

ORIGINAL ARTICLE

Does land consolidation promote livestock production and combat rural depopulation in northern Spain?

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Abstract

This paper evaluates the effect on livestock production and rural population of the land consolidation (LC) processes that occurred over recent decades in Asturias, an autonomous region located in north-west Spain. We use a novel Difference-in-Difference (DiD) model which allows for multiple LCs at different points in time and for spatial spill-overs. As many parishes have been involved in two or more LC processes, we test whether we can simplify our analysis using a specification for these parishes that accumulates the effect of consecutive, and often distant, LC processes. We find that this simplification can be implemented when we analyse the effect of the LC processes on parishes' livestock production, but not when we examine their effects on parish population. We find that parish livestock production increases on average by about 3% once we take into account spatial effects, and that LC processes have especially attenuated the decline in the number of farms in (coastal) parishes where dairy farms predominate. We do not find strong evidence regarding the effectiveness of LC processes in redressing rural depopulation, except in some of the parishes located in western Asturias.

KEYWORDS

agricultural land consolidation, DiD, livestock production, rural depopulation

JEL CLASSIFICATION

C21, D24, Q15

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1 | INTRODUCTION

Agricultural land consolidation (LC) has been acknowledged as an effective instrument to redress the effect of land fragmentation (LF) on agriculture and improve the competitiveness of agricultural products in Europe and other countries. Assessments of the economic consequences of land fragmentation have a long history in agricultural economics and related disciplines. Most empirical studies have concluded that the division of holdings operated by a single farmer into discrete plots that are dispersed over a wide area, negatively affects agricultural production and food security (e.g., Knippenberg et al., 2020; Orea et al., 2015). These findings have highlighted the need for policies to both improve land and labour mobility and promote the transfer and long-term leasing of agricultural land (see, e.g., Bradfield et al., 2021). The economic impact of these LC measures has also attracted the attention of many applied researchers. A summary of this literature can be found in Álvarez et al. (2020). Their review shows that the methodologies used in this literature vary from country to country. This is due to a variety of reasons, including data availability, differences in both data disaggregation and data collection, the existence of different objectives of land-use policy or because different categories of LC effects are being analysed. Furthermore, contradictory conclusions have been found regarding the impact of LC on several of the above categories.

Land fragmentation may also offer some positive outcomes. For instance, as Clough et al. (2020) point out, landscapes with small fields may have some positive effects in terms of reducing weather and pest risk or enhancing biodiversity. In this sense, it should also be pointed out that some studies (e.g., Zhang et al., 2014) show that LC has had a negative impact on the value of ecosystem services and on landscape diversity, whereas other papers find a positive ecological effect (e.g., Hartvigsen, 2014; Yu et al., 2010).

This paper evaluates the effect on livestock production and rural population of the LC processes that occurred over recent decades in Asturias, an autonomous region located in north-west Spain. A predominantly traditional agricultural economy and a historical tradition of property inheritance by subdivision within families have contributed towards a high degree of LF in rural Asturias. Regional policy-makers have implemented more than 250 public LC processes in this region since the 1960s in order to improve economic activity in rural areas, increase farmer income, and stabilise rural populations. According to the information provided by the Principality of Asturias, the LC processes carried out in Asturias over this period have involved more than 28,000 owners and about 60,000 hectares of land with an average investment amounting to €2300 per hectare. These LC processes have resulted in a reduction of the number of plots from 224,000 to 58,000, thus representing an average decline of 70%. From the point of view of the observation units (parishes) used in our estimations, it is worth highlighting that the share of parish areas that were subject to LC is on average about 24%, with LC processes in some parishes involving almost 100% of their area. Moreover, a combination of access to European funds and a new regulation that avoided negotiation and legal costs and allowed the public administration to change access routes to the new plots has served to intensify the number of LC processes since 2000.¹

Our contribution to the existing literature on agricultural LC is twofold. First, we perform our analysis using highly disaggregated data. Indeed, our observations are *parishes*, that is, Christian territorial entities that are much smaller than the standard municipalities used in previous studies. An advantage of this over previous papers examining LC processes is that it allows us to introduce

¹This sizeable enforcement is most likely to have been caused by the Legal Decree 80/1997 that established the conditions under which farmers can request the regional government to initiate an LC process. This regulation avoids negotiation and legal costs and allows the public administration to change access routes to the new plots. Nevertheless, following the principles established in the Agrarian Regulation and Rural Development Law of 1989, the public administration itself can also promote a local LC process (Boletín Oficial Del Principado de Asturias, 1989, 1997).

spatial interdependence into our analysis, understood as the benefits obtained by a parish when using the plots and infrastructures existing in other parishes. A literature exists at micro-level (farms) that introduces spillover effects based on the idea that a farmer's productive performance may be related to one of its neighbours via different channels, such as the imitation, motivation and learning effects that occur between neighbouring farmers in the adoption of new technologies and in the application of more efficient practices (see, e.g., Areal et al., 2012; Billé et al., 2018; Skevas & Lansink, 2020). However, to the best of the knowledge of the present authors, no studies actually analyse these effects in the case of LC processes. Moreover, as the consolidation of farming lands always involves several farms or households, the use of micro-level or farm-level data gathered via questionnaires might underestimate the real effects of the LC processes. The proper nature of LC thus calls for using geo-spatial data that aggregates neighbouring farms.

Our second contribution has to do with the Difference-in-Difference (DiD) approach used to measure the LC effects. The LC processes examined in this paper do not take place at the same time and thus the so-called 'treatment periods' vary across parishes. Moreover, most DiD applications assume that each unit (parish) at most receives a unique treatment. This is not the case in our application as many parishes have been involved in two or more LC processes. Extending the previous framework to a multi-treatment setting is far from simple and opens new issues and questions. Using a novel DiD specification, we show that we can accumulate sequential treatments as long as they have the same effect on outcome. Therefore, in addition to the well-known 'parallel trends' (PT) assumption, in a multi-treatment DiD model, we should test a new assumption labelled as the 'common sequential parameter' (CSP) assumption.

Although we have information on all the public LC processes in Asturias, including those that ended before 2000, we focus our analysis on the period 2001–2017 because of the lack of reliable data on farm activity at parish level in the period prior to this. We will focus our analysis on three different categories of LC effects: livestock activity measured in terms of farm figures; restructuring of livestock production measured as average cows per farm; and parish population. Unfortunately, it is not possible to extend the study to other categories such as the impact on the environment, the local economy and other social effects.

2 | EMPIRICAL SPECIFICATION

In this section we develop a simple *multi-treatment* two-way FE estimator to estimate the effect of LC on parishes' outcome. In our application a treatment is equivalent to a LC process executed in a particular parish. As several LC processes have been executed in some of our parishes at different points in time, we extend the *one-treatment* framework introduced by Borusyak and Jaravel (2017) and Strezhnev (2018) to a multi-treatment setting.

We first introduce the notation to be used throughout this section. Consider a panel of $i = 1, \dots, N$ parishes or units observed in $t = 1, \dots, T$ periods. Let Y_{it} be the outcome of interest for unit i at time t . We first consider the units that receive a single treatment during the sample period. As is customary, we will use a binary dummy variable (D_{it}) to indicate when a unit has been treated. Borusyak and Jaravel (2017) define two useful temporal variables. Let E_i be the first period under which each unit is treated, or *event time*. They next define the so-called *relative time* $K_{it} = t - E_i$, which denotes the number of periods relative to (i.e., since) the event. In our application/setting, this variable simply measures the age of a land consolidation process, that is, the time that has passed since a land consolidation process took place in a particular parish. Once a parish has been treated, we assume that it will stay treated forever.²

²This also occurs in our application as the plot reallocation and new local infrastructures are expected to last decades.

Imai et al. (2018) labelled this assumption as the *stable policy change* (SPC) assumption. Under the SPC assumption, the treatment indicator D_{it} is equal to zero if $t < E_i$, and equal to one if $t \geq E_i$.

In a fully flexible specification of our model we should allow for differences in the treatment effects over time and across units. In order to limit the number of treatment parameters and facilitate their economic interpretation, we first assume that the treatment effect varies with the age of the treatment (K_{it}).³ As this assumption might imply that the treatment effects are the same for all units, except for their different treatment timings, we next assume that they also depend on the intensity of the treatment ($I_i \geq 0$) (see, e.g., Abadie, 2005; Alonso & Andrews, 2019).

As unobserved time-varying factors might cause the failure of the so-called *parallel trend* (PT) assumption, we try to explicitly model the unobserved time-varying heterogeneities. A widely used strategy (see, e.g., Wolfers, 2006) is to add a set of group-specific linear trends to a conventional two-way FE model that already includes a fixed effect parameter for each unit (α_i) and a fixed parameter for each time period (δ_t).⁴ As Xu (2017) points out, this strategy works if treatment is randomly assigned *conditional* on both the fixed effects and the imposed trends.⁵ A second strategy aimed at making the PT assumption more credible relies on a set of control variables (X_{it}) that, in addition, allows the treatment effects to depend on units' observable characteristics.⁶

Recall that some units receive more than one treatment during the sample period. To distinguish them, each specific treatment received by unit i is denoted by superscript $m = 1, \dots, M$, where M counts all LC processes that a parish could potentially undergo. When a unit has been treated several times, we can test whether sequential treatments have the same effect on outcome. We refer to this as the *common sequential parameter* (CSP) assumption. If this assumption is not rejected, the second LC process has the same effect as the first one, the third LC process has the same effect as the second one, and so on. In this case, we can considerably simplify the model and replace all the dummy variables indicating whether a parish was exposed to an intervention at some point with a single variable measuring the number of LC processes. The age and intensity of each treatment can also be aggregated in a similar fashion under the CSP assumption (see Appendix). This assumption is not only very helpful when many treatments exist but also facilitates any analysis of the average effects per treatment.⁷

In summary, under the *stable policy change* (SPC) and *common sequential parameter* (CSP) assumptions, the simplest multi-treatment two-way FE model to be estimated is:

$$Y_{it} = \alpha_i + \delta_t + \tau_g t + \pi X_{it} + \gamma n_{it} + \beta K_{it}^M + \mu I_{it}^M + \varepsilon_{it}, \quad (1)$$

³Borusyak and Jaravel (2017) show that the standard two-way FE estimator suffers from severe biases in a multi-period setting. Although they advocate running non-parametric specifications of treatment effects and averaging the effects manually to deal with this issue, they alternatively assume a *parametric* specification in their simulation exercise where the treatment effects change at a constant rate. In our application, we use this approach to allow the LC effects to vary over time.

⁴In our application, the groups are municipalities.

⁵Nilsson (2019) points out that participation in LC programmes in Rwanda was not random but concentrated on the districts with better agroecological conditions. We do not need to mitigate this selection bias in our application because we are using an FE estimator and the Department of Planning and Rural Infrastructures of the Government of the Principality of Asturias has confirmed that, as in Nilsson (2019), most of the conditions that should be in place before a LC project is undertaken are *time-invariant* as they are geographical in nature—for example, land quality, location of natural resources, distribution of current infrastructures, the existence of appropriate legislation, and so on.

⁶We are aware that measuring the treatment effects using this conditional (on X-covariates) model can be problematic if X_{it} is part of the causal effect of D_{it} on Y_{it} . We propose measuring the total treatment effect as $\gamma_{it} + \pi \partial X_{it} / \partial D_{it}$, where $\partial X_{it} / \partial D_{it}$ is computed using an auxiliary regression of X_{it} on D_{it} .

⁷As pointed out by a referee, our multi-treatment concept can be viewed as a sort of measure of the intensity of *all* LC processes executed in a particular parish. The validity of this interpretation depends, however, on the CSP assumption.

where $n_{it} = \sum_{m=1}^M D_{it}^m$ is the number of treatments received by unit i at period t ; $K_{it}^M = \sum_{m=1}^M K_{it}^m D_{it}^m$ represents the cumulative age of the treatments; $I_{it}^M = \sum_{m=1}^M I_{it}^m D_{it}^m$ represents the treatment intensities; g stands for municipality; and ε_{it} is a mean-zero error term.⁸ The municipality-specific parameter τ_g allows us to control for the existence of municipality-specific trends. The parameter γ can be interpreted as the *initial* effect of an LC with *no* investment in the development and implementation of the LC process. Whereas β allows the treatment effect to vary with the age of the treatments, μ allows it to vary with their intensity. For a never treated or control unit, n_{it} , K_{it}^M and I_{it}^M only take zero values.

Note that the above specification assumes that the treatment effects only depend on LC cumulative ages and intensities. This assumption has two implications. First, it implies that the treatment effects do not depend on unit characteristics, which is a strong assumption in our application as LC might be more (less) effective in parishes with relatively more milk (beef) livestock production and/or using more (less) traditional production systems. Second, the treatment effects in Equation (1) are *neutral* in the sense that the units' outcome function (technology) does not change with, say, the number of treatments. In order to get a non-neutral specification of our model, we propose estimating the following *non-neutral* model:

$$Y_{it} = Y_{it}^* + \underbrace{\gamma n_{it} + \beta K_{it}^M + \mu I_{it}^M}_{\text{Neutral effect}} + \underbrace{(\gamma_x n_{it} + \beta_x K_{it}^M + \mu_x I_{it}^M) X_{it}}_{\text{Non-neutral effect}} + \varepsilon_{it}, \quad (2)$$

where $Y_{it}^* = \alpha_i + \delta_t + \tau_g t + \pi X_{it}$ is the *outcome function* with no interventions.

The foregoing models do not allow for differences across cohorts of treatments, except for their different timings and intensities of treatment. This seems to be a strong assumption in our application because the LC processes executed each decade are to some extent of a different nature (see Section 3.5). In order to take into account this issue, we also estimate a model with cohort-specific parameters in the spirit of Borusyak and Jaravel (2017) and Strezhnev (2018), where the treatment cohorts are defined in terms of decades. The neutral effect in this model is specified as follows:

$$\sum_{j=1}^J \gamma_j D_{C_{ji}}^M + \sum_{j=1}^J \beta_j K_{C_{ji}}^M + \sum_{j=1}^J \mu_j I_{C_{ji}}^M, \quad (3)$$

where $d_{m \in C_j} = 1$ if treatment m belongs to cohort $j = 1, \dots, J$, C_j is the set of treatments that belong to cohort j , $D_{C_{ji}}^M = \sum_{m=1}^M D_{it}^m d_{m \in C_j}$, $K_{C_{ji}}^M = \sum_{m=1}^M K_{it}^m d_{m \in C_j}$, and $I_{C_{ji}}^M = \sum_{m=1}^M I_{it}^m d_{m \in C_j}$.⁹ Notice that, as we now split all treatments into different cohorts, we can redefine the number of treatments and their cumulative age and intensity as summations over cohorts. That is, n_{it} , K_{it}^M , and I_{it}^M can now be expressed as $\sum_{j=1}^J D_{C_{ji}}^M$, $\sum_{j=1}^J K_{C_{ji}}^M$, and $\sum_{j=1}^J I_{C_{ji}}^M$, respectively. It is then straightforward to conclude using these expressions that Equation (2) can be obtained from a more general model (i.e., Equations 2 and 3 together) that imposes common cohort-specific parameters in Equation (3), that is, $\gamma_j = \gamma$, $\beta_j = \beta$, and $\mu_j = \mu$.¹⁰ Notice finally that Equations (2) and (3) do not allow for cohort-

⁸Notice that while I_{it}^m does not have a temporal subscript because it does not change over time, I_{it}^M does because it might aggregate the intensity of several LC processes.

⁹Although D_{it}^m switches from zero to one at $t = E_{it}^m$, note that $d_{m \in C_j}$ and I_{it}^m do not vary over time as they capture two time-invariant characteristics of treatment m , namely its cohort and intensity.

¹⁰As pointed out by a referee, it is worth mentioning that the above cohort specification of our model somehow relaxes the CSP assumption. An important remark here is that we can use a cohort specification in a simple application where the treated units receive a single treatment if the treatments are distant in time (e.g., in two different decades). On the one hand, notice that the CSP assumption is irrelevant in this case. On the other hand, the CSP assumption can still be valid in a cohort specification if the units receive several treatments within a cohort window (decade). This implies that the cohort specification and the CSP assumption are two related but different features of a DiD model.

specific coefficients for the interaction terms, and hence we do not estimate a fully non-neutral cohort-specific model. We have selected this specification not only to simplify our analysis, but also due to the lack of sufficient LC processes in each cohort with a large range of values for the X_{it} variables.

Finally, we highlight that the effects of the LC variables are parish-specific as we have interacted the LC variables with observed parish characteristics (such as the number of farms). Using Equations (2) and (3), the direct effect of LC¹¹ can be computed using the following difference of two *conditional* expected productions:

$$\text{LCE}_{it} = E[Y_{it} | \alpha_i, \delta_t, H_{it}]_{n_{it} \geq 1} - E[Y_{it} | \alpha_i, \delta_t, H_{it}]_{n_{it} = 0}, \quad (4)$$

where H_{it} includes the remainder of the parameters and variables of Equation (2). Equation (4) presents the effect of LC as the difference between the expected production of a parish that has been involved in a LC process (i.e., when $n_{it} \geq 1$) and the expected production of a *similar* but *hypothetical* parish that has the same explanatory variables (and coefficients) than the aforementioned parish but which has not been involved in any LC process (in this case n_{it} should take a zero value). Notice that (4) is conditional on parish effects, α_i . Therefore, we are controlling for time-invariant differences between the two mentioned parishes. We are also controlling in (4) for differences in the value of δ_t before and after the first LC process took place. This prevents us from wrongly attributing to the LC processes any change in parish production that is more likely related to exogenous factors common to all farms and parishes.

3 | SAMPLE AND DATA

The data used in our study come from two complementary sources and allows us to have a panel of parishes from 2001 to 2017. On the one hand, SADEI has provided us with annual information at the parish level that contains the following variables: population, total land area for each parish, number of bovine farms, total bovine herd (both beef and dairy), and livestock units.¹² On the other hand, the Principality of Asturias has provided us with information on the processes of LC carried out from 1963 to the present, with data about the parishes and municipalities affected, the treated hectares, the initial and final plot numbers, the date of taking possession of the new plots, the volume of public investment in the development and implementation of the LC processes, and so on. Notice that the observation unit used in our application (parishes) is not the same as the unit to which treatment (LC) is applied (e.g., at plot or farm level). As we have information on the parishes affected by each LC process, we matched each LC plan to a single parish before carrying out our empirical analysis.

3.1 | Land consolidation variables

The cumulative number of LC processes that have been executed at time t in parish i (n_{it}) is the main treatment variable used in our empirical analysis. Notice that this variable is the simple sum of the dummy variables that counts the number of LC processes that unit i has accumulated at time t . As this is an accounting variable, it ignores differences across LC processes.

¹¹The reason for adding the 'direct' label to this effect is explained later in Section 4.2.

¹²SADEI (*Sociedad Asturiana de Estudios Económicos e Industriales*, <https://www.sadei.es>) is a public company whose task is the preparation and dissemination of multiple socioeconomic statistics of the Asturian region.

For this reason, we also include in our applications other LC variables that permit the effect of each LC process to change over time and in intensity. Under the CSP assumption, this implies that parish production (farms/population) also depends on their cumulative age and intensity.

We use the investment per hectare involved in each LC plan (I_{it}) to capture the differences across them.¹³ Like other continuous variables, it is measured in logs. Next, they are aggregated to obtain a global or cumulative measure of intensity (I_{it}^M) that takes into account all LC processes executed in a parish. Whereas n_{it} simply measures the quantity of LC processes, I_{it}^M measures their overall intensity. As each LC process is likely to require two or more years to have an effect on each parish outcome, we follow Borusyak and Jaravel (2017) and compute a variable (K_{it}) that measures the age of each LC process, that is, the time that has passed since the date of taking possession of the new plots. These are then aggregated to get a cumulative measure of the age of all LC processes executed in a parish (K_{it}^M).

We use investment per hectare to measure LC intensity for several reasons. First, it is a relative measure of LC intensity that also captures the complexity of the LC projects. The mobility gains tend to be larger in more complex LC projects than in LC projects with no public investment in infrastructure. Second, investment per hectare is also the LC feature that has changed the most across decades. Finally, investment per hectare is one of the indicators used in the literature to evaluate the economic effect of land consolidation processes (see, e.g., Guo et al., 2015).

3.2 | Livestock production and farm size

We first examine whether LC has exerted broad impacts on promoting farm size. As is customary in regional economics, we treat the parishes in Asturias as production units. Thus, our observations are not individual farms as in most papers examining the effect of LF on farm productivity and efficiency, but rather aggregate production units comprising many farms. In this sense, we will hereafter assume that our production units ‘employ’ farms, and other *unobserved* inputs captured by parish-specific effects, to produce dairy and beef products. While an adequate indicator to assess dairy (beef) production is the production of milk (beef) in litres (kilograms) or farmers' sales in monetary units, there is no data source from which these volumes can be measured directly at parish level. In this sense, it should be pointed out that most of the literature in agricultural economics shows that the most important input in dairy (beef) production is the dairy (beef) livestock number, and thus both variables are highly correlated. For this reason, we use parish cattle as proxy for livestock production in each parish.¹⁴

We first estimate a production function using the natural logarithm of the total number of parishes' bovine animals (i.e., $Y_{it} = \ln y_{it}$) as the dependent variable. Bovine farms (i.e., $X_{it} = \ln x_{it}$) are included in the model because it is the main time-varying variable that is more related with the production factors used within the parish to produce dairy and beef products. As the estimated coefficient of LC in this model is *conditional* on farm figures, this model allows us to examine whether LC has exerted broad impacts on promoting the scale of livestock production, measured as average cows per farm. To distinguish between traditional (extensive) and non-traditional (intensive) farms in each parish, we have included in our production function the ratio livestock units to total bovine herd, z_{it} . The z -ratio is less than unity because

¹³The LC projects often involve very localised public investments in road infrastructure and other necessary infrastructures. In the case of large-scale infrastructure facilities, the LC process provides solutions regarding access from farm buildings to land plots by building bridges and underpasses for agricultural access combined with a new road or path network design. In some cases, communal investments are also made, such as agricultural/livestock waste clean points or communal facilities for livestock management.

¹⁴This is not the first time where input and output variables are used for the same purposes. For instance, the relative size of a particular industry is often given by either its value-added share or its labour share (see, e.g., Balk, 2016).

adult cows count as one livestock unit, while younger animals count as less than one livestock unit. The higher the value of the z -ratio, the less weight the younger animals have in the herd of cattle.

Although the z -ratio is a maturity indicator of farm cattle, z_{it} can also be viewed as an indicator of the traditional (extensive) character of livestock in each parish. In the case of dairy farms, the lower the z -ratio, reflects the greater weight the heifers have in the herd. This means that the farms require a high rate of annual replacement of cows because high production dairy cows usually have a shorter productive life. Therefore, in the case of milk orientation, the lower the value of the z -ratio, the greater the intensification of productive activity (cows with higher production, with more feed consumption per cow, etc.). Nevertheless, in the case of beef farms, the lower the z -ratio, the more weight the calves have (breeding and baiting). The higher the value of the z ratio, the lower the weight of the calves in the herd, thereby indicating that the meat holdings have a small number of calves subject to the fatten process. This would be the case of those farms that decide to sell the calves after only a few months of life to be fattened on other more professional farms (feedlots) outside the parish.

As pointed out by a referee, a limitation of our empirical application is that we cannot examine the LC effect on crop production because we do not have this information at parish level. If there is a shift to crop production over time, then the actual LC impacts on the overall agricultural production may be different than the estimated impacts for the livestock sector. It is germane to mention in this sense that, according to the Ministry of Agriculture and Fisheries, 78.6% of the agricultural production of Asturias in 2000 came from livestock production derived from cattle. Other livestock production and crop production only represented 7.5% and 14%, respectively. The picture is similar in 2017 but with a slight increase in crop production that now represents 27% of total agricultural production. This increase in crop production has to do with the livestock activity because the crop production numbers include the value of forage produced within the farms to feed their livestock.

3.3 | Number of farms

Our previous model aims to measure the economic impact of LC processes at the parish scale, *conditional* on the number of farms. To obtain the *unconditional* effect of the LC processes on parish production, we need to estimate the effect of our LC-based variables on the number of farms using an auxiliary regression.¹⁵ In this auxiliary regression model we regress the logged number of farms ($X_{it} = \ln x_{it}$) on the maturity indicator of farm cattle (z_{it}) and its squared value, as well as the LC variables. This model is again estimated using a two-way FE estimator. Again, this model includes parish-specific and time-specific dummy variables. In this case, the parameters of the time dummy variables measure the ‘natural’ decline in the number of farms over the last 17 years.

3.4 | Parish population

In order to acquire a social perspective of the subject, we also estimate an additional auxiliary regression that allows us to measure the effect of our LC-based variables on parish population. The second auxiliary regression model simply regresses the natural logarithm of parish population ($\ln P_{it}$) on the cumulative number of LC processes, their cumulative age, and their cumulative intensity, as well as the set of parish-specific and time-specific dummy variables. In

¹⁵We labelled this model as ‘auxiliary regression’ because it does not rely on well-known theoretical concepts in production economics as occurs with our production function model.

this case, the parameters of the time dummy variables measure the ‘natural’ decline in parish population over the last 17 years.

3.5 | Cohorts of LC processes

We also estimate multi-cohort specifications for our models in the spirit of Borusyak and Jaravel (2017) and Strezhnev (2018), where we distinguish between three different cohorts of LC processes (C_1 , C_2 and C_3). Our cohorts are defined in terms of decades because their LC processes are, to some extent, of a different nature. We distinguish between three different cohorts of LC processes. The first cohort involves LC processes that took place in the 1990s, but with possibly non-negligible effects during our sample period. The Department of Planning and Rural Infrastructures of the Government of the Principality of Asturias ensures that these LC processes are probably more effective than other LC processes because they were mainly promoted in the most agriculturally oriented municipalities of Asturias. One can perceive this greater agricultural orientation in our data. For instance, on average the LC processes that took place in the 1990s involved more farms, plots, and hectares than those executed after 2000. The second cohort involves the LC processes developed during the economic boom of the Spanish economy, that is, from 2001 and 2008. Due to the good financial situation of most Spanish and European institutions, these LC processes involved increasing resources for investment in rural and villages infrastructures. This allowed the implementation of more complex LC projects that required much larger public investments per hectare. The third cohort includes the LC process that ended in the period 2009–2017. Unlike the previous ones, the Government of the Principality of Asturias allocated fewer and fewer financial resources towards these LC processes due to the stringent financial restrictions caused by the severe economic crisis in Spain. Interestingly, despite the financial restrictions, the investment per hectare was even larger than in the previous decade because the geographic area involved in the individual LC processes was substantially smaller.¹⁶

3.6 | Descriptive statistics

Table 1 provides the summary statistics of the variables used to estimate the proposed models. As the observation unit used in estimations are parishes, they have been computed for each parish. The sample period is 2001–2017. As our sample includes 292 parishes, the total sample size is 4964 observations with 1056 observations having been involved in one or more LC processes. For presentation ease, we ignore cohorts of LC processes and simply include in this table the summary statistics of the cumulative LC variables for the treated parishes. Despite this, the table shows that some parishes have been involved in more than one LC process, and that the number of LC processes in at least one parish is equal to five. This thus justifies estimating our models using a multi-treatment framework. Regarding I_{it}^M , it should be pointed out that by itself it cannot be interpreted easily because I_{it} is measured in logs. However, a difference in I_{it}^M can be interpreted as a proportional difference in investment per hectare. Finally, at first sight one may think that the maximum cumulative age (65 years) is too large because our sample period goes from 2001 to 2017. However, it should be taken into account that we are

¹⁶Although the above three cohorts of LC processes do not totally coincide with natural decades, we still prefer saying that the treatment cohorts are defined in terms of decades to keep the explanation simple.

TABLE 1 Descriptive statistics.

Variable	Description	Units	Obs.	Mean	Std. dev.	Min	Max
x	Beef and dairy farms	No. of farms	4964	23.26	18.39	0	153
	Beef farms	No. of farms	4964	15.35	11.95	0	80
	Dairy farms	No. of farms	4964	6.41	10.49	0	118
y	Beef and dairy livestock	Herds of cattle	4964	617.55	545.91	0	3586
	Beef livestock	Herds of cattle	4964	333.93	337.96	0	3317
	Dairy livestock	Herds of cattle	4964	283.61	454.34	0	2779
z	Maturity indicator of farms' cattle	Livestock units/total bovine herd ^a	4964	0.71	0.10	0	1
P	Population	No. of people	4964	329.51	668.74	3	7228
n	Sum of LC processes	No. of LC processes	1056	1.46	0.78	1	5
I^M	Sum of investment per hectare ^b	ln[euros/hectare] ^{c,d}	1056	10.27	5.51	0	38.82
K^M	Age of all LC processes	Years	1056	12.25	11.38	0	65

^aThe livestock unit is a reference unit which facilitates the aggregation of livestock from various groups of age as per convention via the use of specific coefficients established initially on the basis of the nutritional or feed requirement of each type of animal.

^bWe take logs before computing this summation.

^cIn parishes with several LC processes, we have added several logged values to compute I^M .

^dWe have added one euro before taking natural logarithms.

including in our analysis the LC processes executed in the 1990s as they might have non-negligible effects during our sample period.¹⁷

4 | RESULTS

4.1 | Testing the PT and CSP assumptions

To investigate the PT assumption, we estimate a couple of two-way FE models using only pre-treatment observations. While one includes a specific set of time-dummies for the treated units, the other includes a specific time-trend for such units. Both specifications are estimated without any treatment effect as the coefficients of the LC-based variables are not identified in this case. An F -test of the compound null in which all the coefficients of the time-dummies are jointly zero is a test of the PT assumption. To test the CSP assumption, we estimate a DiD model that includes a different treatment indicator for each LC process. In this model the effect of each treatment is allowed to change across treatments. The CSP assumption is fulfilled if we cannot reject statistically that the coefficients associated with each LC process are the same.¹⁸

The F -tests carried out to check the PT assumption suggest that we cannot reject this assumption at any reasonable level of significance when we estimate the parishes' production

¹⁷Information on the individual LC processes (i.e., before they are aggregated to get their cumulative values) is not provided because the observation unit used in estimations are parishes. Some information on the individual LC processes has however been provided previously when we defined our cohorts of LC processes.

¹⁸The F -test performed to check whether both PT and CSP assumptions are supported by the data can be found in Orea et al. (2021, appendix A).

function, regardless of whether we include a set of specific time-dummies or a specific time-trend for the treated units. When we estimate the auxiliary regression aimed at explaining the changes in parish farms or their population, we find that the PT assumption cannot be rejected at any reasonable level of significance if we include a specific time-trend for the treated units. When we use specific time-dummies for the treated units, the PT assumption is rejected at the 5% level of significance. In summary, these tests seem to suggest that our DiD models are able to properly measure the causal effects attributed to the LC processes.

The F -tests carried out to check the CSP assumption suggest that we cannot reject this assumption at any reasonable level of significance when we estimate the parishes' production function and the auxiliary regression aimed at explaining the changes in parish farms. In these two cases, therefore, we can simplify our analysis using a specification that measures the cumulative effect of several treatments with only three LC-based variables: the number of treatments (n_{it}), their cumulative intensity (I_{it}^M), and their cumulative ages (K_{it}^M). Unfortunately, the same simplification cannot be implemented if we aim to measure the effect of the LC processes on parish population. As we reject the null hypothesis of common sequential parameters in this case, we are forced to use a more comprehensive model that includes a different treatment indicator for each LC process when explaining the changes in parish population.

4.2 | Parameter estimates and LC effects

4.2.1 | Farm size

The parameter estimates of the parishes' production function are shown in Table 2. This table shows the results of a *one-cohort* specification of the model that does not distinguish between LC cohorts and a *multi-cohort* specification that distinguishes between LC processes implemented in the 1990s, 2000s and 2010s.

The first set of coefficients (and variables) captures the characteristics of parish livestock production technology. The natural logarithm of the total number of farms and the z -ratio are measured in deviations with respect to the sample mean. This allows the first-order coefficients to be interpreted as elasticities or derivatives for a 'representative' parish. The second set of coefficients measures the cumulative effect of three LC-based variables on representative parish livestock production. The third set of coefficients allows the LC effects to depend on parish characteristics.¹⁹

Regarding the characteristics of parish livestock production technology, we find a positive effect of the number of farms on total bovine livestock. The estimated elasticity is on average less than unity, indicating the existence of decreasing returns to scale at the parish level. In other words, parishes with more farms tend to have smaller farms in terms of beef and dairy cattle. The effect of the number of farms on total herds adopts a form of inverted U due to the first-order effect proving positive and the quadratic term being negative. Finally, it is worth mentioning that the coefficient of the interaction term between the total number of farms and the z -ratio is positive and statistically significant, indicating that the scale elasticity of more extensive farms is larger than the scale elasticity of an equivalent but more intensive farm.

The next two sets of coefficients measure the cumulative effect of the LC processes on livestock production. As some of the LC-based variables are highly correlated, we should pay more attention to global effects (i.e., taking into account all LC variables and their interactions

¹⁹Notice that Table 2 (and the following tables) do not include the coefficients of D_{it}^M and I_{it}^M because it is impossible to estimate non-parametrically the effects of the cohort of LC processes that took place before our sample period. See, e.g., Strezhnev (2018, n. 6, p. 11). However, their time-varying effect can be measured parametrically because K_{it} varies over time.

TABLE 2 Parameter estimates of the parishes' production function.

Dep. var. = $\ln y_{it}$	One-cohort model			Multi-cohort model		
Regressors	Coef.	Std. err.	Robust- <i>t</i>	Coef.	Std. err.	Robust- <i>t</i>
$\ln x$	0.897***	0.083	10.71	0.899***	0.083	10.85
z	0.008	0.006	1.43	0.008	0.006	1.39
$1/2\ln x^2$	-0.280***	0.068	-4.12	-0.278***	0.068	-4.05
$1/2z^2$	-0.001***	0.000	-4.84	-0.001***	0.000	-4.83
$\ln x \cdot z$	0.009***	0.002	3.37	0.009***	0.002	3.34
n	-0.251***	0.098	-2.54			
$D_{C_1}^M$						
$D_{C_2}^M$				0.046	0.286	0.16
$D_{C_3}^M$				-0.151**	0.072	-2.08
I^M	0.032***	0.012	2.59			
$I_{C_1}^M$						
$I_{C_2}^M$				-0.007	0.036	-0.19
$I_{C_3}^M$				0.014	0.009	1.60
K^M	0.003	0.003	1.07			
$K_{C_1}^M$				0.004	0.004	0.81
$K_{C_2}^M$				0.002	0.004	0.58
$K_{C_3}^M$				0.004	0.007	0.65
$n \cdot z$	-0.016*	0.009	-1.69	-0.007	0.007	-0.90
$I^M \cdot z$	0.002**	0.001	1.98	0.001	0.001	1.15
$K^M \cdot z$	-0.000	0.000	-0.71	-0.000	0.000	-0.72
$n \cdot \ln x$	0.321***	0.127	2.53	0.233*	0.123	1.90
$I^M \cdot \ln x$	-0.046***	0.016	-2.80	-0.033**	0.015	-2.17
$K^M \cdot \ln x$	-0.007**	0.003	-2.31	-0.007**	0.003	-2.12
Intercept	5.960***	0.094	63.10	5.954***	0.098	60.31
Time dummies	Yes			Yes		
Municipality trends	Yes			Yes		
Fixed effects	Yes			Yes		
# Obs.	4964			4964		
# Treated obs.	1056			1056		
# Parishes	292			292		
Within <i>R</i> -sq.	0.769			0.769		
Between <i>R</i> -sq.	0.817			0.820		
Overall <i>R</i> -sq.	0.808			0.811		
Mean LC effect	-0.048			-0.002		

Note: *, ** and ***Stand for statistically significant at 10%, 5% and 1%.

with other regressors) than to individual coefficients. Table 2 also shows the results of a *multi-cohort* specification that distinguishes between LC processes implemented in the 1990s, 2000s and 2010s. As we cannot reject that the coefficients of different cohorts are the same, the

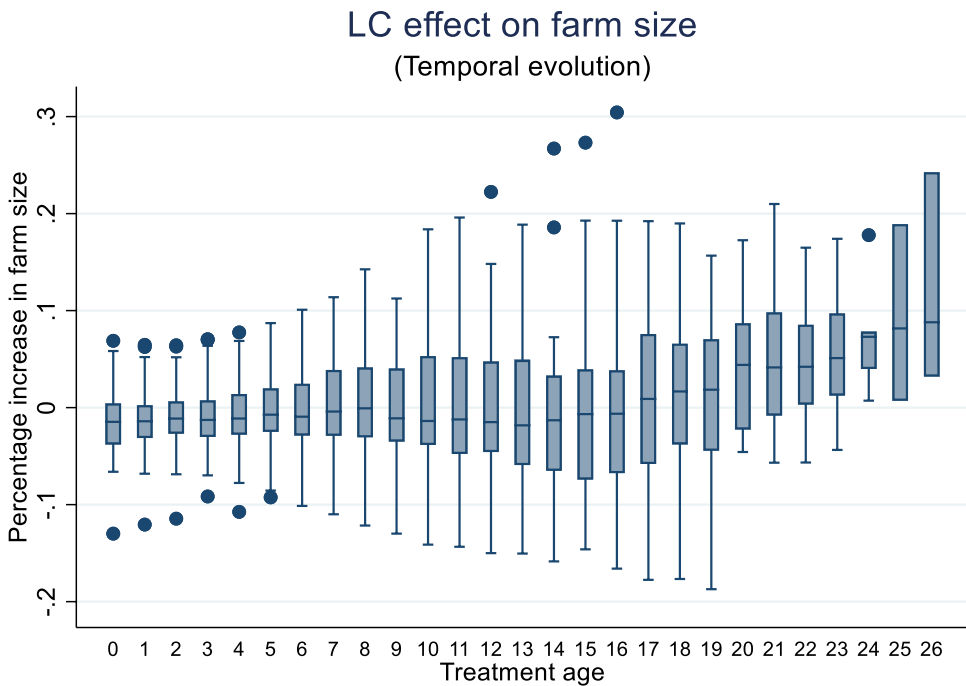


FIGURE 1 Temporal evolution of the direct LC effect on farm size.

different, if any, nature of the LC processes implemented over different decades is being captured by the observed intensity and age variables.

We next proceed to calculating the effect of LC on parish livestock production using the parameter estimates of the multi-cohort specification in Table 2. Very similar effects are found using the one-cohort specification. We find a negligible average LC effect on parish livestock production. Several issues might explain this result. First, it should be pointed out that the effects estimated here are conditional on the number of farms of each parish. Later on in this paper we obtain larger unconditional (total) effects on parish livestock activity once we take into account the changes in farm figures caused by both internal and external LC processes. We should also bear in mind that the public investment in LC processes might have positive effects on other variables not considered in our model, such as the satisfaction of the inhabitants of rural areas with the improvements made on roads and access to plots and villages. Third, while cattle numbers may decrease, milk and meat production may remain unchanged or even increase if the LC processes have induced gains in productivity (e.g., by reducing transport cost) in terms of larger yields per dairy or beef.²⁰ Finally, our LC effects might be downward biased because the FE estimator uses annual changes to estimate the coefficients of the model and some of our LC variables do not often change over time. To detect the LC effects we would most probably need to examine longer temporal windows.

The individual LC effects are, however, very heterogeneous, observable in Figure 1. This figure depicts the estimated effect of a single LC process on farm size over time. The boxplot in this figure suggests a high level of heterogeneity in terms of the individual LC effects. Notice that, despite K_{it}^M not bearing a significant coefficient, this figure suggests larger (positive)

²⁰We do not have data on milk and meat production by parish. For this reason, we are required to work with cattle numbers. Data at regional level seems to corroborate this conjecture. Indeed, according to the Government of Asturias, the ratio of thousand litres per cow was 5.50 in 2001. This ratio increases up to 8.04 in 2017.

effects attributable to the LC as time passes, in line with Crecente et al. (2002), p. 142). The larger effects found for aged LC processes are also linked with the fact that these processes were implemented in the 1990s, probably proving more effective than other LC processes because they were mainly promoted in the most agricultural-oriented municipalities of Asturias.

Although the individual coefficients should be interpreted with caution, we find a positive and significant effect of the investments per hectare (I_{it}^M) on the livestock production of a representative parish. The positive (negative) and statistically significant coefficient of $I_{it}^M z_{it}$ ($I_{it}^M \ln x_{it}$) indicates that the public investments in infrastructures tend to have a larger effect in parishes where the local farms use more traditional systems of livestock production or in parishes with few farms. We find that n_{it} has a negative coefficient. However, this somehow counterintuitive result could be caused by the fact that more recent LC processes usually involve less farms, plots, and hectares than older LC processes. Notice as well that the effect of n_{it} on livestock production tends to be positive when the number of farms increases. Indeed, the coefficient of $n_{it} \ln x_{it}$ is positive and statistically significant, indicating that adding new LC processes is more effective when the number of farms located in any one parish is large.

4.2.2 | Farm numbers

Table 3 shows the parameter estimates of the auxiliary regression aimed at explaining changes in parish farms, using the one-cohort and multi-cohort specifications of the model. The first set of coefficients (and variables) aim to control for the traditional (extensive) and non-traditional (intensive) orientation of the farms located in each parish. The second set of coefficients measures the cumulative effect of three LC-based variables on representative parish livestock production: the number of treatments (n_{it}), their cumulative intensity (I_{it}^M), and their cumulative ages (K_{it}^M). The third set of coefficients allows the LC effects to depend on the main farm characteristics, that is, their system of livestock production.

Both the parameter estimates and LC effects are robust when using a single or multi-cohort specification. As it is difficult to interpret separately the coefficients of the three LC indicators, our analysis is again focused on the estimated effects attributable to the LC processes. We find that the effect of LC processes on the number of farms is more relevant when these farms are of an extensive type. Similar to our production function model, we find larger (positive) effects attributable to the LC with the passage of time.

We also find that the LC processes have specially attenuated the decline in the number of farms in coastal parishes (municipalities).²¹ As most of the dairy livestock is in these municipalities, this distribution suggests the existence of a positive effect in parishes where the dairy-oriented farms predominate. On the one hand, this result simply suggests that the LC activity requires the existence of dairy farms to be effective at attenuating the decline in the number of farms. On the other hand, while the LC processes were able to attenuate the decline of (extensive) farms located close to or in coastal parishes or municipalities, they were less effective at mitigating the decline of (intensive) farms located far from the coast. In these parishes, the LC processes have helped to maintain livestock production by favouring the concentration of production in larger farms.

4.2.3 | Population

Table 4 shows the parameter estimates of the auxiliary regression aimed at explaining changes in parish population. As the focus here is on social issues, this model does not

²¹The geographical distribution of the estimated effects attributable to the LC processes that have taken place in western Asturias can be found in Orea et al. (2021, figures 6 and 7).

TABLE 3 Parameter estimates of the parish farm numbers function.

Dep. var. = $\ln x_{it}$	One-cohort model			Multi-cohort model		
Regressors	Coef.	Std. err.	Robust- <i>t</i>	Coef.	Std. err.	Robust- <i>t</i>
<i>z</i>	0.006	0.004	1.57	0.007	0.004	1.57
$1/2z^2$	−0.001***	0.000	−2.77	−0.001***	0.000	−2.77
<i>n</i>	0.023	0.058	0.39			
$D_{C_1}^M$						
$D_{C_2}^M$				0.295	0.321	0.92
$D_{C_3}^M$				0.047	0.038	1.24
I^M	−0.006	0.008	−0.79			
$I_{C_1}^M$						
$I_{C_2}^M$				−0.046	0.044	−1.04
$I_{C_3}^M$				−0.008	0.005	−1.41
K^M	0.001	0.003	0.26			
$K_{C_1}^M$				0.000	0.005	0.00
$K_{C_2}^M$				0.005	0.004	1.11
$K_{C_3}^M$				−0.007	0.007	−0.95
<i>n · z</i>	0.013	0.011	1.19	0.013	0.010	1.22
$I^M · z$	−0.002	0.001	−1.16	−0.006	0.001	−1.08
$K^M · z$	0.000	0.001	0.68	0.001	0.000	0.57
Intercept	3.300**	0.057	58.16	3.314***	0.061	54.28
Time dummies	Yes			Yes		
Municipality trends	Yes			Yes		
Fixed effects	Yes			Yes		
# Obs.	4964			4964		
# Treated obs.	1056			1056		
# Parishes	292			292		
Within <i>R</i> -sq.	0.646			0.647		
Between <i>R</i> -sq.	0.228			0.238		
Overall <i>R</i> -sq.	0.192			0.196		
Mean LC effect	0.002			0.005		

Note: *, ** and ***Stand for statistically significant at 10%, 5% and 1%.

include observed variables for the livestock activity carried out within the parishes. As we have rejected the null hypothesis of common sequential parameters in this model, here we also present the parameter estimates of a more comprehensive model that includes three dummy variables identifying the three first LC processes, three variables measuring the intensity of each LC process and three variables measuring their corresponding ages. To facilitate the econometric analysis and because the results are robust for this modelling issue, both models have been estimated using a one-cohort specification. The impact of the LC processes on population is on average close to zero. However, the LC processes have been able to attenuate, at least to some extent, the population decline observed in some of the parishes located close to or several kilometres from the coast, or very close to the Galician border.

TABLE 4 Parameter estimates of the parish population function.

Dep. var. = $\ln P_{it}$	With CSP assumption			With no CSP assumption		
Regressors	Coef.	Std. err.	Robust- <i>t</i>	Coef.	Std. err.	Robust- <i>t</i>
<i>n</i>	0.071***	0.026	2.72			
<i>D</i> ₁				0.112***	0.018	6.10
<i>D</i> ₂				0.056	0.055	1.01
<i>D</i> ₃				0.022	0.034	0.64
<i>I</i> ^{<i>M</i>}	−0.009***	0.003	−2.52			
<i>I</i> ₁				−0.018***	0.003	−6.44
<i>I</i> ₂				−0.005	0.007	−0.75
<i>I</i> ₃				0.011*	0.006	1.88
<i>K</i> ^{<i>M</i>}	−0.001	0.001	−0.84			
<i>K</i> ₁				−0.002	0.002	−0.78
<i>K</i> ₂				0.001	0.004	0.28
<i>K</i> ₃				−0.012***	0.004	−2.41
Intercept	5.254***	0.037	138.6	5.251	0.036	144.6
Time dummies	Yes			Yes		
Municipality trends	Yes			Yes		
Fixed effects	Yes			Yes		
# Obs.	4964			4964		
# treated obs.	1056			1056		
# Parishes	292			292		
Within <i>R</i> -sq.	0.754			0.758		
Between <i>R</i> -sq.	0.044			0.011		
Overall <i>R</i> -sq.	0.007			0.006		
Mean LC effect	0.001			−0.002		

Note: *, ** and ***Stand for statistically significant at 10%, 5% and 1%.

4.3 | Robustness analyses and further results

4.3.1 | Dairy versus beef-oriented livestock production and farms

The results using a single production function model or a multi-output distance function (that distinguishes between milk- and beef-oriented farms) are quite similar in terms of both parameter estimates and LC effects.²² The distance function model, however, allows us to conclude that adding new LC processes is more effective in parishes with several beef-oriented farms and that the effect found for large parishes seems to be more persistent over time.

Regarding the auxiliary regressions estimated separately for dairy and beef-oriented farms, we find similar parameter estimates to those obtained using a single auxiliary regression model, except for the time dummy variables. Their different coefficients simply reflect the more pronounced decreasing trend in the number of dairy farms when compared with the

²²The parameter estimates of these alternative specifications are available from the authors upon request.

decline of beef-oriented farms. We also find that, while the average effect of the LC processes on the number of dairy-oriented farms is negligible (or even negative), it is positive when we estimate the auxiliary regression for beef-oriented farms.

4.3.2 | Spatial spillovers

A common feature of the above models is that they ignore the spatial structure of the data. In other words, LCE_{it} in Equation (4) is only capturing a *direct* effect on parish production ignoring that the local LC processes might also have an *indirect* impact on neighbouring parish outcomes. Obviously, similar comments can be made for the auxiliary regressions. To examine this issue we have extended our preferred models by adding the LC variables of neighbouring parishes in the same fashion as a standard spatial lag model (SLX) does.²³

Table 5 provides a summary of the estimated total effects of the LC processes on farm size as well as their disaggregation into direct and indirect effects. We observe that the indirect (spatial) spillovers are as relevant as the direct (internal) LC effects, thereby confirming the importance of considering the notion of spatial interactions in studies that rely on very disaggregated spatial information. This finding thus indicates that the LC effects are likely to be underestimated if we only examine the local economic impacts of such processes.

4.3.3 | Conditional versus unconditional effects

Table 6 shows the conditional, farm-induced and unconditional (or total) LC effects on parish livestock production computed using the parameter estimates of our production function model that aims to measure the impact of LC processes at the parish scale (i.e., conditional on the number of farms) together with the auxiliary regression that uses the number of farms as the dependent variable. This table shows that, taking into account the two mentioned channels, we find that parish livestock production increases about 3% if we take into account the spatial (indirect) effects. Interestingly, we also find that both the conditional and farm-induced effects are highly correlated. This result thus seems to indicate that the farm-induced channel through which the LC processes might affect parish livestock production should not be ignored specially in those parishes with large (conditional) LC effects on farm size in terms of livestock number.

5 | CONCLUSIONS

Land concentration processes, like any other agrarian policy measure, must be subject to assessment. In this sense, this paper can be viewed as an evaluation of one of the most durable policy measures implemented by the Asturian Government to maintain both agricultural (economic) activity and population in the rural areas.

We do not find strong evidence to support the effectiveness of the LC processes in mitigating the decline in livestock production in rural Asturias. At most, we find that parish livestock production only increases about 3% on average once one or more LC processes are implemented. Despite this, we find positive impacts of these measures in the medium and long term. Therefore, and in line with previous papers, we conclude that both policy-makers and researchers should analyse the strengths and weaknesses of these types of measures using a long temporal perspective.

²³The parameter estimates of the spatial specifications of our models are available from the authors upon request.

TABLE 5 Direct, indirect and total LC effects.

	Obs.	Mean	Std. dev.	Min	Max
Farms' size					
Parishes with internal LC processes					
Direct effect	1056	-0.0023	0.0823	-0.2716	0.4335
Indirect effect	1056	0.0103	0.0285	-0.2123	0.1027
Total effect	1056	0.0080	0.0841	-0.2947	0.4345
Parishes without internal LC processes					
Direct effect	3908	0	0	0	0
Indirect effect	3908	0.0117	0.0240	-0.0025	0.2496
Total effect	3908	0.0117	0.0240	-0.0025	0.2496
Number of farms					
Parishes with internal LC processes					
Direct effect	1056	0.0048	0.0754	-0.2462	0.3190
Indirect effect	1056	0.0429	0.0375	-0.0153	0.1966
Total effect	1056	0.0477	0.0821	-0.1825	0.3775
Parishes without internal LC processes					
Direct effect	3908	0	0	0	0
Indirect effect	3908	0.0164	0.0269	0.0000	0.2205
Total effect	3908	0.0164	0.0269	0.0000	0.2205
Population					
Parishes with internal LC processes					
Direct effect	1056	-0.0023	0.0613	-0.0606	0.2661
Indirect effect	1056	-0.0123	0.0323	-0.1865	0.0525
Total effect	1056	-0.0146	0.0637	-0.1827	0.2778
Parishes without internal LC processes					
Direct effect	3908	0	0	0	0
Indirect effect	3908	0	0.0027	-0.0246	0.0201
Total effect	3908	0	0.0027	-0.0246	0.0201

The impact of many LC processes might be modest due to the fact that their effectiveness also depends on other policy measures and the evolution of other economic and social factors. These may include a reduction in farm numbers, more accentuated for dairy than in meat-oriented ones, the territorial concentration of dairy farms in certain regions, the change in productive orientation from non-competitive dairy to meat farms, the lack of generational replacement, and so on. Therefore, in most cases, alternative actions (e.g., facilitating services to livestock farmers and enhancing local resources or favouring the development of agri-food production and promoting the agri-food industry linked to this production), should be launched in order to attenuate, or reverse, the depletion of livestock activity in Asturias.

In line with Deininger and Xia (2016), we find that the effect of a localised LC project expands beyond the area in which such measure has been implemented. This finding first indicates that the LC effects are likely to be underestimated if we only examine the local economic impacts of such processes. Another important implication of the above result is that Asturian policy-makers should try to initiate broader LC processes involving several parishes

TABLE 6 Conditional and unconditional LC effects on livestock production.

	Obs.	Mean	Std. dev.	Min	Max
With no spatial spillovers					
Conditional effect	1056	−0.0023	0.0823	−0.2716	0.4335
Farm-induced effect	1056	0.0107	0.0486	−0.1237	0.2628
Unconditional effect	1056	0.0084	0.1034	−0.2998	0.6301
With spatial spillovers					
Conditional effect	1056	0.0080	0.0841	−0.2947	0.4345
Farm-induced effect	1056	0.0219	0.0610	−0.1280	0.4141
Unconditional effect	1056	0.0299	0.1080	−0.2718	0.7081

simultaneously in the event that the aim is to promote livestock (or economic) activity in a particular rural area, rather than initiating dispersed or poorly coordinated LC processes. Overall, our results advocate using coordinated LC measures by regional governments to take full advantage of this important policy.

Our study also uncovers several factors that can positively or negatively affect the effectiveness of the LC processes. On the one hand, the proposed methodology has allowed us to identify parishes (municipalities) where the LC processes might present better results—information of obvious use to policy-makers in planning future actions or initiatives. For instance, LC processes have contributed to attenuating the reduction in farms in coastal parishes or parishes near the coast, where the dairy-oriented farms predominate. In the case of inland parishes, the LC processes have helped to maintain livestock production by favouring the concentration of production on larger farms. Moreover, the effects attributable to LC processes are larger for beef-oriented farms than for dairy-oriented farms. Compared to most of the inland parishes, the coastal area is characterised by flatter terrains, susceptible to easier mechanisation and provision of fodder and silage (corn, ray grass), presenting better communications with the central area of Asturias. All of the latter factors have influenced the dairy industry in opting towards milk collection in these coastal areas to the detriment of other mountainous areas with worse access. In this sense, it should be noted that another fundamental element for the maintenance of livestock activity is the existence of a strong agri-food industry working closely with their farmers. The aim is to favour not only their ability to survive in an increasingly competitive context, with more regulatory demands, but also enhance the profitability and future sustainability of agricultural activity in general. Policy-makers should also take into account that LC processes in these parishes have also facilitated a progressive production re-orientation towards meat in the less competitive farms and those with aging farmers.

We have not been able to find strong evidence about the effectiveness of LC processes in securing the level of rural population. In general, if this is the case, we might conclude that reversing rural depopulation most probably requires a reorientation of current rural policies and related investment decisions. In terms of population, the greatest positive effects are found in parishes close to Galicia (Taramundi, Villanueva de Oscos, Santa Eulalia de Oscos, and inland Vegadeo). It is worth mentioning that in the 1980s the Asturian government put into practice a new form of rural development in this area partially based on rural tourism, agri-food production and the revaluation of local heritage. This result highlights the need to address the maintenance of the rural population with an integrated and broader perspective, where land concentration can play a positive role.

In summary, given that the LC processes are expensive, and financial and human resources are increasingly limited, future processes should have a more selective approach,

focusing on parishes that have the most appropriate characteristics for the maintenance and development of agricultural/livestock activity. In addition, these processes should be implemented with an integrated and broader perspective, complementing other measures that allow the access of the rural population to the necessary services for the development of their projects, be they vital or economic, and seeking to enhance any of the spillover spatial effects revealed by this study. Furthermore, as scientific evidence exists with respect to the problems faced by LC when seeking to maintain biodiversity (see, e.g., Clough et al., 2020), research and innovation must be promoted to minimise any environmental damage caused by their implementation.

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APPENDIX

SPECIFICATION OF A MULTI-TREATMENT MODEL UNDER THE CSP ASSUMPTION

We show in this appendix that we can accumulate sequential treatments as long as they have the same effect on outcome. A general multi-treatment two-way FE model that abstracts from other specification issues can be written as:

$$Y_{it} = \alpha_i + \delta_t + \sum_{m=1}^M \gamma_{it}^m D_{it}^m + \varepsilon_{it}, \quad (\text{A1})$$

where α_i is a fixed effect parameter for each unit, δ_t is the fixed parameter for each time period, D_{it}^m is the treatment indicator defined in Section 2, but which is now defined for each treatment, ε_{it} is a mean-zero error term, and the effect of each treatment (γ_{it}^m) is allowed to change across treatments and treated units. In order to allow the LC effects to vary over time and across units, we follow Borusyak and Jaravel (2017) and model γ_{it}^m as a parametric function of treatment ages and intensities:

$$\gamma_{it}^m = \gamma^m + \beta^m K_{it}^m + \mu^m I_{it}^m. \quad (\text{A2})$$

We next impose some restrictions on γ_{it}^m in order to limit the number of treatment parameters to be estimated and to facilitate their economic interpretation. If we impose in (A2) that sequential treatments have the same effect on outcome (i.e., $\gamma^m = \gamma$, $\beta^m = \beta$ and $\mu^m = \mu$) and

replace γ_{it}^m in Equations (A1) with (A2), we obtain the following simplification of the unrestricted two-way FE model:

$$Y_{it} = \alpha_i + \delta_t + \sum_{m=1}^M (\gamma + \beta K_{it}^m + \mu I_{it}^m) D_{it}^m + \varepsilon_{it}, \quad (\text{A3})$$

which is equivalent to:

$$Y_{it} = \alpha_i + \delta_t + \gamma n_{it} + \beta K_{it}^M + \mu I_{it}^M + \varepsilon_{it}, \quad (\text{A4})$$

where $n_{it} = \sum_{m=1}^M D_{it}^m$ is the number of treatments received by unit i at period t , $K_{it}^M = \sum_{m=1}^M K_{it}^m D_{it}^m$ is the cumulative age of the treatments, and $I_{it}^M = \sum_{m=1}^M I_{it}^m D_{it}^m$ is the treatment intensities. This suggests that we can accumulate sequential treatments as long as the so-called *common sequential parameter* (CSP) assumption is satisfied.