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Evaluating the double effect of land fragmentation on technology choice and dairy farm productivity: A latent class model approach.

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Abstract

Land fragmentation affects dairy farming through its influence on foodstuff production. As such, its impact is expected to be larger on extensive farms (which use a large land area per cow) than on intensive ones. Given this, land fragmentation could also constitute an obstacle to adopt extensive production technology. As direct payments of the Common Agricultural Policy to protect the environment and preserve rural heritage concern extensive farming, land fragmentation can reduce the effectiveness of this rural development aid. We propose using a stochastic frontier latent class model approach to evaluate this double effect of land fragmentation, namely its different impact on extensive and intensive farms' productivity and its influence on the technology choice. The model is estimated using a sample of Spanish dairy farms located in a region where land is highly fragmented. Based on the results obtained, a simulation analysis is carried out to evaluate the impact of land consolidation processes on both the technology choice and farms' productivity.

Key words: Milk production, latent class model, land fragmentation

1. Introduction

Land fragmentation, in which a single farm uses several parcels of land, is a common feature in many countries (Blarel et al., 1992; Wan and Cheng, 2001; van Dijk, 2003). This characteristic is usually expected to have a negative effect on farms' productivity due to several reasons: 1) fragmentation causes an increase in traveling time between fields which induces both lower labor productivity and higher transport costs for inputs and outputs; 2) it reduces the efficiency of machines in relation to that obtainable in large, rectangular fields (Buller and Bruning, 1979); 3) land is lost when forming plot boundaries and access routes; and 4) the need for additional machinery, secondary buildings or external service expenses. Therefore, land consolidation processes have been developed around the world to avoid the negative impact of land fragmentation on agricultural productivity (Vitikainen, 2004; Pasakarnis and Maliene, 2010; Niroula and Thapa, 2005).

On the other hand, land fragmentation (LF hereafter) is also expected to have some positive aspects for farmers. For instance, farmers could take advantage of differences in both elevation and soil type as crops at lower elevations mature before than those at higher elevations, and plots with different soil types permit a farmer to produce a more diversified portfolio of crops. Differences in elevation and soil type would thus allow the synchronization of harvests with available family labor, thereby reducing requirements for hired labor. Additionally, LF is expected to reduce production risk associated with the influence of hailstorms, floods or fire.

The empirical literature measuring the effect of LF on agricultural production is quite limited, though it is evolving.[1] While most papers examine this issue by including an LF measure as an additional input in the farm's production function (Wan and Cheng, 2001; Wu et al., 2005), Wadud and White (2000), Rahman and Rahman (2008) and other studies use the Stochastic Frontier Approach (SFA) to analyze its effect on farms' productivity (i.e. efficiency).[2] Most empirical studies conclude that fragmentation negatively affects agricultural productivity (Wan and Cheng, 2001; Rahman and Rahman, 2008) but, in some cases, LF shows a non-significant effect on agricultural production (Wu et al., 2005). Therefore, it seems that the effect of LF could depend on the characteristics of the production process analyzed.

Focusing on milk production, Corral et al. (2011) found a negative impact of LF on farms' productivity and profitability, which suggests that LF generates some difficulties for foodstuff production inside the farm. In this study we try to extend the empirical study carried out by Corral et al. (2011) and test two additional, but related, hypotheses. First, we analyze whether the effect of LF is larger in *extensive* farms, which use a large proportion of own-produced feed,[3] than in farms using a large proportion of purchased foodstuff, usually known as *intensive* farms (Alvarez and Corral, 2010; Alvarez et al., 2008). Second, as LF is expected to be more relevant for extensive farms, and the choice of production processes is not external to dairy farmers (i.e. it is an endogenous decision), we also examine whether LF has conditioned the current choice of production process. In particular, our approach allows us to examine whether farms tend to select more (less) extensive methods as the degree of LF increases.

Both farmers and policy makers are likely to find the empirical results of this paper interesting. Regarding farmers, the degree of market competition is expected to increase due to the disappearance of milk quotas in 2015, and the probable reduction in milk prices could compromise the economic viability of dairy farms. Therefore improving farms' technical efficiency could be necessary to permit the farms to survive. Additionally, intensive dairy production is profitable when a large production per cow compensates the large expenses on (purchased) concentrates. This often occurs when the ratio between the price of milk and the price of concentrates is high. However, given that feeding costs (most of which are concentrate purchases) represent 80% of variable costs, farms will likely be forced to adopt more extensive systems of milk production in order to use more self-produced foodstuff if the milk price falls. The struggle for survival will thus likely rely on improving farms' technical efficiency and adopting extensive production processes, and both may depend on the degree of LF.

[1] Exceptions are Di Falco et al. (2010), Del Corral et al. (2011), and Latruffe and Piet (2013) in Europe; Nguyen et al. (1996), Wang and Cheng (2001), Carter and Estrin (2001), Tan et al. (2010) for China; and Parikh and Shah (1994), Jabarin and Epplin (1994), Wadud and white (2000), Rahman and Rahman (2008), Kawasaki (2010), Manjunatha et al. (2013) for other (Asian) countries.

[2] Technical efficiency is measured in this literature as the ratio between the actual production and the one attained by fully exploiting the technological potential.

[3] Extensive farms are usually characterized by high values of land per cow ratio and low values of concentrates per cow ratio.

On the other hand, as extensive production processes generate lower ground and water pollution (Haas et al., 2001; Basset-Mens et al., 2009), the Common Agricultural Policy includes actions to incentivize its adoption by dairy farmers (Council Regulation No 74/2009). In this sense, our results on the choice of intensive or extensive production processes contribute to our understanding of whether LF is indeed an obstacle to adopting less polluting production processes.

To carry out our analysis we propose using a latent class stochastic production frontier model. The model is estimated using a sample of Spanish dairy farms located in Asturias, a region located in the northwest of Spain where land is highly fragmented.[4] Our empirical strategy allows both the identification of the technological differences between intensive and extensive dairy farms as well as the measurement of the impact of LF on the choice of a milk production system. In addition, the frontier nature of the milk production function allows an assessment of the impact of LF on the technical efficiency of intensive and intensive farms. Finally, several simulation exercises are also performed to analyze the effects of a potential reduction in the number of plots due to a hypothetical land concentration process.

2. Empirical model

In contrast to the common practice of estimating a single production function for all farmers regardless of whether they are actually using extensive or intensive systems of milk production, we will assume that the technologies of these two groups of farms may be different. However, the use of one technology or another is not directly observed by the researcher. At most, only partial technological indicators, such as the ratios of concentrates per cow or land area per cow, are available.

Most papers have used a two-stage procedure to deal with the issue of production heterogeneity. In the first step, the sample is split into a number of mutually exclusive groups (classes) based on some *a priori* information about farms, and in the second stage different functions are estimated for each class/sub-sample separately (e.g. Hoch, 1962; Newman and Matthews, 2006; Kumbhakar et al., 2009). As this (clustering) approach allows the estimation of different technological characteristics for farms belonging to different groups, this is the most common approach followed in the literature to address the issue of farm production heterogeneity. However, if the *a priori* classification is not precise it will generate some errors in the first (allocation) stage of the procedure, which might also bias the technological parameter estimates of the second stage. In addition, Orea and Kumbhakar (2004) pointed out that two-stage procedures are not efficient because they do not use the information contained in one class to estimate the technology of other classes. This inter-class information may be quite important in our empirical application because farms belonging to different classes share some common features, although their technologies may be different.

To account for farm production heterogeneity, we advocate using a latent class model (hereafter LCM) that combines the stochastic frontier approach with a latent class structure. An LCM, also known as a finite mixture model, assumes that there is a

[4] The Agrarian Census conducted in 1999 (Agrarian Censuses are performed every ten years and the last one including the number of plots per farm is that from 1999) shows that the average number of plots per farm in Asturias is 12.5 (INE, 2014a).

finite number of structures (classes) underlying the data. These models classify the sample into several groups and each farm can be assigned to a particular group using the estimated probabilities of class membership.[5] Like other clustering methods, the LCM can be viewed as a clustering procedure that separates the sample and estimates the technology for each group, but in only one stage. Hence, in the absence of a precise prior classification of farms, the LCM clusters the farms by searching for differences in the production technology, which is exactly what we are looking for. Additionally, as both clustering and parameter estimation are carried out simultaneously, it does not ignore the above-mentioned inter-class information.

In this paper, we use an LCM to estimate the technology of dairy farms according to their degree of intensification. Since we are interested in the efficiency of each group, the latent class model is applied in a stochastic frontier framework. The general specification of a stochastic frontier LCM production function can be written as follows:

$$\ln y_i = f(x_i, \beta_j) + v_{i|j} - u_{i|j} \tag{1}$$

where i stands for farms and $j = 1,\ldots, J$ for class. The t subscript is dropped from all variables for notational ease. y_i is a measure of firms' output, x_i is a vector of explanatory variables, $v_{i|j}$ is a noise term that follows a normal distribution with zero mean and class-specific constant variance, and $u_{i|j}$ is a class-specific one-sided error term capturing farms' inefficiency.[6] In an LCM setting, the number of classes J should be chosen in advance by the researcher. In our application we assume that there are two classes corresponding to extensive and intensive systems of milk production, i.e. J=2. As the set of parameters β_j is j-specific, the technological characteristics vary across classes. It is worth noting that only between-group and not individual heterogeneity is controlled using a LCM because all farms belonging to a particular group share the same technology.[7]

Letting θ_j denote all parameters associated with class j, the conditional likelihood function of a firm i belonging to class j is $LF_{ij}(\theta_j)$. The unconditional likelihood for firm i is then obtained as the weighted sum of their j-class likelihood functions, where the weights are the probabilities of class membership, P_{ij}. That is:

$$LF_i(\theta, \delta) = \sum_{j=1}^{J} LF_{ij}\left(\theta_j\right) P_{ij}\left(\delta_j\right), \qquad 0 \le P_{ij}\left(\delta_j\right) \le 1, \qquad \sum_{j=1}^{J} P_{ij}(\delta_j) = 1$$

[5] Finite mixture models have been broadly used in several fields of research (see Beard et al., 1991; or Gropper et al., 1999, for simple applications; and Battese et al., 2004; or O'Donnell et al., 2008, for more comprehensive applications that aim to examine technological gaps using a metafrontier approach).

[6] Later on we assume that the variance of the inefficiency term varies across farms, and hence our stochastic frontier model can be viewed as a heteroscedastic model using the terminology coined by Kumbhakar and Lovell (2000).

[7] Several non-clustering methods have been also proposed to deal with unobserved heterogeneity across firms. Of particular interest are the panel data estimators recently introduced by Greene (2005), where unobserved heterogeneity is captured through a set of firm-specific intercepts that are to be estimated simultaneously with other parameters. However, this approach imposes common slopes for all farms, so all of them would share the same technological characteristics such as output elasticities and economies of scale.

(2)

where, θ=(θ_1,…, θ_j), δ=(δ_1,…, δ_j) and the class probabilities are parameterized as a multinomial logit model:

$$P_{ij}(\delta_j) = \frac{\exp(\delta_j' q_i)}{\sum_{j=1}^{J} \exp(\delta_j' q_i)}, \qquad j = 1, \dots, J, \qquad \delta_J = 0$$

(3)

where q_i is a vector of farm-specific variables. Therefore, the overall likelihood function resulting from (2) and (3) is a continuous function of the vectors of parameters θ and δ, and can be written as:

$$\ln LF\ (\theta, \delta) = \sum_{i=1}^{N} \ln LF_i\ (\theta, \delta) = \sum_{i=1}^{N} \ln \left\{ \sum_{j=1}^{J} LF_{ij}\ (\theta_j) P_{ij}\ (\delta_j) \right\}$$

(4)

Maximizing the above likelihood function gives asymptotically efficient estimates of all parameters. It should be pointed out that in this framework each farm belongs to one and only one class. Therefore, the probabilities of class membership just reflect the uncertainty that researchers or regulators have about the true partition of the sample. The estimated parameters can be used to compute posterior class membership probabilities using the following expression:

$$P(j|i) = \frac{LF_{ij}(\hat{\theta}_j) P_{ij}\ (\hat{\delta}_j)}{\sum_{j=1}^{J} LF_{ij}\ (\hat{\theta}_j) P_{ij}\ (\hat{\delta}_j)}$$

(5)

These posterior probabilities of membership can be then used to allocate each farm to a particular class, e.g. each farm could be allocated to the class with the higher posterior probability. It is worth noting that posterior probabilities can vary over time and therefore farms are allowed to switch between the extensive and intensive regimes.

3. Data

The empirical application is based on data proceeding from dairy farms located in the region of Asturias in northwest Spain. The agricultural sector in Asturias is specialized in milk production, which accounted for 52% of agricultural production in 2011 (SADEI, 2011). Asturias and the North of Spain in general are characterized by a high degree of LF. As policy makers are worried about the effect of LF on agricultural production, some land consolidation mechanisms have been implemented in the region over several decades. In particular, land consolidation processes affected 7,545 farms during the 2001-2010 period. Specifically, 17,395 hectares divided into 59,284 plots were concentrated into 15,720 plots over this period (SADEI, 2011).

The data used in the empirical analysis consist of an unbalanced panel of 144 Spanish dairy farms that were enrolled in a voluntary record-keeping program that was conducted by the regional government over a 13-year period from 1999 to 2011. This record-keeping program collects information about nine Dairy Farmers Management Associations located in Asturias. These associations are funded by the regional government and their main objective is to provide managerial advisory services to its associated farmers. To collect the data necessary for the advisory service, each farm is visited monthly by a technician. The monthly information is combined with annual inventories to carry out an annual report on each farm.

Furthermore, in 2008 a survey was conducted among the farmers affiliated with the Dairy Farmers Management Associations to determine the number of plots that each farm had in 2007. Our analysis was carried out assuming that the number of plots does not change if the number of hectares remains constant. That is, if for some farm the number of hectares in 2004 (2009) is different from that in 2007, then its observations corresponding to 2004 and previous years (2009 and following years) are excluded from the data. This explains why the number of observations reaches its maximum around 2007. This selection process leads to an unbalanced panel that contains 1,524 observations.

The dependent variable is the production of milk (y) and is measured in liters. Five inputs are considered: Labor (x_1) includes family labor and hired labor and is measured using Social Security expenses; Cows (x_2) is defined as the number of adult cows in the herd; Feed purchases (x_3) includes expenses on concentrates and forage purchases; Forage production expenses (x_4) are defined as the costs of seeds, fertilizers, machinery, fuel and land; and Animal expenses (x_5) are defined as livestock supplies, breeding and veterinary expenses. To take into account possible technological differences we include the dummy variable Coast which is equal to 1 for farms located in a coastal county. Time dummy variables were introduced to control for common factors that affect all farms and that vary over time, such as weather conditions and technical change (1999 is the base year). All the above monetary variables are expressed in 2011 Euro.

We have included five variables as efficiency determinants: Plots (z_1) is the (log) number of plots and is used as an LF measure; Family labor (z_2) is defined as the ratio of family labor to total labor; Own land (z_3) is the ratio of owned land to total land; Housing (z_4) is defined as a dummy variable equal to 1 for farms that use freestall housing (Cabrera et al., 2010); and Milking (z_5) is a dummy variable that takes the value 1 if the farm uses a milking parlor (Cabrera et al., 2010). Regarding the sample separating variables, we have included the ratio Concentrates/cows (q_1) to anchor our two classes to differences in milk production systems; Land (q_2) is the logarithm of farm land measured in hectares and the logarithm of the number of plots (q_3).[8,9]

Table 1 provides a descriptive summary of the variables used in this study. The dairy farms in the sample are highly specialized with more than 80% of farm income coming from dairy sales. The average farm size in the sample is larger than the average

[8] LF can be measured in several ways; including the Simpson index (Simpson, 1949; used by Blarel et al., 1992 and Wu et al., 2005; among others), the Januszewski index (Januszewski, 1968; used by Austin et al., 2012); the average plot size (Nguyen et al., 1996; Wadud and White, 2000) and the number of plots (Wan and Cheng, 2001; Falco et al., 2010). The use of the Simpson or the Januszewski indexes is not possible given that the data does not contain information about the plots' surface (only the farm land surface and number of plots is available). Thus, in this study LF was measured using the number of plots.
[9] Note that q_3 is the same variable as z_1.

Spanish farm (31 cows in 2010; Eurostat, 2014) but quite similar to the average farm size in some of the main milk producing countries in Europe such as France or Germany (46 cows; Eurostat, 2014). Differences among farms are quite important as the standard deviation of milk production is 69% of mean production. Finally, it is worth noting that land is highly fragmented since the average number of plots per farm is approximately thirteen.

INSERT TABLE 1

4. Results

We assume that the frontier production function in (1) is a Translog function where, as is customary, the explanatory variables have been divided by their geometric mean. In particular, the model to be estimated is:

$$\ln y = \beta_0 + \sum_{k=1}^{5} \beta_{k|j} \ln x_k + \frac{1}{2}\sum_{k=1}^{5}\sum_{h=1}^{5} \beta_{kh|j} \ln x_k \ln x_h + \beta_{C|j} Coast + \sum_{t=2000}^{2011} \beta_{t|j} D_t + v_{|j} - u_{|j} \tag{6}$$

where the β*'s* are parameters to be estimated, and the first-order coefficients can be interpreted as output elasticities for a farm characterized by an input endowment equal to the sample geometric mean. The stochastic part of the model is decomposed into a noise term, v, and an inefficiency term, u. While v is assumed to be normally distributed, the inefficiency term is assumed to follow a half-normal distribution.

Unlike most papers which have estimated LCM stochastic frontier models, we assume that the variance of the inefficiency term is heteroscedastic and varies across farms. In particular, we model the standard deviation of u as a function of the technical efficiency determinants mentioned in Section 3, that is:

$$\ln \sigma_{u|j} = \alpha_{0|j} + \alpha_{1|j} z_1 + \alpha_{2|j} z_2 + \alpha_{3|j} z_3 + \alpha_{4|j} z_4 + \alpha_{5|j} z_5 \tag{7}$$

Regarding the prior class probabilities, the probability of belonging to the extensive group (hereafter $P(\delta)$) is parameterized as follows:

$$P(\delta) = \frac{\exp(\delta_0 + \delta_1 q_1 + \delta_2 q_2 + \delta_3 q_3)}{1 + \exp(\delta_0 + \delta_1 q_1 + \delta_2 q_2 + \delta_3 q_3)} \tag{8}$$

The estimation was carried out using the econometric package GAUSS. The parameter estimates of $P(\delta)$ are shown in Table 2. The coefficients of the three variables are significant and show the expected sign. Thus, large values of the concentrates/cow ratio (q_1) characterize intensive farms and, therefore, diminish the probability of belonging to the extensive group. The probability of being an extensive farm increases with farm land (q_2), an expected result because extensive farms need land for foodstuff production. The more important result for this study is that the number of plots (q_3) diminishes the probability of using an extensive technology, as would be expected. This outcome seems to indicate that LF has been an important obstacle to adopting extensive production processes in our sample.

INSERT TABLE 2

Based on the estimated prior class probabilities, posterior probabilities of belonging to either the extensive or intensive groups were computed using equation (5). While 823 observations were classified as extensive, 701 observations were considered as intensive. It is worth noting that the classification of each observation was quite clear in general as the average posterior probability of being extensive (intensive) of those observations classified in the extensive (intensive) group was very high, 87.2% (84.5%).

Table 3 provides the average value of the variables included in the empirical analysis for each group. In addition to the fact that intensive farms are slightly larger than extensive farms, other differences comply with the expected characteristics of both types of farms. For example, while intensive farms use more concentrates per cow, extensive farms use a larger land area. The greatest difference by far has to do with the number of plots. The number of plots of intensive farms is almost double that of extensive farms, despite having a smaller average land area. The latter result seems to indicate again that the adoption of extensive systems of milk production has been conditioned by the degree of LF.

INSERT TABLE 3

Tables 4 and 5 provide the estimated production frontier parameters for extensive and intensive farms respectively. In general, notable differences in estimated parameters are found between the types of farms. For instance, the first-order coefficient of Labor (x_1) is not statistically significant for extensive farms. [10] The lack of significance of labor is not unusual in studies analyzing family farms with very little hired labor (see, for example, Ahmad and Bravo-Ureta, 1995; Cuesta, 2000; Roibas and Alvarez, 2012). This is the case in our application where hired labor represents only 5% of total labor on extensive farms. Interesting enough, the proportion of hired labor in intensive farms is almost double and the labor elasticity is highly significant in this technology. The elasticity with respect to cows (x_2) for intensive farms is quite larger than that for extensive farms, an expected result given that the production per cow is higher for intensive farms. While the elasticity of feed purchases (x_3) is larger for extensive farms, most likely due to the diminishing returns to the use of concentrates, the elasticities of forage production expenses (x_4) and animal expenses (x_5) are relatively low, though slightly larger in both cases for the extensive technology. We also find significant differences in productivity in favor of coastal farms for the intensive technology, whereas no difference was found for extensive farms. Time dummy variables show rather similar values for both technologies. The parameter estimates indicate that the productivity in 2011 was 18% larger than in 1999. This result suggests that some technological change took place over the sample period due to genetic

[10] Differences in the first-order parameters must be interpreted with caution because these parameters are related to the input elasticities of the sample average farm using both technologies, and the sample average farm does not correspond with either the average intensive farm or the average extensive farm. When the output elasticities in each group are calculated using the average observation belonging to the corresponding group, the computed elasticities are slightly closer than those obtained through the first order parameters.

progress,[11] feeding technologies or cow comfort improvements. However, the time dummy parameters do not follow a monotonic path. The maximum productivity was achieved in 2006 for both technologies which suggests that other period characteristics like weather conditions also play a role in determining farm productivity.

INSERT TABLE 4

INSERT TABLE 5

We have also calculated the elasticity of scale for both types of farms and tested whether they are significantly different from 1 using the Wald test. While the elasticity of scale takes a value of 1.002 for the extensive technology, it is equal to 1.144 for the intensive one. Whereas the Wald test does not reject the constant returns hypothesis for the extensive farms, it rejects this hypothesis for intensive farms.[12] Therefore, the larger size of intensive farms is likely (or partially) caused by the existence of increasing returns to scale.

Tables 6 and 7 provide the parameter estimates of the determinants of farms' inefficiency. We have also used the estimated coefficients of equation (7) to calculate the expected technical efficiency of each observation.[13] As in Alvarez and Corral (2010), on average the technical efficiency of intensive farms was found to be slightly larger (92.2%) than that corresponding to extensive farms (90.2%). Moreover, notable differences between the technologies with regard to efficiency determinants were also found. For instance, while the effects of the proportion of own land (z_3), freestall housing (z_4) and use of a milking parlor (z_5) on intensive farms' efficiency are statistically significant, they are not significant determinants of extensive farms' efficiency. In particular, the proportion of own land is found to reduce technical efficiency. This effect may be due to the possibility of choosing optimal rental land in a context where many farms abandon production, leaving its land unused.[14] As in Corral et al. (2011), freestall housing is found to improve technical efficiency and the use of a milking parlor diminishes technical efficiency. On the other hand, the number of plots (z_1) reduces the technical efficiency of extensive farms, as was expected, while it is not significant for the intensive farms (though it is almost significant at the 10% level). A Wald test allows us to reject the hypothesis that both effects are of the same magnitude in both technologies.[15] As expected, the impact of LF on farm productivity is larger for those (extensive) farms where milk production is mostly dependent on self-produced foodstuff.

INSERT TABLE 6

INSERT TABLE 7

We have also performed several simulation exercises to analyze the effects of a potential reduction in the number of plots due to a hypothetical land concentration process. In particular we examine the evolution of milk production, farms' variable

[11] See Roibas and Alvarez (2010), Roibas and Alvarez (2012)

[12] In this case, the value of the Wald test is 89.29, which is significant for any usual level of significance.

[13] The expected technical efficiency is calculated using the formula $E[u] = \sigma_u\sqrt{2/\pi}$

[14] The number of farms in Asturias descend from 42824 in 1999 (INE, 2014a) to 22688 in 2009 (INE, 2014b)

[15] It takes a value of 4.31, which is significant at 5% level.

profits and the probabilities (both prior and posterior) of adopting the extensive technology when the number of plots is progressively reduced from its current value to 10% of this value. This range of values includes the reduction in the number of plots achieved in the land concentration processes carried out in Asturias, which roughly corresponds to a 27% reduction of its initial value.

The simulation exercises rely on the estimated coefficients of the efficiency determinants to calculate the technical efficiency of each observation associated with a particular number of plots, maintaining the rest of the efficiency determinants constant. For each observation, the simulated production level is obtained by multiplying the technically efficient production level (which is computed using the parameter estimates of both extensive and intensive frontiers) and the corresponding technical efficiency score. Figure 1 shows the average increase in production for extensive and intensive farms depending on the percentage reduction in plots.[16,17] Figure 2 resumes the impact of the reduction in the number of plots on the variable profits of extensive and intensive dairy farms. The simulated variable profits were computed by multiplying the simulated production by milk price and then subtracting feed purchases, forage production expenses and animal expenses.

INSERT FIGURE 1

INSERT FIGURE 2

Figure 1 shows that reducing the number of plots to 27% of its current value generates a 6% production increase for extensive farms and a 2% increase for intensive farms. Therefore, our calculations show that a land consolidation process would have a much larger impact on extensive farms' productivity. In addition, our simulation in Figure 2 shows that reducing the number of plots to 27% of its current value would increase extensive farms' profits by 16%, while this profit increase would be much lower (6%) for intensive farms. This result is roughly in line with Corral *el al.* (2011), who, considering a common technology for the whole set of farms, found an 11.7% increase in variable profits with a similar reduction in the number of plots.

Prior probabilities of belonging to the extensive group were simulated using the parameters presented in Table 2. Again, we calculate the prior probabilities using the current number of plots and the reductions described above, given the values for each observation of land and concentrates per cow. Posterior probabilities were calculated using the simulated prior probabilities and assuming that the reductions in the number of plots do not affect the relative goodness-of-fit of both (i.e. intensive and extensive) sets of parameters.[18] Figures 3 and 4 provide the average probability of belonging to the extensive group for extensive and intensive farms respectively.

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[16] The simulation uses the parameters in Tables 6 and 7. It is worth noting that the effect of the number of plots on intensive farms' efficiency is not significant and the results related to these farms must therefore be interpreted with caution.

[17] Percentage increases in production do not exactly correspond to increases in technical efficiency because while the former are calculated by dividing the increase in production due to the reduction in the number of plots by the expected production with the current number of plots, the latter are calculated using as denominator the efficient and not the expected production.

[18] In particular, we assume that the reductions in the number of plots do not alter the ratio of likelihood functions:

INSERT FIGURE 3

INSERT FIGURE 4

Both figures show that the probability of belonging to the extensive group increases when the number of plots declines. In particular, Figure 4 shows that a 50% reduction in the number of plots leads the average prior and posterior probabilities of intensive farms to be 69% and 59% respectively. Hence, a 50% reduction in the number of plots could provide sufficient incentives for most of the intensive farmers to adopt extensive production processes. Moreover, a reduction in the number of plots similar to that achieved by the concentration processes carried out in Asturias would yield prior and posterior probabilities values of 90% and 84% respectively. Consequently, such a reduction in the number of plots would induce most intensive farmers to choose the extensive technology.

4. Conclusions

LF has frequently been found to be a handicap in agricultural production, suggesting that land consolidation processes could help in improving farms' productivity and profitability. As the effect of LF on dairy farm productivity is related to foodstuff production inside the farm, two different hypotheses are analyzed in this study. First, as LF may make it difficult to produce foodstuff, we test whether its impact is larger on extensive farms, which are more dependent on self-produced feed, than on intensive farms. Second, as LF may mainly affect extensive production, we test whether it will be an obstacle to adopting such a technology. Both hypotheses have been analyzed using a latent class stochastic frontier approach where the number of plots is included as a determinant of technical efficiency and as a variable conditioning the technology choice by farmers.

Our results show that, in effect, the impact of LF is larger on dairy farms using extensive production processes. Therefore, any policy reducing the number of plots will mainly affect the productivity - and thus the profitability - of extensive dairy farms. In a context where the price of milk is expected to fall due to the disappearance of production quotas, a land consolidation process may be crucial for the survival of dairy farms even in regions where the climatic conditions are ideal for milk production.

Our analysis also indicates that LF conditions the technology choice of farmers and proves to be an important obstacle to the adoption of extensive production processes. This is an important result given that the extensive production technology generates less ground and water pollution than the intensive technology. For this reason the Common Agricultural Policy provides incentives to dairy farmers to adopt extensive production processes. However, our results demonstrate that the change from an intensive to an extensive technology is unlikely when the farm land is highly fragmented. Land consolidation processes could be considered as a necessary complement to other environmental policies in order to encourage intensive dairy farmers to adopt a less polluting technology.

$$\frac{LF_{ij}(\hat{\theta}_j)}{\sum_{j=1}^{J} LF_{ij}(\hat{\theta}_j)}.$$

Future research should explore the technology change from intensive to extensive production processes. Indeed, our simple latent class model ignores the temporal nature of the data, with the consequence that a given farm may move freely from one class to another over time. Although switching from intensive to extensive production processes is technically possible in our case (and vice versa), we would expect some degree of persistence in class membership, as adoption of a different technology is likely to involve important adjustment costs. To appropriately deal with this issue, an alternative latent class model which explicitly considers the transition from one class to another should be developed. Such an analysis would require a database including information about the farms' number of plots during the whole sample period.

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Table 1: Summary Statistics of the Dairy Farms

Variable	Average	Std. Dev.	Max.	Min.
Milk	330900	227033	1322276	9079
Labor	4577	2623	53310	160
Cows	42	23	151	3
Feed purchases	158433	120749	1172081	10809
Forage production expenses	29915	24413	195297	675
Animal Expenses	15324	11964	160366	769
Coast	0.70	0.46	1	0
Plots	13.29	7.92	46	2
Family labor	0.93	0.19	1	0
Own land	0.56	0.28	1	0
Housing	0.53	0.50	1	0
Milking	0.49	0.50	1	0
Concentrates/cow	3546	1214	14801	885
Land	19	10	82	2

Table 2: Prior probability of using extensive technology

Variable	Estimates	t-Statistic
Constant	0.343	1.547
q_1	-4.612***	-6.366
q_2	1.386***	3.539
q_3	-4.141***	-6.416

*Indicates significance at 10%; ** significance at 5%; *** significance at 1%

Table 3: Average values of variables for extensive and intensive farms

Variable	Extensive Farms	Intensive Farms
Milk	305611	360591
Labor	4595	4556
Cows	41	43
Feed purchases	135186	185727
Forage production expenses	28645	31406
Animal Expenses	14410	16397
Coast	0.78	0.61
Plots	9.49	17.75
Family labor	0.95	0.91
Own land	0.54	0.58
Housing	0.47	0.61
Milking	0.44	0.54
Concentrates/cow	3050	4128
Land	20	18

Table 4: Production function frontier parameters for extensive farms

Variable	Estimates	t-Statistic	Variable	Estimates	t-Statistic
Constant	12.423***	539.114	**$(\ln x_4)^2$**	0.032	0.969
$\ln x_1$	0.005	0.307	**$\ln x_4 \times \ln x_5$**	0.015	0.499
$\ln x_2$	0.367***	10.610	**$(\ln x_5)^2$**	0.035	0.866
$\ln x_3$	0.448***	21.516	**Coast**	-0.013	-0.927
$\ln x_4$	0.080***	5.647	**D_{2000}**	0.015	0.546
$\ln x_5$	0.102***	5.812	**D_{2001}**	0.034	1.289
$(\ln x_1)^2$	0.066	1.553	**D_{2002}**	0.078***	2.808
$\ln x_1 \times \ln x_2$	0.344***	5.220	**D_{2003}**	0.142***	5.235
$\ln x_1 \times \ln x_3$	-0.118***	-2.911	**D_{2002}**	0.158***	5.953
$\ln x_1 \times \ln x_4$	-0.076**	-2.507	**D_{2005}**	0.246***	9.159
$\ln x_1 \ln x_5$	-0.019	-0.476	**D_{2006}**	0.260***	10.213
$(\ln x_2)^2$	-0.310***	-2.844	**D_{2007}**	0.227***	9.247
$\ln x_2 \times \ln x_3$	-0.210***	-2.622	**D_{2008}**	0.150***	6.156
$\ln x_2 \times \ln x_4$	0.156**	2.465	**D_{2009}**	0.174***	6.869
$\ln x_2 \times \ln x_5$	0.100*	1.934	**D_{2010}**	0.221***	8.152
$(\ln x_3)^2$	0.215***	3.503	**D_{2011}**	0.181***	6.806
$\ln x_3 \times \ln x_4$	-0.075**	-2.516	**Ln σ_v**	-2.422***	-25.671
$\ln x_3 \times \ln x_5$	-0.063*	-1.677			

Table 5: Production function frontier parameters for intensive farms

Variable	Estimates	t-Statistic	Variable	Estimates	t-Statistic
Constant	12.428^{***}	659.608	**$(\ln x_4)^2$**	0.082^{***}	2.774
$\ln x_1$	0.081^{***}	5.831	**$\ln x_4 \times \ln x_5$**	0.081^{***}	3.067
$\ln x_2$	0.719^{***}	23.256	**$(\ln x_5)^2$**	-0.104^{***}	-2.598
$\ln x_3$	0.245^{***}	10.374	**Coast**	0.049^{***}	5.178
$\ln x_4$	0.042^{***}	3.201	**D_{2000}**	0.040^{**}	2.161
$\ln x_5$	0.058^{***}	4.304	**D_{2001}**	0.061^{***}	3.265
$(\ln x_1)^2$	0.032	1.161	**D_{2002}**	0.095^{***}	4.664
$\ln x_1 \times \ln x_2$	0.047	0.923	**D_{2003}**	0.114^{***}	5.970
$\ln x_1 \times \ln x_3$	-0.056	-1.355	**D_{2002}**	0.136^{***}	7.023
$\ln x_1 \times \ln x_4$	0.008	0.309	**D_{2005}**	0.207^{***}	10.834
$\ln x_1 \ln x_5$	-0.027	-0.979	**D_{2006}**	0.254^{***}	14.153
$(\ln \mathrm{x}_2)^2$	0.691^{***}	4.575	**D_{2007}**	0.209^{***}	10.989
$\ln x_2 \times \ln x_3$	-0.371^{***}	-3.559	**D_{2008}**	0.140^{***}	7.354
$\ln x_2 \times \ln x_4$	-0.273^{***}	-5.297	**D_{2009}**	0.194^{***}	10.159
$\ln x_2 \times \ln x_5$	0.021	0.366	**D_{2010}**	0.208^{***}	9.983
$(\ln x_3)^2$	0.088	0.896	**D_{2011}**	0.189^{***}	8.822
$\ln x_3 \times \ln \mathrm{x}_4$	0.089^{**}	2.465	**$\mathrm{Ln}\ \sigma_v$**	-2.885^{***}	-25.311
$\ln x_3 \times \ln x_5$	0.089^{*}	1.858			

Table 6: Efficiency determinants for extensive farms

Variable	Estimates	t-Statistic
Constant	-1.870***	-13.923
z_1	0.665***	3.192
z_2	0.661	1.607
z_3	-0.242	-1.504
z_4	-0.143	-0.688
z_5	-0.003	-0.013

Table 7: Efficiency determinants for intensive farms

Variable	Estimates	t-Statistic
Constant	-2.572***	-13.096
z_1	0.188	1.611
z_2	0.240	1.022
z_3	0.727***	3.002
z_4	-0.524*	-1.781
z_5	0.903***	2.860

Figure 1: Increase in production

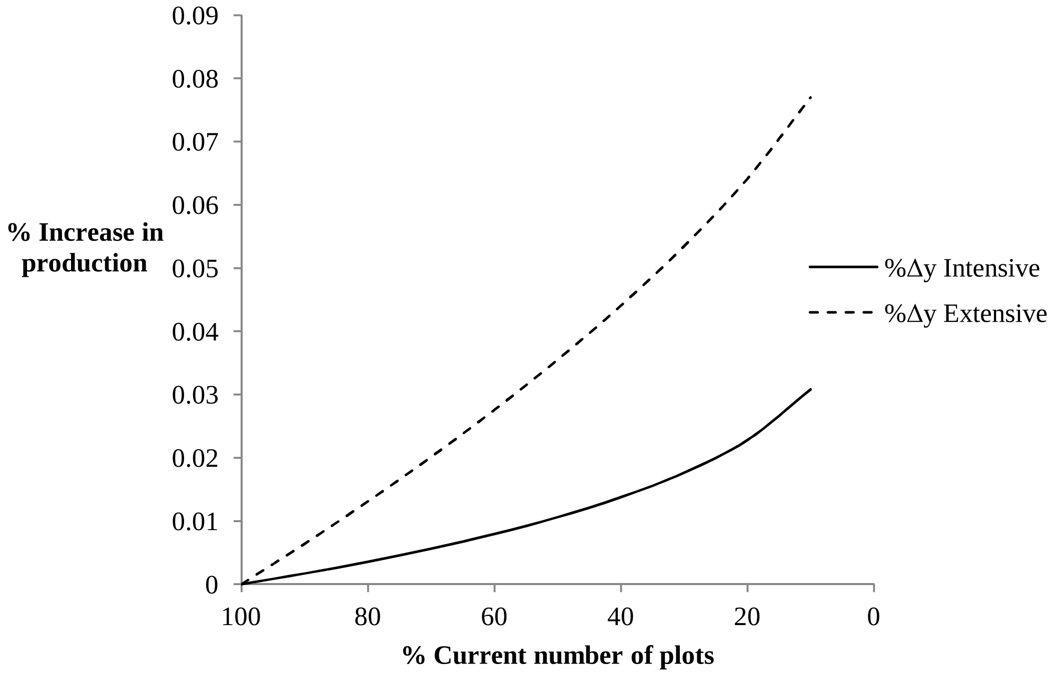

Figure 2: Increase in profits

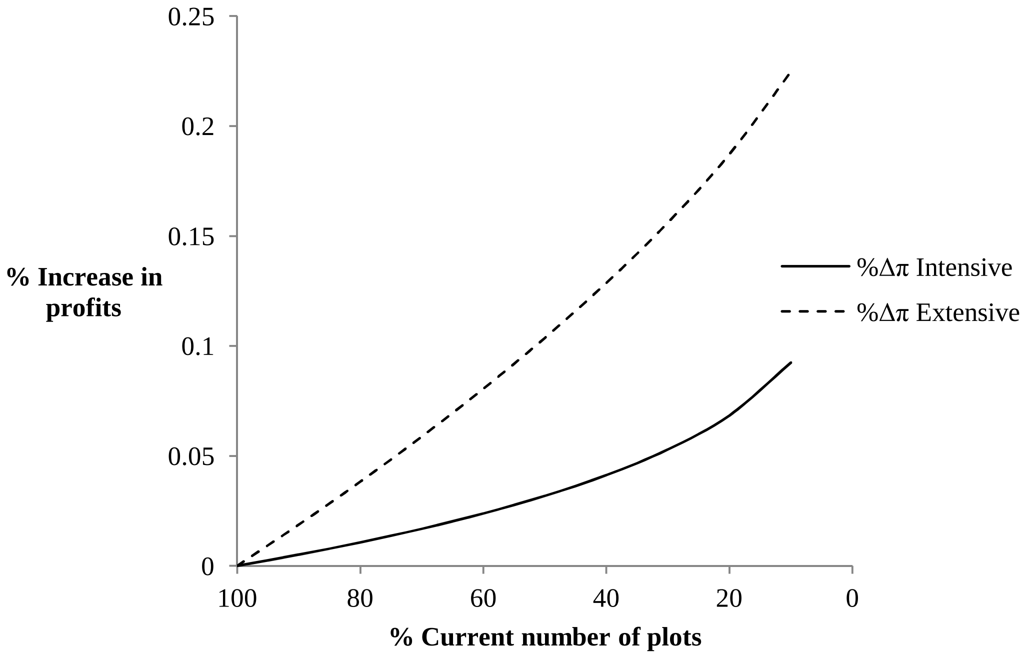

Figure 3: probability of extensive (extensive group)

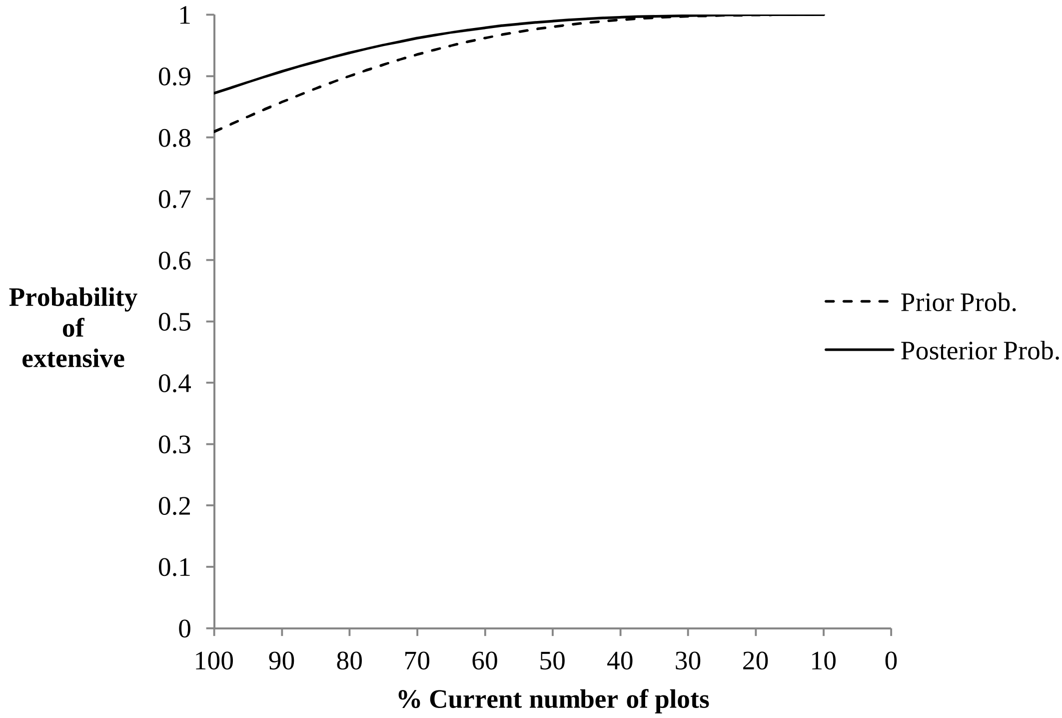

Figure 4: probability of extensive (intensive group)