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Exploring factors affecting on-farm renewable energy adoption in Scotland using large-scale microdata

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ABSTRACT

This paper uses large-scale micro data to identify key factors affecting the decision to adopt renewable energy generation (wind, solar and biomass) on farms in Scotland. We construct an integrated dataset that includes the compulsory agricultural census and farm structural survey that cover almost all farms in Scotland. In addition to farm owner demographics and farm business structures, we also assess the effect of diversification activities such as tourism and forestry, as well as the spatial, biophysical and geophysical attributes of the farms on the adoption decision. We find that diversified farms are more likely to adopt renewable energy, especially solar and biomass energy. Farms are also more likely to adopt renewable energy if they have high local demand for energy, or suitable conditions for renewable energy production. We find that biophysical factors such as the agricultural potential of farm land are important in adoption decisions. We identify adopter profiles for each type of renewable energy, and map the geographic location of potential adopters. We argue that renewable energy policy should be more integrated with farm diversification policy and farm support schemes. It should also be tailored for each type of renewable energy, for the potential adopter profiles of wind, solar and biomass energy all differ in farm characteristics and geographic distribution.

1. Introduction and policy background

Scotland has set ambitious goals for addressing climate change: reducing greenhouse gas (GHG) emissions by 42% by 2020 and by 80% by 2050 (Climate Change (Scotland) Act, 2009 (SP 17)). The Scottish government has also committed to meet 100% of Scotland's electricity demand from renewable sources by 2020, with an interim target of 50% to be met by 2015, the vast majority of which is expected to be met by hydro and onshore wind (Granville et al., 2009). However, despite the introduction of Renewables Obligation Certificates (in 2002) and Feed in Tariffs (in 2010) both of which financially incentivise renewable energy generation, the current production rates are lower than targeted. One of the biggest sources of renewable energy production in Scotland is the agricultural sector, which accounts for a third of the renewable energy operating capacity in 2012 (Scottish Government, 2014). In 2015, it was estimated that Scottish farms and estates had a capacity of 119 MW, or 42% of the total production capacity of renewable energy in Scotland (Scottish Government, 2015). In this paper we assess factors affecting on-farm renewable energy production, in order to better inform policy design for renewable energy production.

Farms play an important role in achieving renewable energy production targets in Scotland, since they provide the space needed for wind or solar power production and the raw materials needed for biomass production. Farmland can be employed to install wind turbines without causing significant interference with traditional livestock grazing and other farming activities (Howard et al., 2009). Solar photovoltaic panels can be installed on existing farm roofs with no need for additional space to site the equipment. Photovoltaics have become an economically viable energy source, which can be used either on-farm or sold to the national grid (Spertino et al., 2013; Tudisca et al., 2013). Finally, by-products from farming, livestock production, and commercial forestry can be used as input in various forms of biomass production (Faaij, 2006; Prochnow et al., 2009a, 2009b).

This paper uses large-scale micro data[1] (the June Agricultural Census (JAC) data and Farm Structural Survey (FSS)) to study factors

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E-mail address: Jiaqi.Ge@hutton.ac.uk (J. Ge).

[1] Ruggles (2014). Big microdata for population research. Demography 51, 287–297., which defines large-scale microdata as “Individual-level data on population such as census data, usually consist of high-density samples or complete census enumerations”.

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influencing on-farm renewable energy adoption in Scotland. We have constructed an integrated dataset that includes farm diversification and the geophysical conditions of the farm, to enhance our understanding of how various factors interact to influence on-farm adoption decision, and provide a richer context for policy making.

The paper proceeds as follows. Section 2 reviews relevant literature on the drivers and barriers of on-farm renewable energy uptake and state our contribution to the existing literature. Section 3 presents empirical methodology. Section 4 describes data and integration of data from multiple sources. Section 5 discusses results. Finally, Section 6 concludes.

2. Drivers and barriers of on-farm renewable energy uptake

A number of factors influence farmer uptake of renewable energy. These include demographic attributes of the farm owner such as their age and education level, as well as business aspects, such as the type of land tenure, farm size and farm business structure. For example, studies found that farm owners who are younger (Jensen et al., 2007; Tate et al., 2012; Tranter et al., 2011; Willis et al., 2011) and better educated (Tranter et al., 2011) are more likely to be adopters. Land tenure is also found to be a significant factor: owner occupied farms are found to be more likely to adopt (Tate et al., 2012; Tranter et al., 2011). Regarding farm size, larger farms are found to be more likely to be adopters (Mola-Yudego and Pelkonen, 2008; Panoutsou, 2008; Tranter et al., 2011). Finally, regarding the type of the farm business, Panoutsou (2008) observed that in Greece, cereal farmers are more likely to be adopters of biomass production than non-cereal farmers, whereas Mola-Yudego and Pelkonen (2008) observed that in Sweden, farms with livestock are less likely to adopt bioenergy production.

Regarding policy and structural factors, Wilkinson (2011) reviewed the policy, structural, biophysical, social and economic conditions of farming in Germany and Australia, in an attempt to explain the major differences in adoption rate of biomass production between the two countries. The author concluded that although regulation and policy incentives are important factors, they are insufficient to guarantee a large scale uptake of biomass energy. Since Germany imports over 60% of its energy demand whereas Australia exports two-thirds of its domestic energy, biophysical and structural differences are more fundamental factors in the uptake of biomass energy. Similarly, Tate et al. (2012) conducted a survey of farmers in the West Midlands Region in the UK and found that the attractiveness of government schemes is less influential than farm attributes. However, Sutherland et al. (2015) studied the role of agriculture sector in renewable energy transitions, and concluded that owing to the subsidy dependence of many forms of renewable energy production, perceived stability of these subsidies is highly important to uptake. Finally, del Río and Unruh (2007) shows that existing institutional structures could also pose a barrier to renewable energy uptake.

In terms of financial barriers, Jensen et al. (2007) conducted a survey of Tennessee farmers on their willingness to adopt biomass and supply switchgrass to the energy market. Almost 30% of the respondents indicated that they are willing to adopt only if it is profitable. Sherrington et al. (2008) and Sherrington and Moran (2010) argued that concerns over income security and uncertainties from contracts are the main concern of farms when making decision to adopt energy crops. Bocquého and Jacquet (2010) found that in central France agronomic and economic conditions, switchgrass is less profitable than traditional economic crops, although it can be a good diversification crop.

Studies have also looked at the social, cultural and institutional barriers to renewable energy adoption. For example, Ehlers and Sutherland (2016) study how media coverage relates to interest in renewable energy, and show the important role of information in the diffusion of renewable energy. Studies have shown that opinions, attitudes and individual identity can influence farmers' tendency to adopt renewable energy (Bergmann et al., 2006; van der Horst, 2007).

Table 1
Number of adopters for wind, solar and biomass energy.

	Full Sample	Farms larger than 3ha	Farms receiving SFP
N total	20,946 (100%)	19,900 (100%)	15,361 (100%)
N wind	173 (0.83%)	171 (0.86%)	140 (0.70%)
N solar	88 (0.42%)	83 (0.42%)	60 (0.30%)
N biomass	175 (0.84%)	168 (0.84%)	118 (0.59%)

In summary, studies to date have mainly focused on farm structure, farm owner characteristics, attitudes, preferences and motivations, and the cultural, institutional and policy aspects. Few studies have investigated the role of biophysical and geophysical characteristics of the farm in combination with the other factors. As Wilkinson (2011) has pointed out, biophysical and geophysical characteristics can play an essential role in renewable energy uptake, and are probably more fundamental than regulations and incentive schemes. In this analysis, we will include the geophysical and biophysical factors of the farms, and study their role in farmers' decisions to adopt various types of renewable energy.

In addition, recent evidence has shown that farmers pursue renewable energy production as a farm diversification strategy and that diversified farms are more likely to undertake renewable energy production in future (Sutherland et al., 2016). However, the nature of the relationship between farm diversification activities and renewable energy uptake remains to be explored. In this paper, we will study how on-farm diversification activities such as agri-tourism, commercial forestry, wood and farm products processing affect the decision to adopt various types of renewable policy. The analysis in this paper will enhance our understanding of the drivers and barriers of on-farm renewable energy uptake, and thus inform policy decisions.

3. Methodology

3.1. Empirical model

Since the dependent variable in the paper is binary (whether or not to adopt renewable energy production on the farm), we used logit models to estimate the factors' effects. The logit model is a regression model of discrete choice based on random utility theory. First introduced by McFadden (1973), the logit model has become an established method to estimate discrete choice models. The logit model assumes that an individual i can choose between j alternatives (two in our case) and each alternative j provides the individual with a utility as follows,

$$U_{ij} = \boldsymbol{\beta} X_{ij} + \epsilon_{ij} \tag{1}$$

The first term $\boldsymbol{\beta} X_{ij}$ is the representative utility which is usually specified to be linear: X_{ij} is a vector of observed explanatory variables relating to alternative j, and $\boldsymbol{\beta}$ is a vector of coefficients to be estimated. The second term ϵ_{ij} is the unobserved random component, assumed to be independent and identically distributed extreme value. With this specification, the logit probabilities become

$$P_{ij} = \frac{\exp(\boldsymbol{\beta} X_{ij})}{\sum_{k} \exp(\boldsymbol{\beta} X_{ik})} \tag{2}$$

which is the basis for the maximum likelihood estimation of coefficients $\boldsymbol{\beta}$.

After integrating various data sources (more details in Section 3.2), we have identified 20,946 individual holdings, which will be our full sample. However, some holdings in the sample are very small. For example, the smallest holding in the sample has only 0.43 ha. It is likely that some holdings in the sample are inactive farms, especially the very