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.

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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; Prochnow et al., 2009b).

This paper uses large-scale micro data[2] (the June Agricultural Census (JAC) data and Farm Structural Survey (FSS)) to study factors 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.

[2] Ruggles, S., 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".

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).

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 farms' decision 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,

$$U_{ij} = \boldsymbol{\beta} X_{ij} + \epsilon_{\mathrm{ij}} \qquad [1]$$

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

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

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 hectares. It is likely that some holdings in the sample are inactive farms, especially the very small ones, and might behave very differently to formal farms. To exclude the inactive farms, we construct a second sub-sample consisting only of holdings larger than 3 hectares. Moreover, since farms need to be active in agricultural activities to receive the single farm payment (SFP) from the Scottish government, we construct a third sub-sample consisting only of farms that received the SFP in 2011. Table 1 show the number of adopters in each of the three samples.

[Insert Table 1 here]

Table 1 demonstrates the small number of adopters in the sample. With all three types of renewable energy, the number of adopters is less than 1% of the population. The problem with low adoption rates is that the estimation of the standard logit model could be subject to small sample bias, which means that the probability of the rare event (in our case adoption) might be underestimated.

To solve the exact issue of low occurrence of one event in a binary choice situation, (King and Zeng (2001)) proposed an alternative estimation method, called the Firth method, to correct small sample bias where one choice occurs much more rarely than the other. First proposed by Firth (Firth, 1993), the Firth method is a penalized likelihood method (see also (Heinze, 2006)). It is used to estimate logistic regression when one outcome has extremely low prevalence. Consequently, for some combination of explanatory variables all the observations have the same event outcome (known as "separation"), which might cause estimation problems. The Firth method is a standard approach to binary data with separation, for which packages are available in major statistical software such as Stata (Coveney, 2015), SAS (Heinze and Ploner, 2004) and R (Ploner et al., 2010), and is shown to have outperformed other existing methods in providing consistent estimates, correcting for underestimation, and improving computing efficiency (King and Zeng, 2001; Tomz et al., 2003).

3.2 Data and methodology

We integrate several datasets to construct a large-scale micro dataset with factors that can affect adoption decision. The datasets we use include the June Agricultural Census (JAC)[3] data, European Farm Structural Survey (FSS)[4], Macaulay Land Capability for Agriculture (LCA) 1988 classification, rainfall and solar radiation data from the United Kingdom Meteorological Office (MET), Ordnance Survey (OS) terrain 5 data, the Scottish Urban Rural 6-fold Classification URC), Integrated Administration and Control System (IACS), and the Scottish Natural Heritage (SNH) data. Both JAC and FSS are compulsory and cover almost all farms in Scotland, providing a large and unbiased sample. Furthermore, the census survey asks about farmers' actual adopting decisions, rather than adoption intentions, which could be different from the actual behaviour.

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[3] For more information on June Agricultural Census, please see http://www.gov.scot/Topics/Statistics/Browse/Agriculture-Fisheries/PubFinalResultsJuneCensus
[4] For more information on European Farm Structure Survey, please see http://ec.europa.eu/eurostat/web/agriculture/farm-structure

We study three types of renewable energy: wind, solar and biomass (charcoal, wood, straw and other solid matter). We exclude other types of renewable energy in the analysis because the number of adopters are too low (i.e. less than 30 incidents in the data for each type) to merit statistical analysis. Some wind turbines are owned by separately established companies, so legally not part of the farm; hence the farmers involved would not feel required to include them in their census return. We thus have an issue of under reporting of wind turbines. To partially address this issue, we use a second dataset from Scottish Natural Heritage (SNH) to complement the JAC data, which has information of onshore wind turbines higher than 50 meters.

For explanatory variables, first we include the standard demographic and business attributes such as farm and business attributes, on farm agricultural activities, and the demographics of the farm owner or manager. We also include on-farm non-agricultural or diversification activities such as tourism, forestry, processing of farm products and wood. Non-agricultural activities are important parts of agricultural businesses. In fact, according to the census data, around 20% of Scottish farms have participated in some type of non-agricultural activities, and 5% generate more than half of their overall turnover from non-agricultural activities. Non-agricultural activities also contribute to local energy demand and by-products.

Second, we include the biophysical attributes of the farm. The data for biophysical attributes is derived from LCA[5] (Bibby et al., 1982). LCA divides all of Scotland's land into 13 classes and subclasses based on an assessment of its potential productivity and cropping flexibility, and the extent to which the land's physical characteristics (soil, climate and relief) impose long-term restrictions its agricultural use. LCA values are calculated using a number of physical factors, including climate, gradient, soil texture and structure, stoniness, shallowness, draughtiness, fertility, wetness and erosion. In this paper, we use four land capability classes from LCA: 1) arable agricultural, 2) mixed agricultural, 3) improved grassland, and 4) rough grazing, in decreasing order

[5] For more information on Macaulay land capability for agriculture classification, please see http://www.hutton.ac.uk/learning/exploringscotland/land-capability-agriculture-scotland

of agricultural capacity. For each farm, we calculate the area of land that fall into each of the four classes, as an indication for the agricultural potential of the farm. A significant proportion of farmland in Scotland has limited agricultural potential, which arguably makes it suitable for renewable energy production, such as installing as wind turbines and solar panels.

Third, we include location and geophysical attributes of the farm. Location factors include the level of rurality from Scottish Urban Rural 6-fold Classification (Granville et al., 2009)[6], distance to the coast, as well as the latitude and longitude of the centroid of the farm. We use quadratic parametrization of latitude and longitude (includes latitude, longitude, latitude squared, longitude squared, and the multiplication of latitude and longitude) to account for the geographic location, which is a standard approach in the housing literature (Owusu-Ansah et al., 2013). Geophysical attributes include average wind speed, solar radiation rate, elevation, and rainfall and temperature in the four seasons. The data for geophysical attributes is derived from the United Kingdom Meteorological Office[7] and Ordnance Survey Terrain 5 data[8]. To date, few existing studies have included the above geophysical characteristics in the analysis of renewable energy adoption decisions, yet they are key in determining the holding's suitability and competiveness in producing a certain type of renewable energy (Wilkinson, 2011).

Table 2 lists all the dependent explanatory variables included in the study, Table 6 in the Appendix lists the summary statistics of the explanatory variables, and Table 7 in the Appendix list the Variance Inflation Factor, which is a test for multicollinearity, of the explanatory variables.

[Insert Table 2 here]

[6] For more information on the Scottish urban rural 6-fold classification, please see http://www.gov.scot/Topics/Statistics/About/Methodology/UrbanRuralClassification
[7] For more information on and integrated administration and control system, please see http://ec.europa.eu/agriculture/direct-support/iacs/index_en.htm
[8] For more information on Ordnance survey terrain 5 data, please see https://www.ordnancesurvey.co.uk/business-and-government/products/os-terrain-5.html

4. Results and Discussion

4.1.Wind

Table 3 lists the significant factors with a positive (left) or negative (right) effect on wind energy adoption estimated from the logit model. Table 8 in the Appendix shows the full logistic regression result for wind energy adoption. Throughout this section, we will use the conventional 5% level as the p-value threshold for significant factors, which we mark with an asterisk.

[Insert Table 3 here]

The results show that, as should be expected, holdings on land with high wind speed are more likely to install wind turbines. Farms that engage in tourism are less likely to have wind turbines on the property. Holdings with large crop and fallow land, large mixed agricultural land or large improved grass land are more likely to install wind turbines. Holdings that are in high latitude (northern) areas are more likely to have wind turbines, although the effect diminishes further north. Holdings in areas with low rainfall in autumn and high rainfall in winter are more likely to install wind turbines. Finally, holdings with large sheep flocks are more likely to install wind turbines.

We then use the above estimated logistic model to predict the potential wind energy adopters in the future. For each farm holding, we use its characteristics in the estimated model to derive its predicted probability to adopt wind energy. We identify farms whose predicted adoption probability is larger than 10%, and project them onto the map of Scotland.

Figure 1 shows the geographic distribution of the actual and potential wind energy adopters across Scotland. We see from Figure 1 that many potential adopters (those who are currently non-adopters but have more than 10% predicted adoption probability) are located in the northern highland area in northern Scotland and in central Scotland. Moreover, they are less likely be located in the Cairngorms National Park[9].

[Insert Figure 1 here]

4.2.Solar

Table 4 lists the significant factors with a positive (left) or negative (right) effect on solar energy adoption estimated from the logit model. Table 9 in the Appendix shows the full logistic regression result for solar energy adoption.

[Insert Table 4 here]

The results show that holdings with a younger owner or manager are more likely to adopt solar panels. Poultry farms are more likely to adopt solar energy. In terms of non-agricultural activities, farms that diversify into tourism, processing of farm products and wood are more likely to install solar panels on the farm. Farms with a higher percentage of severely disadvantageous area are more likely to install solar panels. Similarly, farms with larger rough grazing area are also more likely to install solar panels. Finally, farms with a higher percentage of owned area is more likely to have solar panels installed on the farm. Interesting, the level of solar radiation on the farm does not seem to be a significant factor in the decision to install solar panels.

Similar to wind energy, we use the above results to predict the potential solar adopters and identify farms with more than 10% predicted probability to adopt solar energy.

Figure 2 shows the geographic distribution of actual and potential solar energy adopters across Scotland. There are fewer potential solar energy adopters, and most are located in central north and southwest Scotland.

[9] The Cairngorms National Park is a national park in northeast Scotland.

[Insert Figure 2 here]

4.3.Biomass

Table 5 lists the significant factors with a positive (left) and negative (right) effect on biomass energy adoption estimated from the logit model. Table 10 in the Appendix shows the full logistic regression result for biomass energy adoption.

[Insert Table 5 here]

We find that farms with younger managers are more likely to adopt biomass energy production. Farms are also more likely to adopt biomass energy if the occupier of the farm spends time on other paid work, or if the household consumes more than half of the value of the farm's production. On the other hand, if the farm is managed by a professional manager, it is less likely to adopt biomass energy. Farms with large mixed agricultural or rough grazing land area are more likely to adopt biomass energy. Regarding non-agricultural activities, farms that provide tourism, accommodation and leisure are more likely to adopt biomass energy. Also, farms that are engaged in commercial forestry, farm products and wood processing are more likely to adopt biomass energy, most likely because they provide as a by-product the raw materials needed for biomass production. Like for solar energy, farms with owned land are more likely to be biomass adopters. Finally, farms situated in Loch Lomond and The Trossachs National Park are more likely to adopt biomass energy.

We use the above logistic estimation results to predict the potential solar adopters. Just as for wind and solar energy, we identify farms that have more than 10% predicted probability by applying the estimated linear logistic model.

Figure 3 shows the distribution of actual and potential biomass energy adopters across Scotland. Notably, the potential biomass energy adopters are more scattered geographically than potential wind and solar energy adopters, which suggest that biomass production is less reliant on the geophysical and biophysical conditions than is wind and solar energy, and hence has greater potential for Scotland-wide adoption.

[Insert Figure 3 here]

4.4. Discussion

Many of our results are consistent with what is found in previous studies. For example, we find that age is a significant factor in the adoption probability of solar and biomass energy, and younger farmers are more likely to be adopters of renewable energy, as in previous findings (Jensen et al., 2007; Tate et al., 2012; Willis et al., 2011). We find that land ownership or tenure is important in the adoption decision of solar and biomass energy: farms that own land are more likely to adopt both solar and biomass energy, which is also consistent with previous findings (Tate et al., 2012; Tranter et al., 2011). We also find that the land and livestock herd and flock sizes are important in the adoption of wind and solar energy, as have earlier studies (Mola-Yudego and Pelkonen, 2008; Panoutsou, 2008).

In addition, the integrated dataset allows us to study factors that have not been captured previously. For example, we find that farms that diversify into tourism, accommodation and leisure services are more likely to adopt solar and biomass energy, but less likely to adopt wind energy. One could argue that tourism related services are energy intensive, and these incentivise the farm to generate energy locally from available renewable energy resources. However, concerns over wind turbines disrupting scenery may deter farms that engage in tourism and accommodation services from installing wind turbines (Frantál and Kunc, 2011). We also find farms that diversify in other types of non-agricultural activities such as commercial forestry, processing of farm products and wood are more likely to adopt solar or biomass energy, partially because those diversification activities provide the input needed for biomass production, and partially because these activities are also energy intensive.

Finally, the results show that poultry farms are prone to solar energy production, because it has high on-farm energy demand for ventilation and large roof areas suitable to install solar panels.

As for biophysical factors, we find that the agricultural potential of the land plays an important role in all three types of renewable energy. For wind energy, farms with large area of mixed agricultural land or improved grassland are more likely to be adopters. For solar energy, farms with large areas of rough grazing land and a high percentage of severely disadvantageous area are more likely to be adopters. The results generally confirm our expectation that farms with large land area of low agricultural potential are more willing to use the land for renewable energy production. We find that the pattern is more pronounced with the adoption of solar energy: farms with large areas of severely disadvantageous or rough grazing land (the lowest agricultural potential) are more often used to install solar panels.

Regarding geophysical factors, we find that they are important in the decision to install wind turbines, but not so much in the decision to adopt solar or biomass energy. For example, as expected, high wind speed is a positive factor in wind energy adoption. Farms in the north are also more likely to install wind turbines than those in the south. In addition, both temperature and rainfall are significant factors affecting the likelihood of a wind turbine on the farm. Where farmers are aiming to supplement income by generating electricity for the national grid, geographical concentration of suitable sites and potential adopters is advantageous with respect to prioritizing upgrades to grid infrastructure. By contrast, we do not find these geophysical factors to be significant in the adoption decision of biomass or solar energy, except that farms located in Loch Lomond & The Trossachs National Park are more likely to adopt biomass energy.

Finally, we use the model to derive predicted adoption probability and project on a map farms with higher than 10% adoption probability for wind, solar and biomass production. We find that for wind energy, most potential adopters are located in the northern highland area in northern Scotland, as well as in central Scotland, and they are less likely to be in the Cairngorms national park. The model predicts fewer potential adopters of solar energy, most of who are clustered in central north and southwest Scotland. Potential adopters of biomass energy, on the contrary, are less clustered geographically than potential wind and solar adopters, probably because the production of biomass energy is less reliant on geophysical and biophysical conditions.

One limitation of this study is the small number of adopters in the sample, despite the sample's high coverage of Scottish farms. Our knowledge regarding the adopter characteristics have to be based on existing adopters, and it is likely that the typical adopter profile will change after a large-scale adoption takes place. The application of the study is thus limited to the early stage of renewable energy uptake. In addition, due to data limitations, some factors that can affect the adoption decision are not included in this study, such as a farmer's political standing and attitudes towards renewable energy. Finally, although we use a second dataset to supplement wind turbine report, there might still be wind turbines not covered in both datasets.

5. Conclusions and Policy Implications

In this paper, we integrated multiple datasets to construct large-scale microdata to study factors affecting on-farm renewable energy uptake in Scotland. The compulsory agricultural census and farm structural survey provide a representative picture of the situation of on-farm renewable energy adoption in Scotland. We include factors that are largely omitted in previous literature, such as on-farm diversification activities, the geophysical and biophysical factors. The analysis provides a rich empirical framework for researchers and policy makers to understand the complex decision to adopt renewable energy on farm. The results of this paper are useful to supply the context and supporting interpretation for the design of renewable energy policy.

We find that diversified farms are more likely to adopt renewable energy, especially solar and biomass energy. The UK government has been encouraging farm diversification – including grants to establish on-farm renewable energy production - since the 1980s (Sutherland et al., 2016). Findings suggest the importance of aligning renewable energy and diversification subsidy strategies. At present, farmers who access grants to establish renewable energy production are not eligible for subsidies for the energy produced. Sutherland and Holstead (2014) found that leveraging the capital necessary to invest in turbines in particular, can be prohibitive.

Second, farms are more likely to adopt renewable energy if they have high farm demand for energy, such as farms with tourism services and poultry farms. We believe farmers with high energy demands are more likely to see the potential of renewable energy production. Consequently, policies should aim at raising awareness of renewable energy production opportunities among farms with low on-farm energy demand.

Third, we show that biophysical factors are important in the adoption decision of renewable energy. In particular, farms with large land of low agricultural potential, such as rough grazing land and other less favoured land are more likely to adopt renewable energy production as an alternative to farming. Therefore, the design of renewable energy policy should also take into account agricultural policy such as the Less Favoured Areas Support Scheme (Schwarz et al., 2006) .

Finally, the results show that the adopter profiles are different for different types of renewable energy. For example, large scale enterprise is a positive factor for wind and solar energy, but a negative one for biomass energy. Geographically, the model predicts that potential wind adopters are more likely to be in northern and central Scotland, potential solar adopters are clustered in southwest Scotland, and potential biomass adopters are spread throughout Scotland. Therefore, policies aiming at promoting different types of renewable energy should target at different farm types and geographic regions.

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Appendix

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