al. \(2019b\)](#) who found that the IST is more effective in reducing income inequality if farmers' contributions to MF are proportional to their income.

Table 8: Income distribution effects

Scenarios	Baseline	CAP 2014-2020		Omnibus Regulation	
		CAP2014-S1	CAP2014-S2	Omnibus-S1	Omnibus-S2
Gini index (adopters)	0.585	0.581	0.577	0.543	0.516
Gini index (all farmers)	0.636	0.461	0.459	0.461	0.458

Source: Model results

### 4.3 Crop diversity effects of IST adoption

Table 9 presents the effects of the simulated scenarios on crop diversity for potential IST adopters, measured by the Shannon index (Shannon and Weaver, 1949).

Results reported in column 10 of Table 9 show that the variation of the Shannon index is negative (loss of crop diversity) in all scenarios. The greatest losses are recorded under the Omnibus Regulation scenarios, in particular when farmers' contribution to the fund is proportional to their income (a loss of 5.8% in *Omnibus-S2*). As expected, the loss of crop diversity increases with the increase in subscriptions to this fund. In other words, with the adoption of IST farmers become less risk-averse and tend to be more specialised (less diversified) in their production. This is similar to the negative correlation between crop diversification and the adoption of insurance scheme reported in the literature (Di Falco and Perrings, 2005; Di Falco et al., 2014)

Results by farm specialisation presented in columns 5 and 9 of Table 9 indicate that, in all scenarios, the loss of crop diversity is more pronounced for farms specialised in other field crops. These expected results are explained by the high adoption rate of IST in this farm specialisation, which implicitly incentivise monocropping.

Results by specialisation and economic size reveal that the loss of crop diversity depends on farm specialisation. For farms specialised in COP crops, the loss of crop diversity is more pronounced for small farms, whilst for farms specialised in other field crops, the loss of crop diversity is more significant for large farms. This result is not surprising given that small COP crop farms often have a more diversified cropping pattern than large ones, so the introduction of IST will encourage them to choose the most profitable crops and, therefore, towards less diversification. Whereas for large farms specialised in other field crops, the adoption of the IST will reinforce their specialisation in risky crops, such as potatoes and pulses and, thus, reduce their crop diversity.

Table 9: Crop diversity effects (% change relative to baseline)

Specialisation	Specialist COP				Specialist other field crops				Average
Economic size (1000€)	25 < SO ≤ 100	100 < SO ≤ 250	250 < SO	Aver- age	25 < SO ≤ 100	100 < SO ≤ 250	250 < SO	Aver- age	
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CAP2014-S1	-5.7	-1.6	-2.2	-2.7	-0.7	-7.2	-7.4	-6.7	-3.9
CAP2014-S2	-8.5	-2.0	-2.3	-4.6	-5.5	-4.4	-5.7	-5.3	-4.8
Omnibus-S1	-10.0	-2.2	-4.2	-4.1	-4.6	-3.8	-9.9	-7.2	-4.9
Omnibus-S2	-10.8	-2.0	-3.3	-5.3	-5.4	-3.0	-9.5	-6.9	-5.8

Source: Model results

## 5 Discussion and conclusion

This paper analyses the potential impacts of the Income stabilisation Tool in France for the field crop sector. This is achieved using a farm-level model based on positive mathematical programming with risk. The model was applied to a sample of 1375 farms representative of the field crop sector in metropolitan France derived from the French FADN database. Four scenarios were simulated and analysed. The first two scenarios represent the initial IST scheme as proposed by the CAP 2014-2020, while the last ones depict the adjusted IST scheme as specified in the Omnibus Regulation.

Findings from this study reveal interesting patterns. First, consistent with previous literature, the uptake rate of the IST once deployed in France is expected to be relatively low (less than 37%) and its impact on farmers' utility is fairly limited (low than 1.5% in average). This is particularly true for the initial IST scheme proposed by the CAP 2014-2020. The introduction of the Omnibus Regulation would foster adoption of the IST, but still insufficient to attract large numbers of farmers. This finding enforces the view that the acceptability of the IST encounters some difficulties and further government efforts are required to better understand non-adopters' needs and to facilitate them access to this tool (Rippo and Cerroni, 2022). Second, our analysis confirms previous findings by Finger and El Benni (2014) and Severini et al. (2019b), that IST would reduce income inequality among both IST subscribers and non-subscribers, mainly when farmers contributions to MF are proportional to reference income. This result strengthen the argument of setting IST premium that explicitly account for farm heterogeneity. Third, the relationship between adoption rate and farm economic size is expected to be mixed depending on contribution forms. It is a direct relationship when farmer's contribution to MF is flat rate

based and indirect, or inverse, when farmer's contribution is income based. Finally, the introduction of IST would stabilise and boost adopters' income, nevertheless, it would lead to loss of crop diversity. As for crop insurance (Di Falco et al., 2014), the uptake of the IST discourages farmers to diversify their cropping systems, given that they now have an instrument dealing with risks. The above finding implies that additional incentives (restrictions) are needed to encourage (enforce) farms to maintain crop diversification once they decide to adopt IST, provided that this intervention would not lead to an economic situation even further away from a second-best solution.

Our findings, however, need to be considered with some caution, on account of the model's assumptions and data limitations. First, our analysis assumes rational behaviour and perfect information. This is questionable given that it is difficult for farmers to obtain all the information needed to pursue optimal decision rules in complex and uncertain decision environments. However, our model, like the majority of economic models, relies on the assumption of bounded rationality (Simon, 1957), which emphasises that agents are rational given the available information. Second, output market prices are assumed to be exogenous. This implies that market feedback is not taken into account in the model and, therefore, our simulations would overestimate the overall IST effects. Third, some farms are assumed to adopt IST on top of insurance already owned, which is disputable and may lead to an overestimation of IST subscribers. Fourth, the covariance between prices and yields, which could reduce revenue variability and, thus, farm risk, is not considered in our analysis. Fifth, the three mandatory measures of the CAP greening which are important for our analysis (particularly crop diversification measure), are not-explicitly modelled (i.e. they are captured by the behavioural activity function). A relaxation of this assumption would allow isolating the effects of IST scheme from greening measures. Finally, the data set used covers only commercial farms. Small farms that are most vulnerable and exposed to climate and market risks are not included in our analysis. A careful analysis of each of these limitations is, therefore, needed when examining simulation results.

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## 6 Appendix 1: model calibration

The aim of the calibration process is to ensure that, (i) the observed activity levels during the base year period (2012) are exactly reproduced by the optimal solution of the primal model (equations (1) and (2)) and, (ii) the simulated supply elasticities from this model are consistent with the literature. This is performed in two steps: first, the unknown parameters ( $d$ ,  $Q$ ,  $\rho$ ,  $\varphi$ , and  $\sigma$ ) of the primal model are simultaneously estimated in each region and farm-type using data for the three-year average around 2018 (2018, 2019 and 2020). Second, the parameter  $d$  of the behavioural activity function is adjusted so that the first-order conditions (FOCs) are satisfied for the single year 2020, allowing the model to replicate the situation in this year.

Following [Louhichi et al. \(2018\)](#), we use a Bayesian highest posterior density (HPD) ([Heckelei et al., 2008](#)) approach and cross-sectional data to estimate the unknown parameters of the primal model. The main advantage of the HPD approach is that it allows a direct and transparent use of prior information, which increase the robustness of the estimates. Specifically, we use prior information on crop supply elasticities, variance-covariance matrix of per hectare crop revenues, dual values of resource constraints and constant relative risk aversion coefficients. To implement the HPD approach, we make the following assumptions:

- For activity levels  $\bar{x}_{f,i}$  and coupled payments  $\bar{s}_{f,i}$ , we assumed that they are accurately reported in FADN and thus are error-free. However, for prices  $p_{f,i}$ , yields  $y_{f,i}$  and accounting costs  $C_{f,i}$ , given that they are not directly reported in FADN but either derived from gross production and total output or estimated, we assumed that they involve measurement errors which follow a normal distribution with a prior mode (mean of normal distribution) of zero.
- A single resource is considered (land) and defined in an equality constraint, avoiding a complementary slackness condition in the estimation. The mean  $\tilde{\rho}_{ft,m}$  and standard deviation  $\tilde{\sigma}_{ft,m}^\rho$  of land rent<sup>14</sup> derived from FADN are used as prior information for dual values of the land constraint.
- Based on the literature ([Anderson and Dillon, 1992](#); [Petsakos and Rozakis, 2015](#); [Basnet et al., 2021](#)), a positive relative risk aversion coefficient is assumed (risk-lover behaviour is

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<sup>14</sup>Land rent is calculated from FADN as the rent paid divided by the rented Utilised Agricultural Area.

excluded) with prior mode of 1 and a variance of 4.

- Farm-type own-price elasticities of supply  $\tilde{\varepsilon}_{ft,i,i}$  used as prior mode are obtained from a disaggregation, following the methodology by [Garnache and Mérel \(2015\)](#), of the estimated regional crop supply elasticities by [Jansson and Heckelei \(2011\)](#). Their standards deviations  $\tilde{\sigma}_{ft,i,i}^{\varepsilon}$  are assumed to be 50 per cent of the mean (prior mode).
- Variables and parameters that carry a farm-type index are assumed to be common to all farms of similar size, specialisation and located within the same region (i.e. common geographical location).

The HPD model minimises for each farm-type<sup>15</sup>  $ft$  within a NUTS2 region<sup>16</sup>  $r$  the deviations between the estimated parameters and their prior, subject to a set of data consistency constraints. The general formulation of the HPD problem can be written as follows:

$$\min HPD_{r,ft} = \left\{ \begin{array}{l} \sum_i \psi_{ft,i} \frac{(\varepsilon_{ft,i,i} - \tilde{\varepsilon}_{ft,i,i})^2}{(\tilde{\sigma}_{ft,i,i}^{\varepsilon})^2} \\ + \sum_i \psi_{ft,i} \sqrt{\frac{1}{\dim(\Sigma)} \sum_{i'} \frac{(\Sigma_{ft,i,i'} - \tilde{\Sigma}_{ft,i,i'})^2}{|\tilde{\Sigma}_{ft,i,i'}|}} \\ + \sum_m \psi_f \frac{(\rho_{f,m} - \tilde{\rho}_{ft,m})^2}{(\tilde{\sigma}_{ft,m}^{\rho})^2} \\ + \sum_f \psi_f \frac{(\varphi_f - \tilde{\varphi})^2}{(\tilde{\sigma}_{\varphi})^2} \\ + \sum_{f,i} \psi_{f,i}^y \frac{(\epsilon_{f,i}^y)^2}{2} + \sum_{f,i} \psi_{f,i}^p \frac{(\epsilon_{f,i}^p)^2}{2} + \sum_{f,i,k} \psi_{f,i,k}^C \frac{(\epsilon_{f,i,k}^C)^2}{2} \end{array} \right. \quad (9)$$

$$gm_{f,i} - d_{f,i} - \sum_{i'} T_{f,i,i'} \bar{x}_{f,i} - \sum_m A_{f,i,m} \rho_{f,m} = 0 \quad (10)$$

$$gm_{f,i} = p_{f,i} y_{f,i} + \bar{s}_{f,i} - \sum_k C_{f,i,k} \quad (11)$$

$$\bar{y}_{f,i} - y_{f,i} = \epsilon_{f,i}^y \quad (12)$$

$$\bar{p}_{f,i} - p_{f,i} = \epsilon_{f,i}^p \quad (13)$$

<sup>15</sup>We use the TF14 FADN classification to define farming types.

<sup>16</sup>NUTS2 refers to regions belonging to the second level of the EU's Nomenclature of Territorial Units for Statistics.

$$\bar{C}_{f,i,k} - C_{f,i,k} = \epsilon_{f,i,k}^C \quad (14)$$

$$b_{f,m} - \sum_i A_{f,i,m} \bar{x}_{f,i} = 0 \quad (15)$$

$$T_{f,i,i'} = Q_{f,i,i'} + \frac{\varphi_f}{\omega_f} \sum_{ft} \Sigma_{ft,i,i'} \quad \forall f \rightarrow ft \quad (16)$$

$$Q_{f,i,i'} = \sum_{ft} \gamma_{f,i} B_{ft,i,i'} \gamma_{f,i'} \quad \forall f \rightarrow ft \quad (17)$$

$$B_{ft,i,i'} = \sum_j lb_{ft,i,j} lb_{ft,i',j} \quad ; \quad lb_{ft,i,i'} = 0 \quad \forall i' > i \quad (18)$$

$$V_{ft,i,i'} = \sum_j lv_{ft,i,j} lv_{ft,i',j} \quad ; \quad lv_{ft,i,i'} = 0 \quad \forall i' > i \quad (19)$$

$$\sum_l T_{f,i,l} T_{f,l,i'}^{-1} = 1 \quad \forall i = i' \quad (20)$$

$$\sum_l T_{f,i,l} T_{f,l,i'}^{-1} = 0 \quad \forall i \neq i' \quad (21)$$

$$\varepsilon_{ft,i,i'} = \frac{\sum_f \omega_f \bar{x}_{f,i} \varepsilon_{f,i,i'}}{\sum_f \omega_f \bar{x}_{f,i'}} \quad \forall f \rightarrow ft \quad (22)$$

$$\varepsilon_{f,i,i'} = \left[ T_{f,i,i'}^{-1} - \sum_m \left( \sum_j A_{f,j,m} T_{f,i,j}^{-1} \left( \sum_{j,j'} A_{f,j,m} T_{f,j,j'}^{-1} A_{f,j',m} \right)^{-1} \sum_j A_{f,j,m} T_{f,j,i'}^{-1} \right) \right] \frac{\bar{g}m_{f,i}}{\bar{x}_{f,i}} \quad (23)$$

where indices  $j, j'$  (similar to  $i, i'$ ) denote the agricultural activities and products,  $K$  the intermediate inputs and  $m$  the resource (land) constraints.  $\tilde{\varepsilon}_{ft,i,i}$  and  $\tilde{\sigma}_{ft,i,i}^\varepsilon$  are, respectively, the mean and standard deviation of farm-type own-price supply elasticities;  $\tilde{\Sigma}_{ft,i,i'}$  is the variance–covariance matrix of per hectare crop revenues observed in the FADN data over the period 2010-2020;  $\tilde{\rho}_{f,m}$  and  $\tilde{\sigma}_{f,m}^\rho$  are the mean and standard deviation of the farm-type (arable and grassland) land rents; and, finally  $\tilde{\varphi}$  and  $\tilde{\sigma}^\varphi$  are the mean and standard deviation of the relative risk aversion coefficients. All data on means and standard deviation are used as prior information to increase the robustness of the parameter specification. Notice that  $\sum_{i,i'} \frac{(\Sigma_{ft,i,i'} - \tilde{\Sigma}_{ft,i,i'})^2}{|\tilde{\Sigma}_{ft,i,i'}|}$  is the Chi-square distance between the estimated and the observed farm-type variance-covariance matrix of crop revenues and  $\frac{1}{\dim(\Sigma)}$  is a scaling factor.

$\bar{x}_{f,i}$  is the observed activity level (average over the three years around 2018) for activity  $i$  and  $\bar{p}_{f,i}, \bar{y}_{f,i}, \bar{s}_{f,i}, \bar{C}_{f,i,k}$ , and  $\bar{gm}_{f,i}$  are its corresponding price, yield, coupled payment, accounting variable costs and gross margin.  $\gamma_{f,i}$  is a scaling factor with  $\gamma_{f,i} = \sqrt{\frac{1}{\bar{x}_{f,i}}}$ ;  $\psi_{ft,i}$  and  $\psi_f$  are weighting factors representing the land share of activity  $i$  in total farm-type land (it allows activities with a large land share to dominate) and the farm share within the farm-type sample, respectively; and, finally,  $\psi_{f,i}^y$ ,  $\psi_{f,i}^p$  and  $\psi_{f,i,k}^C$  are scaling factors representing the inverse of  $\dim(\bar{y}_{f,i})$ ,  $\dim(\bar{p}_{f,i})$  and  $\dim(\bar{C}_{f,i,k})$ , respectively.

The endogenous variables of the HPD problem defined in equations (8)–(22) are the farm-type crop supply elasticities,  $\varepsilon_{ft,i,i'}$ ; the farm-type behavioural parameters,  $B_{ft,i,i'}$ ; the farm-type variance-covariance matrix of crop revenues,  $\Sigma_{ft,i,i'}$ ; the elements of the lower triangular Cholesky decomposition related to  $B_{ft,i,i'}$  and  $\Sigma_{ft,i,i'}$  parameters,  $lb_{ft,i,i'}$  and  $lv_{ft,i,i'}$ ; the farm-specific CRRA coefficients,  $\varphi_f$ ; the farm-specific land rental prices,  $\rho_{ft,m}$ ; the farm-specific behavioural parameters,  $d_{f,i}$  and  $Q_{f,i,i'}$ ; the farm-specific behavioural and risk parameters,  $T_{f,i,i'}$  (including the inverse value  $T_{f,i,i'}^{-1}$ ); the farm-specific gross margin for activity  $i$ ,  $gm_{f,i}$ ; and, finally, the assumed measurement errors for farm-specific crop yields,  $\epsilon_{f,i}^y$ ; crop prices,  $\epsilon_{f,i}^p$ ; and crop accounting variable costs,  $\epsilon_{f,i}^C$ .

Equation (8) defines the HPD measure to be minimized. Equations (9) and (13) represent the FOCs of the optimization model for production activities. Equation (14) represents the FOCs for (arable and grassland) land constraints. Equation (15) calculates the farm-specific behaviour-risk parameters,  $T_{f,i,i'}$ . Equation (16) calculates the farm-specific behavioural parameters,  $Q_{f,i,i'}$ . Equations (17) and (18) are the Cholesky decomposition of  $B_{ft,i,i'}$  and  $\Sigma_{ft,i,i'}$  matrices, respectively. Equations (19) and (20) calculates the inverse of farm-specific behaviour-risk parameters,  $T_{f,i,i'}^{-1}$ . Finally, equations (21) and (22) compute supply elasticities at farm and farm-type levels, respectively.