LAND USE CHANGE FROM AGRICULTURE TO FORESTRY: A STRUCTURAL MODEL OF THE INCOME AND LEISURE CHOICES OF FARMERS

Mary Ryan[1*], Cathal O'Donoghue[1] and Vincent Upton[1]

[1] Teagasc, Rural Economy and Development Programme, Athenry, Co. Galway, Ireland
* Mary.ryan@teagasc.ie

Paper prepared for presentation at the EAAE 2014 Congress
'Agri-Food and Rural Innovations for Healthier Societies'

August 26 to 29, 2014
Ljubljana, Slovenia

Abstract

The role of forests in our environment is increasing in importance due to the multifunctional benefits forests provide to urban and rural communities in relation to climate change mitigation, water conservation and the provision of fibre for bioenergy. However, afforestation targets across Europe are not being met. Using Ireland as a case study, we try to understand why farm afforestation rates are falling, despite the availability of generous forestry subsidies. We use a novel technique to examine the afforestation participation decision using a life cycle choice methodology where we apply revealed choice methodology to afforestation for the first time. We find that the model coefficients coincide with expected economic theory relative to the utility maximisation of income, leisure and wealth (long term land value). However, we observe a cohort of farmers who do not plant forestry regardless of income derived, reflecting their preference to maintain the flexibility of the long term value of their land by continuing to farm.

JEL Classification: Agricultural and Rural Policy, Environmental and Resource Economics,

Econometrics

Key Words: Afforestation decision, life-cycle analysis

1. Introduction

The recognition of the value of forests has led to international efforts to increase afforestation. While EU forests expanded continuously for the last 60 years, expansion has slowed in recent years (EU Commission, 2013). While the timber benefits from forests have long been valued, it is recently increasingly recognised that both urban and rural societies also have a growing need for the multifunctional products provided by forests. Wood is still the main source of financial revenue from forests but wood fibre is becoming an important source of raw material for emerging bio-based industries. Forests play a major role in water conservation and in mitigating climate change and are vital for rural sustainability as they support economic welfare and jobs. However, despite the provision of economic incentives, afforestation targets across Europe are not being met.

In an effort to understand why farm afforestation rates are falling, we examine the attitudes towards forestry and the factors affecting the afforestation decision and then, using Ireland as a case study, we model the afforestation participation decision of farmers. The long term nature of the income streams from forests necessitates a different modelling approach to that employed in modelling agricultural returns. We therefore use a life-cycle choice model which has been used to investigate other long-term decisions but which has not before been used in a land use context. We estimate a structural behavioural model of the forestry planting decision which captures the preferences of the utility function where the planting decision involves a trade-off between the attributes of the choice i.e. income and leisure, thereby providing valuable empirical information on the farm and farmer characteristics that influence the farm afforestation decision.

Afforestation targets

In the EU 28, forests and other wooded land cover a slightly higher proportion of land area (42.4%) than that which is used for agriculture. In the UK, forest expansion has dropped back from a high of 40,000 hectares (ha) per year in the early 1970s to an average of about 10,000 ha per year (Forestry Commission, 2013). The Flemish region of Belgium which is characterised by low forest cover has a target to expand the forest area by 10,000 ha to 12% forest cover. However afforestation in Flanders has actually declined and expectations are that it will be difficult to realize an increase in the forest area (Van Gossum et al. 2012). It would appear that the Dutch policy goal to increase forest cover by 66,000 ha by 2020 will not be realised either (Van Gossum et al., 2010). The decline in forest expansion is perhaps most pronounced in Ireland, where the introduction of incentives saw afforestation increase from over 5,000 ha annually in 1985 to almost 24,000 ha in 1995, then falling off to just over 6,000 ha in 2013 (Forest Service, 2013). Despite having soils and climatic conditions which are particularly suited to timber and fibre production, Ireland has one of the lowest forest covers in Europe at 11% (Eurostat, 2013). Even with strong financial incentives, annual afforestation has fallen well short of the target afforestation rate of 20,000 hectares per year (DAFF, 1996) and the reduced target of 10,000 ha per year (Govt. of Ireland, 2009). This has consequences for downstream timber processing; for the increasing demand for wood fibre; and for the potential of forests to sequester carbon and mitigate greenhouse gases generated by other sectors such as agriculture.

Factors affecting the afforestation decision

In a meta-analysis of econometric studies of non-industrial private forest owners, Beach et al. (2005), assessed the factors driving decision-making among forest owners and categorised them as follows: owner characteristics (and preferences); plot/resource conditions (soil type and plot size); policy variables (factors that affect the forest investment decision); and market drivers (costs and returns from forestry and alternative enterprises). Country specific studies differ in the relative importance of these factors but there is strong commonality around attitudes towards afforestation.

Edwards and Guyer (1992) report on the relatively poor response by farmers to early forestry incentive schemes in Northern Ireland and find a parallel response in England. The principal constraints were perceived as lack of land, duration of the commitment and the inability of the annual payments to compete with agricultural returns. Moons and Rousseau, (2007) discuss the reluctance of Flemish farmers to afforest and suggest that the fear of being committed to forestry for a long time deterred farmers from participating in the programme, while Van Gossum et al. (2012) and Moons and Rousseau, (2007) suggest that farmers are reluctant to afforest because the subsidy is not high enough. According to Van Gossum (2010), the absence of financial benefits for farmers was one of the main reasons for the limited uptake by farmers in the Netherlands. Studies that examined farmers' attitudes towards afforestation in Ireland, (Frawley and Leavy (2001), O'Leary et al. (2000), McDonagh et al. (2010) Ní Dhubháin and Gardiner (1994) and Duesberg et al. (2013) cite the reluctance to plant land that is suitable for farming. McDonagh et al. (2010) and Duesberg et al. (2014) both found that the most important barriers to planting were the desire to farm and the reluctance to limit the future potential of land by locking themselves into a permanent land use choice such as forestry.

Methodological requirements

From a methodological perspective we want to examine revealed preferences around the forestry participation decision, therefore we need to estimate a model that contains choice specific attributes, i.e. a choice model. However as we cannot easily undertake a randomised control experiment, we rely on data that contains only attributes associated with the actual choice. Therefore to undertake this analysis, we require a methodology where counterfactual attributes are simulated. This methodology has been widely used in labour supply economics (see Van Soest, 1995), but has only recently been used in an agricultural and land use contexts recently by Murphy et al., (2014) who examined the decision to participate in agri-environment schemes.

In order to estimate our model, we need to include both economic and non-economic factors, such as the long term nature of the land use change, the relative productivity of the land for agriculture and forestry, as well as innate preferences for agriculture or forestry, We include a variable for self-reported land value (long term wealth) in the models as this has not previously been investigated and may give us some insight into the long term nature of the decision. In addition to these factors, the reduction in working hours associated with forestry may result in farmers making a decision to trade-off between income and leisure. While the neo-classical literature suggests that farmers should behave rationally to maximise profit, we know from the non-neo-classical literature that farmers like to farm and may choose to maximise their utility by remaining in farming even if they lose money. The aim of this paper is to fill the gaps in the literature by using micro level data to construct an afforestation choice model which considers the utility maximising decisions of farmers when presented with a range of afforestation choices. This is a novel approach which to our knowledge has not been used before in the land use context. In section 2 we investigate the literature examining long-term participation decisions in order to develop a theoretical framework. Section 3 describes the generation of the variables used in the models and section 4 presents the results from the models. We finish with discussion and conclusions.

2. Theoretical framework

The purpose of this section is to build a framework that will allow us to develop a methodology to understand the preferences of farmers in relation to the afforestation decision. The decision to afforest in Ireland is a long term land use change decision which necessitates the examination of agriculture and alternative forestry income streams over a long time horizon. Therefore, we need to use a methodology that will estimate a life cycle choice for afforestation. As this methodology has not previously been used in the land use context, we utilise the existing literature relevant to long-term participation decisions in other disciplines for the construction of our theoretical framework.

Life cycle analysis

The life cycle approach was first used to explain the decision to participate in higher education in studies carried out by Mincer (1958) Becker (1964) and Ben Porath (1967), which identified the link between the life cycle of earnings and an individual's investment in human capital, so that the investment decision in human capital is based on expected returns and costs of that investment. Life cycle models have also been applied successfully to models of labour supply (Heckman and Macurdy, 1980). In this paper we will adapt a life cycle model which has previously been utilised by Flannery and O'Donoghue (2013) to explain the education participation decision and we will modify the framework to incorporate the variables we use to explain the afforestation decision.

Random Utility Maximisation (RUM) theory and Discrete Choice

According to neo-classical economic theory, preferences or utility can be derived from one of two goods: income (and the resulting ability to consume) and leisure. Ben-Akiva and Lerman (1985) outline a framework whereby individuals facing a choice problem firstly determine the alternatives available to them; then evaluate the attributes of each alternative relevant to the choice under consideration; and finally use a decision rule such as random utility maximisation RUM to select an alternative and make their choice. Random utility theory, as it is understood today, was developed by McFadden (1973). The utility maximization rule states that an individual will select the alternative from his/her set of available alternatives that maximizes his/her utility. Further, the rule implies that there is a function containing attributes of alternatives and characteristics of individuals that describes an individual's utility valuation for each alternative. The utility function *U* has the property that an alternative is chosen if its utility is greater than the utility of all other alternatives in the individual's choice set. RUM provides a framework in which the decisions of individuals, over a finite set of alternatives, can be understood in a consistent and meaningful way and analysed probabilistically facilitating forecasting. The choices are modelled using a standard conditional logit (CL) model (McFadden, 1973) and modified by Van Soest (1995) which models the expected utilities in terms of characteristics of the alternatives rather than attributes of the individuals. The probability of i being chosen from a set of alternatives by an individual n, is derived as;

$$P_{ni} = \frac{\exp(\beta x_{ni})}{\sum_{j=1}^{J} \exp(\beta x_{nj})}$$

Where x represents the income, land value and hours worked associated with each of the alternative choices faced by individual n.

3. Methodology and Data

Hynes and Garvey (2009) conducted an empirical examination of the participation decision of farmers in voluntary agri-environment schemes in Ireland and DeFrancesco et al. (2008) examined the participation decisions of Italian farmers. These studies provide information about the type of farmers participating in these schemes by comparing selected variables on the farms of participants with variables on the farms of non-participants. The literature to date on the afforestation decision has focused either on the attitudes of farmers or on empirical reduced form models which relate the decision to farm and farmer characteristics. In this paper, we are attempting to develop a structural model which relates the participation decision to the attributes of the choice confronting the farmer. We observe the choices made by farmers using a Teagasc[1] National Farm Survey[2] (NFS) database. We then derive the five variables of interest namely, forest market income; forest subsidy income; agricultural gross margin (GM); hours worked on-farm and; self-reported land value. In order to estimate the CL model, we also need information on the counterfactual choices available to farmers. This approach was used in a recent study by Murphy et al. (2014) who used farm level data to generate both actual and counterfactual observations for participants and non-participants in an agri-environment scheme. This study adopts a similar approach which allows for the comparison of individuals with counterfactual versions of themselves who differ only with regard to their afforestation participation.

The ultimate goal of the study is to examine how the income, land value and hours worked associated with different alternative land-uses impact on farmer decision making. This study focuses on the share of total land, expressed in 5% categories, which a famer could assign to forestry. Thus, it is assumed that a farmer faces 11 alternatives each year, i.e. to plant 0, 5, 10, 15, 20, 25, 30, 35, 40, 45 or 50% of their land, and that farmers base this decision on the affect this change in land use would have on three attributes or factors: net income, the perceived land value and the hours worked, each of which differs depending on the proportion of land in forestry. 50% was chosen as the maximum proportion as this reflected the maximum established by any one farmer in the dataset.

Forest market income streams are generated using the Teagasc forest bio-economic model (see Ryan et al. 2013). Forest subsidy streams are modelled using the Teagasc forest subsidy model (see Ryan et al., 2014) which models all policy changes in afforestation grants and premiums since 1981, based on year of participation in a given afforestation scheme. Actual agricultural GM, on-farm and off-farm hours worked and self-reported land values are generated using the Teagasc NFS panel data for each farmer in each year of the dataset. This study uses NFS data from 1988 to 2012 as this reflects the period when farmers were compensated for loss of agricultural income. Counterfactual variables are also created using the NFS panel dataset and the forestry bio-economic model. These values represent the income and leisure status of forest farms if they had not participated in afforestation and the income and leisure status of non-participants if they had decided to participate in afforestation schemes. Net revenue streams are projected forward for the relevant rotation lengths and then discounted to present day values and presented as net present values (NPV). The discount rate

[1] Teagasc – The Agriculture and Food Development Authority of Ireland

[2] The Teagasc National Farm Survey (NFS) determines the financial situation on Irish farms by measuring the level of gross output, costs, income, investment and indebtedness across the spectrum of farming systems and sizes and provides data on Irish farm incomes to the Farm Accountancy Data Network (FADN) of the European Union. A sample of approximately 1,000 farms representing 90% of output is surveyed each year.

employed is 5%, which is the standard rate applied to forest investments in Ireland (Clinch, 1999).

The forest bio-economic model utilises a cost benefit analysis (CBA) framework to generate the forest income stream that arises when changing land use from an agricultural enterprise to a commonly planted conifer mixture of 80% Sitka spruce and 20% Japanese larch up to the time of first clearfell (reforestation costs are not included). The model generates yield, cost and income projections across a range of species and soil types. The inputs include forest establishment and maintenance costs, afforestation subsidies, harvested timber volumes generated using yield models (Edwards and Christie, 1981) and ten year average timber prices. The forestry income streams include an opportunity cost for agricultural income foregone in the form of market GM which is defined as gross output minus direct costs. The assumption is that farmers entering forestry could accommodate forestry on the farm without having to increase their stocking rate, therefore they would have the opportunity to reduce average land use equally across all their enterprises, rather than selecting their lowest GM enterprise.

Soil type is a determining factor for the productivity of both agricultural and forest enterprises. The Teagasc NFS collects data on soil type that essentially describes the range of use or limitations of six soil categories. Table 1 shows estimates for forest productivity (Yield Class)[3] generated by Farrelly (2011) which are assigned to each of the NFS soil categories thus enabling the incorporation of the comparative effect of soil type on both forestry and agricultural outputs. The financially optimal rotation is the point at which the NPV is maximised (Edwards and Christie, 1981).

Table 1. Forest Yield Classes assigned to NFS Soil Classes for Sitka spruce (SS)

NFS Soil Class	Soil type/Use limitations	Yield Class (SS)	Rotation (yrs)
1	No limitations	24	38
2	Minor limitations	24	38
3	Higher elevations, heavier, poorer structure	20	40
4	Poor drainage	20	40
5	Agricultural potential greatly restricted	18	42
6	Mountainous, steep slopes, shallow soil	14	46

Source: Upton et al., 2012

4. Results

Our results section is divided into three components,

- models of land value and labour used as inputs into the simulation of counter factual choice attributes
- parameter estimates of the conditional logit choice models
- analysis and discussion

Models of land value and labour

In order to understand the effect of entering forestry on hours worked and land value, two fixed effects models of the observations in the NFS panel data are specified. Hours worked is modelled against the farm and farmer characteristics (including share of land in forestry), while land value is modelled against the characteristics of the farm. From these results the influence of forestry share on hours worked and land values is derived, holding all

[3] Yield Class is a measure of timber volume production over a forest rotation expressed in m^3/ha/yr. The higher the yield class; the higher the volume production per ha and the shorter the rotation length.

other variables constant i.e. the only structural changes modelled are the increase in forestry share.

On Farm Hours and Land Value per Hectare

In table 2 we report the model coefficients for two random effect panel data models necessary to impute counter factual choice attributes for these variables. As would be expected, on-farm hours worked increases with farm size and is higher for dairy enterprises and higher stocked farms. It is however lower for better land, for older farmers and those with off-farm employment. Participation in the REPS agri-environment scheme results in increased hours of work. The coefficient on the share of land under forestry is negative and positive in the square (albeit the square is not significant), indicating a small reduction in labour hours as a result of planting forestry. In the second model, we see that conditional on the lagged value of land, planting forestry reduces the self-reported land value. This information facilitated the estimation of the hours worked and reported land value associated with each of 11 alternative forest share categories.

Table 2. Model Estimates, On Farm Hours and Land Value per Hectare

Dependent Variable	Logged (On Farm Hours Worked)		Logged (Land Value per Ha)	
Variable	Coefficient	SE	Coefficient	SE
New planting of forestry			-0.0784604	0.0303393
Land Value Per Hectare	-0.0347959***	0.0047629	0.0237427***	0.000768
Farm Size	0.0006258***	0.000194	-0.007641***	0.000306
Farm Size Squared	-0.00000132***	0.000000379	0.0000082***	0.0000007
Age	-0.0063361***	0.0002223		
Age Squared	-0.00000331***	0.000000149		
Has Off Farm Employment	-0.2557415***	0.0067486		
Spouse Has Off Farm Employment	0.0365909***	0.0065043		
Share of Tillage Are	-0.0912856***	0.0245297	-0.0057107	0.0341525
Share of Dairy Forage	0.3095096***	0.0208	-0.292136***	0.0293949
Share of Sheep Forage	0.0464083***	0.0195076	-0.0914707***	0.0273024
Sheep Number of Livestock Units	0.0002874	0.0001951	-0.0005788***	0.0002543
Cattle Number of Livestock Units	0.0010292***	0.0001441	0.0002015	0.0001959
Dairy Number of Livestock Units	-0.00112***	0.0002271	0.0048817***	0.0003092
Teagasc Client	-0.0048332	0.0046329		
Has REPS payment	0.0200803	0.0058272		
Forestry Share	-0.2406437*	0.1300629	-0.0021915	0.0806725
Forestry Share Squared	0.3545833***	0.3188345		
Constant	7.202518	0.0230464	-0.81892	0.0205573
Share of Variance due to Fixed Effect	0.70104273		0.607808	
R2	0.3284		0.5214	
N	35333		27219	

*** significant at 5% level   * significant at 10% level

Choice Models

We produce the choice specific attributes required to estimate the utility function i.e. simulated counter-factual agricultural GM's forestry market income using our bio-economic model forestry subsidies using the subsidies model and land value and hours worked using our panel data models described above. Two discrete choice models are estimated in this paper, a) a Restricted Model, incorporating the three economically relevant choice attributes, income, wealth (land value) and labour and b) a taste shifter model, adjusting the first model to account for differential preferences for different farm types. In each case, there are 11 potential choices derived by varying the share of forestry for each farm from 0% up to 50% of total farm size. Therefore for each farm in the model, there are 11 rows representing each of the forestry share choices. This generates a dataset of over 30,000 observations per choice. Although we simulate different income sources separately (agricultural income, forestry income and forestry subsidies), we amalgamate them into a single income variable. As forestry planting involves a long-term decision involving costs and benefits over a long period of time (up to 46 years) we express the alternative income streams as NPV's for each choice.

The restricted model is relatively simple and implies that the participation decision of a farmer in forestry will be determined by a limited number of factors. However, we know from the literature that the participation decision is more complex and may be influenced by a range of factors. These factors or 'taste shifters' such as farm system, age, soil, children and whether the farmer has a farm advisory contract, are incorporated into a second choice model and interacted against the NPV income variable. Model parameters from the CL model are reported in table 3. These coefficients reflect the marginal utility with respect to the attribute.

Table 3. Choice Models

	Model 1: Restricted Model			Model 2: Taste Shifters		
	Coeff.	Std. Err.	P>z	Coeff.	Std. Err.	P>z
NPV Income	4.91E-06	2.74E-07	O			
NPV Income x Has Children				0.0000092	0.0000010	0
NPV Income x Best Soil				0.0000023	0.0000011	0.036
NPV Income x Worst Soil				-0.0000059	0.0000013	0
NPV Income x Share of Dairy Forage				0.0000857	0.0000042	0
NPV Income x Share of Cattle Forage				-0.0000057	0.0000012	0
NPV Income x Share of Sheep Forage				-0.0000080	0.0000015	0
NPV Income x Share of Tillage Area				0.0000104	0.0000028	0
NPV Income x UAA				0.0000000	0.0000000	1E-03
NPV Income x Teagasc Extension Client				0.0000015	0.0000009	0.10
NPV Income x Age of Farmer Squared				0.0000000	0.0000000	0
NPV Income x Off Farm Employment				-0.0000012	0.0000011	0.275
Land Value per Hectare	0.219705	0.009809	0	0.1838919	0.0103420	0
Hours Worked on Farm	-0.00953	0.001087	0	-0.0166450	0.0013129	0

In model 1, we find that the coefficients are significant and reflect what one would expect from economic theory, namely that the first derivative of utility increases in income and wealth and decreases in labour hours. While the level of the coefficients themselves are not immediately interpretable as the different variables have different scales, the relative size on the land value per hectare is however noteworthy. In terms of the forestry choice, the preference for land value dominates the other variables, reflecting conclusions in the literature in relation to preferences for more flexible uses of land, resulting in low forestry planting preferences.

In the second model, we interact taste shifters, or farm specific attributes with the net present value of income to understand preference heterogeneity in relation to the personal attributes. We find that the presence of young children increases the income preference, reflecting life-cycle need. Personal attributes associated with commercial farming such as good soils, or dairy and tillage farming (which in Ireland have the highest margins) are positively associated with land, reflecting a greater preference to make a choice that maximises income relative to other choices. Similarly being a Teagasc extension client is positively associated with income. Meanwhile less commercial farming systems such as cattle and sheep or attributes such as older age and off-farm employment see a lower value of income relative to other attributes such as time or wealth. Table 3 shows that across the 11 alternative forestry share choices, if income increases for any alternative, there is a higher probability of that alternative being chosen. Similarly for land value, if any of the 11 alternatives show an increase in land value, there is a higher probability of that alternative being chosen. In the case of hours worked however, the effect is opposite – if hours worked increases, the probability of that alternative being chosen is lower.

Underlying trends

The issue that this paper is attempting to illuminate relates to the apparent conundrum in Irish forest policy whereby, despite generous afforestation incentives which in many cases are higher than agricultural GM's, the afforestation rate has dropped back to less than a third of the area planted in the peak afforestation years. An examination of the underlying trends in the forestry and agricultural income streams generated shows that in real terms, forest subsidies increased strongly over the period and timber prices reflected the economic situation as prices increased dramatically at the height of the construction boom and dropped back equally dramatically once the country went into recession (Upton et al., 2013). In real terms there was a strong downward trend in agricultural GM's as input prices rose and output prices remained relatively stable (Hynes and Hennessy, 2012). Perhaps one of the most significant factors is the upward trend in land value as there was a dramatic increase in land prices particularly over the period 1992 to 2007 (Breen et al., 2010). We have seen from the simple choice model that land value exerts a very strong influence on the choice as it accounts for 90% of utility. These trends in aggregate may influence farmers to choose to maintain the flexibility of their land over time, rather than make a long-term irreversible afforestation decision

Farm and farmers characteristics explored

In trying to understand the characteristics of the farmers who planted and those who didn't, we examine these characteristics for all the farmers in the dataset as a function of their economic incentives. We categorise farms on the basis of whether they have forestry or not and whether the forestry NPV is higher than the agricultural GM. The average values generated are presented in Table 4. The total number of observations is 30,380 over the period 1988 to 2012. Of these, just over 14% have forestry. This percentage is consistent with Irish Forest Service statistics on forest ownership but also means that the averages are heavily influenced by those who don't have forestry.

Table 4. Categorisation of farms by forestry participation and income

		Has Forestry	
		No	Yes
Forestry Income >= Agricultural Income per ha (%)	No	91	9
	Yes	79.5	20.5
Total (n=30,380)		85.9	14.1

We also generate average values for each of the taste shifter characteristics as presented in Table 5. This allows us some valuable further insights. When we look at forestry NPV relative to agricultural GM, we see that on 45% of farms, forestry income per hectare is higher than the agricultural GM. Within this cohort 35.5% of farms would have been better off financially if they had planted but they chose not to. These farms are characterised by low GMs (average = €154/ha), are largely cattle systems and are smaller farms on average. The farmers are slightly older, have relatively high farm work hours and less than a third are Teagasc extension clients.

In comparison, the 9.5% of farms in this category who have forestry have large farms (average 70 ha). They are also largely cattle farmers. This is consistent with findings reported by Ryan et al., (2008) in relation to farms of larger farm size and cattle systems being most likely to plant. This cohort has more than double the agricultural GM of the cohort that didn't plant forestry (average €343/ha) but work 25% less hours on average per year. They are younger and over half are extension clients.

Table 5. Average farm and farmer characteristics by participation and income

Row Characteristics	Forestry Income >= Agricultural Income per ha	0	0	1	1
	Has Forestry	0	1	0	1
Mean Characteristics	Has Children	0.46	0.51	0.34	0.47
	Share in Top Soil Cat	0.54	0.59	0.38	0.44
	Share in Bottom Soil Cat	0.08	0.05	0.22	0.15
	Share of Dairy Forage	0.33	0.33	0.02	0.15
	Share of Cattle Forage	0.54	0.54	0.72	0.63
	Share of Sheep Forage	0.10	0.11	0.23	0.18
	Share of Tillage Are	0.09	0.13	0.04	0.06
	Average UAA (ha)	48.00	75.56	46.75	70.32
	Teagasc Client	0.39	0.49	0.29	0.52
	Age (yrs)	48.13	46.51	53.68	51.70
	Has Off Farm Income	0.13	0.07	0.31	0.22
	Stocking Rate (LU/Ha)	1.83	1.88	1.17	1.34
	Land Value (€)	7078	6683	7965	9535
	Hours worked on Farm	2267	2414	1798	2066
Share of Type	Dairy Farm	0.39	0.34	0.02	0.19
	Mixed Dairy	0.28	0.33	0.18	0.16
	Cattle	0.17	0.12	0.57	0.42
	Sheep	0.06	0.06	0.17	0.14
	Market GM per Ha (€)	851	849	154	344

An analysis of the 55% of farms where the agricultural GM is higher than the forestry NPV also throws up some interesting insights. As might be expected, with a high opportunity cost of participating in afforestation, only 5% of these farms have forestry. However it is interesting that the average agricultural GMs are almost the same for those who have forestry and those who haven't (€849 and €851 respectively). On closer examination of the data, a number of factors are revealed: more of the farmers who have forestry have children and they are the youngest cohort of farmers (46 yrs) on average. They have the smallest proportion of off-farm income and they work the longest hours. They have the highest stocking rates and on average have larger farms than the high GM farmers who don't have forestry. Again, it would appear that more of the large farms have forestry. This is again consistent with the literature. Howley et al., (2012) found that the more intensive farmers with high stocking rates and less likely to plant. In the case of the lower GM farmers, almost 90% of farmers chose not to plant, even though they would have been better off financially. Farm size appears to be the differentiating factor between those who planted and those who didn't. These farms are largely cattle and sheep farmers, operating an extensive system with spare capacity. It could be hypothesised that the relatively low level of labour input required to manage forests is a significant attraction for these farmers.

It is evident form the results that there is a cohort of older farmers with low stocking rates on less productive soils, in cattle and sheep systems who chose not to plant and thereby, not to maximise their income. This would initially appear to contradict the results of our choice model but when we dig deeper, we see that this cohort also has the highest proportion of off-farm income (31% on average compared to 22% for the low GM farmers who chose afforestation). Thus it would appear that their behaviour is income maximising in accordance with our choice model, but they chose to maximise their income with off-farm income, rather that undertake afforestation. What is particularly interesting about this cohort of farms is that they have the highest average self-reported land values of all four cohorts. This is the case despite having the lowest GM's from agriculture and the largest proportion of land in the poor soil category. It is unlikely that these farms will plant land and restrict the future use of an asset which they obviously hold in great value. It is likely also that there is an intergenerational aspect underlying this behaviour. Howley et al. (2012) suggest that having a successor reduces the probability of a farmer being motivated by economic or lifestyle goals and suggest the main motivation is to maintain the farm in good condition for the successor.

5. Conclusions

In countries where agriculture is the dominant land use, policy makers need more information about the motivation for planting and the incentives required for farmers to make a choice between agriculture and forestry. The objective of this paper was to develop a greater understanding of the factors that influence that choice. We estimated a choice model to measure the preferences based on a utility maximising approach where farmers make a trade-off between income, leisure and wealth. In estimating the model, we collected data on actual choices and choice specific attributes and simulated counter-factual attributes. We found that the coefficients of our choice model are robust and are consistent with economic theory: utility increases with the NPV of income and wealth decreases with labour i.e. farmers prefer choices that give them more income or wealth and prefer those choices that require less labour. Although the NPV of forestry income is often higher than the NPV of the alternative land use (forestry) and requires less labour per hectare on average, we see that it is at the expense of a fall in wealth due to the decline in land values as a result of a more inflexible land use activity. Thus, on balance, many farmers prefer to farm than to plant forestry, even when their income is higher; the gain in income and leisure is not sufficient to off-set the decrease in wealth once land is planted.

Decomposing the analysis further we looked at the characteristics of farmers in terms of the relationship between their NPV of agricultural and forestry income and whether they planted forestry. This gave us a greater understanding of the characteristics of different farmers in terms of their choice and relative income position. While our choice models show that farmers will on average choose an alternative if the income is higher, we see that many farmers do not plant where it might be in their interest to do so and vice versa. However, we also observe a cohort of farmers who do not plant forestry regardless of income derived, reflecting their preference to maintain the flexibility of the long term value of their land by continuing to farm.

This is consistent with recent qualitative literature. Duesberg et al. (2014) found that only a quarter of farmers want to 'maximise' profit, half want a 'satisfying' rather than maximum profit and the remainder are 'hobby' farmers. There is a common thread which runs through the literature on the afforestation decision (Frawley and Leavy (2001), O'Leary et al. (2000), McDonagh et al. (2010), Ní Dhubháin and Gardiner (1994), Duesberg et al. (2013), Upton et al. (2013) and Howley et al. (2012). Farmers want to farm and are reluctant to plant land that they can use for food production. One might assume from these results that farms with these farm and farmer characteristics are unlikely to plant and may indeed be the farmers referred to in this literature as displaying a "negative cultural attitude" towards forestry.

This analysis provides significant new insights into the average preferences of farmers when considering forestry, utilising a new methodology applied to land use change. While significant numbers of farmers plant forestry (about half a percent of the population per annum), large numbers of farmers do not plant, even when there is a higher NPV from forestry. Similarly some farmers do plant when they have a lower NPV. Our study has focused on average preferences in the population. However there are likely to be different underlying preference groups in the population (latent classes). Future work will extend this modelling strategy to utilise a discrete choice framework that can better capture preference heterogeneity utilising a random utility maximising process that incorporates more heterogeneity (see Haan, 2006) and to undertake separate estimations for different latent classes (see Greene and Hensher, 2003).

References

Beach, R.H., Pattanayak, S.K., Yang, J.-C., Murray, B.C., and Abt, R.C. 2005. Econometric studies of non-industrial private forest management: a review and synthesis. Forest Policy and Economics 7: 261–281.

Becker, G., (1964) Human Capital theoretical analysis with special reference to education. New York: Columbia University Press for NBER Policy and Economics 7: 261–281.

Ben-Akiva, M. E. and Lerman, S. R. (1985). Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press, Cambridge, Ma

Ben Porath, Y. (1967) The Production of Human Capital and the Life Cycle of Earnings. The Journal of Political Economy, Vol 75, No. 4, part 1: 352-365.

Bourguigon, F., Ferreira, F.H.G., Leite, P.G. (2003). Conditional Cash Transfers, Schooling and Child Labor: Micro-Simulating Bolsa Escola. Delta Working Paper no. 2003-07

Breen, J., Clancy, D., Ryan, M. and Wallace, M. (2010). Irish land use change and the decision to afforest: an economic analysis. Irish Forestry 67: 6–20

Clinch, J. P. (1999) Economics of Irish Forestry: Evaluating the Returns to Economy and Society. COFORD. Connolly, L., Kinsella, A., Quinlan, G. and Moran, B. (2009) Teagasc National Farm Survey 2009. Teagasc, Oak Park, Carlow.

DAFF (1996). Growing for the Future - A Strategic Plan for the Development of the Forestry Sector in Ireland. Department of Agriculture, Food and Forestry. The Stationery Office, Government Publications Sales Office, Molesworth Street, Dublin.

Duesberg S., O'Connor, D. and Ní Dhubháin, A. (2013) To plant or not to plant—Irish farmers' goals and values with regard to afforestation Land Use Policy 32: 155– 164

Duesberg, S., NiDhubhain, A. and O'Connor D. (2014) Assessing policy tools for encouraging farm afforestation in Ireland. Land Use Policy 38:194-203

DeFrancesco, E., Gatto, P., Runge, F. & Trestini, S., (2008). Factors affecting farmers' participation in agri-environmental measures: a northern Italian perspective. Journal of Agricultural Economics59, 114-131.

Edwards, P.N. and Christie, J.M. (1981) Yield Models for Forest Management, Forestry Commission Booklet 48, HMSO, London.

Edwards, C. and Guyer, C. (1992) Farm woodland policy: an assessment of the response to the farm woodland scheme in Northern Ireland. Journal of Environmental Management 34(3):197-209

European Commission (2013) Ministerial Conferences www_foresteurope_org 2011

Eurostat (2013) Agriculture, forestry and fishery statistics 2013.

Farm Accountancy Data Network. (2012). FADN public database. Available at: http://ec.europa.eu/agriculture/rica/database/database.cfm Accessed Jan 14

Farrelly, N., NiDhubhain, A., and Niewenhuis, M. (2011). Modelling and mapping the potential productivity of Sitka spruce from site factors in Ireland. Irish Forestry. 68, (1&2): 23-40.

Flannery, D. and O'Donoghue, C. (2013) Demand for higher education: A static structural approach accounting for individual heterogeneity and nesting patterns. Economics of Education Review.34: 243-257

Forestry Commission, (2013) Available at: http://www.forestry.gov.uk/website/forstats2013 Jan 2014

Frawley, J. and Leavy, A. (2001). Farm forestry: land availability, take-up rates and economics, Project report No. 4256, RERC, Teagasc.

Forest Service (2013) Afforestation Statistics. Department of Agriculture Food and Marine.

Government of Ireland (2009) Renewed Programme for Government. http://www.defence.ie/WebSite.nsf/72804bb4760386f380256c610055a16b/2a49a2267d0f095b80257754004d3e17/$FILE/94315182.pdf/Renewed_Programme_for_Government,_October_2009.pdf

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological, 37*(8), 681-698.
Haan, P. (2006). Much ado about nothing: Conditional logit vs. random coefficient models for estimating labour supply elasticities. Applied Economics Letters, 13(4), 251-256.
Heckman, J. and Macurdy, T. (1980). A Life Cycle Model of Female Labour Supply, The Review of Economic Studies, Vol. 47, No. 1, Econometrics Issue. (Jan., 1980): 47-74.
Howley, P., Hynes, S., O'Donoghue, C., Farrelly, N. and Ryan, M. (2012) Farm and farmer characteristics affecting the decision to plant. Irish Forestry 69 (1&2): 33-43.
Hynes, S. & Garvey, E., (2009). Modelling farmers' participation in an agri-environmental scheme using panel data. An application to the REPS Scheme in Ireland. Journal of Agricultural Economics, 60, 546-562
Hynes, S. and Hennessy, T. (2012) Agriculture, fisheries and food in the Irish economy. The World Economy. Doi:10.1111/j.1467-9701.2012.01487.x Accessed Jan 2014.
McDonagh, J., Farrell, M., Ryan, M. and Mahon, M. (2010). Missed opportunity or cautionary steps? Farmers, Forestry and Rural Development in Ireland. European Countryside. 4: 236-251
McFadden, D. (1973) Conditional Logit Analysis of Qualitative Choice Behaviour. In Zarembka, P. (ed.) Frontiers of Econometrics. New York: Academic Press.
Mincer, Jacob. (1958). "Investment in Human Capital and Personal Income Redistribution", Journal of Political Economy, Vol. 66, 4, 281-302.
Moons, E. and Rousseau, S. (2007) Policy for afforestation in Flanders Ecological Economics 64:194-203
Murphy, G., O'Donoghue, C., Hynes, S. and Murphy, E. and, (2014) The participation decision in the Rural Environment Protection Scheme (REPS): a conditional logit approach using simulated counterfactual data for farmers. Paper presented to European Association of Agricultural Economists Congress, Ljubljana, Slovenia, August 26-29 2014.
Ni Dhubhain, A. & Gardiner, J. (1994). Farmers attitudes to forestry. Irish Forestry 51:19-26.
Ryan, M., McCormack, M., O'Donoghue, C. and Upton, V. (2014) Analysing the role of subsidy payments available to a typical cattle farmer in Ireland on their uptake of forestry from 1984 to 2012. Irish Forestry (forthcoming)
Ryan, M., O'Donoghue, C., Upton, V., Phillips, H. and Farrelly, N. (2013) Modelling Inter-temporal Differential Returns to Agricultural and Forestry Land Use. Paper presented at 87th Conference of the Agricultural Economics Society, University of Warwick, UK.8-10 April.
.Ryan, M., Kinsella, A. and M. Cushion. 2008. An assessment of farmer intentions to plant a forest. Agricultural Research Forum. Teagasc.
Upton, V., Ryan, M., Farrelly, N. and O'Donoghue, C. (2013)The potential economic returns of converting agricultural land to forestry: an analysis of system and soil effects from 1995 to 2009. Irish Forestry 70 (1&2): 61-74
Van Gossum, P., Arts, B. and Verheyen, K. (2012) Smart regulation: Can policy instrument design solve forest policy aims of expansion and sustainability in Flanders and the Netherlands? Forest Policy and Economics 16:23-34
Van Gossum, P Arts, B. van Laar, J.and Verheyen, K. (2010). Implementation of the forest expansion policy in the Netherlands in the period 1986–2007: Land Use Policy, 27 (4):1171-1
Van Soest, A. (1995) 'Structural Models of Family Labour Supply: A Discrete Choice Approach', The Journal of Human Resources, 30(1), pp. 63–88.