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Understanding farmers' uptake of organic farming

An application of the theory of planned behaviour

Doris Läpple[1,2] and Hugh Kelley[1]

[1] Department of Economics, National University of Ireland, Galway

[2] Rural Economy Research Centre, Teagasc, Athenry, Co. Galway, Ireland

Doris.Laepple@teagasc.ie

Summary

Whilst the adoption of agricultural techniques has received considerable attention in the literature, the ability and willingness of potential adopters to change their current farming system is often overlooked. This paper is concerned with the intention of conventional farmers to convert to organic farming by using the social-psychology theory of planned behaviour. Drivers and barriers of conversion to organic farming are identified by applying a belief based concept, which is confirmed using principal component analysis. In addition, accounting for heterogeneity regarding farmers' environmental attitudes masks considerable differences, notably at intention, attitudes and control perceptions. Overall, results reveal that conversion is indeed affected by attitudes of the farmer, perceived social pressure and ability to convert.

Keywords: Organic farming; Theory of planned behaviour; Principal component analysis; Heterogeneity

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1. Introduction

Research into the uptake of environmental schemes has developed rapidly in recent years. In this context, the main body of the literature is concerned with explaining adoption decisions by comparing a set of farm and farmer characteristics of adopters and non-adopters using a range of techniques (Defrancesco *et al.*, 2008; Burton *et al.*, 2003; Wynn *et al.*, 2001). However, while these studies provide insight into the characteristics that are advantageous for adoption, the willingness and ability of farmers' to change their current farming system is not considered. However, these factors are of particular interest if an increase in the uptake of environmental measures is of concern and is addressed in this paper.

Organic farming is perceived by many as part of the solution to environmental degradation (Lampkin and Padel, 1994) and consequently, several European countries actively encourage farmers to convert to organic farming. However, despite the financial support available to farmers, the sector represents only a small portion of the total utilizable agricultural area (UAA) in most European countries. Furthermore, several European countries have set targets to increase the size of their organic sectors. For example, the Irish government aims to have 5% of UAA in organic farming by 2012. However, with only 1.2% of the UAA currently under organic farming, achieving this target requires the conversion of existing conventional farms. The extensive nature of the Irish conventional drystock sector implies that many farmers could easily switch to organic techniques with very little entry costs. In addition to organic subsidy payments, which are amongst the highest levels of EU member states, market opportunities exist for Irish organic beef. This includes emerging export opportunities mainly to the UK and Germany. These characteristics make Ireland an ideal case study as it begs the question as to why are more farmers not converting and if there are any social or technical barriers of conversion?

In the context of farmers' conservation behaviour, there appears to be a weakness in economic models to fully explain the complexity of that decision (Lynne *at al.,* 1988). Consequently, several studies accounted for a possible influence of farmers' attitudes to explain conservation behaviour (Defrancesco *et al.,* 2008; Burton *et al.,* 2003). However, to fully understand farmers' decisions to take up environmental schemes, a more sophisticated approach is required that goes beyond merely accounting for general farmer attitudes. In this context, several authors suggest using social-psychology models (Lynne, 1995; Burton, 2004) which specify attitudes and beliefs in a defined framework in order to provide a thorough understanding of the behaviour.

Social-psychology models, with the most widely applied models being the theory of reasoned action (TRA) and the theory of planned behaviour (TPB), are used to understand and also to predict why individuals act in the way they do. However, despite the wide application in other areas, for example in explaining leisure choice (Ajzen and Driver, 1992) or consumer choice (Cook *et al.,* 2002; Arvola *et al.*, 2008), the number of studies that have applied social psychology models to explain the uptake of agricultural technologies is small. One example is a study by Lynne *et al*. (1995) who apply the TPB to predict water saving technology adoption and technology investment behaviour for Florida strawberry farmers. The results underline the importance of perceived behavioural control in farming decisions, though in testing for the theory of derived demand, actual control appears to be important as well. Rehman *et al.* (2007) explain factors influencing the uptake of new technologies on dairy farms in South-West England using the TRA. They identify significant drivers and barriers of adoption based on farmers' beliefs. For example, expected economic benefits of the new technology were found to be drivers, whereas the study also found that farmers are afraid that the technology will demean their own knowledge and experience. Hattam (2006b) looks at the intention of Mexican small-scale avocado producers to convert to organic practices applying the TPB. Results indicate that farmer attitudes, whilst positive, are not a significant influence on intention, suggesting that attitudes alone are not sufficient to explain behaviour. However, the influence of others as well as perceptions of control were found to be significant on the intention to convert. Another example is a study by Pennings and Leuthold (2000) using a wider framework of the TPB to explain the usage of futures contract by Dutch hog farmers. They found a significant influence of the farmer's community as well as other psychological constructs on that decision. Accounting for heterogeneity regarding the probability of using futures revealed important differences, mainly in risk attitude, suggesting that accounting for heterogeneity within the sample increases insight into farmer decisions.

Furthermore, considering the conservation behaviour of farmers, environmental attitude is widely regarded as an important determinant of the adoption of such behaviours (Defrancesco *et al.*, 2008; Genius *et al.*, 2006; Burton *et al.*, 2003; McCann *et al.*, 1997). For example Defrancesco *et al.* (2008), investigating participation in agri-environmental measures in Northern Italy, reveal that farmers' opinions with regard to environmentally friendly practices have an important effect on the adoption of such techniques. McCann *et al.* (1997), looking at similarities and differences between organic and conventional farmers in Michigan, found that organic farmers express a higher level of environmental concern than their conventional counterparts. In general, these studies are concerned with how these attitudes relate to behaviour, but less attention is paid if differences exist between groups with different attitudes. Therefore, this paper extends previous literature by investigating possible differences in the factors affecting farmer decisions by segmenting the sample into groups with different levels of environmental concern.

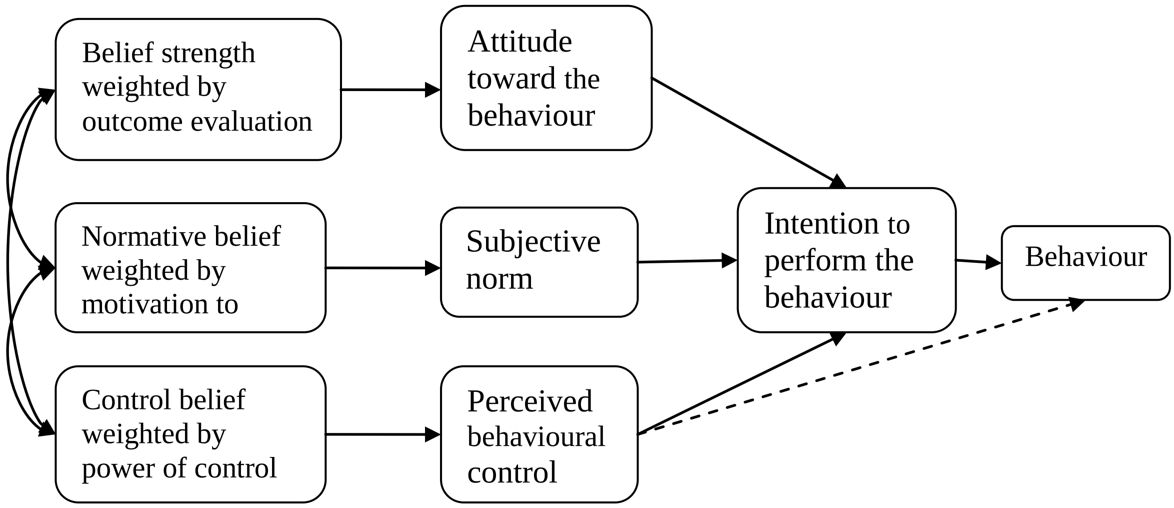
Following from the literature reviewed, the objectives of this paper are twofold. First, the social-psychology theory of planned behaviour is applied to explain farmers' intention to convert to organic farming. In order to increase understanding, attitude is divided into cognitive and affective sub-dimensions. This is confirmed by principal component analysis and effects on intention are analysed with ordinal regression analysis. Second, to account for heterogeneity in environmental attitudes, latent class cluster analysis is applied to reveal possible differences in the factors that affect the intention to convert between different groups.

The paper is structured as follows: In the next section the social-psychology theory of planned behaviour is explained, while in section three the survey design and the calculation of variables is outlined. Section four introduces the applied methodology. In section five results of the various models are presented, while these are discussed in section six followed by some final conclusions.

2. The theory of planned behaviour

The theory of planned behaviour (Ajzen, 1985; 1991) is an extension of the theory of reasoned action (Fishbein and Ajzen, 1975; Ajzen and Fishbein, 1980). Whereas the TRA seeks to explain behaviour through behavioural intent based on attitude and subjective norms, the TPB addresses the issue of incomplete volitional control over the behaviour in question and consequently adds another component, that of perceived behavioural control. As shown in Figure 1, the TPB postulates three conceptually independent components of intention. In this context, the attitude toward the behaviour is the person's positive or negative evaluation of performing the specific behaviour. Subjective norm represents perceptions of social pressure or influence from others on carrying out the behaviour. The last component, perceived behavioural control, deals with ability and factors that facilitate or impede performance of the behaviour (Ajzen, 2005). Although perceptions of control rather than actual control are measured, given sufficient information about the behaviour, perceived behavioural control generally serves as a good proxy of actual control, which is indicated by the broken arrow between perceived behavioural control and behaviour (Figure 1).

Figure 1: The theory of planned behaviour (adapted from Ajzen, 2005)



Intention to perform the behaviour is the central factor as it is the immediate antecedent of any behaviour. The stronger the intention to perform the behaviour, the more likely should be its performance. The underlying assumption of these models is that people behave rationally following the beliefs they hold and that behaviour is a function of salient beliefs that are relevant to the behaviour (Ajzen, 1991). In general, beliefs represent the information a person has about an object, regardless of whether this information is correct (Beedell and Rehman, 2000). This implies that people take account of available information and consider the outcomes of their behaviour (Ajzen, 2005). As a result from the TPB components, three kinds of beliefs are distinguished. Behavioural beliefs are considered as antecedents of attitude, normative beliefs explain subjective norm and control beliefs constitute the underlying determinants of perceived behavioural control (Figure 1). The belief based measures are thought to be the more accurate measures, as they reveal why people hold certain attitudes, subjective norms or control perceptions. The belief based measures are calculated following the expectancy-value model (Fishbein and Ajzen, 1975) which introduces the link to the subjective exceptive utility model in economics (Lynne, 1995).

In this context, attitudes are determined by accessible beliefs about the outcomes of the behaviour and by the evaluation of this particular outcome. Following the expectancy-value model (Fishbein and Ajzen, 1975) a belief based measure of the attitude (A) is obtained by multiplying belief strengths (bs) and outcome evaluation (oe) and summing the products according to

$$A \propto \sum bs_i \times oe_i. \quad [1]$$

Belief strength is defined as the subjective probability that a given behaviour will produce a certain outcome (Fishbein and Ajzen, 1975) and the outcome evaluation can be regarded as the utility received of that outcome occurring.

In the same way, measures for the other components are obtained. Subjective norm (SN) results from multiplying strength of normative belief (nb) with motivation to comply (mc) and summing the results following

$$SN \propto \sum nb_i \times mc_i. \quad [2]$$

Finally, perceived behavioural control (PBC) is obtained by multiplying control belief strength (cb) with power of control (pc) and summing the results by applying

$$PBC \propto \sum cb_i \times pc_i. \quad [3]$$

Consequently, all components that measure behavioural intent consist of direct as well as belief based measures following the expectancy-value model. To validate the model, the belief based measures should correlate well with the global measure of the specific component (Ajzen, 1991). This reveals salient beliefs, which are then used for further analysis.

Based on the three components of the TPB that are derived following the expectancy-value model, the model to explain the behavioural intention (BI) becomes:

$$BI = \beta_1 A + \beta_2 SN + \beta_3 PBC + \epsilon, \quad [4]$$

where β are empirically determined weights to estimate the importance of each component and ϵ is an error term. Depending on the context and the person, the influence of attitude toward the behaviour, subjective norm and perceived behavioural control on behavioural intention can vary. In general, the more positive the attitude, subjective norm and perceived behavioural control the more likely the person is to perform the behaviour under study. However, due to social consequences and not having full control over the implementation, attempting to perform the behaviour may not necessarily lead to actual performance of the behaviour. The analysis in this paper will reveal how these components influence the intention to convert to organic drystock farming.

3. Survey design

The TPB aims to assess people's beliefs with regard to the behaviour under study and thus a survey of the population of interest is a suitable instrument to achieve this. Typically, developing the survey consists of two distinct stages: First, identification of salient beliefs with respect to the behaviour of interest and second, development of a quantitative survey, based on identified salient beliefs.

Following Ajzen (1991), salient beliefs are best elicited from the respondents themselves or from a sample of respondents that is representative of the population of interest. This is regarded as being superior to an intuitively selected set of beliefs by the researcher, for example based on a literature review. In this study, 53 open interviews with conventional farmers were undertaken in order to identify the salient beliefs. The open interviews included questions about expected advantages and disadvantages of 'going organic'. In addition, important other people and information sources related to farming decisions, as well as perceived problems with respect to the possible conversion of the individual's own farm, were identified in these interviews.

In the second step, the elicited beliefs need to be incorporated in the quantitative survey. According to the theory, it is important to transform these beliefs into suitable questions, so that the principle of compatibility is followed. This means that each question has to be defined at the same level of specificity in terms of target, action, context and time (Ajzen, 2005). In this study, the target is defined as 'organic meat', the action is 'producing meat organically', the context is 'the specific farm' and the time frame is set as 'five years'. Since behavioural intentions may change over time, the time between measurement of behavioural intention and behaviour should be minimized to maximize prediction (Beedell, 1996). However, implementing the behaviour might require some amount of time. For example, Hattam (2006a) found that Mexican farmers expressed stronger intentions to convert to organic avocado production measured in the more distant future (10 years) than in the short term (1 year).

All responses were measured along five-point fully anchored scales. Attached labels were dependent on the factor under consideration. The data were collected through face-to-face interviews with 193 conventional farmers by professional farm recorders from the Teagasc National Farm Survey Department between July and November 2008.

3.1 Measurement of components of the TPB

Intention

Intention was measured by two statements scaled in a unipolar way from 1 to 5, one capturing self-prediction and the other one capturing behavioural intention (Armitage and Conner, 2001). Therefore, intention was measured by asking 'How likely is it that you will produce organic meat on your farm within the next five years?' evaluated on a unipolar scale labelled with very likely (5) to very unlikely (1) and 'How strong is your intention to produce organic meat on your farm within the next five years?' evaluated by very weak (1) to very strong (5).

Attitude

Direct attitude was elicited by three questions in total, such as 'Producing organic meat on your farm within the next five years would be…' evaluated on two bipolar (-2 to +2), five-point semantic-differential scales, evaluated on an affective scale such as foolish/wise and good/bad. In total, five behavioural beliefs followed by their evaluation were included, three attempting to elicit the cognitive and two attempting to measure the affective component of the attitude (Ajzen and Driver, 1992). In assessing the cognitive part of an attitude an approach suggested by Lynne *et al.* (1995) was followed where the focus is moved to the action rather than the attribute to avoid ambiguity. Strength of belief of the cognitive part was measured by asking the degree to which the person agreed or not with: 'If you produce organic meat you will …' (1) save on fertilizer costs, (2) receive higher prices, (3) increase farm income due to higher support payments, followed by the assessment of importance of the outcome. The affective component was measured as follows: 'Producing organic meat on your farm will…' (1) lead to farming as it was 50 years ago and (2) provide a product only rich people can afford, again followed by the evaluation of the outcome, however measured on a good/bad scale. The behavioural beliefs are defined as the subjective probability that a given behaviour will produce a certain outcome and therefore scaled in a unipolar fashion from 1 to 5, whereas evaluations are usually assumed to vary from a negative evaluation on one end to a positive evaluation on the other end and are therefore scaled in a bipolar form from -2 to +2 (Ajzen, 1991). This scaling produces a range from -10 to + 10, and overcomes the problem of 'double negative' when both scales are bipolar.

Subjective Norm

Direct subjective norm is assessed by two statements measured on a bipolar scale (-2 to +2): 'Most people who are important to you think you should produce organic meat on your farm within the next five years…' measured on a definitely false to definitely true scale as well as by 'In general, would people who are important to you approve or disapprove of you producing organic meat on your farm within the next five years?' evaluated from definitely disapprove to definitely approve. Subjective belief is identified by the question 'How likely is it that the following think you should produce organic meat on your farm within the next five years?' followed by a list of the identified referents. The degree of motivation to comply is measured by asking 'How motivated would you be to follow the opinion/advice of those listed below regarding producing organic meat on your farm within the next five years?' followed by the same list of referents. Following the recommendation from Ajzen and Fishbein (1980), normative beliefs are scored in a bipolar way (-2 to +2) and motivation to comply is scaled in a unipolar manner (1 to 5).

Perceived behavioural control

Two global measures of perceived behavioural control are included, both scaled bipolar from -2 to +2. The first one elicits perceived difficulty by asking 'Producing organic meat on your farm within the next five years would be…' measured on a definitely possible to definitely impossible scale. The second one captures self-efficacy: 'How confident are you of your technical ability to produce organic meat on your farm within the next five years?' Control belief and power of control are measured by five paired questions asking the respondents to rate how true or false a particular statement was, for example 'You have the knowledge and the skills to produce organic meat on your farm' or 'It is possible for you to maintain good animal health on your farm based on prevention' and then express their level of agreement as to how much easier this particular statement would make the production of organic meat. Control beliefs were scaled bipolar (-2 to +2) and the corresponding perceived power was scaled unipolar from 1 to 5 (Ajzen, 1991).

3.2 Calculation of variables

A mean score for the direct components can be calculated if all statements within a group are correlated. All components of the direct measures for attitude, perceived behavioural control and subjective norm were significantly correlated. The belief based measures are calculated by multiplying the individual paired questions following the previously explained expectancy-value model. For example, the score of the behavioural belief 'If you produce organic meat you will receive higher prices' is multiplied by the score of its outcome evaluation 'Receiving higher prices is…'. A belief is considered to be salient if the belief based measure correlates significantly with the corresponding direct measure (Hattam, 2006a). Hence, the correlations of the values obtained with the specific component of the direct measures are calculated. Consequently, only the components that show a significant correlation to the corresponding direct measure are retained in the analysis. Four of the behavioural belief statements show a significant correlation with the direct attitude, whereas all of the belief based measures of subjective norm and perceived behavioural control correlate significantly with their direct components. The belief based measures are calculated by summing the significantly correlated paired questions. Table 1 presents the correlation coefficients of the calculated belief based measures with the direct components, based on non-parametric Spearman type correlations.

Table 1: Correlation coefficients of belief based measures with direct components

Behavioural belief:	**Correlation with attitude**
$\sum bs \times oe$ (cognitive)	0.305***
$\sum bs \times oe$ (affective)	0.453***
$\sum bs \times oe$ (2-5)	0.492***
Normative belief:	**Correlation with SN**
$\sum nb \times mc$	0.490***
Control belief:	**Correlation with PBC**
$\sum cb \times mc$	0.540***

The overall correlations between calculated and direct components indicate a good fit, considering a meta-analysis of different behaviours (Armitage and Conner, 2001). In this meta-analysis, a mean correlation of 0.50 between direct and belief based measures of attitude, as well as normative beliefs and direct subjective norm was found. For measures of perceived behavioural control, a mean correlation of 0.52 between control beliefs and direct components is reported.

4. Methodology

Several empirical approaches exist to test for the proposition that intentions to convert to organic farming can be predicted from attitudes towards organic farming, subjective norms and perception of control. The most common approaches are multiple regression analysis (Ajzen and Driver, 1992; Lynne *et al.*, 1995; Cook *et al.*, 2002; Hattam, 2006b) or structural equation modelling (Pennings and Leuthold, 2000; Arvola *et al.*, 2008). The latter approach is more concerned with testing the theory as well as model confirmation. Since the aim of this study, is to estimate and to predict effects on intention, regression analysis is the preferred modelling technique. In addition, validation of belief based components using factor or Principal Component Analysis (PCA) is used to confirm the theory. Although this approach helps to empirically confirm patterns in the components, it is not a standard procedure of TPB or TRA analysis, with exceptions being Ajzen and Driver (1992) and Rehman *et al.* (2007). Finally, cluster analysis helps to account for heterogeneity within the sample. The different methodologies applied in this study are described in more detail in the following sections.

4.1 Principal component analysis

In a first step, PCA with varimax rotation is used to validate and confirm belief based components of the TPB. PCA is a statistical technique that creates a smaller set of uncorrelated linear combinations of the original variables that explains most of the information of the original variables (Lewis-Beck, 1994).

Despite that PCA is usually regarded as being similar to factor analysis, differences exist between the two methods. Factor analysis and PCA aim to represent the covariance (correlation) matrix Σ as well as possible. Both methods involve the description of a set of p random variables $y' = (Y_1, Y_2, \ldots, Y_p)$ with $m \leq p$ random variables $x = (X_1, X_2, \ldots, X_m)$ and p residuals $\varepsilon = \left(e_1, e_2, \ldots, e_p\right)$. Both approaches can be expressed as,

$$y = A\,x + \varepsilon, \qquad [5]$$

where A is a $p \times m$ matrix of calculated scores. Due to the requirement of $x = A'y$ in PCA, the covariance matrix of ε cannot be diagonal and of full rank. Whereas in factor analysis, the covariance matrix of ε must be diagonal and of full rank (Velicer and Jackson, 1990). Consequently, in PCA the objective is to produce components that explain as much variance as possible, which implies a concentration on the diagonal elements of Σ, whereas the objective of factor analysis is to produce factors that explain the correlations among a list of variables and thereby focusing on the off-diagonal elements of Σ (Jolliffe, 2002). PCA is a weighted linear composite of the observed variables, whereas factor analysis, in contrast, provides a latent variable which accounts for the observed variables and sampling error.

However, from an empirical aspect, there is little basis to prefer one method over the other (Velicer and Jackson, 1990). In this study, since the effect of the original variables is of interest, PCA is the preferred approach as the effect of an observed variable on the dependent variable can be calculated using the weighted linear combinations of variables, which is not possible using factor analysis.

As already mentioned PCA is concerned with explaining as much variance of the original variables as possible. It aims for a reduction of complexity by transforming the original variables to a smaller set of principal components (PC) that explain most of the original variance. This is achieved as follows: PCA looks for a linear function y_i of the elements of x having maximum variance,

$$y_1 = \alpha_{11}x_1 + \alpha_{12}x_2 + \cdots + \alpha_{1k}x_k = \sum_{i=1}^{k} \alpha_{1i}x_{i,} \qquad [6]$$

where α is a vector of k constants, which is an eigenvector of Σ corresponding to its kth largest eigenvalue λ_k. PCA finds the eigenvector α that maximizes $\alpha'\Sigma\alpha$ given the constraint that $\alpha_k^{'}\alpha_k$ =1 (Lewis-Beck, 1994). Then it looks for a second linear function y_2 uncorrelated with y_1, having maximum variance and so on, so that at the mth stage, with $m \leq k,$ a liner function of y_m is found that has maximum variance, but is uncorrelated with the other linear combinations (Joliffe, 2002). The derived variables are the PCs and as many components as variables can be calculated. In general, the first few principal components explain most of the variance in x and a smaller set of PCs is used to replace the original variables. To avoid the influence of different variances of variables, PCA is conducted on standardized variables. The original variables x are replaced by $x^* = x_i/\sqrt{\sigma_{ii}}$, where σ_{ii} is the variance of x_i. Then the covariance matrix for x^* is the correlation matrix of x (Joliffe, 2002). Also, while it is not an integral part of PCA, components can be rotated to simplify interpretation. Therefore, in a second step the components are rotated using varimax rotation. Varimax rotation is the most common orthogonal rotation procedure. The varimax method maximizes the sum of the variances of the squared loadings within each column of the loading matrix (Lewis-Beck, 1994).

4.2 Probit model

The intention of farmers' to convert to organic farming can be ranked from very unlikely to very likely. This implies that the dependent variable can be ordered, and a specific value, which is not arbitrary, can be assigned to each category. However, distances between categories are unknown, and due to that the dependent variable cannot be treated as interval and requires special treatment. Therefore, an ordered regression model appears to be the appropriate choice.

In the first step, an ordered probit model is applied to the whole sample. The dependent variable consists of four ordered categories. For this purpose the mean of the intention items is divided into four categories, with the following interpretation of intention to convert: $j = 1$ representing very unlikely, $j = 2$ unlikely, $j = 3$ uncertain and $j = 4$ implying (very) likely conversion within the next five years. Due to few responses in the higher categories, it was not possible to decompose the responses which were in the likely and very likely categories. In the second step, due to a split sample and therefore fewer observations in each model, a binary probit model is applied. In this model intention is divided into two categories, with $j = 0$ implying (very) unlikely and $j = 1$ representing answers from uncertain to very likely conversion. The ordered probit model is an extension of the binary probit model, which will become apparent in the following paragraphs.

In this context, the assumption is that underlying the ordered response is a latent, continuously distributed random variable representing intention to convert. The model becomes a latent regression model of the form

$$y^* = x^{'}\beta + \varepsilon, \qquad [7]$$

where y^* is a latent variable ranging from $-\infty\ to + \infty$, x' represents the explanatory variables, β is a coefficient to be estimated and ε is an error term assumed to be normally distributed across observations with a mean of zero and a variance of one (Greene, 2008). The observed variable y_i represents incomplete information about an underlying y^* following the equation (Long, 1997)

$$y_i = j\ if\ \mu_{j-1} \leq y_i^* < \mu_j\ for\ j = 1\ to\ J, \qquad [8]$$

where J is the number of categories and μ are the threshold parameters. The categories 1 and J are defined by open-ended intervals ($\mu_0 = -\infty$ and $\mu_J = \infty$), and when $J = 2$ the model collapses to a binary probit model. The relationship between the observed y_i and the latent variable y_i^* can be expressed as follows:

$$y_1 = \begin{cases} = 1 & if -\infty \leq y_i^* < \mu_1 \\ = 2 & if\ \mu_1 \leq y_i^* < \mu_2 \\ \vdots & \vdots \\ = J-1 & if\ \mu_{j-1} \leq y_i^* < \infty \end{cases} \quad [9]$$

The threshold parameters $\mu_j, j = 1, \dots, J-1$, are unknown parameters to be estimated with β. In the ordered model the $J-1$ threshold parameters are specified as free parameters, and the intercept term in addition to the error term, is normalized to zero, to set the otherwise arbitrary scale of the latent variable y^*. In the binary model, one of the threshold parameters and the error term is normalized to zero, which explains the constant in the model. The probability that $y_i = j$ is given by:

$$\Pr(y_i = j|x) = \Pr(y_i = j|x) = \Phi(\mu_j - x'\beta) - \Phi(\mu_{j-1} - x'\beta) \quad [10]$$

Estimation of the parameters follows maximum likelihood estimation:

$$lnL[P_i(y_i) = \sum_{j=1}^{J} \sum_{y_i=j} \ln[\Phi(\mu_j - x_i'\beta) - \Phi(\mu_{j-1} - x_i'\beta)] \quad [11]$$

Interpretation of the coefficients is based on fully standardized coefficients to compare the estimators of the different models. The fully standardized coefficient is given by $\beta_i^S = \frac{\sigma_i \beta_i}{\sigma_{y^*}}$, where σ_i is the standard deviation of x_i and σ_{y^*}, the standard deviation of the latent variable that can be estimated by calculating the variance following the equation:

$$\widehat{y_{y^*}^2} = \hat{\beta}'\Sigma\hat{\beta} + Var(\varepsilon), \quad [12]$$

with Σ being the covariance matrix of the x variables, $\hat{\beta}$ contains the estimates and $Var(\varepsilon) = 1$.

4.3 Latent-class cluster analysis

To identify heterogeneity in environmental attitudes latent class (LC) analysis is used for clustering. LC cluster analysis is similar to cluster analysis and both can be described as a classification of similar objects into groups (Vermunt and Magidson, 2000). Following a study by Aldrich *et al.* (2007) who report strong evidence of robustness between both clustering methods in accounting for heterogeneity in environmental attitudes, the selection between the methods appears to be a matter of choice. In addition, LC cluster analysis can handle ordered data, whereas certain cluster techniques assume continuous data.

LC clustering is a model based approach. This means that a statistical model is assumed for the population from which the sample under study is drawn. In the LC clustering approach, the response patterns of farmers who share similar environmental attitudes will be highly correlated, but will differ from those who express different environmental attitudes (Aldrich *et al.,* 2007). The model assumes that each person belongs to one and only one group but that group membership is latent. In this context, $\pi_{qs|c}$ is the probability that an individual in group c answers level s to question q. $\Pr(c)$ denotes the probability that a farmer belongs to group c. The model can be estimated using the following log likelihood function:

$$lnL = \sum_{i=1}^{N} ln\left[\sum_{c=1}^{C} \Pr(c) \prod_{q=1}^{Q} \prod_{s=1}^{S} \left(\pi_{qs|c}\right)^{x_{iqs}}\right] \qquad [13]$$

where x_{iqs} is a dummy variable that reflects whether farmer i chose answer s on question q. Since class membership is unknown, the expectation-maximization (EM) algorithm is used to maximize the log likelihood. Due to the objective of having a sufficient sample size within each cluster, the number of clusters were restricted to two clusters ($c = 2$).

5. Results

5.1 Descriptive results

An overview of the intention to convert and the direct measures is given in Table 2. Overall intention to convert to organic farming is weak with a mean value of 1.9. However, 6% of respondents express a strong or very strong intention to convert and 23% of the sample are uncertain about possible conversion within the next five years. In general attitudes are neutral, though slightly negative, suggesting that farmers themselves do not have particularly strong opinions about converting to organic farming. Measures of subjective norm show a negative score indicating that farmers do not perceive encouragement from their important others to convert. Perceived behavioural control scores are slightly negative as well. A value close to zero indicates that farmers appear to be uncertain about the possibility to convert considering their own ability and whether their own farm is suitable for organic farming.

Table 2: Descriptive statistics for the direct components

	Range	Mean	(St.Dev.)
Intention	1 to 5	1.907	(0.966)
Attitude	-2 to +2	-0.055	(0.763)
SN	-2 to +2	-0.521	(0.746)
PBC	-2 to +2	-0.238	(0.923)

However, to get insight into why farmers hold certain attitudes, subjective norms or perceptions of control it is important to consider the beliefs. Due to that, the subsequent analysis focuses on belief based measures. Descriptive statistics of the individual belief based measures are reported in Table 3.

Beginning with the belief based attitudes, all three perceived financial incentives are evaluated as important, whereas both affective beliefs are evaluated as negative. This can be interpreted as the expected utility received by the farmer from the particular outcome occurring. The negative scores of the normative beliefs reveal that farmers do not perceive encouragement from others to convert to organic farming. Finally, in terms of perceptions of control, maintaining good animal health based on prevention appears to be a concern, as suggested by the negative value of that particular control belief.

Table 3: Descriptive statistics for the belief based measures

Belief based attitude:	Belief strength		Outcome evaluation		$bs \times oe$	
Range:	(1 to 5)		(-2 to +2)		(-10 to +10)	
	Mean	(St.Dev.)	Mean	(St.Dev.)	Mean	(St.Dev.)
1. Saving on fertilizer costs	4.124	(0.767)	1.083	(0.779)	4.580	(3.576)
2. Receiving higher prices	3.456	(0.935)	1.290	(0.776)	4.461	(3.198)
3. Increasing farm income	3.197	(0.868)	1.275	(0.738)	4.083	(2.692)
4. Farming like 50 years ago	3.197	(1.091)	-0.762	(0.869)	-2.477	(3.417)
5. Product only rich people can afford	3.321	(0.995)	-1.010	(0.685)	-3.523	(2.919)
BA (2+3, cognitive)	3.326	(0.671)	1.282	(0.618)	**4.272**	**(2.448)**
BA (4+5, affective)	3.259	(0.856)	-0.886	(0.610)	**-3.000**	**(2.583)**
BA ($\sum 2-5$)	3.293	(0.497)	0.198	(0.407)	**0.636**	**(1.854)**
Belief based SN:	Normative beliefs		Motivation to comply		$nb \times mc$	
Range:	(-2 to +2)		(1 to 5)		(-10 to +10)	
	Mean	(St.Dev.)	Mean	(St.Dev.)	Mean	(St.Dev.)
1. Family	-1.129	(0.962)	2.477	(1.335)	-2.389	(3.095)
2. Other farmers	-1.072	(0.971)	2.104	(1.099)	-1.922	(2.551)
3. Farm advisors	-0.777	(1.019)	2.580	(1.285)	-1.575	(3.196)
4. Information events	-0.699	(1.076)	2.352	(1.267)	-1.088	(2.828)
5. Farming press	-0.709	(1.103)	2.591	(1.231)	-1.041	(2.908)
BSN ($\sum 1-5$)	-0.877	(0.906)	2.354	(1.074)	**-1.603**	**(2.448)**
Belief based PBC:	Control belief		Power of control		$cb \times pc$	
Range:	(-2 to +2)		(1 to 5)		(-10 to +10)	
	Mean	(St.Dev.)	Mean	(St.Dev.)	Mean	(St.Dev.)
1. Knowledge and skills	0.243	(1.019)	3.624	(0.969)	1.093	(3.961)
2. Time to carry out the work	0.155	(1.064)	3.419	(1.008)	0.582	(4.098)
3. Suitable farm conditions	0.580	(1.102)	3.746	(0.837)	2.394	(4.486)
4. Farming without using fertilizer	0.482	(1.056)	3.404	(0.891)	1.964	(3.386)
5. Maintain good animal health	-0.601	(1.011)	3.259	(0.992)	-1.731	(3.611)
BPBC ($\sum 1-5$)	0.172	(0.653)	3.494	(0.646)	**0.849**	**(2.550)**

BA: belief based attitude; BSN: belief based SN, BPBC: belief based PBC; for comparison all calculated BA, BSN and BPBC measures are reported as averages; highlighted variables are included in the probit analysis (Model 1 and Model 2).

5.2 Results of the principal component analysis

PCA was performed on the calculated belief based variables to extract components that validate the TPB. The rotated component loadings, as explained in equation 6, are presented in Table 4. The analysis confirms the four belief based components based on Kaiser's criterion (Kaiser, 1960), that only PCs whose explained variances (λ_i) exceed 1 are to be retained. The four principal components explain 62.03% of the variance. Although Joliffe (2002) recommends 70 to 90% explained variance as a cut-off point to retain PCs, this can be lower due to practical details in the data set, as it is the case in this study. In some cases 50% of explained variance of the original data set can serve as an adequate summary (Everitt and Dunn, 1991) and 60% is usually regarded as satisfactory in social sciences (Hair *et al.,* 1998).

PC 1 shows high loadings of all belief based subjective norm measures, whereas PC 2 has high loadings on all belief based PBC measures. PC 3 and 4 confirm the two dimensions of the belief based attitude. PC 3 corresponds to the cognitive part and since these beliefs represent economic incentives the component is named economic beliefs. PC 4 shows high loadings on the remaining behavioural belief measures and is consequently named affective beliefs.

Table 4: Principal components (component loadings) for TPB variables

Variables	**PC 1** Belief based SN	**PC 2** Belief based PBC	**PC 3** Economic beliefs	**PC 4** Affective beliefs
Belief based attitude				
Receive higher prices	0.016	0.134	**0.892**	-0.051
Increase farm income due to higher support payments	0.101	0.050	**0.778**	0.121
Lead to farming as it was 50 years ago	0.071	0.056	0.197	**0.820**
Provide a product only rich people can afford	0.363	-0.049	-0.126	**0.680**
Belief based SN				
Your family	**0.702**	-0.028	0.013	0.274
Other farmers	**0.769**	-0.020	0.108	0.081
Farm advisors	**0.892**	0.032	-0.047	0.080
Farm walks/information events	**0.892**	0.002	0.008	0.129
Farming press	**0.857**	0.052	0.050	0.054
Belief based PBC				
Knowledge and skills	0.009	**0.772**	-0.064	-0.101
Sufficient time to carry out the work	0.348	**0.480**	0.129	-0.113
Suitable farm conditions	-0.100	**0.686**	0.159	-0.033
Farming without fertilizer	-0.162	**0.671**	0.225	0.104
Maintain good animal health based on prevention	0.205	**0.522**	-0.179	0.286
Explained variance (λ_i)	3.757	2.050	1.492	1.385

Component loadings (a) are proportional to the elements of the corresponding eigenvector (α) and can be obtained by: $a_{ki} = \alpha_{ki}\sqrt{\lambda_i}$ (Lewis-Beck, 1994).

5.3 Results of the ordered probit model

An ordered probit model is applied to reveal effects of the TPB components on the intention to produce organic meat. The belief based measures are used since these are regarded as the more accurate measure than the direct components. Estimation results are shown in Table 5. In Model 1 the calculated belief based measures from attitude, subjective norm and perceived behavioural control are included, whereas Model 2 distinguishes between cognitive and affective sub-dimensions of attitude. In Model 3 the calculated variables are replaced by the PCA variables.

Model 2 shows a larger log-likelihood as well as a smaller AIC value than Model 1, which indicates a better fit, suggesting that it is important to distinguish between sub-dimensions of attitude. Comparing all three models, Model 3, implementing the PCA variables, is the preferred model, showing the largest log-likelihood in combination with the lowest AIC value.

Table 5: Ordered probit model with belief based TPB components and PCA variables

	Model 1		Model 2		Model 3	
	Estimate	(Std.Err.)	Estimate	(Std.Err.)	Estimate	(Std.Err.)
Belief based attitude	0.040***	(0.013)				
Economic beliefs			0.022	(0.018)	0.176**	(0.088)
Affective beliefs			0.059***	(0.019)	0.433***	(0.092)
Belief based SN	0.050***	(0.008)	0.048***	(0.008)	0.708***	(0.104)
Belief based PBC	0.036***	(0.007)	0.038***	(0.007)	0.478***	(0.093)
Log likelihood	-195.315		-194.155		-193.637	
AIC	402.631		402.309		401.274	
Pseudo- R^2:	0.187		0.192		0.994	

*** p<0.001; **p<0.05.

Beginning with Model 1, all three components of the TPB have a positive significant influence on the behavioural intent and thereby confirming the applicability of the TPB in the context of intention to convert to organic farming techniques. However, dividing the belief based attitude in economic and affective beliefs (Model 2) reveals that economic beliefs have no significant influence on behavioural intent, whereas the affective part of the beliefs correlates significantly with intention. Finally, considering Model 3, all PCA variables show a statistically significant effect on behavioural intent. In order to compare the effects of the individual components on the intention of the three models, fully standardized coefficients are calculated and presented in Table 6.

Table 6: Fully standardized coefficients of ordered probit models

	Model 1	Model 2	Model 3
Belief based attitude	0.215		
Economic beliefs		0.077	0.126
Affective beliefs		0.223	0.310
Belief based SN	0.444	0.420	0.507
Belief based PBC	0.336	0.346	0.342

Belief based subjective norm has the strongest effect on intention in all models. This implies that farmers are dependent in their farming decisions on the opinion of others, such as fellow farmers or information sources. This is similar to findings of Rehman *et al.* (2007), Hattam (2006b) and Lynne *et al*. (1995), who also report that farmers' decisions are influenced by information sources or the farming community. Perceptions of control have an important impact on the intention in all models as well, suggesting that conversion of the farm may be restricted by the farmer's own ability and the suitability of the farm for organic farming. In this context, Hattam (2006b) found that perceived ability of the producer is an important influence on the conversion to organic farming. In terms of attitudinal variables, affective beliefs show a higher correlation to the intention than economic beliefs (Model 3), implying that farmers' positive or negative feelings about organic farming have a stronger effect than beliefs about economic benefits of organic farming. Similarly, Bergevoet *et al*. (2004) report that farmers rank non-economic goals higher than economic ones.

5.4 Effects of individual beliefs

The estimated coefficients of the ordered probit model provide information about the overall effect of the belief based attitudes, subjective norms and perceptions of control. However, they are not sufficient in investigating the effect of the individual beliefs on intention. This is done by multiplying the regression coefficients with the individual weights given to the original variables provided by the PCA (Kelley, 2010). This procedure gives insight into the impact of individual beliefs on the intention and taking into account the values attributed to the underlying beliefs and evaluations (Table 3), drivers and barriers of conversion can be identified. The calculated effects are presented in Table 7.

Beginning with the economic beliefs, the figures reveal that these beliefs are among those with the lowest impact, which is consistent with the regression results. The affective beliefs show a stronger effect on intention, which suggests that farmers' opinions and perceptions about certain outcomes of organic farming are more influential than economic considerations. Since the affective beliefs were evaluated negatively (see Table 3), this indicates a social barrier of conversion. In terms of the belief based subjective norms, all beliefs show a similar effect on intention. However, considering that farmers do not perceive encouragement of any of these groups to convert (see Table 3) suggests that important others and information sources act as a negative influence on conversion.

Table 7: Calculated effects of belief based measures on intention

	Relative value	Absolute value
Economic beliefs:		
Receive higher prices	0.160	0.198
Increase farm income due to higher support payments	0.210	0.210
Affective beliefs:		
Lead to farming as it was 50 years ago	0.375	0.375
Provide a product only rich people can afford	0.348	0.417
Belief based SN:		
Your family	0.350	0.368
Other farmers	0.319	0.333
Farm advisor	0.359	0.373
Farm walks / information events	0.375	0.375
Farming press	0.357	0.357
Belief based PBC:		
Knowledge and skills	0.215	0.307
Sufficient time to carry out the work	0.264	0.347
Suitable farm conditions	0.203	0.300
Farming without fertilizer	0.235	0.354
Maintain good animal health based on prevention	0.328	0.380
Mean:	0.293	0.335
St. Dev.	0.075	0.063

Finally, within the group of control beliefs, maintaining good animal health based on prevention has the strongest effect on intention. Since this belief had a negative value (see Table 3), it appears that farmers are concerned about keeping good animal health based on prevention.

5.5 Accounting for heterogeneity

LC cluster analysis is applied to test for heterogeneity in environmental attitudes and farmers are segmented into two groups: Group 1 consists of 133 farmers, who express a moderate level of environmental concern, whereas Group 2 consists of 60 farmers who express strong environmental concern. In order to explore the difference between the two groups regarding their intention to convert, a Mann Whitney test is applied. Group 2 shows a significantly higher intention to convert to organic farming than Group 1 ($z = -4.091$; $p = 0.000$). This finding is consistent with the literature that a higher level of environmental concern is associated with conversion to organic farming (Burton *et al*, 2003). Due to the sample size, behavioural intent is reduced to two categories and consequently a binary probit model is applied with 0 representing low to very low intention to convert and 1 representing moderate to high intention to convert. Table 8 reports the results of the binary model estimated for the whole sample (Model 4), and the segmented groups, i.e. the group with moderate level of environmental concern (Model 5) and the group with high environmental concern (Model 6). Since the PCA variables previously generated the best fitting model (Model 3), the original variables are replaced by the PCA variables.

Table 8: Binary probit model with PCA variables

	Model 4		Model 5		Model 6	
	Estimate	(Std.Err.)	Estimate	(Std.Err.)	Estimate	(Std.Err.)
Economic beliefs	0.408***	(0.132)	0.109	(0.181)	0.662***	(0.252)
Affective beliefs	0.509***	(0.134)	0.539**	(0.223)	0.505***	(0.186)
Belief based SN	0.781***	(0.140)	0.825***	(0.187)	1.132***	(0.297)
Belief based PBC	0.548***	(0.131)	0.878***	(0.195)	0.007	(0.233)
Constant	-0.792***	(0.122)	-1.049***	(0.172)	-0.458**	(0.226)
Log likelihood	-81.772		-43.432		-28.017	
AIC	173.545		96.864		66.035	
Pseudo-R^2:	0.2965		0.3528		0.3258	

*** p<0.001; **p<0.05.

A likelihood-ratio chow-type test is performed for the null-hypothesis that all coefficients of the model do not vary between groups. The likelihood-ratio statistic is distributed as χ^2 with 5 degrees of freedom, with a calculated value of 20.65 and the null hypothesis can be rejected at the 1% level. This suggests that the observations from the two different environmental attitude groups should not be pooled together but rather should be analysed using separate models.

Model 4 shows a positive significant effect of all components on intention to adopt and thereby confirming Model 3 (see Table 5). However, when accounting for heterogeneity in environmental attitudes, the conclusions change. Model 5, representing the group with moderate environmental concern, reveals that affective, subjective norm and control beliefs are significantly related to the intention. Interestingly, economic beliefs do not show a significant effect. This indicates that the intention of this group is mainly influenced by the farming community, perceptions of control and opinions about organic farming. In Model 6, representing the group with high environmental concern, perceptions of control do not have a significant influence, suggesting that this group of farmers is not affected by possible problems with the implementation. Considering that this group also expresses a higher intention to convert, this may indicate that possible problems with conversion are already solved. Subjective norm, economic and affective beliefs show a significant effect on intention. This implies that once control issues are overcome, perceived economic benefits appear to become more important.

6. Discussion and conclusion

This paper applies the social-psychology theory of planned behaviour to explain the intention of conventional drystock farmers to produce organic meat. The intention is modelled using belief based measures regarding attitude towards organic farming, subjective norms and control perceptions. In order to increase understanding, attitude was divided into cognitive and affective sub-dimensions. All components were validated and confirmed using PCA. In addition, the study expands earlier work by accounting for heterogeneity regarding farmers' environmental attitude. Overall, the results support previous findings that it is important to take farmers beliefs into account, when intending to explain farmer decisions (Lynne *et al.*, 1988; Bergevoet *et al.*, 2004, Rehman *et al.*, 2007). However, by accounting for sub-dimensions of attitude as well as heterogeneity within the sample, the findings add valuable information that might be of use to increase the size of the organic sector.

The traditional TPB variables show a significant correlation with the intention of a farmer to produce organic meat, which confirms the applicability of the TPB in this context (Model 1, Table 5). The results also clearly support the distinction between cognitive and affective sub-dimensions of attitude, which further increases insight into farmers' decision making (Model 2 and 3, Table 5). Farmers seem to evaluate organic farming in terms of expected economic benefits and personal opinions or perceptions about organic farming. Interestingly, farmers' perceptions about organic farming were found to be stronger predictors of intention to convert than expected financial benefits of organic farming (Table 6). This effect becomes even more evident when accounting for heterogeneity within the sample (Model 5, Table 8). This relates to previous findings that economic models may not be sufficient in fully grasping the complexity of farmer decisions which are usually driven by both economic and non-economic goals (Lynne *et al.*, 1988; Bergevoet *et al.*, 2004).

The significant effect of subjective norms in all models provides strong evidence that social barriers exist. This is based on the negative values of normative beliefs, which indicate that farmers do not perceive encouragement of their important others to convert (Table 3). In addition, further analysis revealed that these variables are among the ones with the strongest effect on intention (Table 7). In this context, Lynne (1995, p.68) points out that "the farmer's perception of what others in the community think is appropriate behaviour may well affect decisions", a statement that appears to be very relevant in this context as well.

Furthermore, the TPB is specifically designed for behaviours that are beyond volitional control. The significant effect of perceived behavioural control implies that there are control issues for the adoption of organic farming (Table 5) and conversion may be hampered by inability of farmers to convert. In this context, belief based TPB analysis revealed concern of maintaining animal health as an obstacle to conversion (Table 3 and Table 7). This highlights one of the strengths of TPB analysis, namely that the analysis provides the opportunity to discover information on beliefs which are acting as barriers.

Overall, the results strongly suggest that policy incentives in terms of support payments are not sufficient to increase the size of the organic sector, since social and technical barriers seem to outweigh financial incentives. However, once these obstacles are overcome, economic incentives appear to be important. TPB is based on the assumption that people take account of information available and act according to this information, which should be used in order to remove obstacles that prevent farmers to take up organic farming. In this context, education, advisory service and market development have to be seen as equally important to subsidy payments in order to increase the size of the organic sector.

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