Do Irish Cereal Producers use Multiple Cropping as a Strategy for Dealing with Risk?

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Abstract

Portfolio theory suggests that risk-averse agents favour a diversified portfolio of assets as a strategy to offset market risk. This paper explicitly tests whether Irish cereal producers decision to engage in multi-crop production (asset diversification) in itself reveals a relatively risk-averse nature. The issue is examined within the context of sample selection bias, where multi-croppers (portfolio diversifiers) are treated as a sub-sample of a general sample (mono + multi croppers) of Irish cereal production.

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1 Introduction

An increasing number of studies examine the risk attitudes of agricultural producers within dual-based production models (e.g. Coyle (1992), Saha, Shumway and Talpaz (1994), Saha (1996), Saha (1997), Coyle (1999), OudeLansink (1999), Boyle and McQuinn (2001), Sckokai and Moro (2002a) and Sckokai and Moro (2002b)). Most of these approaches consist of a dual production model of price uncertainty. Within these dual systems, output supplies and factor demands are simultaneously determined within an expected utility framework and estimates of producers' risk attitudes and associated risk premia are directly obtained from sample data.

An issue, which typically arises in the application of these production systems to arable producers, is that of corner solutions amongst the data i.e. those producers who plant only one cereal (mono-croppers). For instance, the sample used in Boyle and McQuinn (2001) is restricted to those producers who simultaneously plant both barley and wheat (multi-croppers). Many studies restrict samples in an analogous manner to avoid the problem of corner solutions (see OudeLansink (1999) for example). This is particularly the case where researchers are utilising panel data as the increased number of observations allow the researcher to circumvent the problem of corner solutions by censoring the data.

The results achieved in studies such as Boyle and McQuinn (2001) and OudeLansink (1999) are specific to those multi-cropper producers. In itself, these results are highly important in terms of the production practices of that particular sample. However, an interesting related question which arises is the relationship between the risk attitudes of the overall sample of crop producers (mono + multi-croppers) and those of the multi-croppers sub-sample. For example, can the results from the multi-croppers be 'extrapolated' to the general population? In general, results from a sub-sample can be extrapolated to those of the general sample if the sub-sample is representative of the general sample. However, in the case of risk, the decision of producers to engage in multi-crop production *a priori* suggests a relatively risk-averse disposition on the part of producers.

This paper examines the planting behaviour and production decisions of specialist Irish cereal producers between 1984 and 1998 using a panel data set from the

National Farm Survey (NFS) conducted by Teagasc.[1] The paper seeks to determine whether multi-croppers practice portfolio theory/asset diversification as a specific strategy to offset risk, where the employment of a diversified crop portfolio, in itself, reveals a relatively risk-averse nature. Or, whether producers' multi-cropping strategy is a function of farm-specific factors which are unrelated to risk. The issue is tackled within the Heckman (1979) model of sample selection bias. The first stage of the Heckman approach models the decision to engage in multi-cropping, while the second stage estimates producers' risk attitudes given their decision in the first stage.

The remainder of this paper is laid out in the following manner. A dual output supply model under the highly flexible mean standard deviation (MSU) utility function is presented. The recently specified Roche and McQuinn (2003) model of Irish grains is used to generate expectations of the mean, variance and co-variance of wheat and barley output prices. This is followed by an introduction to the Heckman model for selection bias, where the output supply function under the MSU is the second stage model. Risk attitudes estimated both with and without the Heckman approach are then compared and conclusions drawn.

2 A Production Model under the MSU

The chosen output supply function under price uncertainty is derived from the mean standard deviation (MSU) utility function. This function, proposed by Saha (1997), is a highly flexible utility function, which has the advantage of permitting the data to determine both the *structure* and *degree* of producers' risk attitudes. Alternative, more generic specifications, such as the linear mean variance (LMV) model proposed by Coyle (1992) impose constant absolute risk aversion (CARA) on producers' attitudes and yield information only on the degree of producers' aversion to risk. The MSU builds on earlier work by Meyer (1987), who had established a consistency or compatibility between the expected utility (EU) framework and the mean standard deviation (MS) postulate. The MS approach involves producers ranking risky alternatives according to the value of a function defined over the first two moments of a producer's random payoff. This consistency established between

[1] The Irish Agriculture and Food Development and Research Authority.

the two approaches enables some of the more powerful assumptions of EU analysis to be translated in similar conditions to the MS approach without imposing some of the more traditional restrictions associated with the EU approach The MSU as devised by Saha is given by the following

$$U(\sigma, \mu) = U(M, S) = M^{\Gamma} - S^{\Upsilon} \tag{1}$$

where Γ and Υ are parameters to be estimated and it is assumed that $\Gamma > 0$. Various restrictions can be imposed on the MSU to arrive at more popular EU models. For instance, if $\Upsilon = \Gamma = 1$ is imposed, the linear U(M,S) model is obtained, if Γ is set equal to 1, then CARA attitudes are assumed. Under the MSU, α, the risk attitude measure is given by the slope of the indifference curve in mean standard deviation space

$$\alpha(M, S) = -(U_s/U_M) = (\Upsilon/\Gamma) M^{1-\Gamma} S^{\Upsilon-1} \tag{2}$$

The MSU exhibits

(1) Risk aversion, neutrality and risk preference corresponding to $\Upsilon > 0$, $= 0$ and < 0, respectively,

(2) Decreasing, constant and increasing absolute risk aversion as $\Gamma > 1$, $= 1$, and < 1,

(3) Decreasing, constant and increasing relative risk aversion as $\Gamma > \Upsilon$, $\Gamma = \Upsilon$, $\Gamma < \Upsilon$.

Table II[2] of Saha (1997) summarises the suite of risk attitudes, which can be accommodated within the MSU. The greater flexibility evident in this utility framework can be compared with the more restrictive structures under the traditional Arrow-Pratt measures.[3] The following list of variables are used in the producer's

[2] p.773.

[3] Illustrated in Table I p.772 of Saha (1997).

decision-making process

$\mathbf{q}$ = a two dimensional vector of outputs - barley and wheat,
$\tilde{\mathbf{p}}$ = a two dimensional vector of random output prices,
$\mathbf{p}$ = a two dimensional vector of expected output prices,
$\mathbf{x}$ = a two dimensional vector of actual/planned inputs,
$\mathbf{n}$ = a two dimensional vector of input prices,
$\mathbf{B}$ = a two dimensional vector of cereal areas,
$\mathbf{A}$ = total on farm cereal area,
$\mathbf{D}$ = total cereal compensation payments (post 1992),
$\mathbf{I}$ = total producer off farm income.

Random and mean income are defined as[4]

$$\tilde{\pi} = \tilde{\mathbf{p}}^T\mathbf{q} - C(\mathbf{n}, \mathbf{q}, \mathbf{B}) + \mathrm{D} + \mathrm{I} \tag{3}$$

$$M = \mathbf{p}^T\mathbf{q} - C(\mathbf{n}, \mathbf{q}, \mathbf{B}) + \mathrm{D} + \mathrm{I} \tag{4}$$

A cost function $C(\mathbf{n}, \mathbf{q}, \mathbf{B})$ is defined as $\mathbf{n}^T\mathbf{x}$. Irish cereal production is assumed to be non-joint in variable inputs.[5] While the presence of variable input data for both cereals is not in itself sufficient proof for non-jointness in variable inputs,[6] most barley grown in Ireland is sown in the spring, while wheat tends to be mainly a winter crop. Thus, the assumption is considered appropriate in this case. Given the underlying structure in (3), any random alternatives available to the producer are positive linear transformations of the random variable $\tilde{\mathbf{p}}$ and are thus, related to one another by location and scale parameters. As the producer's income function is linear in $\tilde{\mathbf{p}}$, consistency is ensured between expected utility and $\mathrm{U}(\sigma, \mu)$. As output

[4]Data on I, off farm income, is only available for 1998. As a result, off farm income in 1998 was regressed on a series of explanatory variables for that year. The figure for each farm for previous year was then 'backcast' using the 1998 regression results.

[5]Seperate production functions in variable inputs are assumed for both cereals.

[6]Fertiliser spread on barley could technically end up in a wheat field in which case, it would belong in the wheat production function.

prices by assumption are the only source of uncertainty, the standard deviation of the producer's random income is given by

$$S = \left(\mathbf{q}^T \mathbf{V}\mathbf{p}\mathbf{q}\right)^{\frac{1}{2}} \tag{5}$$

$\mathbf{V}\mathbf{p}$ is the (symmetric, positive definite) covariance matrix of output prices. Following Saha (1997), and using (4) and (5), the MSU can be represented as follows

$$U^*\left(\mathbf{p}, \mathbf{n}, \mathbf{V}\mathbf{p}, \mathbf{B}\right) = \max_{\mathbf{q}} U\left(\mathbf{p}^T\mathbf{q} - C\left(\mathbf{n}, \mathbf{q}, \mathbf{B}\right), \left(\mathbf{q}^T \mathbf{V}\mathbf{p}\mathbf{q}\right)^{\frac{1}{2}}\right) \tag{6}$$

The first order condition is given by

$$U_M\left(\mathbf{p} - C_{\mathbf{q}}\left(\mathbf{n}, \mathbf{q}, \mathbf{B}\right)\right) + U_S \mathbf{V}\mathbf{p}\mathbf{q} = 0 \tag{7}$$

which can be rearranged as

$$\mathbf{p} - C_{\mathbf{q}}\left(\mathbf{n}, \mathbf{q}, \mathbf{B}\right) = -\frac{U_S}{U_M}\mathbf{V}\mathbf{p}\mathbf{q} \tag{8}$$

$U^*\left(\mathbf{p}, \mathbf{n}, \mathbf{V}\mathbf{p}, \mathbf{B}\right)$ is the indirect utility function corresponding to $U\left(M, S\right)$. The standard price equal marginal cost result of perfect certainty is achieved if either U_S is zero, or, if price variances and covariances are zero. Optimal output supplies ($\mathbf{q}^*$) are attained by solving (8) in terms of $\mathbf{q}$. Thus, $\mathbf{q}^*$ will now be a function of input prices $\mathbf{n}$, output price variances $\mathbf{V}\mathbf{p}$ and the area vector $\mathbf{B}$

$$\mathbf{q}^* = \mathbf{q}\left(\mathbf{n}, \mathbf{p}, \mathbf{V}\mathbf{p}, \mathbf{B}\right) \tag{9}$$

The next section presents the functional form used to estimate the output supply function given by (9) and discusses the Roche and McQuinn (2003) model used to derive price expectations.

2.1 Empirical Model

The cost function specified in (3) and (4) is approaximated by the Diewert and Wales (1987) flexible functional form. The form builds on work developed by McFadden and Lau and allows for the imposition of curvature properties with relative ease. Given the assumption of non-jointness in variable inputs, a separate cost function is specified and estimated for both wheat and barley. The cost function for wheat is given as

$$C\left(q_2, \mathbf{n}, \mathbf{z}\right) = h\left(\mathbf{n}\right) q_2 + \sum_{i=1}^{2} s_{ii} n_i q_2 + \sum_{i=1}^{2} s_i n_i + \sum_{i=1}^{2} s_{it} n_i z_i q_2$$
$$+ s_{z_i}\left(\sum_{i=1}^{2} \epsilon_i n_i\right) z_i + s_{qq}\left(\sum_{i=1}^{2} \theta_i n_i\right) q_2^2 + s_{z_i z_i}\left(\sum_{i=1}^{2} \omega_i n_i\right) t_i^2 q_2 \tag{10}$$

where $\mathbf{z}$ is a vector with z_1 = a time trend and $z_2 = b_2$ = wheat area (the second component in the $\mathbf{B}$ vector),[7] θ, ϵ and ω are vectors of parameter values pre-selected by the researcher. The parameters s are the only ones estimated. The function $h\left(\mathbf{n}\right)$ is defined as

$$h\left(\mathbf{n}\right) = \frac{1}{2}\left(\mathbf{n}^T \mathbf{L} \mathbf{n}\right)\left[\upsilon^T \mathbf{n}\right]^{-1} \tag{11}$$

where $\mathbf{L} = \mathbf{L}^T = [l_{ij}]$ is a 2 x 2 negative, semidefinite, symmetric matrix and $\upsilon^T = [\upsilon_1, \upsilon_2] > 0^T$ is a vector of non-negative constants, not all equal to zero and $\mathbf{s}$ is a matrix of parameters to be estimated. Under these set of restrictions, $h\left(\mathbf{n}\right)$ can be shown to be globally concave. As terms involving $\mathbf{s}$ are linear in input prices, they do not appear in the Hessian matrix of C. Thus, $\nabla_{nn}^2 C\left(\mathbf{n}, q, \mathbf{z}\right) = \nabla_{\mathbf{nn}}^2 h\left(\mathbf{n}\right) q$. Therefore, if the estimated $\mathbf{L}$ matrix is negative semidefinite, then the cost function C given by (10) is globally concave in input prices. Negative semi-definiteness can be imposed in various ways. In this instance, the Wiley, Schmidt and Bramble (1973) technique is adopted, with $\mathbf{L}$ being set equal to $-\mathbf{E}\mathbf{E}^T$ where $\mathbf{E}^T = [e_{ij}]$ is an upper triangular matrix. Consequently, the $\mathbf{L}$ matrix in (11) can be shown to be equal to[8]

[7] In the case of barley, $z_2 = b_1$ (the first component in the $\mathbf{B}$ vector).

[8] See Barnett and Zhou (2000) for details.

$$\mathbf{L} = -\begin{bmatrix} e_{11}^2 & e_{11}e_{21} \\ e_{11}e_{21} & (e_{21}^2 + e_{22}^2) \end{bmatrix} = e_{11}^2 \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix}$$

where e_{11} is now the parameter to be estimated. Given the cost function (10), the first order equation, given by (9), may be written as

$$\Gamma M^{\Gamma-1}\Big[p_1 - h(\mathbf{n}) - \sum_{i=1}^{2} s_{ii}n_i - \sum_{i=1}^{2}\sum_{j=1}^{2} s_{iz_j}n_i z_j - 2\sum_{i=1}^{2} s_{q_1q_1}\theta_i n_i q_1 - \sum_{i=1}^{2}\sum_{j=1}^{2} s_{z_jz_j}\omega_i n_i z_j^2\Big] - \Upsilon S^{\Upsilon-1}\Big[\sum_{j=1}^{2} q_j V p_{1j}\Big] = 0 \quad \text{for } i = 1\ldots 3 \tag{12}$$

Re-expressing this in closed-form solution for q_2, yields the following output supply function for wheat

$$q_2 = \frac{1}{\Gamma M^{\Gamma-1} 2\sum_{i=1}^{2} s_{q_2q_2}\theta_i n_i + \Upsilon S^{\Upsilon-1} V p_{22}} \Gamma M^{\Gamma-1}\Big[p_2 - h(\mathbf{n}) - \sum_{i=1}^{2} s_{ii}n_i - \sum_{i=1}^{2}\sum_{j=1}^{2} s_{iz_j}n_i z_j - 2\sum_{i=1}^{2} s_{q_2q_2}\theta_i n_i q_2 - \sum_{i=1}^{2}\sum_{j=1}^{2} s_{z_jz_j}\omega_i n_i z_j^2\Big] - \Upsilon S^{\Upsilon-1} q_1 V p_{12} \tag{13}$$

This output supply function is then used to estimate producers risk attitudes under price uncertainty.

2.2 Price Expectations Model

Most of the published production models of price uncertainty use the Chavas and Holt (1990) model for the expected mean, variance and covariances of output prices (e.g. Chavas and Holt (1990), Chavas and Holt (1996), Coyle (1992), Coyle (1999), OudeLansink (1999), Boyle and McQuinn (2001), Sckokai and Moro (2002a), Sckokai and Moro (2002b) and Garrido, Bielza and Sumpsi (2002)).[9] However,

[9] For a more detailed discussion on this point see McQuinn (2003).

Roche and McQuinn (2003) contend that the Chavas and Holt (1990) approach "is too *ad hoc* given the fact that in the last 15 years there have been many developments in the time series literature for the purposes of estimating conditional first- and second-order moments." Roche and McQuinn (2003) hypothesise a long-run relationship between Irish and UK grain prices and model expected variances and covariances within an ARCH framework. They explicitly test the forecasting performance of their model against the Chavas and Holt (1990) approach using standard forecast statistics (the mean squared error (MSE) and the mean absolute deviation (MAD)) as well as the recently developed test of superior predictive ability (SPA) by Hansen (2001).[10] In all cases, the Roche and McQuinn (2003) model outpreforms that of Chavas and Holt (1990). Therefore, this model is used to generate the price expectations required under the MSU. The model is summarised in Equation (3) of Roche and McQuinn (2003) and is presented in its linear autoregressive distributed lag form as[11]

$$\begin{aligned} p_t^{wir} &= f\left(1, t, p_{t-1}^{wir}, p_{t-2}^{wir}, p_{t-1}^{wuk}, p_{t-2}^{wuk}, e_{t-1}, e_{t-2}, u_t^w\right) \\ p_t^{bir} &= f\left(1, t, p_{t-1}^{bir}, p_{t-2}^{bir}, p_{t-1}^{buk}, p_{t-2}^{buk}, e_{t-1}, e_{t-2}, u_t^b\right) \end{aligned} \tag{14}$$

$$\begin{bmatrix} u_t^w \\ u_t^b \end{bmatrix} = [u_t] \sim MN\left(0, \mathbf{H}_t\right)$$

The series p^{wir} is the price of MCA[12] adjusted Irish feed wheat, p^{wuk} is the price of British feed wheat, e is the punt/sterling exchange rate, p^{bir} is the price of MCA adjusted Irish feed barley, p^{buk} is the price of British feed barley, t is a trend term and the u^i are stochastic error terms. The covariance matrix of Irish grain prices, $\mathbf{H}_t$, is estimated following Baba, Engle, Kraft and Kroner (1991) and Flavin and Wickens (2001) using the following MVARCH(1,1) model

$$\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\left(u_{t-1}u_{t-1}\right)\mathbf{B} \tag{15}$$

[10] The SPA tests for the best standardized forecasting performance relative to a benchmark model.

[11] The model proposed in Equation (3) of Roche and McQuinn (2003) is for the *growth rates* in prices, whereas the model expressed in (18) is for price *levels*.

[12] Monetary Compensation Amount.

The use of the results from the MVARCH model has a number of attractive features. First, the error correction model captures the dynamic nature of price transmissions between the mean Irish cereal prices and that of its largest grain trading partner. Second, allowing for ARCH errors has been shown to improve the efficiency of the results achieved in such a transmission framework (see Bollerslev, Chou and Kroner (1992) for example). The model is estimated on a rolling basis and forecasts are generated for the sample period 1984-1998.

The parameters outlined in (10) are given the following values: $\omega = 1, \epsilon = 1$ and $\theta = 1$. For the parameter υ, the same approach is taken as that outlined in the footnote to p.54 of Diewert and Wales (1987). This implies that υ_i is measured in the units of input i. Therefore, υ_i is chosen to be equal to the average amount of input i ($\overline{x}_i$) as this ensures invariant elasticity estimates.

The next section discusses the Heckman two-step procedure and its application in the present context.

3 The Heckman Two-Step Procedure

The Heckman two-step procedure is used to investigate bias resulting from non-randomly selected samples. The relationship between results of the sub-sample multi-croppers and those which pertain for the general sample may be construed as an example of potential selection bias in that the sample may be unduly risk averse (or less risk averse) relative to the general sample. In setting the issue within the context of the Heckman two-step procedure, the possibility of a non-randomly selected sample may be explicitly tested.

Heckman treated the bias originating from non-randomly selected samples as an ordinary specification or omitted variable bias. The Heckman procedure is a two-step procedure where the first stage models the decision to participate in the sample (plant both cereals simultaneously) and the second stage models the behavioral equation using information acquired in the first stage estimation. In an agricultural context, this approach has been adopted both by Shonkwiler and Yen (1999) and by Sckokai and Moro (2002). Use of the Heckman approach usually requires the specification of an indentification variable - one which is highly correlated with the producer's decision to simultaneously plant both wheat and barley but which is

uncorrelated with the producer's output decision once the producer has decided to plant both cereals.

One such variable that suggests itself to be used to identify the planting decision is a soil index. This index defines the quality of the soil possessed by each producer. The assumption is that the quality of the soil determines whether the producer plants both cereals simultaneously or whether the producer must plant one cereal alone. It is hypothesised that if soil quality is sufficiently good, the producer will plant both cereals simultaneously. However, relatively poor soil quality will result in the producer merely growing one crop. Once the producer is able to grow both cereals, the soil index is not assumed to affect the output decision for either cereal. Shonkwiler and Yen (1999) include variables denoting the geographical locality as well as the agronomic conditions of each farm, in their first-stage probit model. Consequently, in addition to the soil variable, individual producer fixed effects are also controlled for in the producer's first stage decision. This involves adding 164 individual dummies to the probit model. Therefore, the initial decision to plant both cereals is postulated as

$$P_i = \mu \mathbf{\Omega}_i + \varepsilon_{1i} \tag{16}$$

where Planting $= 1$ if $P_i > 0$ and $\mathbf{\Omega}$ is a vector of variables in the second stage equation plus the additional identifying variable and producer level fixed effects. Due to the binary nature of the dependent variable a probit model is used. Therefore, the probability of $(P = 1)$ i.e. of planting both cereals is given by the following

$$\mathbf{Prob}\,(P = 1) = \Phi\,(\mu \mathbf{\Omega}_i) \tag{17}$$

where Φ is the cumulative distribution function for a standard normal variable. Similarly the probability density function $\phi\,(\mu \mathbf{\Omega}_i)$ can be obtained from the same regression. If both Φ and ϕ are combined as follows

$$\frac{\phi\,(\mu \mathbf{\Omega}_i)}{\Phi\,(\mu \mathbf{\Omega}_i)} = \lambda\,(\mu \mathbf{\Omega}_i) \tag{18}$$

the inverse Mills ratio $\lambda(\mu\mathbf{\Omega}_i)$ is obtained. This ratio provides an estimate of the probability of a producer simultaneously planting both cereals. This variable is then added to the second stage equation - the output supply equation where it 'corrects' for the potential selectivity bias introduced by censoring the data for corner solutions. Therefore, the output supply equation for both wheat and barley can be re-written as

$$q_i = \frac{1}{\Gamma M^{\Gamma-1} 2\sum_{i=1}^{2} s_{q_1q_1}\theta_i n_i + \Upsilon S^{\Upsilon-1} V p_{11}} \Gamma M^{\Gamma-1}\Bigg[p_1 - h(\mathbf{n}) - \sum_{i=1}^{2} s_{ii} n_i - \sum_{i=1}^{2}\sum_{j=1}^{2} s_{iz_j} n_i z_j - 2\sum_{i=1}^{2} s_{q_1q_1}\theta_i n_i q_1 - \sum_{i=1}^{2}\sum_{j=1}^{2} s_{z_jz_j}\omega_i n_i z_j^2\Bigg] - \Upsilon S^{\Upsilon-1} q_2 V p_{12} + \beta_\lambda \lambda(\mu\mathbf{\Omega}_i) + \xi_{2j} \quad \forall\, i \quad (19)$$

where $\beta_\lambda = \rho\sigma\xi_{2j}$ and ρ is the correlation coefficient between the errors for q_i and P_i.[13]

4 Data and Regression Results

Data for the analysis is obtained from the National Farm Survey (NFS) conducted by Teagasc.[14] An unbalanced panel, from 1984 to 1998, comprising data on specialist cereal producers who engaged in both multi- and mono-cropping production was compiled.[15] The two variable input items used in the analysis are nitrogenous fertiliser and 'other' inputs. Note, that the 'other' inputs item contains all other variable inputs. The prices for these input items are considered to be non-stochastic and known to producers in advance of the input application decision. In addition to output prices, input prices are also assumed to be constant across space and variable only through time. The prices used for these input items are national aggregate price indices and are from the Irish Central Statistics Office (CSO). The identifying variable - the soil index is based on an index used in the NFS. The NFS index

[13] Disturbances from the second stage estimation are heteroscedastic unless explicitly corrected.

[14] For more on the NFS see Heavey, Roche and Burke (1998).

[15] The general sample totaled 1700 observations, while the multi-cropping sub-sample totaled 913 observations.

ranges from 1 to 5 with 1 denoting the most appropriate cereal growing ground and 5 denoting the least favourable tillage conditions.

The estimation procedure is as follows; the probit model (16) is estimated and the inverse Mills ratio (18) is calculated, the system given by (19) for wheat and barley is then estimated and the risk attitudes in the presence of the inverse Mills ratio are then compared with those estimated from (13). If little difference exists between both sets of results, then Irish multi-croppers would not appear to be a relatively risk-averse sub-sample of the general sample of Irish cereal producers.[16]

Table 1 (insert Table 1 here) documents the results from the first stage probit regression i.e. equation (16). In general, 54 per cent of the coefficients are significant at the one per cent level. The fixed effects nature of the model requires that parameter estimates are based solely on within producer variation. Unsurprisingly, increases in expected output prices have a positive and significant effect on the decision to plant both cereals. Variances and the co-variance of output prices have positive and negative effects respectively on the decision to plant simultaneously, while the input prices have conflicting effects on the probability of multi-cropping.

The sign of the soil variable confirms with *a priori* expectations - the greater the size of the index i.e. the poorer the quality of the soil, the less likely a producer is to plant both crops. The co-efficient is insignificant at conventional levels. To further test for the suitability of the soil variable along with the inclusion of indivdual producer effects, Table 2 (insert Table 2 here) reports the results of likelihood ratio tests examining the inclusion of both the soil variable and producer level dummies. We are unable to reject the constraint of the soil variable coefficient being equal to 0. However, the producer level effects add significant explanatory power to the first stage probit model. Thus, while the quality of a producer's soil in itself may not significantly affect planting decisions, there would appear to be other individual effects - proximity to other multi-cropping producers, other agronomic conditions etc. which do. For instance, Shonkwiler and Yen (1999) use a variable denoting the geographical locality of each far. It may well be that producers in a particular area develop an expertise in 'multi-cropping' which results in a relatively large number

[16] All estimations are conducted using the nonlinear three-stage systems estimators in both SAS/ETS and RATS for Windows Version 5.04. Programs are available from the authors upon request.

of producers in that area attempting to grow both cereals. A mean dummy effect is included in Table 1, however results for the individual 164 producers are available upon request. In total 73 per cent of the dummies were significant at the one per cent level.

The inverse Mills ratio (18) is generated for all multi-croppers from the first stage model and is added as an explanatory variable in (19). Table 3 (insert Table 3 here) contains the parameter estimates from the second stage estimation. From the Table, it may be observed that 61 per cent of the parameters are significant at the 5 per cent level while 52 per cent of the parameters are significant at the 1 per cent level. The risk coefficients, as well as parameter tests are further summarised in Table 4. (Insert Table 4 here) The results presented in Table 4 may be compared with Table II of Saha (1997). Irish cereal producers are risk averse, as both α and Υ are clearly positive. Further tests suggest that the MSU utility function specification constitutes a better representation of producers' risk attitudes than the more restrictive specifications of CARA used in other studies.[17]

From the results presented in Tables 3 and 4, it appears that Irish producers exhibit decreasing absolute risk aversion (DARA) and decreasing relative risk aversion (DRRA). This initial result of DARA is in line with *a priori* expectations i.e. as producers experience increased income, one expects them to become less risk averse. Table 1 of Saha, Shumway and Talpaz (1994) illustrates that in many international studies CARA has been rejected in favour of DARA. Thus, the result of DARA has considerable support in the literature.

The finding of DRRA, that is, a declining level of risk aversion to the same proportional risk, is also noteworthy, as Saha, Shumway and Talpaz (1994) note, studies on relative risk aversion frequently yield ambiguous results. In particular, most studies reveal either CRRA or DRRA. The importance of the flexibility of the utility function adopted is underlined by the finding of DRRA. As noted by Saha (1997), "most prior studies have not investigated whether the nature of relative risk aversion preference differs according to income levels".

The estimated β_λ coefficient is positive but statistically insignificant. This result is of considerable interest. In general, a significant coefficient on the inverse Mills ratio suggests, that, the results of the first stage probit regression adds significant

[17] Such as Coyle (1992) and OudeLansink (1999).

explanatory power to the second stage regression i.e. that there is sample selection bias problem. However, in this case, the insignificance of the coefficient, coupled with the explanatory power of the producer level effects in the probit model, suggest that producers' risk attitudes in themselves do not cause producers to engage in multi-cropping production. In other words, the fact that producers engage in multi-cropping does not in itself signify that these producers are a relatively risk averse subsample of the general sample of specialist Irish cereal producers.

The issue may be further explored by comparing the estimates of the risk coefficients Υ and Γ from (19) and (13) in Table 5 (insert Table 5 here) i.e. both with and without the inclusion of the inverse Mills ratio. If the inverse Mills ratio adds little or no explanatory power to the second stage estimation then both sets of risk parameters should be almost identical. All parameter estimates of (13) are provided in the Appendix to this paper. Comparing parameter results in Table 5, it may be observed that there is very little difference in the results achieved by adding the inverse Mills ratio. No difference exists between the size and sign of the risk parameters. Clearly, any information added to the second stage regression by the inverse Mills ratio does not appear to affect the risk attitudes estimated.

Diagnostic tests were performed on the output supply function both with and without the inverse Mills ratio. In particular, both the White (1980) test for heteroscedasticity and the Baltagi (2001) LM test were performed on sets of output supply functions (13) and (19). The Baltagi (2001) test is for unbalanced panels and has a null hypothesis of homoscedastic errors.[18] The test results are in Table 2 of the Appendix. The null cannot be rejected in any case. Thus, once the planting decision is made, producer specific effects would not appear to effect output decisions.

5 Concluding Comments

This paper has explicitly examined whether multi-cropping production is a concious risk management strategy employed by a sub-sample of Irish crop producers. The

[18] Under the LM test, the error term is hypothesised to have the following structure: $u_{it} = \mu_i + \lambda_t + \nu_{it}$ where μ_i and λ_t are producer specific and time effects. The null hypothesis therefore is $H_0 : \sigma_\mu^2 = \sigma_\nu^2 = 0$.

issue is treated as a potential sample bias problem and risk attitudes of producers are estimated with and without the Heckman two-step procedure.

Preliminary estimation suggests Irish multi-croppers are risk-averse and experience both DARA (in common with many other international studies) and DRRA. Other more restrictive utility function specifications are rejected by the data. Of interest is whether these risk attitudes estimated for a sub-sample can be extrapolated to the general sample of producers.

Application of the Heckman two-step procedure reveals that, multi-croppers would not appear to be more risk-averse then the general sample of producers. A producer's decision to engage in multi-cropping does not reveal in itself a more risk averse nature. While producer specific effects impact on a producer's decision to simultaneously plant two crops as opposed to one, once the planting decision has been made, subsequent production effects are unaltered.

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Table 1: Parameter Estimates of Probit Model (Heckman first stage)

Variable	Parameter Estimate	P-Value
Barley Price Variance	0.096	0.143
Expected Barley Price	0.061	0.000
Expected Wheat Price	0.039	0.000
Wheat Price Variance	0.002	0.517
Nitrogen Price	0.0001	0.052
Other Inputs Price	-0.1E-5	0.886
Barley Output	-0.004	0.534
Wheat Area	0.005	0.773
Wheat Output	-0.001	0.911
Barley Area	0.017	0.306
Prices Covariance	-0.1E-4	0.516
Soil	-0.236	0.322
Mean Dummy Effect	0.342	0.096

Samplesize = 1700 Observations. Results for individual producer level dummies are available from the authors upon request.

Table 2: Likelihood Ratio Test on Soil Variable and Individual Fixed Effects (Heckman first stage)

Variable	χ^2 Calculated	χ^2 Critical*
Soil Variable	1.01	3.84
Fixed Effects	241.3	146.57

*At the 5 % level

Table 3: MSU-type Supply Function Estimates for Irish Wheat and Barley Producers under Price Uncertainty (Heckman second stage)

	Wheat		Barley	
Parameter	Estimate	T-Stat	Estimate	T-Stat
e_{11}	11.57	4.67	31.23	5.91
s_{11}	53.21	7.23	5.74	1.69
s_{22}	0.87	0.11	-44.27	-12.04
s_{1z_1}	1.27	1.30	1.32	1.32
s_{2z_1}	2.19	2.19	0.79	1.51
s_{1z_2}	0.02	1.39	-0.03	-4.34
s_{2z_2}	-0.005	-2.05	-0.031	-3.55
s_{qq}	-0.03	-4.87	0.043	12.22
$s_{z_1z_1}$	-0.04	-0.65	0.012	0.58
$s_{z_2z_2}$	0.6E-5	10.68	-0.0001	-10.64
Γ	8.78	50.73	8.78	50.73
Υ	5.42	44.19	5.42	44.19
β_λ	5.15	0.65	5.15	0.65

Sample size = 913 Observations.

Table 4: Estimated Risk Parameters and Hypothesis tests under MSU for Irish Wheat and Barley Producers (Heckman second stage)

Parameter/Test	Description	Estimate	Std. Error/P-Values
Γ		8.78	(0.000)
Υ		5.42	(0.000)
α^*	$(\Gamma/\Upsilon)\,\mathrm{M}^{1-\Upsilon}\mathrm{S}^{\Gamma-1}$	13493.99	(0.000)
$\mathrm{H_O}$: $\Gamma = \Upsilon = 1$**	Linear U(M,S) model	4435.3	(0.000)
$\mathrm{H_O}$: $\Gamma = 1$***	CARA Attitudes	50.71	(0.000)
$\mathrm{H_O}$: $(\Upsilon - \Gamma) = 0$***	CRRA Attitudes	48.15	(0.000)

Note: * denotes evaluated at the sample mean. ** denotes Asymptotic $\chi^2(2)$ test statistic, p-value in parentheses. *** denotes Asymptotic t-test statistic, p-value in parentheses.

Table 5: Comparison of Risk Attitudes
under MSU Model both with and without Inverse Mills Ratio

Parameter	Model	Estimate	T-Stat
Γ	with Inverse Mills	8.78	50.73
Υ	with Inverse Mills	5.42	44.19
Γ	without Inverse Mills	8.78	50.77
Υ	without Inverse Mills	5.42	44.23

Appendix A

Table 1: MSU-type Supply Function Estimates for Irish Wheat and Barley Producers under Price Uncertainty (without Inverse Mills)

	Wheat		Barley	
Parameter	Estimate	T-Stat	Estimate	T-Stat
e_{11}	11.57	4.67	31.23	5.91
s_{11}	51.52	7.23	5.51	1.70
s_{22}	0.87	0.11	-43.41	-12.18
s_{1z_1}	1.26	1.30	0.65	1.33
s_{2z_1}	2.18	2.19	0.77	1.52
s_{1z_2}	0.02	1.39	-0.03	-4.39
s_{2z_2}	-0.005	-2.05	-0.031	-3.59
s_{qq}	-0.03	-4.87	0.042	12.37
$s_{z_1z_1}$	-0.04	-0.65	0.012	0.59
$s_{z_2z_2}$	0.6E-5	10.69	-0.0001	-10.76
Γ	8.78	50.77	8.78	50.77
Υ	5.42	44.23	5.42	44.23

Sample size = 913 Observations.

Table 2: Diagnostic Tests for All Supply Models

Equation	Multi-Croppers Model	Calculated White Stat	Critical White Stat*	Calculated LM Stat	Critical LM Stat*
Barley	without Inverse Mills	10.1	20.1	7.7	9.21
Wheat	without Inverse Mills	16.1	20.1	3.6	9.21
Barley	with Inverse Mills	3.8	21.67	4.6	9.21
Wheat	with Inverse Mills	9.9	21.67	0.2	9.21

* denotes at the 1 per cent level