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A Bayesian econometrics and risk programming approach for analysing the impact of decoupled payments in the European Union*

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We estimate a risk-based programming, individual farm model and apply it to study the wealth effects of crop-related, decoupled direct payments under the European Union (EU) Common Agricultural Policy. The model expands on previous work on estimating risk-based programming models by applying a robust Bayesian econometric framework. The results indicate that the wealth effect varies greatly between individual farms, but that its impact on aggregate crop production is small. For larger farms, in particular, removing the decoupled payments, while keeping total land constant, increases the diversity of the cropping plan.

Key words: Bayesian econometrics, decoupled payments, positive mathematical programming, risk.

1. Introduction

Before 1992, various price support mechanisms were implemented within the European Union (EU) to increase production and stabilise prices. Since then, the Common Agricultural Policy (CAP) has undergone a number of revisions, for example the MacSharry reform in 1992 and Agenda 2000 in 1998, which move from price support to direct payments (Daugbjerg, 2014). The 2003 CAP reform and the subsequent Health Check in 2008 were pivotal in the decoupling of the per-unit subsidies into a single payment per farm, independent of farmers' production decisions. The decoupling trend came to a halt and was even partly reversed with the 2013 reform, which gave member states increased leeway to link a share of the total payment envelope to

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production[1]. Nevertheless, the single farm payment, currently termed the 'basic farm payment', remains a key component of the EU CAP.

In a high-risk environment, decoupled payments could influence production decisions indirectly by reducing the share of income that is subject to risk. Farmers receiving a larger fixed payment may exhibit less risk aversion in production decisions. This is termed the *wealth effect* of the decoupled payment. Significant efforts have been made to evaluate the effect of the decoupled subsidies on farmers' production decisions, utilising a number of approaches, ranging from partial to general equilibrium models and econometric techniques[2]. Some studies have taken wealth effects into account, but, despite differences in their methodological approach, most have found that decoupled payments had only a small effect on production decisions. In particular, the land area allocated to cereals and the production of sheep and goat meat and beef has declined in the EU-15, whereas crops that were not entitled to direct payments before the 2003 reform (e.g. forage crops and pasture) have increased.

Most previous studies have estimated the impacts of decoupled payments on production decisions without considering risk. Nonetheless, a few studies (e.g. Serra, 2006; Sckokai & Moro, 2006) have considered price volatility when evaluating the impact of decoupled payments in an econometric context. Recently, Matthews (2015) argues that the EU will likely face increased price volatility for agricultural products in the future and risk management tools are, indeed, expected to be components of the future CAP. Arata *et al.* (2017) carried out simulations of a series of crop *price* volatility scenarios and explored the potential risk management role of agri-environmental schemes. *Weather* variability is another risk factor causing crop production loss (Ray & Gerber, 2015). Many studies (e.g. Britz & Arata, 2019; Cortignani & Severini, 2012; Petsakos & Rozakis, 2015; Serra, 2006) have identified crop yield variability as a source of risk in agriculture. Therefore, neglecting yield variability may lead to biased conclusions.

The present study aims to quantify the role of decoupled payments for crop production decisions in an environment of stochastic prices and yields. The analysis is carried out in three steps: first, we develop a mathematical risk programming model based on the Markowitz mean-variance (E-V) framework. We then estimate the model parameters using historical observations on variables, such as crop activity levels, production quantities and output prices available from the Farm Accountancy Data Network (FADN) for a

[1] Now referred to as 'voluntary coupled support', this possibility was previously provided in a more restricted form under Articles 68 and 69 of the preceding regulations.

[2] For more studies on the impacts of decoupled subsidies on farmers' production decisions, see Hennessy (1998); Andersson (2004); Roche and McQuinn (2004); Breen *et al.* (2005); Britz *et al.* (2006); Goodwin and Mishra (2006); Lin and Dismukes (2007); Balkhausen *et al.* (2008); Rude (2008); Serra *et al.* (2009); Femenia *et al.* (2010); Just (2011); Uthes *et al.* (2011); Trubins (2013); Chambers and Voica (2017).

selected European region (Sweden) by applying a Bayesian estimator. Finally, we calibrate the estimated model to base year activity levels and simulate the impacts of removing decoupled payments on farmers' land allocation to crop activities.

The contribution of this paper is twofold: (i) it offers a policy-relevant risk programming model in a Bayesian econometric framework; and (ii) it investigates the production effects of decoupled payments at the farm level, while considering price and yield risks, thereby shedding light on the extent to which decoupled payments affect production decisions at the individual farm level. The empirical issue of the production effects of decoupled payments is relevant to negotiations in the WTO. The methodology developed in this paper, however, extends significantly beyond that application. It allows us to analyse risk-based crop allocation behaviour with a model specification flexibly based on data and prior information. It offers possibilities for analysis at a level of crop resolution not offered by typical econometric models and is, in this respect, similar to Britz and Arata (2019). It may be useful for analysing potential crop insurance schemes under future CAP or assessing the impact of various farm support measures in view of (increasing) weather risks, for example the national drought program in Australia and the agricultural risk coverage programs in the USA.

The remainder of this paper is structured as follows: Section 2 explains the policy concerns in relation to the distortionary effects of decoupled payment on production decisions, while Section 3 presents the microeconomic model of the individual farm. Section 4 describes the data in the EU-FADN data set used in the model estimation, and Section 5 develops the econometric methodology used for estimating it. Section 6 presents the estimate results and applies the model to the case of removing decoupled payments. Section 7 concludes the paper.

2. Policy context

Decoupling was initiated under the 2003 CAP reform. Crop-specific compensation payments were replaced by a payment per farm based on the average level of historical payments per hectare for each farm and the farm's total land use for a list of eligible crops. Subsequently, the decoupling was revised by adding to the list of eligible crops and gradually equalising differences in per hectare subsidies across farms. Further modifications to the farm support payments have been discussed in the literature (Matthews, 2016; Uthes, 2011), and the question was raised as to how decoupled they actually are (Chambers & Voica, 2017; Goodwin & Mishra, 2006). Some studies have found only small production effects from decoupled payments (Brady *et al.* 2009; Breen *et al.* 2005; Femenia *et al.* 2010; Hennessy, 1998; Just, 2011).

Financial transfers are decoupled when their introduction does not lead to production levels exceeding the levels that would exist without compensation. Farmers may exhibit wealth effects in a high-risk environment resulting in an effective behavioural coupling wherein farmers engage in proportionally more high-return, high-risk farming activities due to the safety net provided by financial transfers (under the CAP for example). The larger the share of direct payments as a percentage of farm income, the larger the effect would presumably be. The share of direct payments in Sweden ranges from 15 to 20% of farm income (see Table 1), while this was only 3% in the United States (Makki *et al.* 2004). This suggests that EU farmers, particularly in Sweden, may experience larger influences of direct payment on production decisions. Sweden regularly advocates a reduction in the EU CAP budget, including a downscaling of the direct payment scheme (Uthes *et al.* 2011).

After the 2003 CAP reform, we have observed a decrease in the acreages of certain 'high-risk crops', for example soft wheat, potatoes and sugar beet, over the period 2005–2008 (see Table 1) for the farms in the study sample (see the data presented below). Before the CAP reform, the acreages of these crops increased for the period 2000–2005. This indicates that the decoupled area-based payments might have influenced the acreages of high-risk crops. For major crops, such as rye, barley, oats and rapeseed, the CAP reform did not seem to exert a significant influence on their acreages. The model developed in this paper can help us analyse to what extent these changes depend on the wealth effect and the introduction of the decoupled payment, as it allows us

Table 1 Cropping patterns in Sweden before and after the introduction of decoupled payments in 2003

	Observed levels			Area shares (%)		
	2000	2005	2008	2000	2005	2008
Crop activities ('000 ha)						
Soft wheat	9.59	9.67	9.17	33.39	30.42	30.13
Rye	2.06	1.99	2.02	7.16	6.25	6.63
Barley	7.06	9.47	9.29	24.60	29.82	30.55
Oats	4.32	3.77	4.16	15.06	11.88	13.69
Other cereals	0.35	0.14	0.08	1.23	0.44	0.27
Rapeseed	1.11	2.19	2.69	3.88	6.90	8.85
Pulses	0.70	1.00	0.83	2.43	3.15	2.72
Potato	1.07	1.16	0.87	3.72	3.65	2.87
Sugar beet	1.89	1.82	1.05	6.58	5.71	3.46
Other vegetables	0.50	0.35	0.43	1.73	1.10	1.41
Total acreages	28.71	31.78	30.42	–	–	–
Farm equity (million Euro)	0.25	0.35	0.35	–	–	–
Coupled payments (million Euro)	6.77	0.05	0.05	–	–	–
Decoupled direct payments (million Euro)	–	10.11	11.24	–	–	–
Share of direct payment in family income (%)	–	20.47	17.99	–	–	–

Note: Information on other oil seeds, fodder root crops, flax and hemp is not presented due to the low levels of production.
Source: FADN sample for Sweden (see data section).

to perform counterfactual simulations, where prices and coupled payments are kept constant.

3. Microeconomic model

Following Jansson and Heckelei (2011), we define a quadratic optimisation model to describe farmers' allocation of farmland to crop production activities. The main addition to our model is a risk component in the mean–variance (E-V) approach. We define the microeconomic model for each farm f (index omitted for clarity) in the expected utility framework as:

$$\max_{x \geq 0} U(x) = E(\pi(x)) - \frac{1}{2}\left(\frac{\phi^R}{W}\right) x' \sum x - x'c - \frac{1}{2} x'Qx \tag{1}$$

subject to,

$$\iota' x = b[\lambda] \tag{2}$$

where $E(\pi(\boldsymbol{x}))$ is the expected profit, $\boldsymbol{\phi}^{\mathbf{R}}$ is the *relative* risk aversion coefficient, W is farm wealth, and $\boldsymbol{\Sigma}$ is the variance–covariance matrix of per hectare crop revenues. $\boldsymbol{x}$ is the vector of activity levels, $\boldsymbol{b}$ is the available resource (land), $\boldsymbol{c}$ and $\boldsymbol{Q}$ are behavioural parameters to estimate, and $\boldsymbol{\iota}$ is a unit summation vector. In a general set-up, this constraint is written as $Rx \leq b'$, where $\boldsymbol{R}$ is the vector for farm resource use, such as farmland, labour and water. In this paper, we use a single resource (land) and define an equality constraint, avoiding a complementary slackness condition in the estimation. We define the land constraint as an equality (2), associated with the Lagrangean multiplier λ, implying that no land abandonment is permitted. This assumption is reasonable, as long as we have positive land rents, and it is important in the calibration, as it avoids the need to deal with complementary slackness conditions.

In the remainder of this paper, we use the subscript f for farms, $\boldsymbol{j}$ for crop activities and $\boldsymbol{t}$ for the time period. We adhere to matrix notation, with bold upper-case letters for matrices, bold lower-case letters for vectors and non-bold symbols for scalars. Wherever possible, we omit the time index t (t = 1,2,. . .,T) for legibility.

The utility function in equation (1) can be expressed as $U(\boldsymbol{x}) = U_1(\boldsymbol{x}) + U_2(\boldsymbol{x})$, where $U(x) = E(\pi(x)) - \frac{}{1}\left(\frac{}{\phi}\right)^x \Sigma x$ and $U(x) = -^x c - \frac{}{1}{}^x Qx$. The first term U_1 represents the utility of the expected income plus the disutility of income variation. The second component U_2 $(\boldsymbol{x})$ captures the utility of factors influencing the decisions of the farmer that are not accounted for in U_1 or the constraints.

We define the expected farm income $E(\pi(\boldsymbol{x}))$ resulting from the farmer's cropping land allocation $\boldsymbol{x}$ as:

$$E\left(\pi\left(x_f\right)\right)=\overline{d}_f\left(fixedLand_f+x_l'\iota\right)+s_f'x_f+E\left(p_f'\right)E\left(Y_f\right)x_f-w_j'A_fx_f \quad (3)$$

where d is the rate of decoupled payments per hectare. The scalar 'fixedLand' is the farm area covered by crops that are not modelled, but are eligible for decoupled payments, in particular non-marketable fodder crops, while $^{x}\boldsymbol{l}$ is the sum of areas of crops that are modelled. $\boldsymbol{s}$ is the vector of coupled payments per hectare for each crop, such as the coupled subsidies for pulses. E $(\boldsymbol{p})$ and E $(\boldsymbol{Y})$ are the expected output prices and yields, while $\boldsymbol{w}$ and $\boldsymbol{A}$ are input prices and input coefficients, respectively. Only output prices and yields are considered to be stochastic from the vantage point of the farmer, while input coefficients and input prices are assumed to be known when the production decision is taken.

The (dis-)utility of income variation is defined by the term $-\frac{1}{2}\left(\frac{\phi^R}{W}\right)x'\Sigma x$. The factor $x'\Sigma x$ is the variance of the revenues under the cropping plan. A positive ϕ means that the farmer is risk averse, that is a larger variance of revenues is a disutility. W (for wealth) is the value of assets, such as farm buildings, machinery, breeding livestock, forest and agricultural land. Since wealth appears in the denominator, the model implies that the wealthier the farmer, the less important a given variance in revenues becomes.

The value of land is an important component in farm wealth, and it is known that subsidies coupled to land area increase land prices (see review in Ciaian, Kancs & Swinnen, 2010). To incorporate this 'capitalisation' of the decoupled payment into the farm wealth W, we assume a simplified model of perfect capitalisation of seven times the annual rate of decoupled payments times the area of land owned. The motivation is that the decoupled payments are paid for a typical time period of seven years corresponding to the duration of the EU financial perspective (budget). Since existing decoupled payments are already included in the observed assets, the wealth depends on a *change* in the rate of decoupled payments Δd as $W = W^{obs} + 7\Delta dl' x^{owned}$, where W^{obs} indicates the observed value of farm assets. In the econometric estimation, by definition $\Delta d = 0$. In simulations, we can change farm wealth by changing Δd.

Note that our definition of wealth does not depend on the (stochastic) profits $\pi(\boldsymbol{x})$. This implies that the absolute level of risk aversion $\boldsymbol{\phi^R}/\boldsymbol{W}$ does not vary according to the stochastic variations in profits resulting from yield or price fluctuations, even though risk aversion increases with decreasing (capitalised) farm wealth. This formulation makes the model similar to the one used by Sckokai and Moro (2006).

The parameters $\boldsymbol{c}$ and $\boldsymbol{Q}$ in U_2 determine the unobserved cost and how they change with activity levels. They influence the farmer's response to changes in prices and subsidies. This quadratic function is in the tradition of positive mathematical programming (PMP), originally used to calibrate programming models to observed activity levels. Since we assume that those costs do not correspond to any observable accounting costs, we omit them from the computation of farm income. This is in line with the approach used to calibrate, for example, the TIMES energy model (Lee *et al.* 2019) and the supply models in CAPRI (Jansson & Heckelei, 2011). However, it is in contrast to the original contribution by Howitt (1995), where the behavioural parameters are explicitly considered to be an adjustment of the observable (average) variable cost.

4. Data

The present study used a sample of 287 Swedish farms with an acreage of 34,919 hectares. The sample was obtained from the EU-FADN sample for the period 1998-2008. The farms were classified according to size (Economic Size Units, ESU), specialisation (TF8 according to FADN) and geographic region (NUTS2-region)[3]. In each region, the eight largest groups were selected and the remaining farms were aggregated into a residual group. In total, we obtained 75 farm groups. Only farms that produce marketable outputs, such as cereals, oilseeds and protein crops (COPs) and root crops (e.g. potatoes and sugar beet) (hereinafter referred to as program crops), were selected. We excluded crops with non-marketed outputs, for example fodder and pasture (because prices for these are missing in FADN), vegetables and permanent crops (because they do not generally compete with arable crops and play a minor role in the aggregate land use) and livestock production (because we want to avoid handling animal feeding restrictions). In total, our sample contained 2,836 farm observations, representing 36 farm groups, as listed in Appendix 1. Farms participate in the survey voluntarily and for a limited time period. Therefore, the FADN sample is an unbalanced panel, where the years with data can differ across farms. We considered only farms observed for at least three years to identify farm-level fixed effects when estimating the variance–covariance matrix.

Prices are generally not provided in the FADN sample, but can be inferred from quantities and values. Similarly, yields can be calculated by dividing the observed production volume by the observed crop area. For farm wealth ($\boldsymbol{W}^{obs}$), we used the value of owned assets: farm buildings, machinery, breeding livestock, forest and agricultural land.

In the study sample data, about 70 per cent of the observations were in the southern plains and eastern parts of the country, with a large coverage of COP and root crops. Northern Sweden is characterised by lower crop yields,

[3] NUTS stands for Nomenclature of Territorial Units for Statistics established by Eurostat, TF8 represents levels of agricultural specialisation based on types of farming (TF) and ESU denotes the economic sizes of agricultural holdings. Classification of TF and ESU is available at http://ec.europa.eu/agriculture/rica/diffusion_en.cfm.

but a large share of grassland and protected natural areas Appendix 2 lists further characteristics of the data set for Sweden.

In Sweden, the decoupling of production-based subsidies was initiated in 2005 as part of the 2003 CAP reform. Since then, coupled payments have largely been replaced by direct payments (including set-aside and arable aid payments), with a share ranging from 15 to 20% of farm income. Over the study period, the acreages for 'other cereals' and sugar beet declined, whereas acreages of, for example, rapeseed and vegetables increased, possibly reflecting shifts in prices and subsidy schemes during the period.

5. Model implementation and econometric estimation

The empirical estimation of the model parameters in equations (1) and (2) proceeds in three steps. First, we estimate the covariance matrix $\boldsymbol{\Sigma}$ for per hectare revenues in a preliminary step. Then, we estimate the model parameters ($\boldsymbol{p}$,$\boldsymbol{w}$,$\boldsymbol{Y}$,$\boldsymbol{A}$,$\boldsymbol{\phi}^{\boldsymbol{R}}$,$\boldsymbol{c}$ and $\boldsymbol{Q}$) using the estimated $\boldsymbol{\Sigma}$ and the historical observations of crop activity levels, output prices and production quantities. The behavioural parameter $\boldsymbol{c}$, which would be sufficient to calibrate the model for any particular year, is not year-specific. Therefore, the resulting model does not reproduce the observed activity allocation for any individual year precisely. Consequently, we need to calibrate the model to the year that we want to use as the reference point in a simulation (such as for a removal of decoupled payments). This is the final step of the model implementation, and it is done by adjusting the parameter $\boldsymbol{c}$.

5.1 Step 1 Estimation of the covariance matrix

Following Cortignani and Severini (2012) and Britz and Arata (2019), we approximate the risk factor using the variance–covariance matrix of per hectare revenues observed in the FADN data. To derive the variance–covariance of per hectare revenues, we estimate an expected revenue model for each crop with farm and time fixed effects as

$$r_{fjt} = \gamma_{fj} + \beta_{fj} t + \varepsilon_{fjt}, \tag{4}$$

where r_{fjt} is observed revenue per hectare for farm f for producing crop j at time t, and ϵ_{fjt} is the deviation of each farmer's revenues from the expectations for year t and output j. The term $\gamma_{fj} + \beta_{fj}t$ measures a farmer's expected revenue from each crop activity. In this context, the variance–covariance matrix is computed as.

$$\sigma^2_{gjk} = \sum\nolimits_{ft\in g}\left[r_{fjt} - E_{ft}(r_{fjt})\right]\left[r_{fkt} - E_{ft}(r_{fkt})\right]/\sum\nolimits_{ft\in g}1, \tag{5}$$

where $E_{ft}(r_{fjt})$ is the expected revenue (i.e. mean outcome) from each crop activity, k is an alias of j, and g indicates the farm-type groups categorised by the principal types of farming such as crops, livestock and mixed farming. Farms belonging to the same farm type are assumed to face common economic and weather shocks. To address heteroskedasticity, we employ a feasible generalised least square (FGLS) estimator in four steps. The usual two-stage FGLS estimator can produce non-definite covariance matrices if the panel of residuals is unbalanced, as in our case. Other studies solve that issue by using a balanced panel of prices, for example, by inserting averages for missing values (Britz & Arata, 2019; Chavas & Holt, 1990; Platoni *et al.* 2012) or splitting the unbalanced panel into blocks of balanced panels (Biørn, 2004). In our four-stage FGLS, we calculate a strictly positive definite covariance matrix after each of the ordinary two stages of the FGLS using a 'Hadamard-weighted Frobenius norm Shrinkage estimator' as proposed by Higham (2002). Intuitively, this means that we select the strictly positive definite covariance matrix that is closest, in the Euclidian sense, to the possibly non-definite matrix obtained from the FGLS estimator. Further detail on the estimator of the covariance matrix is provided in Appendix 3.

5.2 Step 2 A Bayesian posterior mode estimation

In the present study, we have adopted Jansson and Heckelei's (2011) approach to estimate the first-order conditions (FOCs) and second-order conditions (curvature) of the primal model using panel data. The parameters in the primal model are not all well identified. Particularly problematic is the combination of land rents λ_{ft} and the behavioural parameter $\boldsymbol{c}_f$, because it is only their sum that is relevant in the FOCs (shifting 1 euro from one to the other would change nothing). In order to be able to identify all of the parameters (and increase the robustness of the estimates), we develop a Bayesian estimator using prior distributions for selected parameters.

Specifically, we use prior information on the distribution of land rent λ, the relative rate of risk aversion ϕ^R, the distributions of the various error terms and the implicit supply elasticity matrix $\boldsymbol{\eta}$, which is a function of the other parameters, in particular $\sum$ (estimated in step 1) and $\boldsymbol{Q}$ (to be estimated). Previous studies also suggest utilising external information on supply elasticities (Britz & Witzke, 2014; Petsakos & Rozakis, 2015) and shadow prices for resources (de Frahan *et al.* 2007) to increase the robustness of the parameter specification.

In this Bayesian approach, the posterior density function of the unknown parameters is derived as the product of a likelihood function and the prior density functions. The likelihood function is the implicit function defined by the first and second-order conditions. It is degenerate, in the sense that it gives a likelihood of ‘1’ for parameters that satisfy the optimality conditions and ‘0’ otherwise. Expressed more intuitively, the optimality conditions define a space of parameters, where all points would give a model that describes the available observations equally well and the prior distributions help us select one particular parameter vector from that space. In practice, we can find the posterior mode by maximising the product of the prior densities subject to the constraint that all first and second-order conditions are satisfied.

The estimations are carried out per farm-type group (see the data section for a definition). Parameters that do not carry any farm index f are thus common to all farms of similar size, specialisation and geographical location. To implement the posterior maximisation approach, we make the following assumptions and re-parameterisations:

1. For activity levels $\boldsymbol{x}_{ft}$, the observed levels are those planned by the farmer, that is no errors are involved.
2. For prices $\boldsymbol{p}$ and $\boldsymbol{w}$, we assume that there are no measurement errors and that the observed prices are those that the farmer used when planning production. In particular, we assume that $E(p_{ft}) = p_{ft}$. The latter is a simplification, given that we assume that price uncertainty is a source of risk. However, we do include an optimisation error (see equation 7) that is assumed to include also any error in price expectations.
3. Yields are not directly observed in FADN, but we do observe the gross production $\tilde{q}_{fot}$ for each output o. We assume that the planned (unobserved) production quantity $\tilde{q}_{fot}$ is gamma distributed with prior mode $\tilde{q}_{fot}$ and use the equation (13), $q_{fot} = \sum_j Y_{fojt} x_{fjt}$ to estimate yields relative to output.
4. Similar to outputs, we assume that the planned gross input use q_{fit} of each input i is gamma distributed with the prior mode equal to the observed gross farm use $\tilde{q}_{fot}$ and define $q_{fit} = \sum_j A_{ijt} x_{fjt}$ (equation 14). In contrast to outputs, where the yield matrix $\boldsymbol{Y}_{ft}$ is diagonal, each input is used by several production activities ($\boldsymbol{A}_t$ is not diagonal). If the number of activities and the number of years of observations are low, the elements of $\boldsymbol{A}_t$ are not well defined. For robust estimates of $\boldsymbol{A}_t$, we assume that it is the same for all farms in the same farm-type group (no f index) and use the national average input coefficients $\tilde{A}_{ij}$ for the use of input i in activity j from the CAPRI model’s (Britz & Witzke, 2014) database for year 2005 as mode of a gamma distributed prior density.
5. The land rents available in the FADN are used as prior modes $\tilde{\lambda}_{ft}$ for a gamma distribution for dual values of the land constraint λ_{ft}. For farms with *own* land, we impute shadow values to use as prior modes using

$\tilde{\lambda}_{ft} = rL_{ft}$, where L_{ft} represents the land asset value in FADN and r is an interest rate of 2% per annum.

6. To increase the robustness of the risk aversion coefficient estimates, we include a prior distribution (gamma density) for ϕ^R. Sckokai and Moro (2006) find the value for ϕ^R in a range of 0.05 to 5.5 for varying levels of farm sizes. Petsakos and Rozakis (2015) define a logarithmic utility function, where by definition ϕ^R is equal to 1. Based on those studies, we assign a prior mode $\tilde{\phi}^R = 1$ Note that the gamma density has support $[0 + \infty)$, and we, thus, exclude negative coefficients (risk-loving behaviour).
7. The matrix of own and cross-crop effects $\boldsymbol{Q}_f$, which strongly influences the supply elasticity of the farm, contains a large number of parameters to estimate. To aid identification in equations (9-12), we (i) introduce a prior distribution for the implied supply elasticity $\boldsymbol{\eta}_{ft}$ in equation (12), and (ii) restrict $\boldsymbol{Q}_f$ to a block structure, where the cross effects between crops are the same for all crops belonging to the same crop group cg of similar crops[4] (equation 9), (iii) require $\boldsymbol{Q}_f$ to be similar across years and farms in the current farm-type group up to a scaling matrix τ_{ft}, which is further described below, and (iv) require $\boldsymbol{Q}_f$ to be strictly positive definite by requiring its factor $\boldsymbol{B}$ to be positive definite (equations 9 and 11) and that the diagonal elements $\boldsymbol{D}$ are all strictly positive. For the own-price supply elasticities, we assumed a prior mode $\tilde{\eta}_{ft}$ of 1.5 across all crops, based on reported empirical estimates of own-price supply elasticities within a range of 0.05-2.5 for different crop activities (e.g. Britz & Witzke, 2014; Haile *et al.* 2016; Hertel *et al.* 2016).
8. There is a residual optimisation error ε_{fjt}^{opt} entering additively in the FOC with respect to crop areas, which is normally distributed with a prior mode of zero, and a co-estimated variance for each crop σ_{jj}^2 with a (inverse chi-square) prior distribution relating to the diagonal $\tilde{\sigma}_{jj}^2$ of the already estimated covariance matrix Σ, $\sigma_{jj}^2 \sim$ Inverse-$\chi^2(\tilde{\sigma}_{jj}^2)$. This reflects the probability that for crops with a larger variance in revenues, optimisation errors are more likely to occur.

As explained above, we maximise the joint prior density subject to the first- and second-order conditions of the primal model. Since the maximum is preserved under monotonic transformations, we simplify the estimation by taking the logarithm of the product of the prior distributions and cancel all the constant terms. Then, the Bayesian posterior density maximisation problem for each farm-type group can be written as follows (see Appendix 5 for a derivation):

[4] Four crop groups are defined as, (i) cereals, including soft wheat, rye, barley, and oats, (ii) other cereals, such as grain maize, (iii) oil seeds such as rapeseed, and (iv) other crops consisting of pulses, potato, and sugar beet.

$$maximise - \left| \begin{array}{c} \sum_{fjt}\left\{\left(\frac{1}{2\sigma_{jj}^2}\right)\left(\varepsilon_{fjt}^{opt}\right)^2\right\} + \sum_{jj}\left\{\frac{1}{2}\left(\frac{\sigma_{jj}}{\tilde{\sigma}_{jj}}\right)^2 - \frac{1}{2}\left(\frac{\sigma_{jj}}{\tilde{\sigma}_{jj}}\right)^2\right\} \\ + \sum_{jit}\left\{(\alpha_{jit}^A - 1)\log\left(\frac{A_{jit}}{\tilde{A}_{ji}}\right) - \beta_{jit}^A\left(\frac{A_{jit}}{\tilde{A}_{ji}}\right)\right\} \\ + \sum_{fit}\left\{(\alpha_{fit}^q - 1)\log\left(\frac{q_{fit}}{\tilde{q}_{fit}}\right) - \beta_{fit}^q\left(\frac{q_{fit}}{\tilde{q}_{fit}}\right)\right\} \\ + \sum_{fot}\left\{(\alpha_{fot}^q - 1)\log\left(\frac{q_{fot}}{\tilde{q}_{fot}}\right) - \beta_{fot}^q\left(\frac{q_{fot}}{\tilde{q}_{fot}}\right)\right\} \\ + \sum_{ot}\left[(\alpha_{ot}^\eta - 1)\log\left(\frac{\eta_{ot}}{\tilde{\eta}_{ot}}\right) - \beta_{ot}^\eta\left(\frac{\eta_{ot}}{\tilde{\eta}_{ot}}\right)\right] \\ + \sum_{ft}\left\{(\alpha_{ft}^\lambda - 1)\log\left(\frac{\lambda_{ft}}{\tilde{\lambda}_{ft}}\right) - \beta_{ft}^\lambda\left(\frac{\lambda_{ft}}{\tilde{\lambda}_{ft}}\right)\right\} \\ + \left[(\alpha^\phi - 1)\log\left(\frac{\phi^R}{\tilde{\phi}^R}\right) - \beta^\phi\left(\frac{\phi^R}{\tilde{\phi}^R}\right)\right] \end{array} \right| \quad (6)$$

subject to

$$\frac{\partial \pi(x)}{\partial x} - \left(\frac{\phi^R}{W_{ft}^{obs}}\right)\Sigma x_{ft} - c_f - Q_f x_{ft} - R'\lambda_{ft} + \varepsilon_{ft}^{opt} = 0 \quad (7)$$

$$\frac{\partial \pi(x)}{\partial x} = \overline{d}_f + s_{ft} + Y_{ft}' p_{ft} - A_t' w_{ft} \quad (8)$$

$$Q_f = l_{ft}\left[\tau_{ft}\tau_{ft}'\right] \circ [D + GBG'] \quad (9)$$

$$H_t = \left(\frac{\phi^R}{\overline{W}_t^{obs}}\right)\Sigma + D + GBG' \quad (10)$$

$$B = LL' \quad (11)$$

$$\eta_t = VecDiag\left(\overline{Y}_{\circ t}\left[H_t^{-1} - H_t^{-1} l' \left[\iota H_t^{-1}\iota\right]^{-1} \iota H_t^{-1}\right] \overline{Y}_t \overline{P}_{\circ t} O_t^{-1}\right) \quad (12)$$

$$q_{fot} = \sum_j Y_{fojt} x_{fjt} \quad (13)$$

$$q_{fit} = \sum_j A_{ijt} x_{fjt} \tag{14}$$

Equations (7) and (8) represent the FOCs of the primal model equations (1) and (2) with respect to activity levels $\boldsymbol{x}_{ft}$. The symbols α and β in the objective function (6) are the two parameters of the gamma prior densities. The superscript denotes the parameter for which the prior applies, and the subscripts denote farm, inputs, crops and time as usual. A 'bar' version of a parameter denotes the average of the parameter across farms in the current farm group.

The gamma distribution was used initially because it has a support of $[0, +\infty)$, that is negative or zero estimates are excluded a priori, and, secondly, because it proved to be numerically stable in estimates (carried out using the programming language GAMS and the CONOPT solver (Drud, 2008)). The two gamma density parameters α and β can be derived from the mode and variance by solving a second-degree polynomial (see Appendix 4). Modes for each prior were defined above. The variances were defined based on blanket assumptions about 'accuracy' on a scale from 0 to 10, where 0 would mean 'entirely uninformative' and 10 would mean that the mode equals two standard deviation (relatively strong prior). For all parameters, we assumed an accuracy of three (implying mode is 0.6 standard deviations) except for the own-price elasticity, where it was set to five (implying the standard deviation is equal to the mode, i.e. 1.5 for all crops).

In equation (9), the behavioural parameter $\boldsymbol{Q}$ is re-parameterised to economise on parameters. This is done by (i) assuming that the off-diagonal interaction terms are similar for crops belonging to pre-defined crop groups and (ii) by assuming that the Q-matrices of farms in the same farm group are similar up to a scaling matrix. To take crop group interactions into account, $\boldsymbol{Q}$ is decomposed to a diagonal matrix $\boldsymbol{D}$ with only own-price effects and the term GBG' for interactions between crop groups. Here, $\boldsymbol{G}$ is the $m \times j$ indicator matrix for group membership of j crop activities in the m crop group and $\boldsymbol{B}$ is the (symmetric) parameter matrix containing $\frac{1}{2}m \times (m+1)$ parameters to estimate. To take the similarity across farms belonging to the same crop group into account, we define the common parameter $\boldsymbol{Q_f}$ for farm f belonging to the same farm group and multiply by the farm-specific scaling factors as in equation (9). The symbol l_t denotes a 'land availability index' and is defined exogenously as the ratio between the average farm area in the group across all years divided by the average farm area in the year t.

The factor $\tau_{ft}\tau'_{ft}$ scales the corresponding elements of the $\boldsymbol{Q}$-matrix for the individual farm relative to the farm group, where each element is computed as $\tau_{fjt} = \sqrt{\frac{x_{fjt}}{\bar{x}_{\bullet jt}} / \frac{p_{fjt}}{\bar{p}_{\bullet jt}}}$. This allows farms with different sizes and price levels to have similar supply elasticities when sharing the same parameters $\boldsymbol{B}$ and $\boldsymbol{D}$. Britz and Arata (2019) discuss this scaling factor in detail and estimate the acreage share model to avoid such a scale bias. Our scaling serves a similar purpose, but also considers the differences in price levels. Equation (10) defines the Hessian matrix $\boldsymbol{H_t}$ and aids in the definition of the elasticity. To ensure definiteness of the Hessian matrix, we define $\boldsymbol{B}$ to be a positive semi-definite using a Cholesky factorisation in equation (11), where $\boldsymbol{L}$ is the lower triangular matrices and all elements of $\boldsymbol{D}$ are strictly positive ($>10^{-6}$).

Note that we only derive the elasticity for the average farm of each farm group – not for each individual observation. The reasons are that (i) the production of individual farms may fluctuate strongly between years due to, for example crop rotation and (ii) implementing the strongly non-linear equation for each observation is very computationally demanding. Equation (12) is the analytical expression for the own-price supply elasticities, where $\boldsymbol{O}_t$ is a diagonal matrix of output quantities (weighted across all farms in the group) with elements on the diagonal defined as $o_{it} = Y_{ijt}\boldsymbol{x}_{jt}$ for farm-type group average yields and acreages, and VecDiag() is a function that converts the main diagonal of a square matrix into a column vector and discards the remainder.

5.3 Step 3 Calibration and simulation

After estimation, the model was calibrated to the situation in 2005, when the initial decoupling was fully implemented. The calibration is achieved by adding the optimisation error ε_{ft} to the estimated parameter $\boldsymbol{c}_f$, so that the FOCs are satisfied without error for that year. In the simulation scenario, we remove the decoupled farm payments for 2005 by setting $\Delta d = -\bar{d}$, while leaving all other (coupled) support payments, prices, total land availability and other parameters unchanged. In the FOCs, we see that a risk-free transfer of the decoupled payments connected with total land use per farm would result in a corresponding variation in the dual value of land. Therefore, our model isolates the wealth effect of decoupled payments in farmers' crop production decisions. To avoid aggregation errors due to farm heterogeneity, we analyse the counterfactual scenario with the farm level of data. However, the simulation experiment may still entail aggregation errors, due to the non-linearity of the model.

6. Empirical application

6.1 Estimate results

Estimation of the model using the EU-FADN data produces coefficients of *relative* risk aversion that range from 0.8450 to 1.2466 across the farm groups, confining them to the neighbourhood of the prior mode. These estimates are constant for the individual farms in each group, but the *absolute* risk aversion coefficients vary with the levels of farm income and capital assets. Figure 1 shows that absolute risk aversion coefficients are lower for larger farm sizes, consistent with the findings of Sckokai and Moro (2006). We also found

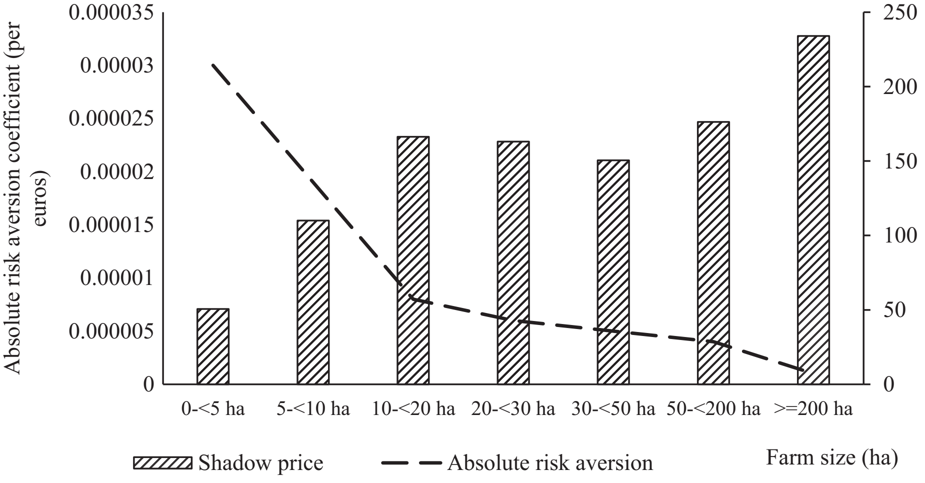

Figure 1 Estimated absolute risk aversion coefficients and shadow prices across farm sizes.

higher farmland shadow prices for large farms, indicating that these farms can obtain larger marginal value added per hectare of land.

The estimated covariance matrix (see Appendix 6) identifies some ‘high-risk crops’, such as soft wheat, potatoes and sugar beet, by their comparatively large estimated variances, while rye, barley, oats, pulses and other cereals have lower variances and are consequently the ‘low-risk crops’. Among the major cereal crops (soft wheat, rye, barley and oats), we observed positive covariance, implying that they require similar conditions for cultivation. Thus, no matter which particular crop is grown in the field, any of the major cereal crops produce better yields in a good year. Pulses, a protein crop identified as a low-risk crop, had a negative covariance with other cereals (e.g. triticale and grain maize). This indicates that pulses could be a potential crop for diversification as a risk management strategy.

The root crops (potatoes and sugar beet) also have negative covariance, meaning that risk- averse farmers can compensate for the potential loss in potato production through the better yield of sugar beet crop and minimise the risk of uncertain revenues in an unproductive environment. Rapeseed, another low-risk crop also has a negative covariance with potatoes, presenting another alternative for diversifying the risk of uncertain revenues associated with potato cultivation. Overall, the estimated covariances identify potential crop production activities for diversifying the risk of uncertain farm revenues in a high-risk environment.

6.2 Simulation results and discussion

Table 2 presents the impacts of removing the decoupled payments on production decisions in relation to different crop activities at the NUTS-2 level of geographical subdivision. Theory suggests that for risk averse farmers, fixed income support attracts farmers to higher risk cropping plans (Andersson, 2004; Hennessy, 1998; Roche & McQuinn, 2004; Serra *et al.* 2009) and we do, indeed, find some substitutions between high and low-risk crops, but at different rates for different farms.

The share of land allocated to high-risk crops (e.g. soft wheat and potatoes) is reduced, as theory predicts. Potatoes, which generally have the highest level of variance in revenue, are more sensitive to the wealth effect as acreage decreases by 0.42% and 2.61% in southern and eastern Sweden, respectively. In northern Sweden, pulses are a low-risk crop, but have a larger value of negative covariance with soft wheat, which is one of the major cereal crops in Sweden. Consequently, activities are diversified with a 2.74% decrease in the acreage of soft wheat and a 1.59% increase in pulses. The impacts on soft wheat are small in southern and eastern Sweden.

The other cereal crops, such as rye and barley, have a lower level of risk in terms of variances and, therefore, respond with an increase in acreages compared to the reference scenario. However, the acreages of these crops are decreased in southern (e.g. rye) and northern Sweden (e.g. barley), as these crops have seen a relatively higher level of risk in these regions. A similar pattern is observed for oats and other cereals, with an increase in acreages where they have lower variances in farm revenues. Roche and McQuinn (2004) also report similar findings for British and Irish grain producers, who were attracted to higher risk crops (e.g. wheat) when a direct payment was available, even though they historically avoided these crops.

Interestingly, rapeseed is established as one of the hedging possibilities for a high-risk potato crop as indicated by a high-negative covariance in revenues. As a result, acreage of rapeseed increased by 0.29-1.23% even though this crop has a medium level of variance in revenues, that is a

Table 2 Regional impact on land allocation of removing decoupled payments

	Baseline (year = 2005)			Simulation			Relative change (%)		
	South	North	East	South	North	East	South	North	East
Crop activities (ha)									
Soft wheat	4707.30	64.70	2451.85	4699.48	62.93	2445.40	−0.17	−2.74	−0.25
Rye	1032.41	47.10	409.10	1028.67	47.57	409.11	−0.36	1.01	0.01
Barley	4884.97	282.00	1645.30	4890.37	281.64	1643.93	0.11	−0.13	−0.08
Oats	1349.67	186.60	1006.80	1352.94	187.48	1006.54	0.24	0.47	−0.03
Other cereals	122.65	–	–	122.72	–	–	0.07	–	0.01
Rapeseed	839.61	51.60	560.90	844.15	51.75	567.78	0.54	0.29	1.23
Pulses	223.20	40.30	244.14	222.56	40.94	246.15	−0.29	1.59	0.82
Potato	1005.76	–	36.70	1001.69	–	35.75	−0.42	−0.33	−2.61
Sugar beet	1647.53	–	–	1650.16	–	–	0.16	–	–

Note: Shaded area indicates negative change; '–'indicates no cultivation of a particular crop in the sample data.

moderate level of risk (see Appendix 6). In general, the wealth effect is small in northern Sweden. Farmers have shown a reluctance to diversify the cultivation of high-risk potatoes[5] with, for example, rapeseed, because the diversification benefits offered might not compensate for the high variability of potato returns. Moreover, the weather conditions also do not favour the cultivation of rapeseed in northern Sweden.

In previous studies[6], there has been a small wealth effect at the aggregate level without consideration of a risk factor. Chambers and Voica (2017) argue that the impact of decoupled payments on production can be small if farmers have (significant) off-farm income. The present study revisits the production effects and results show varying levels of the distortionary effect on individual production decisions, depending upon the level of risk associated with crop revenues and the percentage share of decoupled payments in the family income. Larger negative impacts are observed with high-risk crops and larger positive effects with low-risk crops. Consequently, a rather small wealth effect is estimated when the impacts are aggregated across products. In a high-risk environment, however, the farm-level impacts are larger than those reported in the literature. For some farmers, the decoupled payment is found to comprise up to about 50% of their family income. As Femenia *et al.* (2010), Just (2011) and Chambers and Voica (2017) mention, this large contribution of the direct payment to income could also have resulted in the larger magnitude of the wealth effect.

We see rather small mean impacts on production decisions in Table 3, ranging from −1.59% to +1.53%. These results fall within the range reported in previous studies[7]. However, the magnitude of these effects differs much more at the individual farm level, ranging from −6.91% (5th percentile) to +3.58% (95th percentile). Larger decreases in the acreage responses are observed in high-risk crops, such as potatoes and soft wheat. For low-risk crops, such as pulses and rapeseed, the acreage response increases with the removal of a risk-free direct payment. For the farmers in our sample, the decoupled payment represents a substantial share of farm income (gross value added), varying from 8.70% (5th percentile) to 36.54% (95th percentile) among individuals, resulting in changes from 20.67% (5th percentile) to 333.72% (95th percentile) in the risk aversion coefficients when the payment is removed. This shows that some farmers can be very sensitive to the removal of such a support payment, showing highly risk averse behaviour. We also note that in our model, farmers' absolute risk aversion coefficients by construction are inversely correlated with farm size, allowing small and medium-sized farmers to be more risk averse. Farms with small economic sizes have relatively larger percentages of decoupled payments as a

[5] Potato has a higher variance in revenues than rapeseed. See Appendix 6.
[6] See footnote 2 for a list of selected literature.
[7] See footnote 2 for a list of selected literature. For example, a review by Andersson (2004) reports a 1-14% wealth effect, while Goodwin and Mishra (2006) find 0.01-0.03%, depending upon crop production activities and location.

Table 3 Farm-level impact on land allocation from removing decoupled direct payments

	Activity level in aggregate		Relative change (%) in acreage response at farm level			
	Baseline	Simulation	Mean	5th percentile	50th percentile	95th percentile
Crop (ha)						
Soft wheat	7223.85	7207.80	−0.34	−4.52	−0.08	0.10
Rye	1488.61	1485.35	−0.69	−0.18	0.00	0.56
Barley	6812.27	6815.93	0.05	−0.06	0.04	0.96
Oats	2543.07	2546.95	0.16	−0.10	0.08	1.16
Other cereals	122.65	122.72	−0.06	−0.90	−0.02	0.53
Rapeseed	1452.11	1463.68	1.53	−0.56	0.05	1.90
Pulses	507.64	509.65	1.11	−1.23	0.24	3.58
Potato	1042.46	1037.43	−1.59	−6.91	−0.26	0.00
Sugar beet	1647.53	1650.16	0.14	−0.06	0.01	0.59
Shannon diversity index	112.26	112.24	−0.04	−0.19	0.00	0.24
Absolute risk aversion coefficient (mean)	3.1E-05	7.8E-05	117.75	20.67	63.38	333.72
Share of direct payment in family income[1]	0.00	0.00	21.04	8.70	20.15	36.54

[1]The values in 'Activity levels' for baseline and simulation scenarios are the contributions of the total direct payment dispensed through the decoupled payment system to the aggregated family income of the sample households.

proportion of family income (see Appendix 7). These farms may not consider the decoupled payment to be fully decoupled, especially in a high-risk environment. As a result, we observe more risk averse behaviour (i.e. wealth effects) in these cases.

Following Brady et al. (2009), we also computed the Shannon diversity index (SDI) to evaluate impacts on crop diversity. The SDI in this case shows the entropy of crop shares of the total land area[8]. The higher the SDI value, the more diverse and heterogeneous the crop production activities are on the respective farmland. In the present study, we find a decrease in the mean value of the SDI (−0.04%) for Sweden. This indicates a relative loss of diversification in the crop mix, though the magnitude is small. Looking at the individual farm-level observations, we find a range of variability in the SDI values. The farms with small economic sizes[9], except for those between 4,000 and <8,000 euros, are more likely to decrease crop diversification after removing the decoupled direct payments (see Figure 2). A substantial number of small-sized farms show a decrease in SDI, indicating a more homogeneous pattern in the agricultural landscape. The decoupling of farm support

[8] The SDI is defined as follows: $SDI = -\sum_{i=1}^{I} p \ln(p_i)$, where I is a set of crop activities for land use, $i \in I$, and $_p$ is the share of the total land area covered by the ^{i} crop activity. See Brady *et al*. (2009) for details.

[9] The economic sizes of the farms are defined based on the standard output of a crop product, measured at farm-gate price, in euro per hectare values (Source: Eurostat).

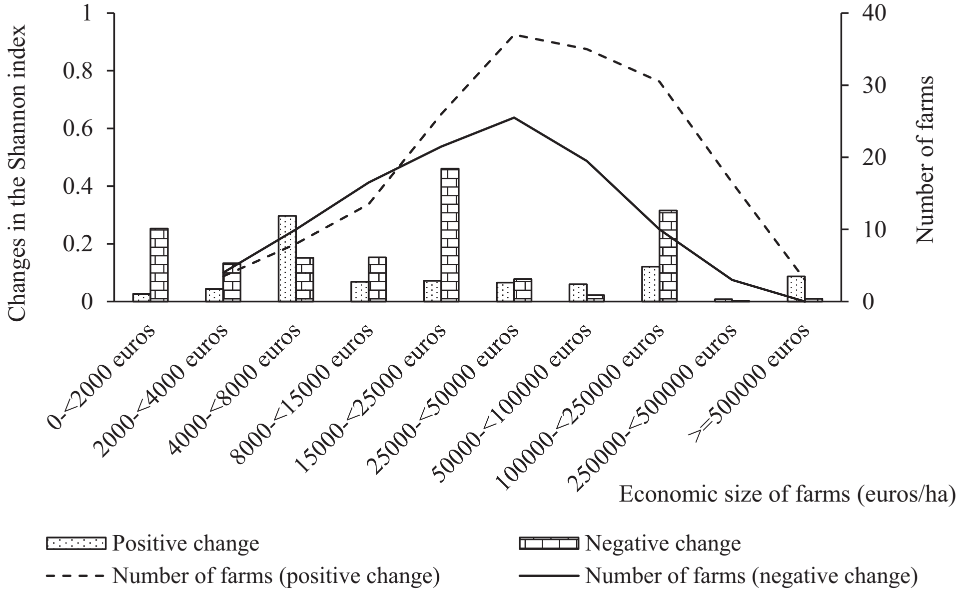

Figure 2 Number of farms in the sample with positive and negative changes in the Shannon diversity index following the removal of decoupled payments.

increases the role of market prices in crop production decisions, which will likely attract farmers to profitable crops and reduce crop diversification. Farms with a decrease in SDI (–0.19% at the 5th percentile, see Table 3) report an increase in the area for major crops[10] (e.g. soft wheat, barley, oats and potatoes). The opposite is true for the increase in SDI (0.24% at the 95th percentile, see Table 3). The acreages of other crops (e.g. rapeseed and pulses) are affected to a larger extent when compared to the major crops (see 95th percentile in Table 3). In line with the findings by Brady *et al.* (2009), the farm-level observations in this study showed that SDI increases with a decrease in the acreage of major dominating crops, allowing for some substitution between crops, but the changes are farm and crop-specific.

7. Conclusions

This study develops a robust risk programming model in a PMP framework and applies it to analyse the wealth effect of CAP direct payments on production decisions at the farm level. The rationale of the farm-level model is to capture the heterogeneity of risk behaviour at the farm level and provide a tool for modelling future agricultural policy options in the face of increasing weather risk. We employ a Bayesian approach to estimate the model parameters, including the relative risk aversion coefficient, while allowing for optimisation errors. We use an unbalanced panel of single farm observations

[10] Major crops in terms of land acreage.

coming from the FADN survey, representing 287 Swedish farms, over the period 1998–2008.

Simulating an abolition of direct payments, the impact on land allocations is found to be small at the aggregate regional level, which confirms previous studies. This implies that decoupled payments may likely have small distortionary effects on agricultural production. This supports the main argument for the EU CAP reform in 2003 introducing the area-based single farm payment and, thereby, decoupling direct payments from production decisions. However, we find that direct payments have a more pronounced effect on the production by capital-constrained farmers. Not surprisingly, larger wealth effects are simulated for farms where decoupled payments constitute a larger proportion of family income, thus provoking a larger change in the absolute risk aversion coefficient when removed.

With respect to changes at the crop level, we find that crops with large variances in revenues are substituted by lower-risk crops after abolishing income support. It appears that the risk-free income transfer in the form of direct payments drives farmers to grow relatively higher risk crops (e.g. soft wheat and potatoes, in the case of Sweden). Overall, the degree of uncertainty associated with crop revenues and the share of decoupled payments as a proportion of family income is the key factor in determining the extent of the wealth effect. In the future CAP, the decoupled payments can become a risk management tool in a risky environment.

The development of a robust risk programming model and the Bayesian approach to estimate its parameters is another key contribution of this study. It will allow for the evaluation of future CAP or other policy options at the individual farm level that can consider high-risk crop allocation choices at a level of crop resolution not offered by typical econometric models. The effects of climate change are expected to increase, even in climates that are currently considered moderate, and the resulting probability of extreme weather events and the impact on crop yields will make such a tool even more valuable. For example, crop insurance schemes may become more prominent and can potentially be evaluated by applying this approach on a larger scale. The model specification proved to be feasible with the EU-FADN as a data source and is therefore straightforwardly transferrable to other EU member states. Additionally, the availability of typical farm accounting data allows researchers to also apply the approach outside of the EU.

A limitation of the present study is its restriction to marketable crop production. Future research should investigate the inclusion of non-arable crops, such as fodder and pasture. Here, the challenge will be finding appropriate data for estimating the variability in production quantity (and quality). Such developments should go hand in hand with the incorporation of livestock production activities to increase the relevance of the tool for analysing a wider set of policy options. The present study carried out counterfactual scenario analysis using farm-level data. However, the simulation experiment may still entail aggregation errors due to the non-linearity of the model.

Data availability statement

Data were derived from the European Union (EU) Farm Accountancy Data Network (FADN) available in the public domain: Agriculture – FADN: F. A. D. N. – FADN PUBLIC DATABASE (europa.eu) at https://ec.europa.eu/agriculture/rica/database/database_en.cfm

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Appendix 1
Grouping of agricultural holdings by type of farming and economic size

NUTS-2 regions	Economic size class (1,000 €)	Principal types of farming
South Sweden	16 ≤ € ≤100	General field cropping + Mixed cropping
	€ ≥100	General field cropping + Mixed cropping
	16 ≤ € ≤100	Specialist dairying
	€ ≥100	Specialist dairying
	€ ≥100	Specialist granivores
	2 € ≤16	Mixed crops-livestock
	16 ≤ € ≤100	Mixed crops-livestock
	€ ≥100	Mixed crops-livestock
Småland and the islands	16 ≤ € ≤100	Specialist dairying
	€ ≥100	Specialist dairying
	€ ≥100	Specialist granivores
	16 ≤ € ≤100	Mixed crops-livestock
	€ ≥100	Mixed crops-livestock
West Sweden	16 ≤ € ≤100	Specialist cereals, oilseed and protein crops
	2 € ≤16	General field cropping + Mixed cropping
	16 ≤ € ≤100	General field cropping + Mixed cropping
	€ ≥100	General field cropping + Mixed cropping
	€ ≥100	Specialist dairying
	€ ≥100	Specialist granivores
	16 ≤ € ≤100	Mixed crops-livestock
	€ ≥100	Mixed crops-livestock
	€ ≥100	Mixed livestock holdings
North middle Sweden	16 ≤ € ≤100	Specialist cereals, oilseed and protein crops
	16 ≤ € ≤100	Specialist dairying
	€ ≥100	Mixed crops-livestock
Stockholm	16 ≤ € ≤100	Specialist cereals, oilseed and protein crops
	€ ≥100	Specialist cereals, oilseed and protein crops
	€ ≥100	Mixed crops-livestock
East middle Sweden	16 ≤ € ≤100	Specialist cereals, oilseed and protein crops
	€ ≥100	Specialist cereals, oilseed and protein crops
	16 ≤ € ≤100	General field cropping + Mixed cropping
	€ ≥100	Specialist dairying
	€ ≥100	Specialist granivores
	16 ≤ € ≤100	Mixed crops-livestock
	€ ≥100	Mixed crops-livestock
	€ ≥100	Mixed livestock holdings

Appendix 2
FADN sample farm structure in the Swedish regions selected for this study

Observed activity level (ha)	South	North	East	Price
Crop activities				
Soft wheat	3,508	99	2,609	113
Rye	755	40	289	104
Barley	3,626	215	1,620	103
Oats	1,184	137	1,234	101

Appendix 2. (*Continued*)

Observed activity level (ha)	South	North	East	Price
Other cereals	110	–	20	95
Rapeseed	563	40	396	201
Pulses	111	20	225	114
Potatoes	700	12	29	116
Sugar beet	1,305	–	–	49
Other vegetables	120	–	–	216
Utilised agricultural area (ha)	21,594	1,046	12,279	
Number of farm observations	1,955	56	825	
Number of individual farms	213	7	67	
Average farm size (ha)	6.69	41.95	12.44	
Compensatory area payment (million euros)	1.75	0.06	1.26	
Decoupled payment (million euros)	4.86	0.18	2.48	

The values are averages of the sample farms over the period 1998–2008. Information on other oilseeds, fodder root crops, flax and hemp is not presented due to the low levels of production. Digits after decimals are removed for a simple exposition. Prices are measured in Euro/metric tonne.

Appendix 3
Estimation of a definite variance–covariance matrix

The proposed four-stage FGLS estimator works as follows:

1. Estimate an ordinary least square (OLS) model. Compute the covariance and call it $\tilde{\Sigma}^1$.
2. Find the positive definite (PD) matrix that is 'closest' to $\tilde{\Sigma}^1$ in a Euclidean sense. Call the result $\hat{\Sigma}^1$.
3. Estimate the generalised least square (GLS) model using the inverse of $\hat{\Sigma}^1$ as a weight matrix. Compute the covariance and call it $\tilde{\Sigma}^2$.
4. Find the PD matrix that is 'closest' to $\tilde{\Sigma}^2$. The result, $\hat{\Sigma}^2$, is the estimate that we are looking for.

For defining what is 'close', we minimise the weighted sum of squared deviations between all elements of a candidate strictly definite matrix and the corresponding elements of a possibly non-definite matrix that resulted from the weighted least squares (WLS) estimate. This is equivalent to the 'Hadamard-weighted Frobenius norm shrinkage estimator' proposed by Higham (2002). This means that the squared difference between each element of the original non-definite matrix and the new well-behaved one is weighted using a different weight. The weight chosen was the number of observations used to compute the relevant entry plus one. The motivation for using the 'plus one' is somewhat arbitrary, but has the advantage of allowing us to impute missing values (observed zero times) using a low weight of '1'.

Appendix 4
Derivation of parameters for the gamma density function

The gamma distribution with two free parameters α and β is defined as:

$$f(x;\alpha,\beta)=\frac{\beta^{\alpha}}{\Gamma(\alpha)}x^{\alpha-1}e^{-\beta x}\ \text{for}\ x\varepsilon[0,\infty)\,\text{and}\,\alpha,\beta>0.$$

where $\Gamma(\alpha)$ is the incomplete gamma function.
The gamma distribution has mode $Mode=\frac{\alpha-1}{\beta}$ for $\alpha\geq 1$ and variance $\sigma^2=\frac{\alpha}{\beta^2}$, we can write:

$$\alpha=\left(\frac{\alpha-1}{Mode}\right)^2\sigma^2.$$

We defined accuracy $Acc=\frac{5\times Mode}{\sigma}$ (it was scaled by five so that an accuracy of 10 is equivalent to the assumption that mode equals two standard deviations, and lower values intuitively means less reliable priors) and can then rewrite the above equation as:

$$\alpha=\left(\frac{\alpha-1}{Mode}\right)^2\left(\frac{5Mode}{Acc}\right)^2$$

Which can be solved for α to obtain:

$$25\alpha^2-\left(50+Acc^2\right)\alpha+25=0$$

We can write the roots of the above quadratic equation as:

$$\alpha=\frac{\left(50+Acc^2\right)\pm\sqrt{\left(50+Acc^2\right)^2-4\times 25\times 25}}{50}$$

where we keep only the positive root. Finally, we can compute

$$\beta=\frac{(\alpha-1)}{Mode}.$$

Appendix 5
Derivation of the posterior density function

In its general form, the joint posterior distribution of the parameters is given by Bayes' theorem as

$$p(\theta|z) \propto I_{[0,1]} p(\tilde{\theta}),$$

where $\theta = \theta(y, A, q, \eta, \lambda, \phi^R)$ denotes the vector of model parameters, z is the set of random variables, and $I_{[0,1]}$ is the indicator function representing a degenerate form of the likelihood function. The notation with 'tilde' indicates the prior mode. We define the degenerate form of likelihood function as:

$$f(z|\tilde{\theta}) := \begin{pmatrix} 1 \ \mathit{if\,optimality\,conditions\,are\,satisfied} \\ 0 \ \mathit{Otherwise}. \end{pmatrix}$$

Given the prior distributions $\varepsilon^{opt} \sim N(0, \Sigma)$, $\Sigma \sim \chi^2(\tilde{\Sigma})$ and $\left(\frac{\theta}{\tilde{\theta}}\right) \sim \Gamma(\alpha, \beta)$, we can obtain the posterior density function as:

$$\left[\underbrace{(2\pi) - \frac{n}{2}|\Sigma| - \frac{n}{2}\exp\left\{-\frac{1}{2}S\Sigma^{-1}\right\}}_{N(0,\,\Sigma)}\right]\left[\underbrace{\frac{|\Sigma|^{\frac{n}{2}-1}}{|\sum|^{\frac{n}{2}}2^{\frac{n-1}{2}}\Gamma\left(\frac{n-1}{2}\right)}\exp\left\{-\frac{1}{2}\Sigma\Sigma - 1\right\}}_{\chi^2(\tilde{\Sigma})}\right]\left[\underbrace{\frac{\beta^\alpha}{\Gamma(\alpha)}\left(\frac{\theta}{\theta}\right)^{\alpha-1}\exp\left\{-\beta\left(\frac{\theta}{\theta}\right)\right\}}_{\Gamma(\alpha,\,\beta)}\right]$$

where $S = \sum_{f=1}^{n} \left(\varepsilon_f^{opt}\right)\left(\varepsilon_f^{opt}\right)\prime$.

Without loss of generality, we can remove the multiplicative constants $(2\pi)^{-\frac{n}{2}}$, $\left|\tilde{\Sigma}\right|^{-\frac{1}{2}}$, $2^{-\frac{n-1}{2}}$, $\Gamma\left(\frac{n-1}{2}\right)$ and $\frac{\beta^\alpha}{\Gamma(\alpha)}$ and rewrite the posterior density function as:

$$exp\left\{-\frac{1}{2}S\Sigma^{-1}\right\}\frac{|\Sigma|^{\frac{n}{2}}}{\left|\tilde{\Sigma}\right|^{\frac{n}{2}}}exp\left\{-\frac{1}{2}\Sigma\tilde{\Sigma}^{-1}\right\}\left(\frac{\theta}{\tilde{\theta}}\right)^{\alpha-1}exp\left(-\beta\left(\frac{\theta}{\tilde{\theta}}\right)\right).$$

The logarithmic transformation takes the form of

$$-\frac{1}{2}S\Sigma^{-1} + \frac{n}{2}\log\left(\Sigma\tilde{\Sigma}^{-1}\right) - \frac{1}{2}\Sigma\tilde{\Sigma}^{-1} + (\alpha - 1)\log\left(\frac{\theta}{\tilde{\theta}}\right) - \beta\left(\frac{\theta}{\tilde{\theta}}\right).$$

In expanded form, we can write the logarithmic form of posterior density function as:

$$\sum_{fjt}\left\{\left(\frac{1}{2\sigma_{jj}^2}\right)\left(\varepsilon_{fjt}^{opt}\right)^2\right\}+\sum_{jj}\left\{\frac{1}{2}\left(\frac{\sigma_{jj}}{\tilde{\sigma}_{jj}}\right)^2-\frac{1}{2}\left(\frac{\sigma_{jj}}{\tilde{\sigma}_{jj}}\right)^2\right\}$$
$$+\sum_{jit}\left\{(\alpha_{jit}^A-1)\log\left(\frac{A_{jit}}{\tilde{A}_{ji}}\right)-\beta_{jit}^A\left(\frac{A_{jit}}{\tilde{A}_{ji}}\right)\right\}$$
$$+\sum_{fit}\left\{(\alpha_{fit}^q-1)\log\left(\frac{q_{fit}}{\tilde{q}_{fit}}\right)-\beta_{fit}^q\left(\frac{q_{fit}}{\tilde{q}_{fit}}\right)\right\}$$
$$+\sum_{fot}\left\{(\alpha_{fot}^q-1)\log\left(\frac{q_{fot}}{\tilde{q}_{fot}}\right)-\beta_{fot}^q\left(\frac{q_{fot}}{\tilde{q}_{fot}}\right)\right\}$$
$$+\sum_{ot}\left[(\alpha_{ot}^\eta-1)\log\left(\frac{\eta_{ot}}{\tilde{\eta}_{ot}}\right)-\beta_{ot}^\eta\left(\frac{\eta_{ot}}{\tilde{\eta}_{ot}}\right)\right]$$
$$+\sum_{ft}\left\{(\alpha_{ft}^\lambda-1)\log\left(\frac{\lambda_{ft}}{\tilde{\lambda}_{ft}}\right)-\beta_{ft}^\lambda\left(\frac{\lambda_{ft}}{\tilde{\lambda}_{ft}}\right)\right\}$$
$$+\left[(\alpha^\phi-1)\log\left(\frac{\phi^R}{\tilde{\phi}^R}\right)-\beta^\phi\left(\frac{\phi^R}{\tilde{\phi}^R}\right)\right]$$

where σ^2 denotes the variance terms of Σ_{ii}.

Appendix 6

Estimated variance–covariance matrices of program crops

	Soft wheat	Rye	Barley	Oats	Other cereals	Rapeseed	Pulses	Potatoes	Sugar beet
South Sweden									
Soft wheat	14,938	7,897	6,198	6,346	1,871	4,279	1,340	23,666	−402
Rye	7,897	15,346	5,269	4,326	265	1,568	2,367	22,415	−3,034
Barley	6,198	5,269	5,870	4,199	1,263	1,544	1,665	22,619	696
Oats	6,346	4,326	4,199	8,988	1,412	1,052	238	29,125	−1,637
Other cereals	1,871	265	1,263	1,412	15,241	1,209	−1,471	42,924	−8,219
Rapeseed	4,279	1,568	1,544	1,052	1,209	1,5436	1,103	−21,470	2,059
Pulses	1,340	2,367	1,665	238	−1,471	1,103	5,700	12,257	1,691
Potatoes	23,666	22,415	22,619	29,125	42,924	−21,470	12,257	1,480,945	−23,812
Sugar beet	−402	−3,034	696	−1,637	−8,219	2,059	1,691	−23,812	108,534
East Sweden									
Soft wheat	23,343	3,704	7,150	4,892	2,428	4,587	2,067	11,666	0
Rye	3,704	6,113	1,541	1,991	1,199	2,584	−45	5,974	0
Barley	7,150	1,541	5,034	1,308	904	2,352	2,089	12,897	0
Oats	4,892	1,991	1,308	6,902	868	773	117	5,331	0
Other cereals	2,428	1,199	904	868	1726	−1,005	−13	17,772	0
Rapeseed	4,587	2,584	2,352	773	−1,005	9,968	2,743	−6,717	0
Pulses	2,067	−45	2,089	117	−13	2,743	9,125	−11,562	0
Potatoes	11,666	5,974	12,897	5,331	17,772	−6,717	−11,562	2,091,095	0
Sugar beet	0	0	0	0	0	0	0	0	0
North Sweden									
Soft wheat	31,416	12,035	2,613	6,072	0	2,898	−1,673	0	0
Rye	12,035	7,993	3,325	1,374	0	−2,011	−398	0	0
Barley	2,613	3,325	17,527	6,334	0	3,997	−817	2,928	0
Oats	6,072	1,374	6,334	5,815	0	2,306	−1,038	−1,574	0
Other cereals	0	0	0	0	0	0	0	0	0

Appendix 6. *(Continued)*

	Soft wheat	Rye	Barley	Oats	Other cereals	Rapeseed	Pulses	Potatoes	Sugar beet
Rapeseed	2,898	−2,011	3,997	2,306	0	4,840	−648	0	0
Pulses	−1,673	−398	−817	−1,038	0	−648	295	0	0
Potatoes	0	0	2,928	−1,574	0	0	0	1,446,724	0
Sugar beet	0	0	0	0	0	0	0	0	0
Sweden									
Soft wheat	19,000	6,963	6,216	5,824	1,964	4,254	1,487	21,266	−402
Rye	6,963	12,680	4,231	3,611	358	1,682	1,474	19,283	−3,034
Barley	6,216	4,231	6,766	3,195	1,180	1,984	1,721	19,729	696
Oats	5,824	3,611	3,195	7,859	1,286	1,075	140	22,187	−1,637
Other cereals	1,964	358	1,180	1,286	12,122	963	−1,263	38,351	−8,219
Rapeseed	4,254	1,682	1,984	1075	963	12,958	1,615	−17,372	2,059
Pulses	1,487	1,474	1,721	140	−1,263	1,615	6,759	5,641	1,691
Potatoes	21,266	19,283	19,729	22,187	38,351	−17,372	5,641	1,615,266	−23,812
Sugar beet	−402	−3,034	696	−1,637	−8,219	2,059	1691	−23,812	108,534

Digits after decimals are removed due to space limitations. ‘0’ indicates no crop activity in the calibrated year, 2005. Per hectare revenues are measured in euros.

Appendix 7

Change in the decision on crop production activities by farm economic size

Economic size	Share of decoupled payment	No. of farms	Relative change (%) in a decision on production of								
			Soft wheat	Rye	Barley	Oats	Other cereals	Rapeseed	Pulses	Potato	Sugar beet
0–<2,000 euros	0.306	6	−2.785	0.032	0.140	0.227	−0.342	–	3.579	−2.056	–
2,000–<4,000 euros	0.315	9	−0.112	−0.003	0.142	0.078	−0.902	0.131	0.693	−2.012	−0.022
4,000–<8,000 euros	0.268	27	−1.522	0.019	0.026	−0.600	−0.027	17.227	0.244	−2.372	−0.196

Appendix 7. *(Continued)*

Economic size	Share of decoupled payment	No. of farms	Relative change (%) in a decision on production of								
			Soft wheat	Rye	Barley	Oats	Other cereals	Rapeseed	Pulses	Potato	Sugar beet
8,000−<15,000 euros	0.300	33	−0.130	0.078	0.078	0.064	0.376	0.162	0.147	−1.298	−0.036
15,000−<25,000 euros	0.278	62	−0.202	−4.100	−0.276	0.389	−0.264	2.325	0.304	−0.476	0.046
25,000−<50,000 euros	0.191	63	−0.065	0.037	0.132	0.092	−0.014	0.066	−0.216	−0.755	0.066
50,000−<100,000 euros	0.155	46	−0.434	0.169	0.117	0.431	0.287	0.110	1.123	−0.521	0.249
100,000−<250,000 euros	0.080	35	−0.206	0.033	0.283	0.563	0.237	0.020	−1.418	−3.297	0.178
250,000−<500,000 euros	0.031	4	0.061	−0.024	0.044	0.415	–	−0.072	–	−0.266	0.113
>=500,000 euros	0.027	2	−0.250	–	0.390	0.058	–	–	–	0.024	0.212

Economic size of farms is defined based on the standard output of the crop product measured at a farm-gate price in euros. The size interval is specified according to the classification criteria available at eurostat (online data code: ef_kvecsleg).