Profitability and efficiency of high nature value marginal farming in England

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Abstract: The UK Brexit vote triggered a new wave of policy development for a future outside the EU. In that context, this paper presents analysis investigating the business performance of English hill and upland farms, characterised by marginal economic conditions but also high nature value (HNV). The analysis aims to help identify farm-level management and policy options for greater economic, environmental and social sustainability. Business performance is measured as technical efficiency and the occurrence and persistence of abnormal profits, estimated through stochastic frontier analysis and static and dynamic panel-data methods. The results help indicate rationales for recent trends including farm enlargement, farm family diversification, and agri-environment scheme entry. The single farm payment was negatively associated with farms technical efficiency but positively associated to short-term farm profitability. Farm adaptation and resilience during a period of likely turbulence in external circumstances is discussed in light of these findings, as well as potential parallels with marginal HNV areas across Europe.

Key Words: upland farming, High Nature Value, resilience, profit persistence, technical efficiency, agricultural policy.

JEL: Q12, Q18, Q57

1 Introduction

In debates surrounding global food security and environmental sustainability, marginal lands are subject to multiple contrasting demands from society. In respect of food security, they can be considered as necessary areas for food production, although characterized by low productivity and thus modest economic returns. For environment, they are often particularly valuable in respect of their distinctive landscapes, biodiversity and ecosystem services (Kang et al., 2013). Indeed, the concept of High Nature Value (HNV) areas was formulated to describe the traditional, extensive and often marginal farmed landscapes of Europe, emphasising their importance in protecting and enhancing nature and cultural landscape quality. In recognition of these combined qualities of economic marginality and HNV ecosystem services, the EU's Common Agriculture Policy (CAP) offers Member States the opportunity to provide targeted aid to these 'Areas of Natural Constraint' (ANC) – formerly Less Favoured Areas (LFAs).

In England most designated ANC are hill and upland areas managed by extensive livestock grazing, which are characteristically rich in semi-natural habitats, hosting rare species of plants and animals. With many areas of deep peat soils, the uplands are also a major carbon store and key water catchment zone, regulating hydrological cycles, as well as providing an important recreation resource for the urban population (Acs et al., 2010). Despite these important roles, England's hill farmers are among the most financially-challenged farming communities in the UK, with comparatively low incomes from agriculture and a heavy dependence upon public subsidy. But the continuation of upland farms through an economically viable system is integral to the protection and enhancement of England's upland landscapes and ecosystems (Dwyer et al, 2010; Reed et al, 2009). This has been a high-profile issue in current discussions concerning the future of support to farms in the UK as it prepares to leave the EU, and must replace the provisions of the CAP with a new framework.

Despite the importance of upland agricultural systems, the amount of recent research on the economics of upland farms is relatively limited. Turner et al. (2008) investigated the impact of product prices and input costs on UK upland farms' incomes, showing that a small increase in input costs (feed and energy) can easily overcome potential gains from products' market prices. They concluded that, although upland farming is a low-input system, its profitability is very sensitive to market risks. Acs et al. (2010) studied potential effects of policy changes on hill and upland farms and found that the decoupling of support reduced grazing intensity, and the Single

Farm Payment increased net farm incomes and reduced land abandonment. Similar conclusions were provided by Turner and Wibberley (2009). For many years now, the Farm Business Survey (FBS) analysis of farming in England's LFA has indicated that upland farms struggle to cover their costs, and depend significantly for their survival upon continuing high levels of subsidy from both Pillars of the CAP (Harvey and Scott, 2012; 2013; 2014; 2015; 2016). The contribution of various on- or off-farm diversification options is also important for farm households. At the same time, these analyses suggest significant differences in performance between farms, with the most efficient businesses making reasonable agricultural income (i.e. net of subsidy), even in relatively poor years (ibid). Linked to this literature, although in a different national context, Barath et al.'s (2017) study indicated that farms in Slovenian upland and mountainous LFAs are not more inefficient than farms in other areas of the country, but rather use different, production–environment-specific technologies: in effect, they are different systems producing equally efficient results.

Considering the importance of upland farming for the maintenance of valuable habitats and ecosystem services, the objective of this paper is to analyse the economic viability of England's upland farms through two complementary analyses based on two fundamental measures of farms' performance, namely efficiency and productivity. In a first analysis, we measure efficiency using stochastic frontier analysis (SFA) which provides an estimate of farms' technical efficiency in converting inputs into outputs, incorporating different exogenous drivers of efficiency via a simultaneous estimation. In a second analysis, the drivers of upland farms' profitability are examined using both static and dynamic panel-data methods, allowing the estimation of the impact of drivers on the occurrence and persistence of abnormal profits (above and below the sector's competitive norm). In other words, we estimate the impact of drivers on farm profitability in the short (one-off occurrence) and in the longer term (persistence over more than one year), where persistence provides information on the resilience of upland farms facing market and policy turbulence. In the second analysis, the upland farms' technical efficiency obtained from the SFA is used as an explanatory variable of profitability, accounting for its potential endogeneity in driving profits. Moreover, our two complementary analyses seek to account for different agro-ecological conditions within the upland eco-system, by controlling for farms located above and below 300m in altitude; as altitude affects the productivity of land and the applicability of enhanced management and diversification.

Through this approach, the paper contributes to the literature on technical efficiency of UK agriculture that since the 1980s has provided important insights into its sectoral and spatially-differentiated development. A comprehensive review of early studies within this literature can be consulted in Hadley (2006). Our results can also be compared and contrasted more broadly with other efficiency analyses for UK farms. These include Wilson et al. (2001) who used SFA to explain the influence of management on the efficiency of wheat farms in eastern England during the period 1993-1997; Karagiannis et al. (2002 and 2004) who analysed the efficiency of dairy farms in England and Wales; Hadley (2006) who estimated stochastic frontier production functions for eight different farm types (cereal, dairy, sheep, beef, poultry, pigs, general cropping and mixed) for the period 1982 - 2002 in England and Wales; and Barnes (2008) who completed the work of Hadley (2006) by estimating efficiency of the same agricultural sectors in Scotland. The paper also has direct relevance to wider literature on the performance of farms in marginal areas, as mentioned in the previous paragraphs.

The paper is organised as follows. The next section provides some background to the policies and factors affecting the economic viability of English upland farming systems and on that basis develops two hypotheses for empirical testing. Section 3 describes and develops the econometric strategy and empirical specifications used to test the hypotheses. Section 4 presents and discusses the results, and section 5 draws some conclusions and sets them in a broader UK and European policy context.

2 Policy background: deriving hypotheses

Upland farming systems in England are characterised by relatively extensive grazing of permanent grassland and other semi-natural vegetation, by sheep and beef cattle. This creates habitats and landscapes of recognised national and international importance.

As reviewed in section 1, the survival of marginal farms such as these is critically dependent on CAP subsidies. However, in the near future changes in public support are expected for marginal farms across Europe, due to a likely reduction in the CAP's budget. In the UK, the Brexit process heralds the creation of an entirely new UK farm policy and trading environment in which the rationale and scale of support may shift significantly, and potentially downwards (Buckwell, 2016; Helm, 2016; Dwyer, 2018).

In the year following the UK referendum vote to leave the EU in June 2016, an informal coalition of practitioners, policy makers and academics known as 'The Upland Alliance' (UA), hosted a series of workshops around England. Their aim was to seek ideas and exchange knowledge about the distinctive characteristics of the English Uplands, with a view to promoting better policy for, and sustainable management of, these areas in future[1]. From these events, we identify an emerging consensus about the economic fragility and yet high public value of the uplands, and an effort to secure broader public recognition of this value and continuing support for the environmental and social benefits that they generate. Nevertheless, the future role, form and significance of commercial upland farm businesses remains uncertain, with some calling for the virtual eradication of farming from upland areas (Monbiot, 2017), while others see it as an essential part of the quality and character of these landscapes (EHFN, 2017). Tensions between these views are inherent, if less explicit, within a wider EU and international literature on the value of marginal and HNV farming in upland and mountainous areas (e.g. Beaufoy, undated; Ruffini and Streifeneder, 2008).

From discussions stimulated at the Upland Alliance events, it is clear that many farmers feel conflicting pressures from the economic signals of markets on the one hand, and agri-environmental policies on the other. Relatively few English upland farms operate without agri-environmental subsidies; most hold contracts which restrict grazing densities on semi-natural habitats and often exclude stock for periods of the year. These agri-environmental conditions trigger a need to find compensatory actions elsewhere within the business, cutting management costs or increasing productivity on land that is not subject to the same constraints, or developing new enterprises which are less land-dependent, such as indoor fattening of livestock, or non-farming diversification. In many of these farmers' eyes, such activities do not represent resilient or sustainable farm business options but short-term necessities; and there is a widespread wish among many upland stakeholder bodies to search for better long-term management strategies.

Potential drivers of upland farm performance in England can be identified from: i) studies that have explored these farms' decision-making and management strategies from a qualitative perspective (e.g. Gaskell et al, 2010; Jones, 2014; Dwyer et al, 2015); also ii) quantitative empirical studies (Turner et al., 2008; Turner and Wibberley, 2009; Acs et al., 2010; Harvey and Scott, 2012

[1] A website collates and publicises the various outputs of the UA events, see https://uplandsalliance.wordpress.com

- 2013; Barath et al., 2017); and iii) the authors' discussions in a wide variety of policy and stakeholder workshops and ongoing research engagement with upland farmers in England and Wales. Collating from these information sources, we designed two hypotheses for testing using the FBS data.

The first hypothesis is built on the common assumption that the most successful upland farms – therefore those which appear most profitable and technically efficient - are those with bigger dimensions (as was identified broadly by Harvey and Scott in 2013). This is in line with a notion of economies of scale applying to England's upland farms and it could also reflect anecdotal opinion that farms are now driven as much by subsidy maximisation (paid on a per-hectare basis) as by the underlying performance of their agricultural production. Based on this assumption, the first hypothesis that we test is:

H1: Upland farms' performance increases by pursuing economies of scale.

The second hypothesis is more complex, and derives from a consideration of market and policy challenges faced by farms in the uplands, over the last decade. These challenges are linked to market liberalisation, increased price volatility and the decoupling of single payment subsidies in 2005, as well as the increased targeting of support to those upland farms delivering environmental services, through agri-environment 'Stewardship' schemes (Silcock et al., 2012). In responding to these combined challenges, we suggest that some farms may be pursuing economies of scope, as a tactic to enhance performance, adopting strategies of either agricultural intensification, or extensification, and/or greater 'risk management', including income diversification. Hence a second hypothesis for testing is:

H2: Upland farms' performance increases by pursuing economies of scope.

3 Methods

3.1 Econometric strategy

What makes some upland farms more successful than others can depend on a wide range of factors. These factors may be linked to structural characteristics of the farm, to its financial position, to the level of public support, and to diversification and management strategies.

A key aspect in studying the impact of these factors is defining how to measure "success". A common measure of farm performance is its efficiency in transforming inputs into outputs (given a certain technological level), which requires strategic decisions on the allocation of resources and management capacity. However, farmers' survival or business success is ultimately governed by profitability. While efficiency and profitability are strongly linked, they may not coincide: for example, some diversification strategies (e.g. equine recreation) might not be technically efficient for agriculture, as they take resources from the main production activity (e.g. producing beef cattle or breeding sheep), thereby reducing scope for economies of scale; but they could nonetheless be highly profitable.

For these reasons we use two different measures of performance, namely technical efficiency and profitability, and we compare the impact of several farm characteristics and management decisions on both measures. We measure the technical efficiency (TE) of upland farms using stochastic frontier (SF) analysis, which allows the estimation of the impact of the determinants of farm efficiency through a simultaneous process: the estimation of the SF production function; and the estimation of the inefficiency model.

The SF model is based on the theory that no economic agent (company or farm) can exceed the ideal "frontier" of the maximum amount of output that can be obtained from a given allocation of inputs – so, it gives a measure of relative technical efficiency in using the factors of production. Any deviations from this frontier are seen as representing an individual farm's relative inefficiency in allocating and using inputs.

The SF production function is estimated with a "true" fixed-effects (TFE) time-varying approach of the following Normal-Truncated Normal model (Greene, 2005a; Greene, 2005b):

$$y_{it} = \alpha_i + \boldsymbol{x}_{\boldsymbol{it}}^{'}\boldsymbol{\beta} + \varepsilon_{it}, \qquad i = 1, \dots, N, \;\; t = 2, \dots, T \tag{1}$$

$$\varepsilon_{it} = v_{it} - u_{it} \tag{2}$$

$$v_{it} \sim N(0, \sigma_v^2) \tag{3}$$

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_u^2) \tag{4}$$

Where y_{it} represents the net output of farm i at year t, α_i is a time-invariant farm-specific parameter, $\boldsymbol{x}_{\boldsymbol{it}}$ is a vector of production inputs (typically land, labour, capital and intermediate inputs), $\boldsymbol{\beta}$ is a vector of parameters to be estimated and ε_{it} is the error term. Note that for this calculation, the total value of output is measured net of CAP subsidies – so, assessing the value of the agricultural outputs alone.

In this model, the error term has two components: the statistical noise v_{it} and the inefficiency term u_{it}. The distribution of the farm's inefficiency (u_{it}) can be determined by a series of (exogenous) factors differing from the inputs and the outputs of the production process, but nonetheless affecting farm performance by shifting the production frontier (Belotti et al., 2012).

To control for such determining factors, the mean of the pre-truncated inefficiency distribution can be parametrized with a vector of variables $\boldsymbol{z_{it}}$ (Kumbhakar et al., 1991; Huang and Liu, 1994). Model (1) – (4) can be completed by the following inefficiency model, where the estimated parameters are identified by ψ:

$$\mu_{it} = \boldsymbol{z'_{it}}\psi \tag{5}$$

Finally, given $\mathbb{E}(u_{it}|z'_{it}\psi) = \boldsymbol{\hat{u}}$, the estimates of farm efficiency (controlling for its exogenous determinants) are obtained by:

$$TE = \exp(-\boldsymbol{\hat{u}}) \tag{6}$$

The key advantage of using Greene's TFE over other types of time-varying models is that it allows a separation of farm-specific heterogeneity from inefficiency. In other words, α_i is treated as a fixed parameter representing farm-specific time-invariant heterogeneity which is not part of inefficiency, therefore separating farms' heterogeneity from inefficiency.

The larger number of α_i (one for each farm) with respect to T can potentially lead to the "incidental parameter problem". However, Greene (2005a and b) demonstrates that with the inclusion of dummy variables for each $i=1,\dots,N$ the incidental parameters problem does not cause significant bias to the estimated parameters.

Another important issue to consider in the estimation of production frontiers is that estimates are conditional on the given technology and if the sample of farms is heterogeneous in terms of production technologies, then the estimation of a single production function can provide biased frontiers, unless such technological heterogeneity is properly accounted for.

Different approaches can be taken to account for heterogeneous production technologies. One is the metafrontier approach, where the sample is divided into groups of units based on *a priori* knowledge of differences in technology. Efficiencies are then estimated for each group and the production frontiers can be compared. However, estimating different frontiers for different groups might not be efficient because inter-group information gets lost and farms in different groups may share common characteristics despite different technologies. Moreover, this approach cannot be used if the researcher cannot observe different technology groups within the sample.

If the sample is structured with unobservable different technological groups, an alternative approach is to use latent class modelling. This second approach exploits multivariate analysis to estimate the probability of a farm belonging in a particular (latent) technological group, thus exploiting all the information contained in the data.

In the case of upland farming, a clear distinction in the sample can be made between farms located above and below 300m of altitude. This threshold is used in the FBS to discriminate between different agro-ecological conditions. The reason is that at higher-altitude land is much less fertile and less productive and this difference in land productivity may induce farms to adopt different strategies in allocating inputs, so different tactics may be needed and different business strategies may be better suited to the harsher conditions. Such a distinction is supported by an examination of the characteristics of the FBS data. Therefore this threshold seems likely also to discriminate between two different technological groups. However, the relatively small sample size for FBS farms in the English LFA represents a limitation to distinguish the effect of heterogeneous technology through latent class modelling. The partial solution taken for this analysis is to control for the potential variation in the technology between farms above and below 300m by including grouping dummy variables within the list of regressors of the efficiency model.

The second measure of farm performance is profit. More specifically, we refer to the literature on "abnormal profit" (Mueller, 1977) – i.e. the difference between a farm's profit and the competitive norm for the sector in a specific period, where profit can be either in excess or below the competitive norm. In this context, we distinguish between two types of profitability, namely the "occurrence" and "persistence" of abnormal profits. The occurrence of abnormal profits is the deviation of farm profit from the competitive norm at a specific point in time. The occurrence of profitability model takes the following form:

$$\pi_{it} = \boldsymbol{X_{it}\beta} + \gamma TE_{it} + \mu_t + \varepsilon_{it} \qquad (7)$$

where $\varepsilon_{it} = \alpha_i + \nu_{it}$

Where π_{it} represents farm profit i at year t, $\boldsymbol{X_{it}}$ is a vector of variables affecting profitability occurrence, α_i is a time-invariant farm-specific parameter, μ_t are year intercept terms, β and γ are parameters to be estimated and ν_{it} is the iid error.

Following Greene and Segal (2004), to examine the association between profitability and efficiency we include in equation (7) the farm-specific time-varying technical efficiency (TE_{it}) estimated through SF. Because efficiency and profitability can be affected by double causality problems (i.e. more efficient farms can obtain higher profits and more profitable farms can improve their level of efficiency), model (7) needs to be estimated correcting for endogeneity.

Conventional instrumental variable (IV) estimators are consistent models correcting for endogeneity. However, if the model is affected by heteroscedasticity, IV estimators are inefficient, preventing valid inference (Baum et al., 2003). The most efficient approach in the presence of heteroscedasticity is to use the generalized method of moments (GMM) estimator.

Therefore, we first test for heteroscedasticity using the White/Koenker statistic on (7) estimated with OLS. If the test is statistically significant it is possible to reject the null hypothesis of no heteroscedasticity, and GMM is the most consistent estimator with an endogenous regressor, where the set of L moments is equal to the number K of instruments for TE.

Profit persistence is defined as the percentage of a farm's profit in one year that remains in the following year (Schumacher and Boland, 2005). Persistence can be considered in the short- (3-10 years) or in the longer-term (>10 years) and abnormal profits in period *t-1* are likely to induce abnormal profits also in the period t (Geroski and Jacquemin, 1988), indicating a persistently (un)successful farm.

In order to estimate the drivers of upland farms' profit persistence, we use a dynamic panel model. Equation (8) is the model estimated:

$$\pi_{it} = \lambda\pi_{it-1} + \boldsymbol{X_{it}\beta} + TE_{it} + \mu_t + \varepsilon_{it} \qquad (8)$$

where $\varepsilon_{it} = \alpha_i + \nu_{it}$

Where $\lambda\pi_{it-1}$ is the autoregressive term and λ is the persistence measure (Hirsch and Gschwandtner, 2013).

Dynamic panel data are characterized by two sources of time-series correlation: the correlation of the lagged dependent variable with the disturbance term (i.e. π_{it-1} is correlated with v_{it}); and the correlation of π_{it-1} with individual effects characterizing farms heterogeneity, α_i. By using classic panel data estimators, it is possible to remove the individual effects, but the lagged dependent variable is still potentially endogenous. Therefore, in order to consistently estimate equation (8), data need to be transformed in such a way that both individual effects and the correlation of π_{it-1} with v_{it} are removed.

Different approaches to estimate dynamic panels have been developed in several stages in the literature. Here we concentrate on the two most widely adopted estimators in the recent literature[2], which are also the ones applied in this paper, namely difference and system GMM estimators. These two estimators are suited for small time series data and allow the use of regressors that are not strictly exogenous.

The first estimator is the one proposed by Arellano and Bond (1991) which is based on the transformation of all regressors into their first-difference and on instrumenting the differences with level lagged variables through GMM estimator. This approach takes the name of "difference GMM". However, the Arellano-Bond estimator has limited efficiency with unbalanced panels with short time-series such as hours and it is not possible to use lags of π_{it} as instruments (Roodman, 2009).

Arellano and Bover (1995) and Blundell and Bond (1998) make an additional stationarity restriction to the Arellano-Bond estimator that results in the assumption that first-differences of instrument variables are uncorrelated with the fixed effects, allowing to introduce more instruments and to improve efficiency. The Blundell-Bond estimator builds a system of two equations ("system GMM"), namely the original equation and the equation in which instruments are differenced, so that level variables are instrumented with differences.

Both difference and system GMM estimators are preferably estimated with two-step rather than one-step GMM estimators, because the two-steps estimator is more robust to any pattern of heteroscedasticity and cross correlation. However, in finite samples, the standard errors obtained

[2] An extensive and detailed discussion of dynamic panel estimators can be found in Baltagi (2013)

through the two-step GMM estimator can be severely biased downwards. This bias can be reduced using the two-step finite-sample correction proposed by Windmeijer (2005).

One additional issue to consider when estimating difference and system GMM models is the (potential) bias caused by weak instruments. This issue has been raised and largely discussed by Bazzi and Clemens (2013), who show how the majority of the applications of system GMM assume that instruments are strong. Currently there are no formal tests for weak instruments in dynamic panel GMM regressions, but there are available weak instrument tests for 2SLS (Kleibergen-Paap LM test; Cragg-Donald and Kleibergen-Paap Wald tests). Therefore, Bazzi and Clemens (2013) suggest the following heuristic approach: construct the GMM instrument matrix of the system estimator and carry out the corresponding regressions using 2SLS; as when the instrumentation in the 2SLS is strong (weak), the performance of the corresponding system GMM is robust (poor).

However, this approach has some limitations. Firstly, Bazzi and Clemens (2013) considered the Kleibergen-Paap test for a cross-sectional setting, therefore not taking into account the clustering of observations in a panel setting (Windmeijer, 2018). Secondly, it relies on Stock and Yogo (2005) critical values which are tabulated only up to two endogenous variables. For these reasons, the standard tests AR(1) and (2), Hansen's *J* and Diff-in-Hansen are taken as the main reference for evaluating the robustness of the difference and system GMM models, here.

Finally, profit persistence can also be interpreted as a measure of economic resilience – i.e. the capacity of a system to retain its functions, organisational structure and performance, withstanding perturbations (Holling, 1973; Di Falco and Chavas, 2008). As explained in section 2, upland farms face a series of different shocks due to changing market and policy conditions at national and global level. The persistence of profits indicates the capacity of farms to cope with such shocks, by remaining economically viable and continuing to deliver vital ecosystem services.

3.2 Data and empirical specification

The analysis uses a panel dataset containing four years of the FBS: 2010/11, 2011/12, 2012/13 and 2013/14. The selection of these years was motivated by the fact that prior to 2010 the sample of farms in the FBS was classified based on Standard Gross Margins (SGM), whereas since 2010 farms have been classified based on Standard Outputs (SO). This difference reduces comparability across the two time periods.

In order to target English upland farms, we use a subsample of 263 farms contained in the FBS dataset. These farms are classified as LFA Grazing Livestock Farms, each one having more than two thirds of its total SO coming from cattle, sheep and other grazing livestock; and 50% or more of its total area within the LFA.

In order to select the most relevant characteristics affecting upland farms' performance, and therefore to test ***H1*** and ***H2***, a variety of variables was used. Initially, a large set of potential drivers of farm performance were tested using comprehensive specifications of both the SFA and profit models[3]. Starting from these comprehensive specifications, it was possible to identify smaller sets of variables with tangible impact on farms' performance and therefore to derive more parsimonious model specifications. This allowed us to better focus the results with respect to ***H1*** and ***H2***. Descriptive statistics and definitions of the variables used in the parsimonious models are presented in Table 1.

With respect to the SF specification, the productivity of upland farms is represented by a Cobb–Douglas[4] stochastic production frontier, estimated through the following maximum likelihood TFE time-varying model (Greene 2005, a and b):

$$lny_{it} = \alpha_i + \beta_1\, lnLabour_{it} + \beta_2\, lnLand_{it} + \beta_3\, lnAssets_{it} + \beta_n \sum lnVariable\ inputs_{it} + v_{it} - u_{it} \qquad (9)$$

Where y_{it} is the value of agricultural output (excluding CAP subsidies) of farm *i* at time *t* and variable inputs are crop (seeds, fertilizers and crop protection), livestock (feed, fodder and veterinary) and machinery (fuel, oil, repairs and rental) costs.

The inefficiency model contains the determinants potentially affecting farm efficiency and is defined by the equation:

$$u_{it} = \delta_0 + \sum_{l=1}^{k} \delta_l\, Determinants_{it} \qquad (10)$$

[3] The results of the comprehensive specifications of the SF and profitability models are presented in Appendix 2, 3 and 4. In addition to the variables used in the parsimonious models, the comprehensive ones included the following variables: standard head-of-household characteristics (age and education); output from recreation activities; percentage of cereals land.

[4] Cobb-Douglas production functions are widely used in the stochastic frontier literature, despite this functional form imposes some restrictive assumptions on the structure of the production technology, return to scales and elasticity of substitution. In order to overcome these limitations, a more flexible functional form, the translog production function, was tested (results available upon request to the authors). The estimation of the tranlog production function failed the monotonicity and strict concavity conditions, suggesting that, with the data at hand, the Cobb-Douglas production function provides more robust results.

Where the group *Determinants* contains a series of factors potentially affecting farms' efficiency.

The specification of the occurrence profitability model is the following:

$$ln\pi_{it} = \beta_1 TE_{it} + \sum_{l=1}^{k} \delta_l \, Determinants_{it} + \varepsilon_{it} \qquad (11)$$

While the specification of the persistence profitability model is:

$$ln\pi_{it} = \alpha\pi_{i,t-1} + \beta_1 TE_{it} + \sum_{l=1}^{k} \delta_l \, Determinants_{it} + \varepsilon_{it} \qquad (12)$$

Where π_{it} are profits and TE_{it} is the technical efficiency estimated in (6). Profits are measured in terms of gross profit (GP), calculated as the difference between total farm's sales and production costs of sold goods, that can be expressed as $GP_{it} = \sum_1^g (Q_{itg}P_{tg}) - \sum_1^g (Q_{itg}C_{tg})$. Q_g is the quantity of good *g* produced and sold by the farm *i* in year *t*, while P_{tg} and C_{tg} are output and input prices, respectively. Quantities Q_{itg} are related to the farm's efficiency (TE_{it}) and productivity, while P_{tg} and C_{tg} are determined by the market; they can fluctuate from year to year and are unrelated to the farm's efficiency.

Following Hirsch and Hartmann (2014), in order to capture abnormal profits, π_{it} is measured as the deviation from the competitive norm, where the sample mean is considered the norm. Therefore, $\pi_{it} = GP_{it} - \overline{GP}_t$. This normalization removes the potential variations in profits due to external influences and business cycles, giving an equal impact on all farms (Hirsch and Hartmann, 2014)[5].

Our variable of interest to test ***H1*** is *Land* (UAA), while the group *Determinants* contains our variables of interest with respect to ***H2***. This group of variables includes proxies for agricultural intensification, the farm's financial situation, the level of public support, and management and diversification strategies. These variables were selected based on the relevant literature on upland

[5] Note that results do not change if π_{it} is measured in level and not as deviation from the sample norm, therefore in this application the distinction between profit and abnormal profit is mainly used to obtain better benchmarking between farms and with the "abnormal profit" literature.

farming and profitability (Hanley et al, 2007; Turner et al., 2008; Turner and Wibberley, 2009), as well as discussion in workshops and meetings with farmers in Exmoor (Dwyer et al, 2015) and national meetings of the Upland Alliance in Cumbria (2015) and London (2016).

In relation to ***H2***, two financial variables are tested. *Tenant* is the share of tenanted land in total UAA. A higher share of tenanted land indicates higher financial exposure of farms, given that land rent is not capitalised into fixed assets but represents a net farm cost. *Loans* is the amount of loans for long-term borrowing for future projects and investments, such as agricultural mortgages (Turner et al., 2008). Traditionally upland farms have operated with low levels of borrowing and this pattern persists, as showed by the low average loans in Table 1.

Among diversification strategies, the spouse off-farm income (*Spouse off-farm*) is the most relevant. According to the CRC report (2010) most upland farmers depend on opportunities for off-farm employment and diversification. In theory, off-farm income helps stabilize the overall household income when agricultural activity is affected by lower performance due to production or market shocks.

Regarding farm management strategies, we tested a series of livestock, land and differentiation strategies. Mixed grazing of livestock is the most traditional and widespread activity in the uplands, as it is considered more robust agronomically than sheep or beef specialization (Turner et al., 2008). This is due to complementarities between the two activities: cattle prefer tall grass and can clean the pasture of nettles and thistles, while sheep graze short grass and keep the sward short. In moorland areas sheep and cattle also favour different food sources. Moreover, mixed grazing may provide more stable income by reducing price risks (as lamb and beef prices do not depend on the same factors) and veterinary risks (i.e. diseases are quite different). These complementarities between beef and sheep may improve the resilience of the upland farming system (ADAS et al, 2007). We represent these complementarities by using the proportion of breeding ewes per beef cow (*Ewe/beef*). Moreover, profitability and efficiency is likely to be affected by potential over- and/or under-grazing of pastures, therefore we account for grazing pressure using grazing livestock units per Ha of land (*LUha*).

In order to investigate the role of public support, we distinguish between payments for agri-environmental agreements (AES - the Upland Entry Level Scheme and the Higher Level Stewardship Scheme, predominantly) and the decoupled CAP Pillar 1 subsidies of the Single Payment Scheme. In both cases, we calculate their average amount per hectare of UAA of the farm, which measures the intensity of subsidy per hectare. The reason for doing this is that total single farm and AES payments are higher for larger farms; hence one potential farm strategy is to increase scale, thus increasing the revenues from these subsidies. However, this strategic behaviour of the farm should already be captured by testing ***H1*** through *Land.* Our purpose here is to estimate the direct impact of the relative intensity of policy support, as higher intensity represents a direct cash flow that stabilizes income and allows for investment and experimentation in alternative practices, at lower risk.[6] For this reason we calculate an adjusted measure of the single farm payment, and total annual agri-environment receipts, per hectare. It should be noted that per ha variables impose homogeneity of degree one on the production technology and hence constant returns to scale (Wilson et al., 2001).

Because of the relationship between Q_{itg} and TE_{it} described above, simultaneity bias between π_{it} and TE_{it} is likely, therefore the occurrence profitability model is estimated with IV techniques. A frequent solution adopted by applied economists to avoid simultaneity problems is to use lagged values of the potentially endogenous variable as instruments. However, there is debate surrounding the use of lagged variables as IVs. Some authors argue that lagged variables do not in all cases remove the endogeneity bias, especially if the lagged variables are insufficiently correlated with the simultaneously determined explanatory variable (Reed, 2015). Bellamare et al. (2017) suggests that researchers should evaluate whether lagging the explanatory variable solves the endogeneity problem. In order to tackle this issue, we compare different instrumentation strategies based on a set of external and internal instruments, comparing their exclusion restrictions and relevance to check the robustness of the profit occurrence model.

Exclusion restrictions of IV lagged variables are valid as TE_{it-1} is correlated to TE_{it} (i.e. the current (in)efficient allocation of production factors will affect the future allocation, especially if factors of production are fixed, such as land and assets); but TE_{it-1} is uncorrelated to GP_{it} as: i) production quantities Q_{itg} depend primarily on climatic and environmental factors, which are

[6] The variability of these amounts per hectare is due to two quite different factors, for the period analysed. For agri-environmental payments, a higher intensity of aid would generally represent more ambitious kinds of environmental management under the Environmental Stewardship scheme's Higher Level (HLS) or the organic entry level scheme (OELS), as compared to the lower level of payment per hectare available under the Upland Entry Level Scheme (UELS). For the Single Farm Payment, higher levels of payment per hectare during this period would reflect farms with more productive land, on average – i.e. a smaller proportion of land within the Moorland category; and a non-moorland area which was attracting higher than average payment rates due to historically higher stocking densities than the average. This historic stocking effect applied only under the minor and declining component of SFP which was based on historic receipts, in this time period. (England chose to adopt a 'dynamic hybrid' approach to decoupled payments, phasing out a historic-based payment rate and phasing in a flat-rate payment, between 2007 and 2012).

independent of the farm's efficiency; and ii) TE_{it-1} cannot affect market prices of outputs and inputs (P_{tg} and C_{tg}).

For external instruments, we use the ratio labour/capital (calculated as *AWU/Assets*). The exclusion restrictions are valid because *AWU/Assets* is not correlated to GP_{it} : that is, i) a higher (or lower) proportion of labour with respect to assets such as machinery does not affect production quantity because Q_{itg} depends on the relative productivity of the production factors, but not their relative allocation. This is apparent when considering the elasticity of substitution of an isoquant between production factors – i.e a farm with many workers and few machines, can produce as much as a farm which has many machines operated by few workers; and ii) *AWU/Assets* cannot affect the market prices of outputs and inputs (P_{tg} and C_{tg}) – it is correlated to TE_{it} as lower values indicate higher technical efficiency, so fewer workers produce the same amount of output.

While the validity of the exclusion restrictions cannot be statistically tested, the relevance of both the internal and external instruments is indicated by their coefficients in the first stage of the IV regression, that are significantly different to zero. More importantly, we can test for over-identification, under-identification and weak identification with the Hansen *J*, Kleibergen-Paap LM, and the Cragg-Donald and Kleibergen-Paap Wald F statistics, respectively.Finally, all the variables included in the models are used in their logarithmic form, so that coefficients can be interpreted as elasticities.

4 Results

The methodology applied to assess upland farms' performance consists of two complementary analyses. First, estimating upland farms' technical efficiency and its drivers; second, estimating upland farms' profitability, taking into account their efficiency. Results are therefore presented following this structure.

Moreover, this section reports the results of parsimonious specifications of each SF, occurrence and persistence of profits models, while the more comprehensive specifications using a full set of 'drivers' variables are reported in the appendixes. The fact that the parsimonious specifications are different across models indicates that there are different drivers affecting different aspects of upland farms' performance.

4.1 *Technical efficiency of upland farms*

Table 2 shows the results of the SF model. Columns 1 to 3 estimate only the production frontier in order to obtain benchmark estimations of the production function and to test whether there are differences in technology between the group of farms located above 300m altitude and those below.

In all columns of table 2, the coefficients of the production function estimation are positive and their sum is <1. A Wald test ensured that the sum of the coefficients was statistically different from 1 (constant return to scale) and the significant test result suggests that upland farms operate under decreasing returns to scale. Previous studies using SFA to estimate TE in UK farming found different returns to scale for different types of farm: constant returns to scale were found in the cereals (Wilson et al., 2001; Hadley, 2006), beef, poultry and pig sectors (Hadley, 2006); increasing returns to scale among dairy and mixed farms; but decreasing returns to scale in the sheep and general cropping ones (Hadley, 2006).

The large difference in the inputs coefficients between column 2 and 3 of table 2 suggests that farms located above and below 300m are likely to operate under different technological levels, and therefore that this difference should be taken into account in estimating the TE of upland farms (see section 3).

The results of the inefficiency model are displayed in column 4 of table 2[7], resulting from the estimation of equations (1) to (5)[8]. The distributions of the efficiencies of the whole sample and of the farms above and below 300m are shown in Figure 1. Farms are relatively efficient with a large proportion of farms operating close to the production frontier. The distributions of the sub-samples are similar, all with negative skewness, but the figure shows that lower-lying farms are, on average, slightly more technically efficient than higher farms (85.5% cf. 83.6% respectively), as would be expected, given the variation in land quality with altitude. On average lower-lying farms are 2.3% more efficient than higher farms. The fact that farms' TE tends to converge towards higher values is not surprising. As Kumbhakar et al. (2015, page 60) highlighted, in sectors that are highly

[7] Column 4 of table 2 presents the results of a parsimonious specification of the inefficiency model. A more comprehensive specification was tested and results are shown in Appendix 1.

[8] Note that the coefficients in the inefficiency part of table 2 concern INEFFICIENCY so a negative sign indicate a negative relation with inefficiency (therefore a positive relationship with EFFICIENCY) and *vice versa*. Coefficients in tables 3, 4 and 5 are more straightforward, so a positive sign indicates higher profitability and a negative sign lower profitability.

regulated and with strong public incentives for a long time, as in the case of agriculture in the UK, TE convergence is likely to move towards the frontier.

Regarding ***H1***, the coefficient of *UAA* in the frontier model of column 4 of table 2 is the largest among the inputs, with 35.4% output elasticity of land. So, larger farms (by area) produce a higher value of output, as would be expected. Previous work from Dawson (1985), Wilson et al.,(1998 and 2001) and Hadley (2006), found that larger farm area is associated with higher efficiency, although for other farm types. However, considering that upland farms operate under decreasing returns to scale, this suggests that it is only up to a certain level of farm size that they can benefit from higher efficiency. Once that level is surpassed, the returns are less than proportional and other factors could become more important than scale.

Concerning ***H2***, we begin by looking at the results of subsidies on technical inefficiency. Higher intensity of SFP is significantly associated with higher inefficiency at the 5% significance level, suggesting that higher SFPs reduce farm efficiency. This result is in line with studies analysing the impact of the CAP on farm productivity in other EU countries (Mary, 2012; Rizov et al., 2013). These studies posit that subsidies, by guaranteeing a minimum income, reduce farmers' incentives to be more competitive and adopt productive technologies and practices, therefore potentially provoking a misallocation of resources. The possibility that higher intensity of subsidies can lead to technical inefficiencies in UK farming is more directly supported by Hadley (2006) who found negative effects on technical efficiency for the majority of farm types (cereal, sheep, general cropping and mixed farms) in England and Wales.

A higher spouse off-farm income is negatively associated with inefficiency at 10% significance level, suggesting that it represents an efficient income diversification. This is an interesting finding, as some have suggested that having half of a typical family unit not working on the farm is a challenge to efficiency as it takes resource from the core business (Dwyer et al, 2015 report this view among farmers in their survey). It also seems plausible that significant off-farm income could induce farmers to 'sit back' and rely on this, rather than improving farm performance. The pattern observed is more consistent with a situation where, when the farm family does not seek off-farm income for a spouse it may be carrying some degree of disguised unemployment. Alternatively, it could be that households where a spouse works 'officially' off-farm actually benefit from unrecorded additional farm labour from that spouse, given informally and unpaid.

Regarding financial variables, a higher percentage of tenanted land is significantly associated with higher inefficiency. This finding confirms similar results from Hadley (2006) and Barnes (2008), this last one related to Scotland. These authors suggest that tenant farmers might have less incentive to look after the rented land, hence achieving poorer results. However, it is possible that this reflects the relatively lower 'room for manoeuvre' of farmers on rented land in achieving optimal resource allocations, which might constrain their capacity to achieve the greatest efficiency.

Financial exposure is captured by *Loans*, and this significantly (10%) increases the inefficiency of upland farms, although the coefficient is relatively small. So, upland farms with greater loans tend to be less efficient or, in other words, lower debts tend to increase farms' efficiency, a conclusion shared also by Hadley (2006). An interpretation of this impact was provided by Paul et al. (2000), suggesting that financially-constrained farms have less capacity to adapt to market and policy changes, therefore decreasing their technical efficiency.

Finally, a higher intensity of livestock grazing (*LUha*) has a negative and large magnitude coefficient, which is significant at 5% level, suggesting that the underlying determinant here could be land capability rather than management strategy *per se*. So, farms with more productive land are able to be more technically efficient.

4.2 Profitability of upland farms

In this section we present the results of both the profit occurrence and persistence parsimonious models (see appendixes 3 and 4 for the comprehensive specifications of both models).

Table 3 shows the results of the profit occurrence model. Column 1 displays results from the pooled OLS estimation used to test for heteroscedasticity. At the bottom of the column, the significant *p*-value of the White/Koenker test indicates the presence of heteroscedasticity. Therefore, GMM is the most consistent estimator for the profit occurrence model.

Columns 2, 3 and 4 of table 3 show the results for the occurrence of profits using static, fixed effects GMM estimators, with different instrumentation strategies to control for the potential endogeneity of *TE*[9]. In column 2 we use the external instrument *AWU/Assets*. In column 3 we use

[9] All regressors have been tested for endogeneity using the endog option after the Stata command xtivreg2. The endog option performs the difference of two Sargan-Hansen statistics: one for the equation where regressors are treated as endogenous, and one for the equation where the regressors are treated as exogenous. Using such test we could not detect other endogenous variables in addition to TE.

two internal instruments, which are lagged 1 and 2 *TE* variables. In column 4 we combine both external and internal instruments. At the bottom of these columns, we test for under-identification (Kleibergen-Paap LM statistic), weak identification (Cragg-Donald and Kleibergen-Paap Wald F statistic) and over-identifying restrictions (Hansen's *J* test).Even though the exclusion restrictions of both the external and internal instruments are valid as discussed in section X, and the coefficients of the instruments in the first stage of the FE GMM are significantly different from zero (see Appendix 1), the external instruments alone do not pass the tests. This suggests that the instrumentation strategy in column 2 is quite weak, while the results in columns 3 and 4 are more robust.

The results of the profit occurrence models across columns 2 to 4 in table 3 are quite consistent, even though the number of observations drops with the lagged instruments. The first important result is that efficiency has positive and significant coefficients. This confirms the important association between farm efficiency and profitability, suggesting that the more technically efficient a farm is, the more profitable also.

Regarding ***H1***, the coefficients of *UAA* are positive and significant at 1% level with the largest magnitudes across the covariates. This suggests that larger upland farms (by area) produce above the norm profits, and not only higher efficiency as demonstrated in table 2. In other words, tables 2 and 3 provide evidence that pursuing economies of scale can be a successful strategy for upland farms to improve their performance in terms of efficiency and occurrence of profitability.

With respect to economies of scope (***H2***), a higher proportion of breeding ewes in the livestock mix increases the occurrence of abnormal profits, although the positive and 1% level significant coefficients are much smaller than those for farm size.

Agri-environmental payments are positively and significantly associated with profit occurrence, although the magnitude of the effect is quite small. It is worth noting that agri-environmental payments affect profit occurrence but not technical efficiency nor profit persistence, as they do not appear in the parsimonious specifications in tables 2 and 4. This could be a reflection of the fact that these schemes guarantee a level of farm income irrespective of market conditions, subject to agreed management prescriptions being followed throughout.

Single farm payments have a positive impact on the occurrence of abnormal profits, significant at 1% level in column 2 of table 3. This positive impact is opposite to the negative impact that SFP have on the technical efficiency of upland farms in table 2, suggesting that direct payments are a useful tool to support upland farms' survival, but that they do not provide incentives to become more productive. This is not surprising considering that the primary objective of SFP is to sustain the stability and the level of farms' income. However, because the instrumentation strategy in column 2 is weak and given our decision to consider SFP intensity per hectare, it could be that these results simply confirm that farms with more productive land generated more profit.

Moving to the results of the profit persistence models, these are displayed in table 4. Column 1 and 2 provide estimates of pooled and fixed effects (within) OLS estimators, which accompany the results of the difference and system GMM models providing upper and lower bounds for the autoregressive coefficients. As one can see, the autoregressive coefficient in column 1 is positive and highly significant, but the one in column 2 is not-significant. Therefore, we mainly rely on the upper limit of 0.848 as a benchmark for the results of the dynamic panel models. At the bottom of column 4 of table 4, the *p*-value reported for AR(1) suggest that there is first order autocorrelation[10].

Regarding the instrumentation strategy, only internal instruments were used. A series of tests have been performed to verify the validity and robustness of the instrumentation strategy. First of all, the Hansen *J* and Sargan tests in table 4 support the validity of the over-identifying restrictions in both difference and system GMM. However, the negative autoregressive coefficient in column 3 casts doubts on the robustness of the difference GMM results, supporting the idea that the system GMM estimator is the most reliable for our model. The system GMM estimator is supported also by the *p*-value reported for the Diff-in-Hansen test for the validity of the additional moment restrictions, suggesting that we cannot reject the null that the additional moment conditions are valid.

The additional heuristic tests proposed by Bazzi and Clemens (2013) are reported in table 5[11]. The *p*-values of the Kleibergen-Paap LM indicate that we can reject the null of under-identification, suggesting that identification is not weak and both the difference and levels equations of the system GMM are correctly identified. Moreover, we can reject the null hypotheses that the relative OLS bias is >30%, suggesting that the instrumentation is able to remove a

[10] It was not possible to calculate the AR(2) test for second order autocorrelation because of the low average number of observations per group, that is 2.53

[11] Stock- Yogo critical values for the Kleibergen-Paap and Cragg-Donald Wald statistics are not tabulated for cases with more than two endogenous variables. Thus, we follow the indications of the online appendix to the paper of Bazzi and Clemens (2013) to take the penultimate available critical value in the given row and column of the table. According to this approach, the Stock-Yogo critical value for our model is 4.73.

substantial portion of OLS bias and therefore we can reject that the instrumentation is weak. To sum up, all our test statistics suggest a proper specification of the system GMM model and that the instruments are valid and not weak.

Looking at the results of column 4 in table 4, the coefficient of the lagged profit π is positive, significant at the 1% level and below the upper bound estimated in column 1 through the pooled OLS. Interestingly, its magnitude (0.768) is higher than the coefficient estimated by Hirsch and Gschwandtner (2013) for the UK food industry (0.304). Such a coefficient indicates that upland farms' profits strongly persist from year to year(lag π close to 1 indicates high profit persistence) even though profit fluctuation is quite high in the UK food industry sector.. Technical efficiency has a key role in this dynamic, as the coefficient is positive and significant at 1% level.

Finally, a few management practices have a significant but negative impact on profitability in table 4, namely the proportion of breeding ewes per beef cow (*Ewe/beef*) and grazing livestock units per Ha of land (*LUha*). The coefficient of Ewe/beef, turns from positive to negative passing from table 3 to table 4, suggesting that, while a higher proportion of breeding ewes can benefit the farms' profitability in the short-term, this is not an equally successful strategy for the long-term. A higher grazing pressure is negatively associated with the persistence of profits, but positively with efficiency. These contrasting results tend to suggest that exogenous sources of volatility, such as shifts in market prices caused by exchange rate fluctuations, or extreme weather events (we note that 2012 was a particularly difficult year, with very high rainfall and persistent low winter temperatures), create real challenges for farms seeking to pursue long-term profitability. In these circumstances, it would seem unwise for farms to focus strongly on tactics for short-term profit at the expense of adaptability and resilience to unforeseen market shocks.

5 Conclusions and discussion

The survival and economic viability of marginal farming in the English uplands has been identified as an important factor in safeguarding these areas' valuable ecosystem services and high nature value.

This paper investigates the drivers that make upland farms more successful and economically resilient. The results show the importance of using two different measures of farming "success" by accounting for farms' technical efficiency and profitability. In other studies, subsidies have been described as the dominant factor assuring net farm incomes (Harvey and Scott, ibid). Our results find a positive profitability impact of agri-environmental subsidies under CAP Pillar 2 , but also a negative effect of basic CAP Pillar 1 Single Farm Payment (SFP) on farms' efficiency. Also, some of the key management strategies adopted by upland farmers seem to have opposite effects with respect to different measures of performance, for example a higher grazing pressure is negatively associated with profitability, but positively with efficiency, while a higher proportion of breeding ewes per beef cow is positively associated with short-term profitability but negatively associated with long-term profitability, possibly due to large fluctuations year on year in exogenous factors including exchange rates, export markets and weather conditions.

The patterns in the data tend to confirm the rationality, but also the significant risks, of some recent trends observed in upland farm change. Firstly, despite low returns from farming, it is apparent that many hill farmers seek any opportunity they can, to enlarge the area of land that they manage as part of the business. Our data suggest that this will help them to improve efficiency and profits, up to a point. However, the fact that upland farms operate under decreasing returns to scale should suggest that enlarging the business scale will eventually reach limits, above which marginal productivity cannot substantially increase.

For this reason, strategies offering economies of scope also appear favoured as a tactic which may consciously or unconsciously enhance both efficiency and profitability. Farms which have the enterprise flexibility to respond to market fluctuations in beef and sheep prices, or those on which a spouse is working off the farm as an income diversification source, may have greater economic viability and longer term resilience than those whose incomes depend on a single on-farm enterprise. The off-farm income effect could be a result of reducing disguised under-employment in farm family labour or conversely of stimulating additional unrecorded (over-) employment within those families where one spouse has an additional income from off-farm work. We could investigate which of these options is more likely through complementary qualitative work.

Reflecting, we note that the results reveal patterns that hold for the majority or the 'average' among farms in these situations. They could therefore have value as indicators of a benchmark among upland farms' performance. Against these results it would be useful to examine specific innovative or unusual upland business models and strategies, to see whether they overcome some of the limitations indicated in these data and relationships. In that sense, the results presented and discussed here can be considered not just as a yardstick of what it is possible to achieve in upland farm business performance, but equally as a stimulus to innovation to challenge existing patterns and norms, particularly in the light of changing market and policy conditions over the next few years.

The authors plan to disseminate the results of this paper to stimulate further knowledge exchange with farmers, policy makers and other upland stakeholders to promote more resilient and successful farming in these areas, in future. In combination with more qualitative and deliberative approaches such as those that continue through the efforts of the Upland Alliance, this should help to ensure that future developments are grounded in current evidence.

Some of the results presented here have potential to serve as evidence for designing future UK agricultural policies. In particular, the possible negative effect on technical efficiency of direct payments and their potential role in affecting management decisions, such as acquiring land in order to obtain more subsidy, could be seen as a rationale to reduce their future influence in favour of other forms of support. On the other hand, this analysis suggests that support targeting agri-environmental management has the potential to bolster profitability whilst also promoting ecosystem services and public goods provision.

Another important result with significant policy implications is related to the financial management of upland farms. The fact that higher financial exposure, either in the form of debts or in having a larger proportion of tenanted land, has a negative impact on the performance of upland farms indicates the fragility of such businesses and the need for well-designed support to provide long-term financial assurance, to promote the conservation of these high-value landscapes.

Beyond the UK, we suggest that the implications of this study also have relevance and resonance with work on the challenges of maintaining sustainable mountains and other similar, remote and high-quality marginal cultural landscapes, across the globe (e.g. Ruffini & Streifeneder, 2008). In all these situations, farmers face continuing challenges to maintain viable businesses whilst also generating, maintaining and protecting biodiversity, landscape and key ecosystem services. In many countries and contexts, policy-makers and stakeholders need better information and understanding to help determine how best that balance can be achieved. It is our hope that by making better use of extant datasets and emerging analytical tools and approaches, particularly in processes which encourage reciprocal knowledge-sharing and exchange between science, policy and practitioner communities, researchers may improve the chances of success in this context.

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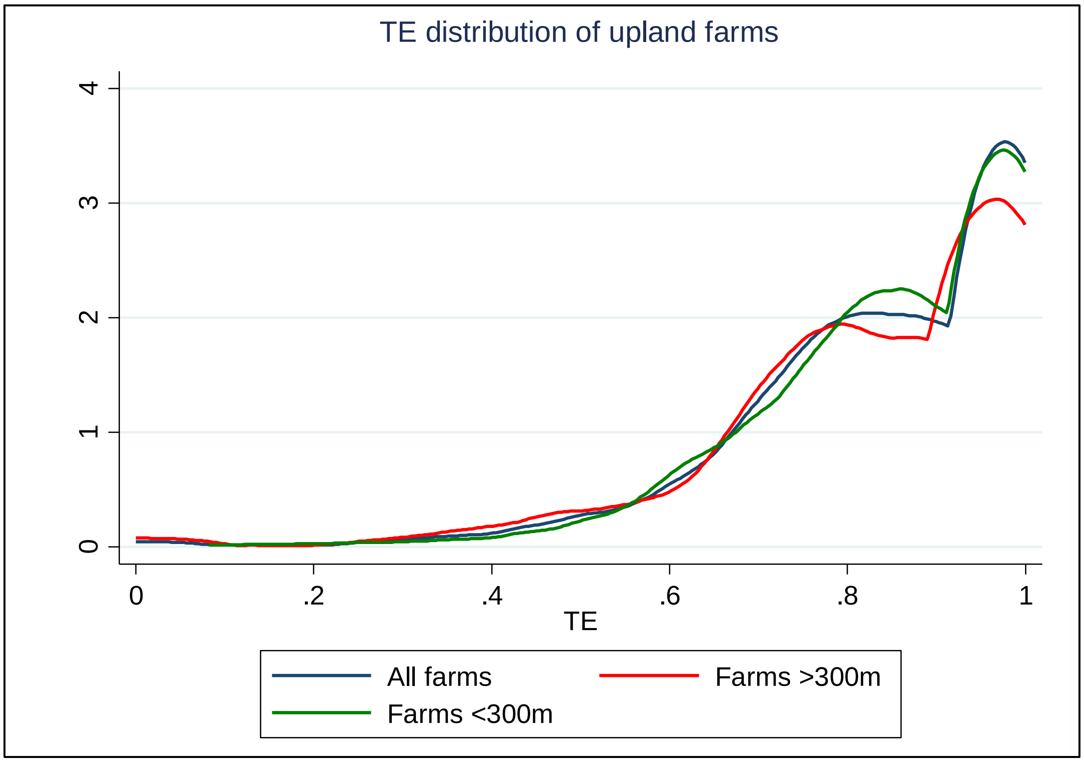
Figure 1 - Distribution of farms' efficiency estimated through SFA



Tab. 1 – Summary description of variables

	Description	Obs	Mean	Std.Dev.	Min	Max
Dependent variables:						
Output	Agricultural output excluding subsidies (£)	1,022	10.998	1.293	0.000	13.555
π	Deviation from the sample's gross profit (£)	1,022	0.000	1.152	-11.162	2.567
Independent variables:						
UAA	Utilized agricultural area (Ha)	1,022	4.764	0.684	1.985	6.787
AWU	Annual working units	1,022	0.409	0.501	-1.316	2.124
Assets	Value of current assets (£)	1,022	10.986	1.030	5.136	13.951
Inputs	Crops, livestock and machinery variable costs (£)	1,022	10.650	0.807	7.625	12.862
Tenant	Percentage of tenanted land	1,022	0.300	0.436	0	1.027
Loan	Total loans account (£)	1,022	3.887	5.326	0	14.569
Spouse off-farm	Income generated off-farm by the spouse (£)	1,022	3.133	4.342	0	11.071
Ewe/beef	Breeding ewes per beef cows	1,022	0.181	0.374	0	1
LUha	Grazing livestock units per Ha	1,022	0.940	0.411	0.094	2.929
AE per Ha	Agri-environmental EU payments (£)/UAA(Ha)	1,022	1.761	0.581	0	2.852
SFP per Ha	Calculated as total Single Farm Payments received (£)/UAA(Ha)	1,011	2.126	0.203	1.595	2.865
TE	Technical efficiency	959	0.846	0.167	0.0001	0.9999

Tab. 2 – Results of SFA estimation

	All Farms (1)	Above 300m (2)	Below 300m (3)	All Farms (4)
Frontier:				
UAA	0.107***	0.261***	0.322***	0.354***
	(0.0001)	(0.00002)	(0.00003)	(0.075)
AWU	0.199***	0.114***	0.121***	0.139**
	(0.0001)	(0.00002)	(0.00002)	(0.058)
Assets	0.157***	0.173***	0.0740***	0.142***
	(0.00002)	(0.00001)	(0.00001)	(0.016)
Variable inputs	0.282***	0.227***	0.0597***	0.205***
	(0.00001)	(0.00001)	(0.00001)	(0.033)
Inefficiency:				
Spouse off-farm				-1.434*
				(0.736)
Tenant				10.370*
				(5.524)
Loan				0.498*
				(0.293)
LUha				-36.190**
				(18.330)
SFP per Ha				17.880**
				(9.092)
Above 300m				-36.250*
				(19.190)
Below 300m				-44.570*
				(22.760)
Regional FE				YES
Observations	970	524	440	959
Usigma	-2.960***	-3.437***	-2.522***	2.056***
	(0.064)	(0.087)	(0.095)	(0.514)
Vsigma	-33.59	-34.05	-35.26	-20.33
	(44.010)	(56.540)	(76.670)	(97.040)

Notes: In parentheses robust standard error. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively.

Tab. 3 – Profitability occurrence model with static panel methods

	(1)	(2)	(3)	(4)
	Pooled OLS	FE GMM	FE GMM	FE GMM
TE	1.363***	1.269***	1.238***	1.197***
	(0.220)	(0.264)	(0.153)	(0.148)
UAA	0.789***	1.501***	1.875***	1.672***
	(0.144)	(0.464)	(0.525)	(0.491)
Assets	0.178***	0.175*	0.244***	0.228***
	(0.022)	(0.096)	(0.053)	(0.051)
Ewe/beef	0.155***	0.159*	0.346***	0.295***
	(0.057)	(0.087)	(0.108)	(0.097)
AE per Ha	0.226**	0.117***	0.199**	0.166**
	(0.089)	(0.045)	(0.078)	(0.072)
SFP per Ha	-0.522	1.667*	1.923*	1.701
	(0.726)	(0.989)	(1.059)	(1.039)
dAltitude	YES	YES	YES	YES
dYear	YES	YES	YES	YES
Constant	-6.025***			
	(2.058)			
Instruments		TE_{t-1}	TE_{t-2}	TE_{t-1} TE_{t-2} TE_{t-3}
White/Koenker *p*-value	0.000			
Hansen's *J* *p*-value		0.486	0.284	0.308
R-sq	0.517	0.237	0.5281	0.5301
Observations	959	640	372	372

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively. OLS estimates do not include farm fixed effects.

Tab. 4 – Profitability persistence model with dynamic panel methods on upland farms

	(1)	(2)	(3)	(4)
	Pooled OLS	FE OLS	Diff GMM	SYS GMM
Lag π	0.848***	0.027	-0.444***	0.768***
	(0.024)	(0.049)	(0.132)	(0.111)
TE	1.274***	1.373***	0.506*	1.772***
	(0.157)	(0.179)	(0.305)	(0.338)
LUha	-0.177***	-0.527*	3.818*	-2.172**
	(0.065)	(0.295)	(2.007)	(1.023)
Ewe/beef	-0.066	0.009	-0.827	-1.000*
	(0.068)	(0.253)	(1.175)	(0.518)
dAltitude	YES	YES	YES	YES
dYear	YES	YES	YES	YES
Constant	-1.048***	-0.738**		1.603
	(0.350)	(0.287)		(1.911)
Instruments			20	24
AR(1) *p*-value			0.260	0.090
Hansen's *J* *p*-value			0.941	0.325
Sargan's *p*-value			0.000	0.000
Diff-in-Hansen *p*-value			0.850	0.242
Observations	686	686	415	686

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively. Both Diff and SYS GMM regressions use the two-step efficient GMM estimator with the Windmeijer (2005) finite sample correction for standard errors. Variables *TE*, *LUha* and *Ewe/beef* are treated as predetermined. The instrument matrix is not collapsed.

Tab. 5 – Underidentification and weak instruments tests of system GMM model based on Bazzi and Clemens (2013)

	Difference equation 2SLS	Levels equation 2SLS
Lag π	-0.486*** (0.014)	-0.021** (0.011)
TE	0.636*** (0.165)	1.188*** (0.157)
LUha	-0.621 (0.566)	-0.556** (0.242)
Ewe/beef	0.044 (0.066)	0.042 (0.097)
dYear	YES	YES
dAltitude	YES	YES
Instruments	4	4
Kleibergen-Paap LM test (*p*-value)	0.000	0.000
Cragg-Donald Wald stat H_0: Relative OLS bias > 30% (*p*-value)	30.256 0.000	52.587 0.000
Kleibergen-Paap Wald stat H_0: Relative OLS bias > 30% (*p*-value)	251.840 0.000	8.879 0.000
Observations	372	372

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively.

Appendix 1 – First stage results of FE GMM estimations in table 3 columns 2, 3 and 4

	(2)	(3)	(4)
	FE GMM	FE GMM	FE GMM
UAA	-0.338**	-0.774***	-0.780***
	(0.154)	(0.254)	(0.256)
Ewe/beef	-0.017	0.030	0.030
	(0.052)	(0.118)	(0.189)
AE per Ha	-0.022	0.032	0.031
	(0.024)	(0.040)	(0.040)
SFP per Ha	-1.046***	-2.282***	-2.295***
	(0.315)	(0.552)	(0.557)
dAltitude	YES	YES	YES
dYear	YES	YES	YES
Instruments:			
AWU/Assets	46.592**		58.987***
	(22.378)		(7.337)
TE t-1		-0.663***	-0.653***
		(0.084)	(0.084)
TE t-2		-0.430***	-0.414***
		(0.066)	(0.067)
Observations	958	372	372

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively. Dependent variable TE_{it},

Appendix 2 – SFA with comprehensive specification of the inefficiency model

	All Farms
Frontier:	
UAA	0.330***
	(0.084)
AWU	0.379***
	(0.064)
Assets	0.102***
	(0.019)
Variable inputs	0.721***
	(0.042)
Inefficiency:	
Age	-3.647
	(4.232)
Education	-5.120
	(4.161)
Spouse off-farm	-1.649*
	(0.964)
Tenant	6.998
	(4.504)
Loan	0.376
	(0.299)
Recreation	-0.95
	(1.391)
Ewe/beef	-6.557
	(4.767)
LUha	-30.180*
	(15.880)
Cereals	-129.700
	(91.110)
AE per Ha	-0.071
	(2.070)
SFP per Ha	14.310*
	(8.353)
Above 300m	-21.12
	(17.010)
Below 300m	-14.16
	(15.040)
Regional FE	YES
Observations	959
Usigma	2.076***
	(0.580)
Vsigma	-27.930
	(3315.400)

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively.

Appendix 3 – Comprehensive specification of the profitability occurrence model

	(1)	(2)	(3)	(4)
	Pooled OLS	FE GMM	FE GMM	FE GMM
TE	1.334***	0.921	0.939***	0.833***
	(0.272)	(0.687)	(0.205)	(0.169)
UAA	0.780***	1.781***	2.215***	2.259***
	(0.138)	(0.479)	(0.712)	(0.711)
AWU	0.410***	0.227	0.084	0.062
	(0.103)	(0.218)	(0.166)	(0.164)
Assets	0.142***	0.127	0.201***	0.182***
	(0.037)	(0.119)	(0.057)	(0.054)
Variable inputs	-0.201**	-0.661	-0.331**	-0.349***
	(0.088)	(0.580)	(0.132)	(0.130)
Age	-0.230***	-0.497	-0.431	-0.407
	(0.081)	(0.657)	(0.276)	(0.273)
Education	0.156***	-0.116	0.000	0.000
	(0.039)	(0.156)	(.)	(.)
Spouse off-farm	-0.003	-0.001	0.003	0.003
	(0.006)	(0.006)	(0.004)	(0.004)
Tenant	0.045	-0.086	-0.046	-0.042
	(0.039)	(0.088)	(0.073)	(0.072)
Loan	0.008**	0.024	0.040	0.041
	(0.004)	(0.015)	(0.025)	(0.025)
Recreation	0.008	0.003	-0.002	-0.002
	(0.008)	(0.012)	(0.012)	(0.012)
Ewe/beef	0.199***	0.208*	0.305**	0.294**
	(0.053)	(0.109)	(0.140)	(0.141)
LUha	0.144	0.245	0.030	0.091
	(0.126)	(0.366)	(0.265)	(0.256)
Cereals	0.897***	1.738	1.430	1.761
	(0.297)	(2.561)	(1.279)	(1.240)
AE per Ha	0.216**	0.089**	0.125**	0.125**
	(0.098)	(0.042)	(0.060)	(0.060)
SFP per Ha	-0.504	1.936*	2.831**	2.844**
	(0.588)	(1.055)	(1.374)	(1.375)
dAltitude	YES	YES	YES	YES
dYear	YES	YES	YES	YES
Constant	-3.111			
	(2.267)			
Instruments		*AWU/Assets*	*TE t-1*	*TE t-1*
			TE t-2	*TE t-2*
			TE t-3	*TE t-3*
				AWU/Assets
White/Koenker *p*-value	0.000			
Kleibergen-Paap LM test (*p*-value)		0.309	0.000	0.000
Hansen's *J* *p*-value		0.000	0.489	0.520
Observations	959	643	372	372

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively.

Appendix 4 – Comprehensive specification of the profitability persistence model

	(1)	(2)	(3)	(4)
	Pooled OLS	FE OLS	Diff GMM	SYS GMM
Lag π	0.702***	0.016	-0.312*	0.499**
	(0.033)	(0.048)	(0.172)	(0.206)
TE	1.205***	1.310***	0.850***	1.362***
	(0.157)	(0.182)	(0.229)	(0.247)
UAA	0.307***	1.737**	3.457*	-0.156
	(0.114)	(0.689)	(2.088)	(0.404)
AWU	0.089	0.238	0.323	0.538*
	(0.077)	(0.277)	(0.302)	(0.287)
Assets	0.078**	0.139	0.266*	0.096
	(0.032)	(0.093)	(0.155)	(0.063)
Variable inputs	-0.165***	-0.634***	0.239	-0.315
	(0.063)	(0.190)	(0.404)	(0.191)
Age	-0.115	-0.375	0.136	-0.121
	(0.147)	(0.698)	(0.838)	(0.378)
Education	0.043	-0.189	-0.111	0.044
	(0.056)	(0.659)	(0.073)	(0.127)
Spouse off-farm	0.002	-0.000	0.001	0.002
	(0.006)	(0.008)	(0.007)	(0.005)
Tenant	0.054	-0.061	-0.141	0.105
	(0.059)	(0.203)	(0.240)	(0.218)
Loan	0.005	0.023	0.025	0.022
	(0.005)	(0.017)	(0.042)	(0.021)
Recreation	0.002	0.006	-0.020	-0.041
	(0.015)	(0.035)	(0.035)	(0.036)
Ewe/beef	0.076	0.192	-0.075	-0.011
	(0.070)	(0.258)	(0.719)	(0.307)
LUha	0.082	0.068	0.842	-0.668*
	(0.103)	(0.355)	(0.723)	(0.353)
Cereals	0.478	0.810	0.571	2.291
	(0.547)	(2.799)	(3.462)	(2.349)
AE per Ha	0.144***	0.096	0.027	0.003
	(0.045)	(0.089)	(0.115)	(0.080)
SFP per Ha	-0.180	2.075	5.580	-2.918*
	(0.316)	(1.697)	(4.050)	(1.544)
dAltitude	YES	YES	YES	YES
dYear	YES	YES	YES	YES
Constant	-1.370	-7.494		
	(1.277)	(7.805)		
Instruments			77	81
Hansen's *p*-value			1.000	0.538
Diff-in-Hansen p-value				0.386
AR(1) p-value			0.307	0.183
Observations	686	686	415	686

Notes: In parentheses robust standard errors. ***, ** and * indicate significance level at the 1%, 5% and 10%, respectively.