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Does land consolidation promote livestock production and combat rural depopulation? A multi-cohort multi-treatment Difference-in-Difference analysis of parishes in northern Spain

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Abstract

This paper evaluates the impact of the land consolidation (LC) processes that have taken place in Asturias over recent decades. These processes received European funding given that their purpose is to improve the economic activity in rural areas. As many parishes have been involved in two or more LC processes, we use a Difference-in-Difference (DiD) approach with heterogeneous treatment timings to examine the temporal evolution of parishes' livestock production and farms. To our best knowledge, a similar DiD model has not been estimated as yet in the literature. We examine whether LC helps to reverse rural depopulation in Asturias. We find that parishes' livestock production increases about 3% on average once one or more LC processes have been implemented, and that the 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 the LC processes in securing the level of rural population, except in some of the parishes located in western Asturias.

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Keywords: Land consolidation, livestock production, rural depopulation, multi-cohort DiD, heterogeneous treatment timings.

JEL codes: C21, D24, Q15

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1. Introduction

Land consolidation (LC) has been acknowledged as an effective instrument for adding new farmland, improving land productivity and promoting sustainable land use (see Zhou et al, 2019 and the references therein). LC always involves land reallocations aimed at mitigating the effect of land fragmentation (LF) on agriculture However such policy measures often encompass other elements ;the provision of relevant infrastructure, e.g. rural roads and irrigation networks; an increased protection of natural resources accompanied by sustainable management; other useful facilities for the local population such as village renewal and the provision of social services, water and sanitation. For this reason, LC policies have increasingly become instruments for rural sustainable development in Europe and worldwide.

The effect of LF on agriculture has worried policymakers for a long time because most empirical studies conclude that fragmentation negatively affects agricultural production. A summary of the most recent literature on this topic can be found in previous manuscripts published by the authors (see Orea et al., 2015, 2020). It is germane to point out here that LF causes an increase in traveling time between parcels located some distance from one another, which induces both lower labour productivity and higher transport costs for inputs and outputs; reduces the efficiency of machines use; and land is lost when forming plot boundaries and access routes. The LC literature examines the other side of the fragmentation issue, i.e. the effect of reallocation of parcels on agricultural production, ecological environment, and population. This literature generally finds that LC has exerted wide-ranging impacts on promoting the scale of agricultural production as well as increasing the competitiveness of agricultural products in Europe and other countries, such as Spain.

Our review of the literature shows that there is not a generally accepted methodology to measure LF and LC effects. The methodologies used in this literature vary from country to country due to lack of data availability, differences in both data disaggregation and data collection, the existence of different objectives of land-use policy or different categories of LC effects, e.g. agricultural production effects, transportation effects, effects on drainage and similar measures, the impact on ecological environment, or the social and regional economic effects.[1] Furthermore, inconsistent conclusions exist as to the impact of LC on several of the above categories.[2]

This paper evaluates the social and economic effects of the LC processes that have occurred over recent decades in Asturias, an autonomous region located in north-west Spain. A dominant traditional agricultural economy and a historical tradition of property inheritance by sub-division within families, have produced a high degree of LF in rural Asturias.[3] As regional policy makers strongly believe that the high degree of LF in

[1] For instance, there are studies that analyse the effects of LF and LC at a micro-level or farm level (Wu et al., 2005; Manjunatha et al., 2013; Orea et al., 2015; Nilsson, 2018), while others carry out the analysis at a spatial level, taking the municipalities or regions as units of study assessing the effect on spatial distribution of economic activities (Crecente et al, 2002; Du et al., 2018; Dudzińska et al., 2018), even focusing on the socio-economic improvement of rural areas and the reduction of poverty in these territories (Zhou et al., 2019).

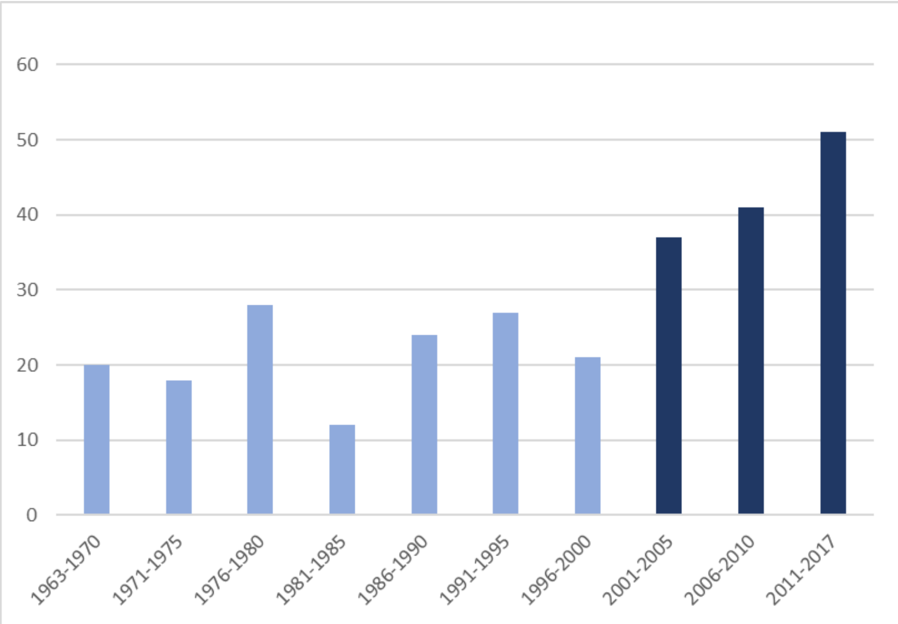
[2] For instance, Zhou et al (2019) point out that while some studies showed that LC has a negative impact on the ecosystem services value and landscape diversity (see e.g. Zhang et al., 2014), other papers found a positive ecological effect (see e.g. Yu et al., 2010 and Hartvigsen, 2014).

[3] As similar comments can be made for Galicia, an autonomous region that is adjacent to Asturias, several authors have tried to measure the economic and social effect of the LC processes in this neighbouring region. For instance, Crecente et al. (2002) show that LC contributes to retaining farmland in agricultural use and improves the population evolution in rural areas. Miranda et al (2006) conclude that LC have

Asturias prevents local farms in being competitive, they have promoted the implementation of more than 250 public LC processes in this region since the 60s in order to mitigate the degree of LF. 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 thousand owners and about 60 thousand hectares of land with an average investment amounting to 2,300 euros per hectare. Moreover, these processes have been able to reduce the number of plots from 224 to 58 thousand plots. These processes have been receiving European funds because of their potential to improve the economic activity in rural areas, increase farmer income, and stabilize rural populations.

Figure 1 shows the number of LC processes carried out in Asturias over the period 1963-2017. Notice that the number of LC processes has intensified since 2000. This sizeable enforcement is most likely caused by the Legal Decree 80/1997 that established the conditions under which farmers can request the regional government to initiate a LC process. This regulation avoids negotiation and legal costs and allows the public administration to change access routes to the new plots. On the other hand, and 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.[4]

Figure 1. Number of LC processes in Asturias (1963-2017)



While other studies have carried out their analyses taking the municipalities or regions as units of study (see e.g. Crecente et al, 2002; Du et al., 2018; Dudzińska et al., 2018), we perform our analysis using even more disaggregated data. Indeed, our observations are *parishes*, i.e. Christian territorial entities that are much smaller than the standard municipalities (provinces) used in urban (regional) economics. This potentially

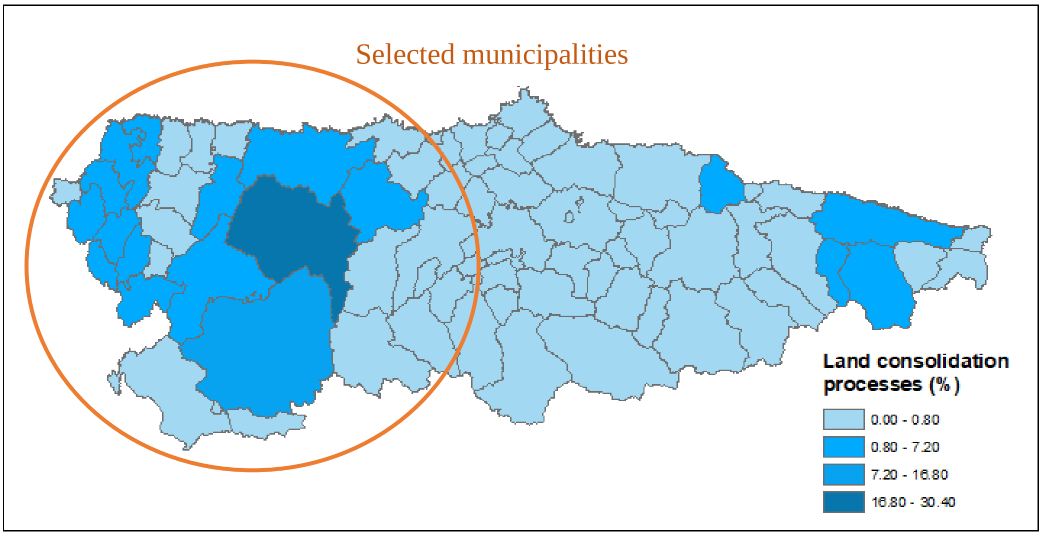
improved agricultural land structure by reducing the number of plots per holding as well as the generalized drop in the number of active holdings, serving also to mitigate the decline in the population of rural areas..

[4] The above two regulations can be found in the Asturias' Official Bulletin (https://sede.asturias.es/portal/site/Asturias/menuitem.048b5a85ccf2cf40a9be6aff100000f7/?vgnextoid=c0c756a575acd010VgnVCM100000bb030a0aRCRD&i18n.http.lang=es&calendarioPqBopa=true).

allows us to identify better the economic and social effects attributable to the LC processes that have taken place in Asturias.

Although we do 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 parishes' farms activity in previous decades. Furthermore, the study is focused on western Asturias because, as shown in Figure 2, since 2001 the LC processes were implemented with great intensity in the western municipalities and parishes of Asturias.[5] Additionally no information is available regarding public investment for many of the LC processes carried out in eastern Asturias.

Figure 2. Land consolidation processes in Asturias (2001-2017)



In our application, we try to distinguish between three different cohorts of LC processes, one of them external to the sample period. The first cohort involves LC processes that took place in the 90s, 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 agricultural-oriented municipalities of Asturias. The second cohort involves the LC processes developed during the economic boom of the Spanish economy, i.e. 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. 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 in these LC processes due to the stringent financial restrictions caused by the severe economic crisis in Spain.

We will focus our analysis on three different categories of LC effects: livestock activity measured in terms of farm figures; restructuration of livestock production measured as average cows per farm; and parishes' population. Unfortunately, it is not

[5] Similar geographical distribution is found for previous LC processes.

possible to extend the study to other categories such as the impact on ecological environment, local economy, and other social effects.

Three hypotheses are tested based on the recent evolution of these three categories in Asturias. Figure 3 depicts the average annual parish farm figures, using our dataset. This figure shows a persistent decline in the number of farms over the last 17 years. Said evolution serves to captures the increasing cessation of livestock activity in the Asturian rural areas. Therefore, the first hypothesis to be tested in this paper is whether the LC processes in Asturias have attenuated the decline in farm figures. Livestock activity not only depends on the number of farms, but also on farm size. Figure 3 also shows the tendency of parishes' average farm size over time. This figure suggests that the above decline in the number of farms has favoured the concentration and intensification of production on larger farms. A second hypothesis to be tested is whether the LC processes in Asturias have stimulated the aforementioned restructuration of livestock production. Moreover, as shown in Figure 4, rural areas are characterised by declining populations as local people have migrated to urban areas and other regions in search of employment. The accelerated process of depopulation is one of the main challenges facing large areas of rural Spain and in particular Asturias. For this reason, we also examine a third hypothesis, i.e., whether LC has been an effective policy measure for reducing the rural depopulation in Asturias. If LC is not helping to reverse rural depopulation, the latter will requires an important reorientation of current rural policies and investment decisions.

Figure 3. Temporal evolution of farms size and farm numbers.

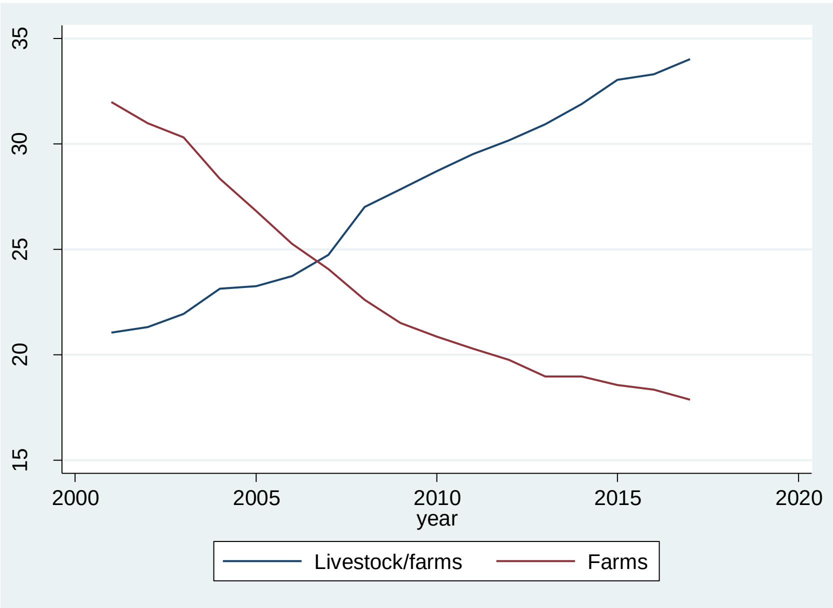
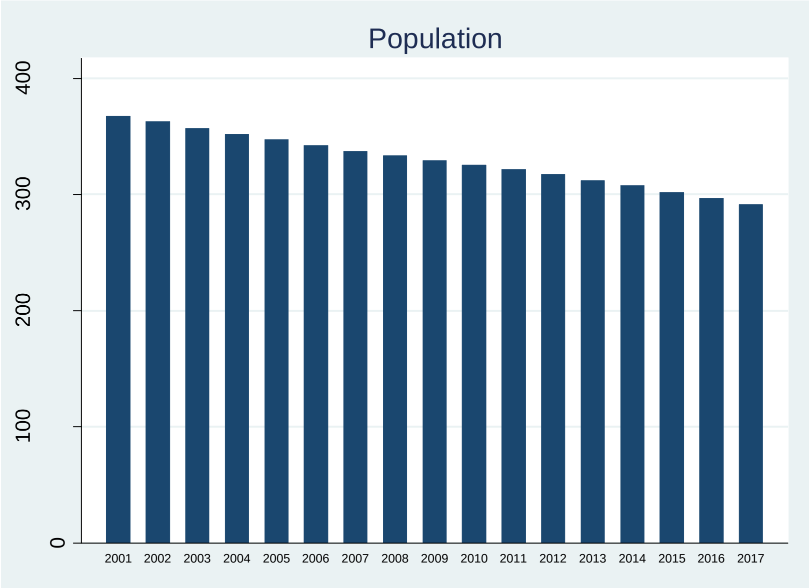


Figure 4. Temporal evolution of parishes' population.



To test the above three hypotheses, we use a multi-cohort multi-treatment Difference-in-Difference (DiD) approach with heterogeneous treatment timings. To the best of our knowledge, a similar DiD specification has not been estimated yet in the literature. The research goal in a DiD model is to estimate the expected effect of the treatment on an outcome variable over a series of time periods. In the two-period setting, the treatment effect of interest can be estimated non-parametrically using the well-known two-way FE estimator (see e.g. Abadie, 2005). However, Borusyak and Jaravel (2017) and Strezhnev (2018) point out that extending the intuition from the two-period DiD case to multiple time periods is much more complicated and much less trivial than expected. For instance, they show that the standard two-way FE estimator suffers from severe biases when different units are treated at different moments (i.e., when the treatment timing is heterogenous across cohorts) and the effect changes over time.[6] This also occurs in our application as the LC processes do not take place at the same time and thus the treatment periods vary across parishes. In this sense, our multi-period setting is just as asymmetric as in the above-mentioned papers.

The above-mentioned papers assumed that each unit at most receives a unique treatment. This is not the case in our application as some parishes are involved in more than one LC process. Therefore, we need to extend the previous framework to an asymmetric multi-treatment setting. Extending the previous framework to a multi-treatment setting is far from simple and opens new issues and questions. For instance, how should we deal with the new treatments? Can different treatments be aggregated? If so, under which conditions? Can the new treatments be considered as different levels of a unique treatment? In this sense, the main contribution of this paper to the DiD literature is to 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. If the CSP assumption is satisfied,

[6] They show that the DiD estimated effect can be expressed as a weighted average of time-varying effects with positive weights on the short-run effects and negative weights on the long-run ones. If they differ, the standard DiD estimator will completely miss this difference and yield completely erroneous results.

the multi-treatment DiD model can be viewed as a one-treatment DiD model where the new treatments are considered as different levels of a unique treatment as Abadie (2005) does in a two-period framework.[7] Our DiD specification can also be interpreted *as if* there was a unique treatment with modest short-run effects and larger long-run effects in the same fashion as Strezhnev (2018). This implies that the generalized parallel assumption and cohort-specific treatment effects examined with a unique treatment are still valid in a setting with more than one treatment.

2. Theoretical framework

In this section, we adapt the multi-period, but one-treatment, theoretical framework introduced by Borusyak and Jaravel (2017) and Strezhnev (2018) to a multi-treatment context. Both papers explicitly take into account the existence of groups of units that initiate treatment at the same time, but at a different moment than other treated units. That is, they use a similar notion of treatment cohorts to that used in our empirical application.[8] These authors also assume that when a unit receives treatment in some period within the sample, it will remain treated forever. Imai et al. (2018) labelled this assumption as the *stable policy change* (SPC) assumption. This also occurs in our application. As the parcel reallocation and new local infrastructures are expected to last decades, LC can be viewed as a permanent rural development policy.

Although their frameworks differ because they are focused on different issues, we find both of them useful. Strezhnev (2018)'s model is completely non-parametric. Although our DiD model is parametric, this framework allows us to discuss the PT assumption that should be satisfied in a multiple period setting as well as the most intuitive (average) treatment effect that might prove of interest for research `purposes. Borusyak and Jaravel (2017) develop their setting using a flexible version of the standard two-way FE estimator. We take advantage of their flexible specification to propose a simple specification of the two-way FE estimator with multiple treatments once we impose the CSP assumption.

2.1. General framework in a multi-period but one-treatment setting.

Consider a panel of $i = 1, \dots, N$ parishes or units observed in $t = 1, \dots, T$ periods. Let be Y_{it} the outcome of interest for unit i at time t. We next assume that some units are treated in some period E_i within the sample, and they will stay treated forever. Each unit i is assigned to some *treatment history* denoted by a $Tx1$ vector $D_i = (D_{i1}, \dots, D_{iT})$. Under the SPC assumption, $D_{it} = 0$ before the treatment period, and $D_{it} = 1$ during the treatment period.[9]

As different units are treated at different moments, and the treatment effect might change over time, Borusyak and Jaravel (2017) and Strezhnev (2018) use the concept of

[7] Indeed, the number of treatments varies across units in the same fashion as the standard intensity variable associated to a unique treatment does if different units are treated at different moments.

[8] Another paper that considers estimation of a DiD model with multiple time periods and variation in treatment timing is Callway and Sant'Anna (2019). They do not use the cohort terminology, but they also define their groups by the time period when units are first treated.

[9] The treatment history of each unit in the two-period case is very simple: $D_i = (0,1)$ for a *treated* unit, and $D_i = (0,0)$ for a *control* unit. The treatment history becomes much more complicated with more than two periods. However, the number of possible treatment histories can be drastically reduced under the SPC assumption.

treatment cohorts. The groups of units initiating treatment at the same time are referred to as a treatment cohort. Therefore, each cohort corresponds to some *event* time E_i or, alternatively, to some value C_i, which denotes the last period under which each unit is under control or not treated. The later variable plays a key role in Strezhnev (2018) framework because a unit's treatment history can be determined entirely by C_i. Units with $C_i = T$ never receive treatment and are always control units. Units with $C_i = c < T$ receive a treatment in period $E_i = C_i + 1$ and are treated units. Borusyak and Jaravel (2017) define another useful temporal variable, the so-called *relative time* $K_{it} = t - E_i$, which denotes the number of periods relative to the event. This variable can also be used to define the treatment history of each unit because the indicator variable for being treated can be written as $D_{it} = 1$ if $t \geq E_i$ or $K_{it} \geq 0$.

Strezhnev (2018) states that the most intuitive treatment effect that can be used in this setting is the so-called *cohort average treatment effects on the treated* (CATT), which can be viewed as a cohort-specific treatment effect measure. If we use a^c to denote the treatment history associated with cohort $C_i = c < T$, an aggregate CATT measure that include all periods for which the cohort is exposed to treatment can be defined as:

$$CATT(c) = \sum_{t=c+1}^{T} \frac{CATT_t(c)}{T-c-1} = \sum_{t=c+1}^{T} \frac{E\left[Y_{it}(a^c) - Y_{it}(a^T) \middle| D_i = a^c\right]}{T-c-1} \tag{1}$$

where $Y_{it}(a^c)$ is the potential outcome observed for unit i in time t if it initiated treatment at time $c + 1$. Strezhnev (2018) shows that $CATT_t(c)$ can be estimated non-parametrically under a generalized PT assumption that compares expected outcomes of units that initiate treatment at time $c + 1$ and units that, in an asymmetric multi-period setting, remain under control up until a period $t > c$. That is, treated units that initiate treatment after a period t are used as control units for those that initiate treatment prior to t. It is worth noting that $CATT(c)$ averages all post-treatment observations of each cohort because treatment may have different effects over time. We also allow the treatment effects to vary over time in our application. For this reason, we present averages of all annual treatment effects as results.

Following Borusyak and Jaravel (2017), a flexible two-way FE specification with different treatment cohorts that however abstracts away from other specification issues can be written as:

$$Y_{it} = \alpha_i + \delta_t + \sum_{k=0}^{T-C_i-1} \gamma_k D_{iC_i+1+k} + \varepsilon_{it} \tag{2}$$

where α_i is a fixed effect parameter for each unit, δ_t is the fixed parameter for each time period, D_{ik} is the treatment indicator, and ε_{it} is a mean-zero error term. Researchers typically report the average treatment effect as the estimated γ_k coefficient. For notation ease, the above model allows the treatment effect to change over time, but not across units because in many applications it is not feasible or very inaccurate to estimate a fully non-parametric specification where γ_k is replaced with γ_{ik}.[10]

It is worth highlighting here that C_i differs across units in an asymmetric multi-period setting. This implies that the temporal effects (δ_t) in a two-way FE estimator with multiple periods will be computed using different sets of observations. In particular, as the number of $D_{it} = 1$ increases with the number of treatment cohorts, δ_t is computed using less observations when t increases. This result can be viewed as the parametric

[10] Some parameterization of the model not only is appealing (compulsory) when the number of post-treatment observations is too large, but also because many of the estimated effects might have difficult economic interpretation.

counterpart of the above-mentioned generalized PT assumption introduced by Strezhnev (2018), because δ_t is estimated using both never-treated units and treated units that initiate treatment after period t.

Note also that not only the treatment timing is heterogenous across units in equation (2), but also the treatment effects change over time. As aforementioned, Borusyak and Jaravel (2017) show that the standard two-way FE estimator suffers from severe biases in this setting. Although they advocate running non-parametric specifications of treatment effects and averaging the effects manually to deal with this issue, they alternatively assumed 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 vary over time. In particular, we use the following parametric counterpart of (2):

$$Y_{it} = \alpha_i + \delta_t + (\gamma_1 + \gamma_K K_{it}) D_{it} + \varepsilon_{it} \tag{3}$$

where γ_1 is the average treatment effect at the event time and γ_K allows the treatment effect to vary with the age of the treatment.

A potential disadvantage of the above specification is the assumption that the treatment effects are the same for all units, except for their different treatment-timings. Some authors replace the binary treatment variable with a continuous but time-invariant variable $I_i \geq 0$ that measures the intensity of the treatment (see, e.g. Abadie, 2005, and Alonso et al, 2019). This allows the treatment effect to differ among units. If the treatment depends on other covariates, we could add I_i as an additional treatment determinant:

$$Y_{it} = \alpha_i + \delta_t + (\gamma_1 + \gamma_K K_{it} + \gamma_I I_i) D_{it} + \varepsilon_{it} \tag{4}$$

2.2. A multi-treatment two-way FE model with cohort-specific treatment effects.

The previous specifications assumed that each unit at most receives a unique treatment that cannot be removed. In our application, some units receive more than one treatment. We next try to develop a simple *multi-treatment* two-way FE estimator from the *one-treatment* models introduced in Section 2.1. We also try to respond to some of the questions that emerge in an asymmetric multi-period *multi-treatment* setting.

2.2.1. Setup

We first introduce the notation to be used throughout this section. Consider again a panel of N units. Each unit is observed over a total of T periods. The observed outcome in time t for unit i is again denoted by Y_{it}. Similar to the setup in Section 2.1, we hereafter assume that some units receive one or more treatments during the sample period. As before, we make the SPC assumption, i.e. once a unit is treated, it will stay treated forever.

Denote the number of treatments received by unit i as M_i. Note that $M_i = 1$ in the one-treatment case. Each treatment is denoted hereafter by $m = 1, \dots, M_i$, and the event time and relative time of each treatment are respectively denoted by E_i^m and $K_{it}^m = t - E_i^m$. We assume that all treatments are sorted by their respective event time. The *overall* treatment history is denoted by a $Tx1$ vector $n_i = \{n_{i1}, n_{i2}, .., n_{iT}\}$, where $n_{it} = \sum_{m=1}^{M_i} D_{it}^m$ is the number of treatments that unit i has accumulated at time t, and D_{it}^m is the treatment indicator defined in Section 2.1, but which is now defined for each treatment.[11] Under the SPC assumption, n_i measures the number of treatments over time. For a never-

[11] The *overall* treatment history can alternatively be defined as $n_i = \sum_{m=1}^{M_i} D_i^m$, where D_i^m summarizes the whole history of the mth treatment received by unit i.

treated or control unit, n_i is a $Tx1$ vector of zero values. An illustration of the new treatment history variables can be found in Figure 5. Each column in Figure 5. represents the treatment history (n_i) of several hypothetical units in an asymmetric multi-period multi-treatment setting. The treatment cohort (i.e., the value of C_i) of never-treated or control units in Figure 5 is equal to 17. The treatment history of a control unit is a vector of zeros as $n_{it} = 0$ from $t = 1$ to $t = 17$. Units 5, 6 and 7 are units that receive one or more treatments during the sample period. This implies that the value of C_i for these treated units is less than T (i.e., 5, 10 and 15, respectively). The treatment history (n_i) of one of these treated unit is a vector of zeros till $t = C_i$. Since then, $n_{it} \geq 1$.

Figure 5. Treatment histories in a multi-period multi-treatment setting

Year	t	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7
2001	1	0	0	0	0	0	0	0
2002	2	0	0	0	0	0	0	0
2003	3	0	0	0	0	0	0	0
2004	4	0	0	0	0	0	0	0
2005	5	0	0	0	0	1	0	0
2006	6	0	0	0	0	1	0	0
2007	7	0	0	0	0	1	0	0
2008	8	0	0	0	0	1	0	0
2009	9	0	0	0	0	1	0	0
2010	10	0	0	0	0	2	1	0
2011	11	0	0	0	0	2	1	0
2012	12	0	0	0	0	2	1	0
2013	13	0	0	0	0	2	1	0
2014	14	0	0	0	0	2	1	0
2015	15	0	0	0	0	3	2	1
2016	16	0	0	0	0	3	2	1
2017	17	0	0	0	0	3	2	1

A general multi-treatment two-way FE model that however ignores group-specific linear trends and control variables can be written as:

$$Y_{it} = \alpha_i + \delta_t + \sum_{m=1}^{M_i} \gamma_{it}^m D_{it}^m + \varepsilon_{it} \quad (5)$$

where the effect of each treatment is allowed to change across treatments and treated units. Under the SPC assumption, each treatment adds a specific effect on top the previous one. We next impose some restrictions on γ_{it}^m in order to prevent estimating too many treatment parameters that might have difficult economic interpretation.

2.2.2. The common sequential parameter assumption

If we impose in (5) that sequential treatments have the same effect on outcome (i.e. $\gamma_{it}^m = \gamma_{it}$), we obtain a first simplification of above unrestricted two-way FE model, where the set of M_i treatment indicators are replaced with a single treatment variable:

$$Y_{it} = \alpha_i + \delta_t + \gamma_{it} n_{it} + \varepsilon_{it} \quad (6)$$

The above specification suggests that we can accumulate sequential treatments as long as their effect on outcome is the same. Therefore, in addition to the PT assumption, we should test the existence of common sequential effects in a multi-treatment setting. We refer to this as the *common sequential parameter* (CSP) assumption. If, in addition, we assume that the treatment effects are common to all units and do not vary over time and across treatments (i.e. $\gamma_{it}^{m} = \gamma$), we obtain the multi-treatment counterpart of a standard two-way FE model:

$$Y_{it} = \alpha_i + \delta_t + \gamma n_{it} + \varepsilon_{it} \tag{7}$$

As in the standard one-treatment case, the estimated γ coefficient can be interpreted as the average effect of a single treatment. In a multi-treatment setting, γn_{it} measures the cumulative effect of several treatments. We find the above simplifications very useful when there are many treatments or when we are interested in average effects per treatment. In this sense, the CSP assumption simplifies the economic interpretation of the two-way FE model in a multi-treatment setting.

It is worth mentioning that n_{it} can always be written as $n_{it}D_{it}^{1}$ if we take into account that all treatments are sorted by their respective event time. Using this notation, equation (7) can be rewritten as:

$$Y_{it} = \alpha_i + \delta_t + \gamma n_{it} D_{it}^{1} + \varepsilon_{it} \tag{8}$$

Note that equation (8) looks like a standard one-treatment two-way FE model with a time-varying and heterogeneous treatment parameter. This implies that, under the CSP assumption, a multi-treatment two-way FE model can be viewed as a sort of one-treatment two-way FE model where the new treatments can be treated as different levels of a unique treatment such as the two-period framework of Abadie (2005), or our own in (4) when we allow the treatment effect to vary with I_i. Like the standard intensity variable (I_i) associated with a unique treatment, n_{it} varies across units in an asymmetric multi-treatment setting. Another appealing interpretation is possible. As n_{it} increases over time in multi-treated units, the above specification can also be interpreted *as if* there was a unique treatment with modest short-run effects and larger long-run effects as in Strezhnev (2018). This implies that the generalized PT assumption and cohort-specific treatment effects examined with a unique treatment are still valid in settings with more than one treatment if the CSP assumption is fulfilled.

2.2.3. Time-varying and cohort-specific treatment effects

As Borusyak and Jaravel (2017) showed that the standard two-way FE estimator suffers from severe biases in multi-period settings with time-varying treatment effects, we next summarize our strategy to parameterize the treatment effects in equation (5) or (6) without imposing the restrictions used in (7) and (8).

The effect of each LC process is allowed to change at a constant rate over time in the same fashion as (3). That is, we hereafter assume that the effect of treatment m on outcome (γ_{it}^{m}) depends on its relative time (K_{it}^{m}). As some characteristics of the LC processes (such as investment per hectare) likely determine these effects, we henceforth assume as well that γ_{it}^{m} depends on treatment intensity (I_i^{m}). Taking these two assumptions together, we obtain the following multi-treatment model under the CSP assumption:

$$Y_{it} = \alpha_i + \delta_t + \gamma_n n_{it} + \gamma_I \Sigma \mathrm{I}_{it} + \gamma_K \Sigma \mathrm{K}_{it} + \varepsilon_{it} \tag{9}$$

where $n_{it} = \sum_{m=1}^{M_i} D_{it}^{m}$, $\Sigma \mathrm{I}_{it} = \sum_{m=1}^{M_i} I_i^{m} D_{it}^{m}$, $\Sigma \mathrm{K}_{it} = \sum_{m=1}^{M_i} K_{it}^{m} D_{it}^{m}$ are respectively the number of treatments received by unit i at period t, their cumulative intensity and their cumulative ages or event times.

The foregoing model does not allow for cohort-specific differences, except for their different treatment-timings and intensities. Figure 5 helps us to explain the implications of this restriction in a multi-treatment setting. While the first four units in Figure 5 are never-treated, the last three units are treated several times. These units belong to three different treatment cohorts: unit 5 belongs to cohort $C_i = 5$; unit 6 belongs to cohort $C_i = 10$; and unit 7 belongs to cohort $C_i = 15$. Equation (9) implies that initial effects on outcome of unit 5, 6 and 7 are same (i.e., $\gamma^1_{5,5} = \gamma^1_{6,10} = \gamma^1_{7,15}$) if we abstract from *observed* differences in relative times and treatment intensities. As unit 5 is firstly treated five and ten years before than units 6 and 7, this seems to be a strong assumption if there are *unobserved* differences among distant cohorts' treatments. For the same reason, the first and second treatment received by unit 5 might be different (i.e., $\gamma^1_{5,5} \neq \gamma^2_{5,10}$). However, the CSP assumption restricts both effects in being equal. Moreover, the above three treated units receive treatment in 2015. As they coincide in time, their nature is likely to be similar. That is, although the effect of their first treatments is expected to differ, it is reasonable to assume that contemporaneous treatments have similar effects (i.e., $\gamma^3_{5,15} = \gamma^2_{6,15} = \gamma^1_{7,15}$). Interestingly enough, this seems to suggest that a common parameter restriction should be imposed across units, not across sequential treatments.

In order to take the above issues into account, but still keeping the CSP assumption, we propose extending our model using treatment cohorts in the spirit of Borusyak and Jaravel (2017) and Strezhnev (2018). Assuming that the treatment cohorts are defined in terms of decades, and that only the initial effect is allowed to vary across cohorts for notational ease, the outcome effect of *each* treatment can be written as:

$$\gamma^m_{it} = \left(\sum_{j=1}^{J} \gamma_{nj} D_{m\in C_j}\right) + \gamma_I I^m_i + \gamma_K K^m_{it} \tag{10}$$

where $D_{m\in C_j} = 1$ if treatment *m* belongs to cohort *j*. Equation (10) can be labelled hereafter as the *treatment effect function*. If we plug (10) into (5) and make the CSP assumption, we get the following multi-treatment model with cohort-specific parameters:

$$Y_{it} = \alpha_i + \delta_t + \sum_{j=1}^{J} \gamma_{nj} n^j_{it} + \gamma_I \Sigma \mathrm{I}_{it} + \gamma_K \Sigma \mathrm{K}_{it} + \varepsilon_{it} \tag{11}$$

where $n^j_{it} = \sum_{m=1}^{M_i} D^m_{it} D_{m\in C_j}$. By definition, $n_{it} = \sum_{j=1}^{J} n^j_{it} = \sum_{m=1}^{M_i} D^m_{it}$. Therefore, we obtain model (9) if we impose common cohort-specific parameters, i.e. $\gamma_{nj} = \gamma_n$.

In our empirical application, the treatment cohorts are defined in terms of decades, and hence only three cohorts are examined (i.e., $J = 3$). We also use an extended version of (10) as cohort-specific coefficients are estimated for K_{it} and I_{it}. It is worth mentioning here that it is not possible to estimate non-parametrically the economic and social effects of the first cohort of LC processes that took place before our sample period. See e.g., Strezhnev (2018, footnote #6, p. 11). However, their time-varying effect can be measured parametrically because K_{it} varies over time.[12]

To make the PT assumption more credible, we extend the two-way FE model in two directions. In both cases we try to model the unobserved time-varying heterogeneities explicitly as the unobserved time-varying factors might cause the failure of the PT assumption. A widely used strategy is to add a set of group-specific linear trends to conventional two-way FE models (see, for example, Wolfers, 2006). In our application, the groups are municipalities and the extended FE model to be estimated is:

[12] Their time-invariant effect can be measured if we take advantage of the CSP assumption and assume that the effect of LC processes that took place in the 90s is equal to the effect of next LC processes.

$$Y_{it} = \alpha_i + \delta_t + \tau_g t + \sum_{j=1}^{J} \gamma_{nj} n_{it}^{j} + \gamma_I \Sigma \mathrm{I}_{it} + \gamma_K \Sigma \mathrm{K}_{it} + \varepsilon_{it} \quad (12)$$

where g stands for municipality. As Xu (2017) points out, this strategy works if treatment is randomly assigned conditional on both the fixed effects and the imposed trends.[13] The second strategy aimed at making the PT assumption more credible relies on a set of control variables that, in addition, allows the treatment effects to depend on units' observable characteristics. This strategy is explained in next sub-section.

2.2.4. Control variables and non-neutral treatment effect

In this sub-section we extend the previous model by adding a set of control variables (X_{it}), which can be written as:

$$Y_{it} = \alpha_i + \delta_t + \tau_g t + \pi X_{it} + \sum_{j=1}^{J} \gamma_{nj} n_{it}^{j} + \gamma_I \Sigma \mathrm{I}_{it} + \gamma_K \Sigma \mathrm{K}_{it} + \varepsilon_{it} \quad (13)$$

We are aware that measuring the treatment effects using this conditional (on X-covariates) model can be problematic if the control variable X_{it} is a bad control in the terminology of Angrist and Pischke (2009). Indeed, if X_{it} is part of the causal effect of D_{it} on Y_{it}, the treatment effect function $\partial Y_{it}/\partial D_{it}$ is likely to either under or over-estimate the global treatment effect because it misses the partial effect $\pi \cdot \partial X_{it}/\partial D_{it}$. As we are not sure whether the alternative 'solutions' proposed in the literature[14] can be used in a multi-treatment setting or, if so, how they should be implemented, we have decided to keep the X-covariates and compute $\partial X_{it}/\partial D_{it}$ using an auxiliary regression of X_{it} on D_{it} for robustness analysis. This allows us to measure the total treatment effect using $\gamma_{it} + \pi \cdot \partial X_{it}/\partial D_{it}$.

Note finally that the above *conditional* specification assumes that the treatment effects only depend on their relative time and treatment intensities. This assumption has two implications. First, it implies that the treatment effects do not depend on units' characteristics, 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 (13) are *neutral* in the sense that the units' outcome function (technology) does not change with, say, the number of treatments. If we, for instance, interpret π as a marginal product (elasticity), equation (13) imposes that this important technological feature does not change with LC. In order to get a non-neutral specification of our model, we assume that each treatment coefficient in (13) is a linear function of X_{it}, that is: $\gamma_{nj} = \bar{\gamma}_{nj} + \gamma_{nx} X_{it}$, $\gamma_I = \bar{\gamma}_I + \gamma_{Ix} X_{it}$, and $\gamma_K = \bar{\gamma}_K + \gamma_{Kx} X_{it}$. Using this new specification of (10), we obtain the following *non-neutral* model:

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[13] Although the DiD method does not require us to specify the rules by which the treatment is assigned (Gertler et al. 2011), it is germane to point out here that the Department of Planning and Rural Infrastructures of the Government of the Principality of Asturias has confirmed that most of the conditions that should be in place before a LC project is undertaken are time invariant as they are geographical in nature, e.g. land quality, location of natural resources, distribution of current infrastructures, the existence of appropriate legislation, etc.

[14] No consensus exists in the literature on how to proceed when the X-covariates also depends on the treatments. Dropping the X-covariates is probably imprudent because it might put the PT assumption in danger, reduce goodness-of-fit notably, and generate severe omitted variable biases. Another option is to use adjusted X-covariates. For instance, Imai et al (2018) suggest the use of pre-treatment covariates. Other authors also condition on pre-treatment observables using matching methods. For example, Abadie (2005) proposes matching before DID estimations. The synthetic control method used e.g. by Abadie et al. (2010, 2015), and Gebel and Vossemer (2014) go one step further as it matches both pre-treatment covariates and outcomes.

$$Y_{it} = \underbrace{\alpha_i + \delta_t + \tau_g t + \pi X_{it}}_{\substack{outcome\\ function}} + \underbrace{\sum_{j=1}^{J} \bar{\gamma}_{nj} n_{it}^{j} + \bar{\gamma}_I \Sigma \mathrm{I}_{it} + \bar{\gamma}_K \Sigma \mathrm{K}_{it}}_{neutral\, effect} +$$
$$\underbrace{\gamma_{nx} X_{it} n_{it} + \gamma_{Ix} X_{it} \Sigma \mathrm{I}_{it} + \gamma_{Kx} X_{it} \Sigma \mathrm{K}_{it}}_{non-neutral\, effect} + \varepsilon_{it} \tag{14}$$

It is worth mentioning that the effects of the LC variables are parish-specific as we have interacted the LC variables with observed parishes' characteristics (such as the number of farms). Although the main focus of our paper is whether LC matters as a whole, the individual coefficients allow us to capture differences among LC processes. That is, the interactions with parishes' characteristics allow us to identify which parishes have benefited the most from the LC processes.

Using equation (14), the direct effect of LC[15] can be computed using the following difference of two *conditional* expected productions:

$$LCE_{it} = E[Y_{it}|\alpha_i, \delta_t, X_{it}, n_{it}^{j}, \Sigma \mathrm{I}_{it}, \Sigma \mathrm{K}_{it}]_{n_{it} \geq 1} - E[Y_{it}|\alpha_i, \delta_t, X_{it}, n_{it}^{j}, \Sigma \mathrm{I}_{it}, \Sigma \mathrm{K}_{it}]_{n_{it}=0} \tag{15}$$

This equation measures 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 (15) is conditional on both parish effects, α_i.Therefore, we are controlling for time-invariant differences between the two mentioned parishes. We are also controlling in (15) 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 parishes' production that is more likely related to exogenous factors common to all farms and parishes.

Notice that while the first conditional expectation in (15) is equal to the so-called outcome function plus the neutral and non-neutral effects in equation (14), all LC-based variables take the zero value when $n_{it} = 0$, and then the second conditional expectation in (15) is equal to the outcome function. As both conditional expectations include the outcome function, LCE_{it} in (15) can alternatively be defined as the sum of the neutral and non-neutral effects attributable to the LC processes, that is:

$$LCE_{it} = \sum_{j=1}^{J} \bar{\gamma}_{nj} n_{it}^{j} + \bar{\gamma}_I \Sigma \mathrm{I}_{it} + \bar{\gamma}_K \Sigma \mathrm{K}_{it} + \gamma_{nx} X_{it} n_{it} + \gamma_{Ix} X_{it} \Sigma \mathrm{I}_{it} + \gamma_{Kx} X_{it} \Sigma \mathrm{K}_{it} \tag{16}$$

3. Sample and data

In this paper we examine three different categories of LC effects. First we examine whether LC has exerted broad impacts on promoting livestock production scale, measured as average cows per farm. This empirical exercise allows us to see whether LC has helped in the restructuration of livestock production already mentioned in the introduction section. We carry out this analysis using a production approach as in Wu et al. (2005). However, while these authors use farm-household data to evaluate the effectiveness of LC projects in China, we use detailed geo-spatial data of Asturian parishes with and without LC processes, as in Crecente et al. (2002) and Miranda et al. (2006) who evaluate

[15] Why we have added the 'direct' label to this effect is explained later in sub-section 4.2.

several LC effects in Galicia, an autonomous region located in north-west Spain that is adjacent to Asturias, the region examined in our paper.[16]

This work has been possible thanks to the availability of statistical information disaggregated by parishes on farms and livestock, as well as specific information on the quantity and the intensity of the LC processes, over a sufficiently long period of time. This allows us to use panel data estimators that control for many variables that are not available at parish level but are likely to be time-invariant.

The data used in our study comes from two complementary sources and has allowed 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, parish's total land area, number of bovine farms, total bovine herd (both beef and dairy), and livestock units (see SADEI, 2011).[17] 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 starting and ending plots number, the date of taking possession of the new plots, the volume of public investment in the development and implementation of the LC processes, etc.

All models are estimated using panel data techniques because, as pointed out by Demetriou (2018), there are many characteristics that affect parishes' production, but which are unobserved at parish level such as geographic conditions, transport connections and accessibility, etc. If these omitted variables are correlated with our regressors, we will get both biased parameters and biased effects attributed to LC processes. However, notice that many of the above unobservable variables are likely to be time-invariant or rarely changing variables. Our two-way FE estimator thus allows us to address this important source of endogeneity.

3.1. Farms' size.

We first examine whether LC has exerted broad impacts on promoting livestock production scale or farms' size.

As it 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 farms' 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 the 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 the 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

[16] Crecente et al. (2002) show that LC contributes to retaining farmland in agricultural use and improves the population evolution in rural areas, although they observe changes in use from cropland to pasture land. Also using very disaggregated geo-spatial data at parish-level, Miranda et al (2006) conclude that LC have improved agricultural land structure by reducing the number of plots per holding, as well as the generalized drop in the number of active holdings, serving also to mitigate the decline in the population of rural areas.
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[17] See http://www.sadei.es/datos/sad/vacas/vacas.aspx

correlated. For this reason, we use parishes' cattle as proxy for livestock production in each parish.[18]

We first estimate a production function using the natural logarithm of the total number of parishes' bovine animals (i.e., $Y_{it} = lny_{it}$) as the dependent variable. The main input of this production function is the natural logarithm of the total number of bovine farms ($i.e., X_{it} = lnx_{it}$). 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 livestock production scale, 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 adult cows count as one livestock unit, while younger animals count 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 farms' cattle, z_{it} can also be viewed as an indicator of the traditional (extensive) character of livestock in each parish. The lower the z-ratio, the greater the intensification of productive activity.[19]

The effect of each LC process on parishes' production is allowed to change with its relative time, as well as its intensity. We use the natural logarithm of the investment per hectare involved in LC plans to measure LC intensity. Under the CSP assumption, this implies that parishes' production depends on the cumulative number of LC processes (n_{it}), their cumulative age (ΣK_{it}), and their cumulative intensity (ΣI_{it}). In order to capture *unobserved* differences among distant LC processes, we also estimate a multi-cohort production model in the spirit of Borusyak and Jaravel (2017) and Strezhnev (2018), where we distinguish between LC processes implemented in the 1990s, 2000s and 2010s. Therefore, we use three cohorts (C_1, C_2 and C_3) in our multi-cohort production model. We not only estimate cohort-specific parameters for the number of LC processes belonging to a particular cohort, but also for their cumulative age and intensity.[20]

Finally, recall that our DiD model not only includes a set of parish-specific but also a set of time-specific dummy variables. As our production function is conditional on the number of farms, the estimated parameters of the time dummy variables measure here the 'natural' tendency of parishes' average farm size over time.

3.2. Number of farms and parishes' population.

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 parishes' production, we need to estimate the effect of our LC-based

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[18] This 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).

[19] In the case of dairy farms, the lower the z-ratio, the more weight the heifers have. This reflects that the farms require a high rate of annual replacement of cows because dairy cows of high production 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.). On the other hand, 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 cattle, thereby indicating that the meat holdings have few calves in the process of bait. This would be the case of those farms that decide to sell the calves after a few months of life to be fattened on other more professional farms (feedlots) outside the parish.

[20] For notational ease, we will label these variables as ΣD_{C_j}, ΣK_{C_j}, and ΣI_{C_j} when presenting our parameter estimates.

variables on the number of farms using an auxiliary regression.[21] In this auxiliary regression model we regress the logged number of farms ($X_{it} = lnx_{it}$) on the maturity indicator of farms' cattle (z_{it}) and its squared value, as well as the cumulative number of LC processes (n_{it}), their cumulative age (ΣK_{it}), and their cumulative intensity (ΣI_{it}). This model is again estimated using a two-way FE estimator. One-cohort and multi-cohort models are estimated as before. 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.

To acquire a social view of the subject we also estimate an additional auxiliary regression that allows us to measure the effect of our LC-based variables on parishes' population. The second auxiliary regression model simply regresses the natural logarithm of parishes' population (lnP_{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 this case, the parameters of the time dummy variables measure the "natural" decline in parishes' population over the last 17 years.

3.3. Descriptive statistics.

As mentioned in the introduction section, our study is focused on western Asturias because the LC processes were implemented with greater intensity in this geographical area. More concretely, our sample includes 292 parishes belonging to 26 municipalities located in western Asturias. Table 1 shows the descriptive statistics of these parishes over the period 2001-2017. The total sample size is 4,964 observations with 1,056 observations having been involved in one or more LC processes. As all LC variables in a parish take a zero value before the first LC process is implemented, the descriptive statistics of the three LC-based variables (i.e. the cumulative number of LC processes, and their cumulative age and intensity) are computed using 1,056 observations.

[Insert Table 1 here]

4. Results

Our first empirical model aims to measure the economic impact of LC processes on parishes' livestock production using a primal representation of parishes' production technology. The effects estimated here can be interpreted as an effect on farms' average size because they are conditional on the number of farms of each parish. In order to achieve an unconditional effect, we next estimate the effect of our LC variables on the number of farms using an auxiliary regression that includes our set of LC-based variables as regressors. The effect of our LC-based variables on parishes' population is estimated using a similar auxiliary regression model where we replace the number of farms with population. Despite their differences, all models are estimated using a two-way FE estimator that includes both parish-specific and time-specific fixed effects.

4.1. Testing the PT and CSP assumptions

Estimating a DiD model does not identify the causal effects of a policy measure or treatment if the standard parallel trends (PT) or common trend assumption is violated. In addition, we cannot view the multiple treatments as a unique treatment with different levels if the common sequential parameter (CSP) assumption that we have introduced in this paper is not fulfilled.

[21] We 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.

To investigate the PT assumption, it is customary to undertake tests to establish if there are systematic pre-treatment trend differences between treated and control units. To check for equality of pre-treatment trends, 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. Using equation (5), this restriction implies that $\gamma_{it}^{m} = \gamma_{it}$ for all $m = 1, .., M_i$ where M_i is the number of LC processes that have taken place in parish i. Similar restrictions are tested if we allow for differences attributed to the age and intensity of the LC processes.

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 function, regardless whether we include a set of specific time-dummies or a specific time-trend for the treated units.[22] When we estimate the auxiliary regression aimed at explaining the changes in parishes' 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 parishes' 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 ($\Sigma \mathrm{I}_{it}$), and their cumulative ages ($\Sigma \mathrm{K}_{it}$). Unfortunately, the same simplification cannot be implemented if we aim to measure the effect of the LC processes on parishes' 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 parishes' population.

4.2. Parameter estimates and LC effects

4.2.1. Farms' 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.

[Insert Table 2 here]

[22] Appendix A provides the F-test performed to check whether both PT and CSP assumptions are supported by the data.

The first set of coefficients (and variables) captures the characteristics of parishes' 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 transformation has no effect on the estimation but 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's livestock production. The third set of coefficients allows the LC effects to depend on parishes' characteristics. Finally, the estimated fixed effects (not shown), not only capture other relevant inputs for farms' production but also other geographical and socio-economic variables that condition farms' size. The estimated coefficients of both the time dummy variables and the municipality-specific linear trends included in the model (also not shown), allow obtaining different natural tendencies over time for each municipality.

Regarding the characteristics of parishes' 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 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 herd adopts a form of inverted U due to the first-order effect proving positive and the quadratic term being negative. Furthermore, the negative coefficient associated with the squared value of z_{it} implies that very extensive (and traditional) farms tend to be smaller as they on average use less cows than more intensive farms. 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 number of treatments, their cumulative intensity, and their cumulative ages on parishes' livestock production. As each LC process is a complex phenomenon it is difficult to interpret separately the coefficients of these three LC indicators. Although we are more interested in overall effects than in individual effects, we find a positive and significant effect of the investments per hectare ($\Sigma\mathrm{I}_{it}$) on the livestock production of a representative parish. We find that n_{it} has a negative coefficient. However, this somehow counterintuitive result could be caused by the fact that the number of LC processes is highly correlated with the cumulative intensity of these processes. Therefore, if we abstract from the age of the LC processes, computing their overall effect on farms' size should take into account the coefficients of both n_{it} and $\Sigma\mathrm{I}_{it}$. Notice that $\Sigma\mathrm{K}_{it}$ does not have a significant negative coefficient. This result seems to indicate that, on average, the LC processes have a delayed impact on Asturian parishes' production (and on average farm size).

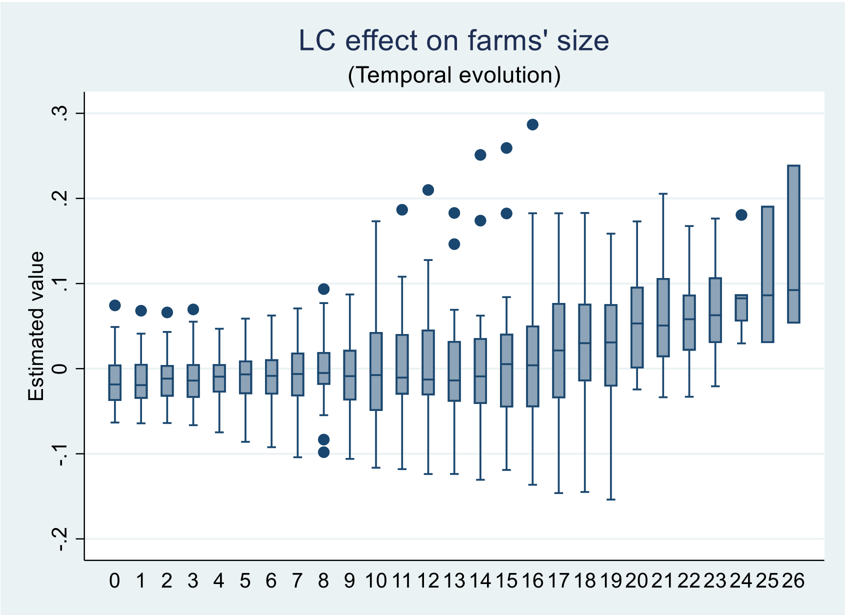
Another remarkable result is the positive and statistically significant coefficient of $\Sigma\mathrm{I}_{it}z_{it}$. This coefficient indicates that the public investments in infrastructures tend to have a larger (positive) effect in parishes where the local farms use more traditional systems of livestock production. Our model includes interactions between our LC indicators and the number of farms, another characteristic of the parishes' production technology. The coefficient of $n_{it}lnx_{it}$ is positive and statistically significant, indicating that adding new LC processes is more effective in parishes with several farms. This result indicates the existence of some synergies between LC processes when the number of farms located in such a parish is large. However, the statistically significant and negative coefficient found for $\Sigma\mathrm{K}_{it}lnx_{it}$ seems to indicate that the better effect found in large parishes deteriorates at a greater rate than the (initially smaller) effect found for parishes with fewer farms.

Table 2 also shows the results of a *multi-cohort* specification that distinguishes between LC processes implemented in the 1990s, 2000s and 2010s. This allows us to examine whether the LC processes implemented in different decades have similar effects on parishes' livestock production. To facilitate the econometric exercise, here we focus our analysis on the average effects, captured by the first-order LC-based variables: the number of treatments (n_{it}), their cumulative intensity ($\Sigma \mathrm{I}_{it}$), and their cumulative ages ($\Sigma \mathrm{K}_{it}$). It is worth mentioning here that our sample begins in 2001 and that the cumulative number of LC processes (n_{it}) does not necessary begin with a zero value in 2001 because it also considers the LC processes that were implemented in the 90s. This implies that it is impossible to estimate a specific-cohort parameter for the cumulative number of LC processes that were implemented in the 90s together with their cumulative intensity because these two variables do not vary over time in our sample. However, a specific-cohort parameter can be estimated for their cumulative age because, in this case, it does vary over time.

We find very similar coefficients using one-cohort and multi-cohort specifications as we cannot reject that the coefficients of different cohorts are the same. The latter result might indicate that the different, if any, nature of the LC processes implemented over different decades is being captured by the observed intensity and age variables. We find a positive and significant effect of the investments per hectare on the livestock production of a representative parish using a one-cohort specification. We now realize that this result is mainly explained by the LC processes that have taken place during the 2010s. The estimated coefficients for the interactions of n_{it} and $\Sigma \mathrm{I}_{it}$ with z_{it} are no longer statistically significant (although they maintain the same sign), indicating that their effects are somehow captured by the new set of cohort-oriented variables. Recall that we can estimate three specific-cohort parameters for $\Sigma \mathrm{K}_{it}$ because this variable varies over time. As in our one-cohort specification, we do not find evidence of a decreasing effect of the LC processes implemented in the 1990s, 2000s and 2010s. As the coefficients of the interactions of these three LC-based variables with parishes' characteristics are robust when using a single or multi-cohort specification, we again obtain a negative and statistically significant coefficient for $\Sigma \mathrm{K}_{it} ln x_{it}$ indicating that, although the LC processes are more effective in large parishes, their effect seems to decrease over time.

We next proceed to calculating the effect of LC on parishes' 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 very heterogeneous individual LC effects. For this reason, on average , it is difficult to obtain a noteworthy LC effect on parishes' livestock production (conditional to the number of farms). Several comments are in order regarding the apparently negligible average effects found here. First, it should be pointed out that in these cases 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. Second, 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 parishes' livestock activity once we take into account the changes in farm figures caused by both internal and external LC processes. Third, as Figure 6 shows, we find larger (positive) effects attributable to the LC as time passes. This conclusion confirms the Crecente et al. (2002, p. 142) findings in the sense that a short temporal window is not enough to capture properly the final effects caused by the LC developments. 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.

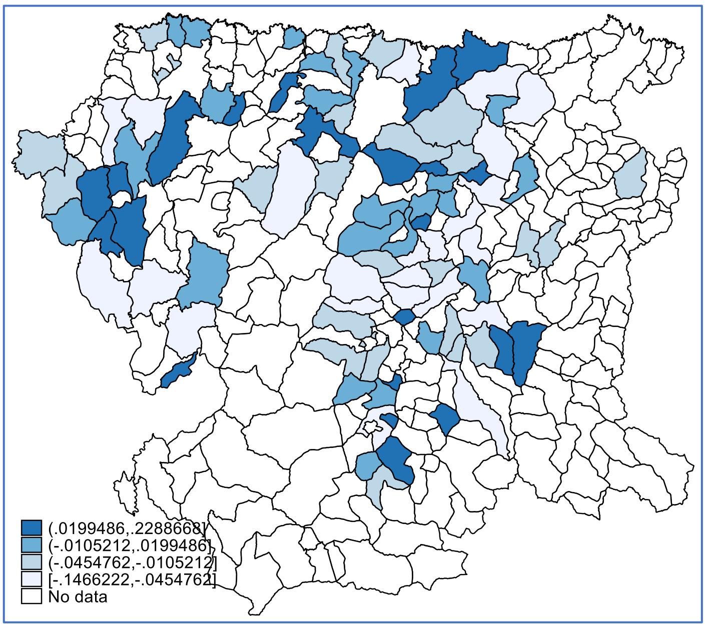
Figure 6. Temporal evolution of the direct LC effect on farms' size



Finally, Figure 7 shows the geographical distribution of the estimated effects attributable to the LC processes that have taken place in western Asturias.[23] We find that some LC processes performed in Villanueva de Oscos, San Matín de Oscos or Cangas del Narcea have had a remarkable effect on farms' size in terms of livestock numbers. These parishes tend to have a small number of farms if we consider both distant and recent LC processes. These farms, in addition, tend to use intensive systems of livestock production to produce beef. The lack of proper plots and infrastructures in these parishes might explain why they are not able to attract more farmers, a problem that is alleviated with land consolidation developments. Therefore, the LC processes implemented in these parishes have helped to maintain livestock production by favouring the concentration of production on larger beef-oriented farms.

[23] The white coloured parishes in this figure are parishes with no internal LC processes.

Figure 7. Direct LC effects on farms' size



4.2.2. Farm numbers

Table 3 shows the parameter estimates of the auxiliary regression aimed at explaining changes in parishes' 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's livestock production: the number of treatments (n_{it}), their cumulative intensity ($\Sigma \mathrm{I}_{it}$), and their cumulative ages ($\Sigma \mathrm{K}_{it}$). The third set of coefficients allows the LC effects to depend on the main farms' characteristic, i.e., their system of livestock production. Finally, the estimated coefficients of the time dummy variables included in the model (not shown), allow capturing the 'natural' deterioration in the number of farms over time that we mentioned in the introduction section.

[Insert Table 3 here]

Both 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. Similar to our production function model, we find very heterogeneous individual LC effects that do not allow us to achieve any noteworthy average LC effect on farm figures.[24] We obtain interesting findings once we split the sample into several groups or we locate the parishes on a map. Figure 8 shows the geographical distribution of the estimated LC effects on the number of farms. We find that the LC processes have specially attenuated the decline in the number of farms in coastal parishes (municipalities).[25] As most of the dairy livestock is in these municipalities, this

[24] Notice that we have not distinguished in Table 3 between dairy and beef-oriented farms. In our robustness analysis section, we examine whether the apparently lack of significance of LC effects can be applied to both dairy and beef-oriented farms.
[25] Notice that a positive effect here does not imply that the number of farms increases over time due to the increasingly negative coefficients of the time dummies included in our auxiliary regression. They rather indicate that the decline in the number of farms is attenuated by the LC processes.

distribution suggests the existence of a positive effect in parishes where the dairy-oriented farms predominate. It should be pointed out, however, that this does not necessarily mean that the dairy farms are the most benefited by the LC processes if the LC processes help the replacement of dairy-oriented farms with beef-oriented farms. This result might simply suggest that the LC activity needs the existence of dairy farms to be effective at attenuating the decline in the number of farms, an issue that will be examined in the sub-section devoted to robustness analyses and further results.

Figure 8. Direct LC effects on parishes' farms

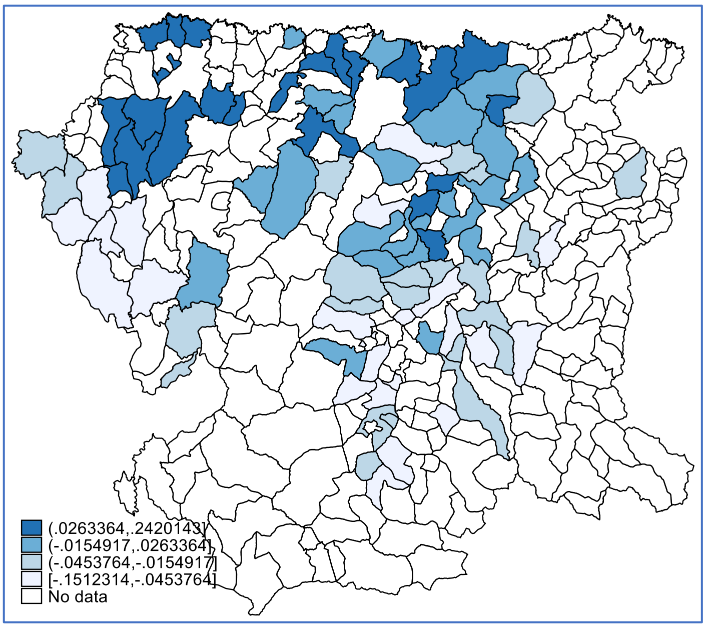
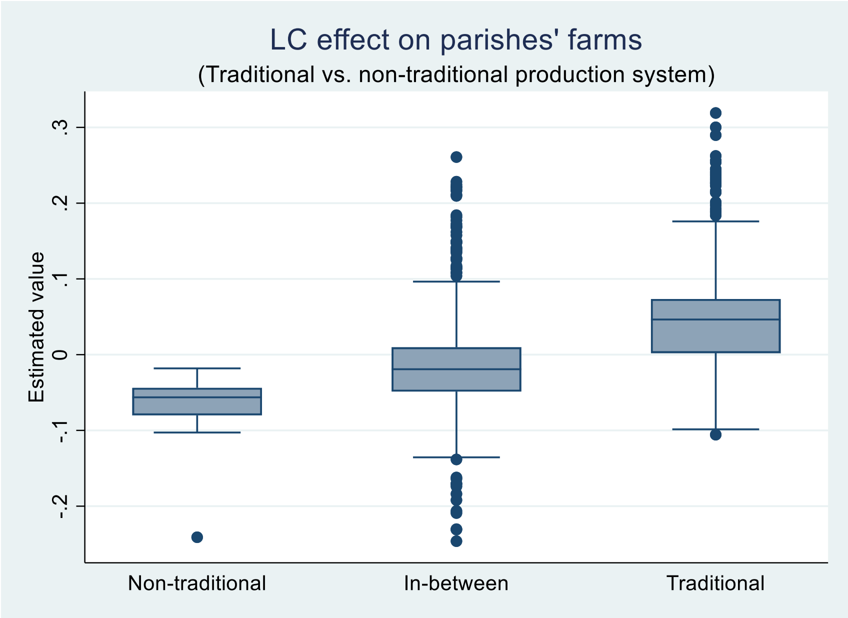


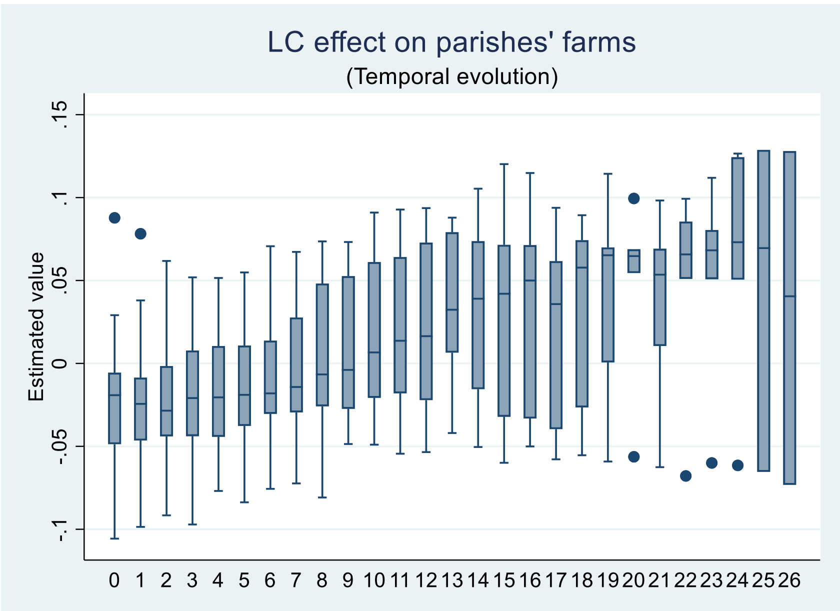
Figure 9 distinguishes the effect of LC processes between parishes with extensive farms using traditional systems of livestock production and parishes with more intensive farms. As in previous studies, we find that the effect of LC processes on the number of farms is more relevant when these farms are of an extensive type. For instance, Orea et al. (2015) also concluded that the LC processes would particularly improve extensive farms' profits rather than those generated by intensive farms. If we compare this map with the previous one, we appreciate that some LC processes performed in parishes located in municipalities close to the Galician border (e.g. Villanueva de Oscos and San Matín de Oscos) or in Cangas del Narcea, the largest Asturian municipality), have had a noticeable effect on farms' size in terms of livestock numbers, but a small effect, if any, on the number of farms. Both maps combined seem to indicate that 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 on larger farms.

Figure 9. LC effect on parishes' farms. Traditional vs. non-traditional.



As aforementioned, on average we do not find noteworthy effects on the numbers of farms located in parishes that have had one or more LC processes. Notice that our FE estimator uses annual changes to estimate the coefficients of the model. As pointed out by Crecente et al. (2002, p. 142), this temporal periodicity is probably insufficient for the purpose of identifying the effects of the LC processes. To detect the LC effects we clearly need to examine longer temporal windows. We do so in Figure 10. This figure depicts the estimated effect of a single LC process over more than one decade. Similar to our production function model, we find larger (positive) effects attributable to the LC as time passes.

Figure 10. Temporal evolution of the direct LC effect on parishes' farms



4.2.2. Population

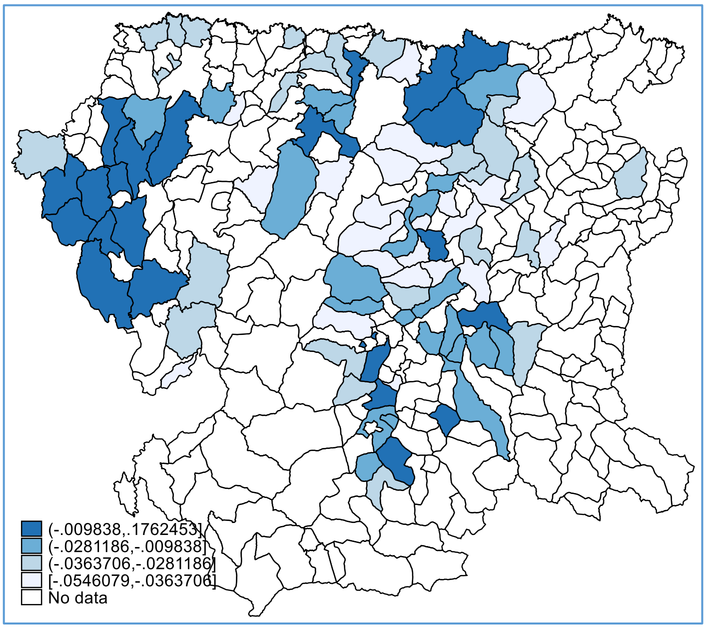
Table 4 shows the parameter estimates of the auxiliary regression aimed at explaining changes in parishes' population. As the focus here is on social issues, this model does not include observed variables on the livestock activity carried out within the parishes. In addition to the LC-based variables, the model again includes fixed and temporal effects (not shown). The estimated coefficients of the time dummy variables included here allow capturing the 'natural' decline of the population in rural Asturias. As we have rejected the null hypothesis of common sequential parameters in this model, we present here the parameter estimates of a simplified specification where we have (incorrectly) imposed the CSP assumption together with a more comprehensive model that includes a different LC-based variable for each LC process that is performed in the same parish. In particular, here our model 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.[26] 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.

[Insert Table 4 here]

As in our previous models, 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 in western Asturias. Figure 11 shows the geographical distribution of the estimated effects on parishes' population. It resembles the previous ones, but with some interesting differences. Except in half a dozen of parishes located close to or several kilometres from the coast (see e.g., Cudillero), the largest positive effects are found in parishes or municipalities located very close to the Galician border (see e.g. Taramundi, Villanueva de Oscos, Santa Eulalia de Oscos and inland Vegadeo). Recall that a positive effect here does not imply that population increases over time. It instead indicates that the population decline is attenuated by the LC processes. Interestingly, while the LC processes were not able to attenuate the decline in the number of farms in many of the parishes located in the two biggest municipalities of Asturias (i.e. Tineo and Cangas del Narcea), they have had a larger effect on their population. It seems that these LC processes have promoted other economic activities in these rural areas due to most likely the improvements in roads and the better accesses to plots and villages. In general, these findings corroborate previous research focused on rural areas at spatial level (see, e.g. Crecente et al., 2002 in Spain, Du et al., 2018 and Zhou et al., 2019 for China or Dudzińska et al., 2018 in Poland) as we also find that the LC processes are key policies in promoting the socioeconomic conditions of rural areas.

[26] Only two parishes accumulate more than three LC processes. In these two cases, we have assumed that the effect of subsequent LC processes is equal to the third one.

Figure 11. Direct LC effects on parishes' population



4.4. Robustness analyses and further results

4.4.1. Dairy vs. beef-oriented livestock production and farms

In order to examine whether our results are robust for model misspecification issues, we also estimated alternative specifications of our models. In particular, we have estimated separately an auxiliary regression model for milk-oriented farms and an auxiliary regression model for beef-oriented farms. Although it is possible to split the overall number of farms in a parish into dairy and beef-oriented farms, we cannot allocate the observed dairy and beef livestock to each farm type. This issue prevented us from estimating two different production functions: one for dairy production and the other for beef production. However, we have taken advantage of production theory and estimated a multi-output distance function (a traditional concept in production economics) that allows measuring the effect of the LC processes on both dairy and beef production using a single equation.[27]

The results using a single production function model or a multi-output distance function are quite similar in terms of both parameter estimates and LC effects. Indeed, we find decreasing returns to scale at parish level using a multi-output distance function, indicating again that parishes with more farms tend to have smaller farms in terms of beef and dairy cattle. When a multi-output distance function is estimated, we find a negative and significant relationship between parishes' beef and dairy production, a somewhat expected result given that it is conditional on the number of farms. As aforementioned, we obtain a positive coefficient for $n_{it} lnx_{it}$ and a negative coefficient for $\Sigma \mathrm{I}_{it} lnx_{it}$ using a single production function. The distance function model includes separate interactions of our LC indicators with the number of dairy and beef-oriented farms. This allows us to examine whether the above two results have more to do with dairy or beef-oriented farms. In both cases, we find that the coefficients of these two interactions are statistically significant when n_{it} and $\Sigma \mathrm{I}_{it}$ are interacted with the number of beef-oriented farms. This seems to indicate that adding new LC processes is more effective in parishes with several

[27] The parameter estimates of this alternative specification are available from the authors upon request.

beef-oriented farms. Moreover, as the coefficient of the interaction of $\Sigma \mathrm{K}_{it}$ with the number of beef-oriented farms was not statistically significant using a distance function, 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,[28] 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 decline of beef-oriented farms. Behind this dynamism is the productive reorientation of some small and uncompetitive dairy farms that took advantage of the plans to abandon dairy production financed by the administration as well as the possibility of selling their milk quota, maintaining their livestock activity with beef cows (see e.g. Parrondo, 2006; García et al., 2007).

We also find very heterogeneous individual LC effects on both dairy and beef-oriented farms. Using a single auxiliary regression model, we have already found that the LC processes were not on average quite as effective in mitigating the decline of the number of farms. When estimating separately two auxiliary regressions, we realize that this result can be explained by the different magnitude of the LC effects found for dairy and beef-oriented farms. That is, 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. Interestingly, the individual effects attributable to LC processes are larger for beef-oriented farms than for dairy-oriented farms, even in parishes where the dairy-oriented farms predominate. In this case, the LC processes have been effective in attenuating the decline in both dairy and beef-oriented farms, but the effectiveness of this policy measure is larger for the latter type of farms. Moreover, we do not find positive LC effects if the proportion of dairy farms is relatively small. That is, the LC activity needs the existence of dairy farms to be effective at attenuating the decline in the number of farms. This somehow bizarre, but expected, result can be explained if the LC processes help the replacement of dairy cows with beef cows and the transformation of the livestock activity from milk to beef production. The LC processes stimulates this transformation as beef production in Asturias is generally developed with more extensive livestock production systems.

4.4.2. Additional Tests

In order to examine whether the performed F-test carried out to check the PT and CSP assumptions were robust to model misspecification issues, we also performed these tests using the above three alternative specifications for the production model and the auxiliary regression aiming to explain changes in the number of farms. Similar F-tests are obtained using these three alternative model specifications. Indeed, both the PT and CSP assumptions cannot be rejected when a multi-output distance function is estimated instead of a production function that does not distinguish between dairy and beef production. Regarding the auxiliary regressions, we find that we cannot reject the CSP assumption when we estimate separately an auxiliary regression for milk and beef-oriented farms. On the other hand, the PT assumption is not rejected at any reasonable level of significance if two different auxiliary regressions are estimated for milk and beef-oriented farms, regardless of whether time-dummies or a time trend for the treated units are used.

[28] The parameter estimates of these two auxiliary regression models are available from the authors upon request.

One of the specifications used to investigate the PT assumption relies on the significance of the coefficient of a time-trend only included in the model for the treaded units. For robustness analyses, we also used the estimated coefficient of this specific time-trend in order to adjust the outcome values of the treated units with the aim of ensuring that on average both treated and control units move in tandem, conditional on the control variables. The distributions of the LC effects were in all cases very similar to those obtained without the proposed adjustment, indicating that our causal effects are robust to deviations from the temporal pattern captured by the (common) time dummy variables.

4.4.3. 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 (15) and (16) is only capturing a *direct* effect on parishes' production ignoring that the local LC processes might also have an *indirect* impact on neighbouring parishes' outcome.[29] Obviously, similar comments can be made for the auxiliary regressions. As we use very small administrative units, for robustness analysis 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.[30] In order to examine whether the parishes that have internal LC processes also have larger spatial spillovers from the LC processes implemented in neighbouring parishes, we estimate different coefficients for the spatially lagged variables for parishes with and without internal LC processes.[31,32]

Table 5 provides a summary of the estimated total effects of the LC processes on farms' size as well as their disaggregation into direct and indirect effects, understood as the effects from LC processes performed inside the parishes and those from the surrounding ones. Several comments are in order regarding the estimated indirect effects shown in this table. 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. Deininger and Xia (2016) draw a similar conclusion in their application to Mozambique. This finding thus indicates that the LC effects are likely to be underestimated if we only examine the local economic impacts of such processes. Notice as well that the parishes with no internal LC processes almost always take advantage of the LC processes performed in neighbouring parishes, regardless of whether we examine livestock

[29] One stylized result from the regional economics literature is that the direct effect of own variables on production reduces when the territorial disaggregation of locations increases because a larger portion of the overall effect spills over neighbouring units (see e.g. Álvarez-Ayuso et al, 2016). Substantial spatial spillovers might appear in our application, given that we use very disaggregated spatial information, and a parish might benefit from other parishes if it uses the plots and infrastructures existing in neighbouring parishes (Da silva et al., 2017).

[30] The spatial lags of the LC-based variables are computed using a spatial weight vector with elements that are equal to zero if a particular parish j is not a neighbour of parish i and equal to one if the two parishes are neighbours or adjacent.

[31] The parameter estimates of the spatial specifications of our models are available from the authors upon request. We only mention here that the coefficients of the spatially lagged variables were statistically significant in most models.

[32] While in our production function model the direct LC effect of each parish (LCE_{it}) is computed using equation (16), the indirect or spatial effect of neighbours' LC processes ($ILCE_{it}$) can be computed by multiplying the spatial lags of the LC-based variables with their estimated coefficient. Next we can compute the *total* effect of LC on parishes' outcome ($TLCE_{it}$) by adding both direct and indirect effects, that is: $TLCE_{it} = LCE_{it} + ILCE_{it}$. The indirect and total LC effects on both parishes' farms and population are obviously computed using a similar procedure.

production, farm numbers or population. Therefore, the effects only computed with parishes that have internal LC processes can be considered as a lower bound of the overall effect attributable to LC processes. The indirect effect found for the parishes with internal LC processes is unclear, as sometimes it is positive, but negative in other cases. Interestingly, we find a slightly negative correlation between the effects caused by LC processes performed inside the parishes and those from the surrounding ones. This result may be indicative of backwash Myrdal´s effects (Gude et al., 2018) in the sense that it may arise through competition in financial support between parishes.

[Insert Table 5 here]

4.4.4. Conditional vs. unconditional effects

As previously discussed, LC processes might affect Asturian parishes' livestock production via the number of farms. To explore this possibility, we have estimated a set of *auxiliary regressions* that include not only internal LC indicators, but also their spatial lags as explanatory variables of the number of farms. If we use the complete sample of observations, we do not obtain significant direct effects of the LC processes on the number of farms. Recall, however, that we have split the sample into dairy and beef-oriented parishes in order to take into account the different composition of the farms located in each parish and found that the LC processes have attenuated the decline of beef-oriented farms. Moreover, the results shown in Table 5 confirm the positive spillovers coming from the LC processes in adjacent parishes. Overall these results suggest that the farm-induced channel through which the LC processes might affect parishes' livestock production should not be ignored, especially in parishes where the beef-oriented farms predominate.

Table 6 shows the conditional, farm-induced and unconditional (or total) LC effects on parishes' 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.[33] This table shows that the farm-induced effect of LC on farm numbers is on average positive for the whole set of parishes that were involved in LC processes. This favourable effect is even larger when we take into account the spatial spillovers from LC processes performed in surrounding parishes. Therefore, we can conclude that the unconditional effect of the LC processes on parishes' livestock production tends to be smaller (larger) than the conditional effect when the proportion of dairy (beef) farms located in a particular parish is sufficiently high. Taking into account the two mentioned channels, we find that parishes' 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, regardless of whether we include spatial spillovers or not. This result thus seems to indicate that the farm-induced channel through which the LC processes might affect parishes' livestock production should not be ignored specially in those parishes with large (conditional) LC effects on farms' size in terms of livestock number.

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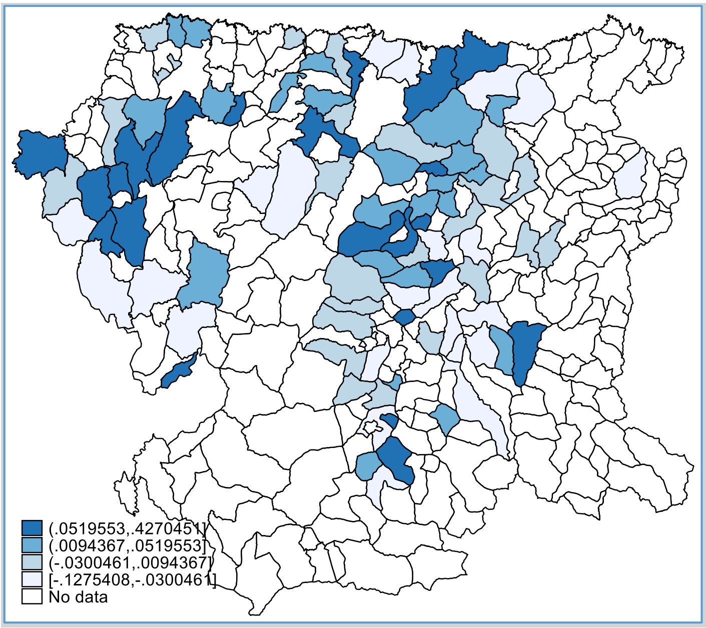
[33] If we denote the effect of LC on parishes' farm numbers as $XLCE_{it}$, the unconditional effect of the LC processes on parishes' production can be computed as $LCE_{it} + \varepsilon_{it} XLCE_{it}$, where $\varepsilon_{it} = \partial lny_{it}/\partial lnx_{it}$ is obtained from the production model.

[Insert Table 6 here]

Figure 12 shows the geographical distribution of the unconditional effects on parishes' livestock production. Obviously, it resembles Figure 7 and Figure 8 given that it combines the information contained in these two figures. As the farm-induced effect tends to complement the conditional effect, the coloured parishes in Figure 12 are associated with larger effects than in the case of Figure 7, which only takes into account the conditional effects on parishes' livestock production. Again, the largest positive effects are found in half a dozen parishes located close to or several kilometres from the coast, parishes or municipalities located very close to the Galician border and in a set of parishes located in Tineo and Cangas del Narcea, the two biggest Asturian municipalities whose main economic activity is livestock production.

Figure 12. Unconditional LC effects on parishes' livestock production



5. Conclusions

The objective of this research is to evaluate the economic and social impact of the land consolidation (LC) processes that have taken place in Asturias during the period 2001-2017. This is a relevant topic for several reasons. During the last decades, and particularly during the period under study, Asturias has received European funding aimed at promoting concentration processes. Second, the land has traditionally been fragmented in Asturias. Third, previous research has often found that LC processes are important tools for improving the economic activity of rural areas, increasing farmer income and stabilizing rural population. Finally, regional regulation in Asturias has contributed to the development of those processes.

We have focused our analysis on parishes' livestock activity measured in terms of farm figures; restructuration of livestock production measured as average cows per farm; and parishes' population. Unfortunately, it is impossible to extend the study to other categories such as the impact on ecological environment, local economy, and other social effects.

First, we estimate a production function model using parishes' herds as a proxy for livestock production and the number of farms as the main input. It also includes several LC-based variables that capture not only the number of LC processes implemented in each parish, but also their intensity and age. This model allows us to examine whether LC has exerted broad impacts on promoting livestock production, conditional on the number of farms. We also analyse the effect of LC-based variables on parishes' farms and population using a couple of auxiliary regressions. The first auxiliary regression allows us to obtain the unconditional effects of the LC processes on parishes' production and test whether the LC processes in Asturias have attenuated the decline in farm figures. The second one allows us to examine whether the LC efforts made by the Asturian Government have helped to secure the level of rural population and the economic activities in the territory.

Our main contributions to this literature include the panel data techniques used to estimate all models and the spatial interdependence that has been incorporated into our analysis by adding the LC indicators of neighbouring parishes. This last feature allows us to decompose the total effects attributable to LC into direct and indirect effects. To test the above three hypotheses, we use a multi-cohort multi-treatment DiD approach with heterogeneous treatment timings. To the best of our knowledge, a similar DiD specification has not been estimated yet in the literature. We show that we can accumulate sequential treatments (LC processes in our application) 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 test a new assumption that we label as the common sequential parameter (CSP) assumption. Moreover, in our application, we try to distinguish between three different cohorts of LC processes, one of them outside the sample period, as they are likely to be of a different nature.

We do not find strong evidence to support the effectiveness of the LC processes in mitigating the decline in livestock production in rural Asturias. Taking into account the effect on farms' size, the so-called farm-induced effects and the spatial (indirect) effects, we find that parishes' livestock production only increases about 3% on average once one or more LC processes are implemented. This modest effect simply reflects that many other factors explain the continuation of livestock production in western Asturias. Therefore in most cases, alternative actions should be launched in order to attenuate, or reverse, the depletion of livestock activity in Asturias.

Although the average effect is not noteworthy, we find quite large impacts in some of the parishes that have had LC processes. For instance, we find that the LC processes have especially attenuated the decline in the number of farms in coastal parishes (municipalities), where the dairy-oriented farms predominate. Interestingly, these are the parishes where we observe more LC processes. Therefore, it seems that the Asturian policy makers have already contemplated a potentially larger effect in these parishes as compared to the beef-oriented parishes. The LC processes were less effective at attenuating the decline of (intensive) farms located far from the coast. In 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 given that LC processes tend to stimulate the transformation of livestock activity from milk to beef production. Finally, as expected, we find larger (positive) effects attributable to the LC on livestock production as time passes.

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. Overall these results advocate using spatial econometrics techniques in the empirical examinations of economic effects attributable to LC processes. They also advocate using coordinated LC measures by regional governments in order to take full advantage of this important policy. Policy makers should also be aware that the impact of their LC processes might depend on parishes' characteristics and that the expected effects might be underestimated if the spatial spillover effects of such measures are ignored.

Regarding our third hypothesis, we have not been able to find strong evidence about the effectiveness of the LC processes in securing the level of rural population. If this is the general case, we might conclude that reversing rural depopulation most probably requires a reorientation of current rural policies and related investment decisions. However, the LC processes have been able to mitigate, at least to some extent, the population decline observed in some of the parishes located in western Asturias.

Acknowledges

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References

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *Review of Economic Studies*, 72(1): 1-19.

Abadie, A. Diamond, A. and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." Journal of the American statistical Association, 105(490): 493-505.

Abadie, A. Diamond, A. and Hainmueller, J. (2015). Comparative politics and the synthetic control method." American Journal of Political Science 59(2): 495-510.

Alonso, J. M., and Andrews, R. (2019). Governance by targets and the performance of cross-sector partnerships: Do partner diversity and partnership capabilities matter?. *Strategic Management Journal*, 40(4), 556-579.

Álvarez-Ayuso, I., Condeço-Melhorado, A.M., Gutiérrez, J., Zofío, J.L. (2016): "Integrating Network Analysis with the Production Function Approach to Study the Spillover Effects of Transport Infrastructure", *Regional Studies*, 50:6, 996-1015, DOI: 10.1080/00343404.2014.953472

Angrist, J.D. and Pischke, J-S (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Balk, B. (2016): "The dynamics of productivity change: A review of the bottom-up approach". In Productivity and efficiency analysis., W. Greene, L. Khalaf, R. Sickles, M. Veall, and M-C. Voia (Eds.), Chapter 2, 15-49, Springer, Cham.

Borusyak, K., and Jaravel, X. (2017). Revisiting event study designs. Available at SSRN 2826228.

Callaway, B., and Sant'Anna, P. H. C. (2019). Difference-in-Differences with Multiple Time Periods (SSRN Scholarly Paper No. ID 3148250). Social Science Research Network, Rochester, NY.

Crecente, R., Alvarez, C., Fra, U. (2002): "Economic, social and environmental impact of land consolidation in Galicia", *Land Use Policy*, 19:135–147.

Da Silva, F.C., Diego, Paul Elhorst, J.P., da Mota, R. (2017): "Urban and rural population growth in a spatial panel of municipalities", *Regional Studies*, 51(6): 894-908.

Deininger, K., Xia, F. (2016): "Quantifying Spillover Effects from Large Land-based Investment: The Case of Mozambique", *World Development*, 87:227-241.

Demetriou, D. (2018): "Automating the land valuation process carried out in land consolidation Schemes", *Land Use Policy*, 75, 21–32.

Du, X., Zhanga, X., Jinb, X. (2018): "Assessing the effectiveness of land consolidation for improving agricultural productivity in China", *Land Use Policy*, 70:360-367.

Dudzińska, M., Bacior, S., Prusc, B. (2018): "Considering the level of socio-economic development of rural areas in the context of infrastructural and traditional consolidations in Poland", *Land Use Policy*, 79:759–773.

García, F.S., Iglesias, E.L., Fernández, R.L., Paços, B.V. (2007). El proceso de ajuste en la ganadería bovina de la Cornisa Cantábrica. In *Políticas agrarias y ajuste estructural en la agricultura española*. Ministerio de Agricultura, Pesca y Alimentación. 261-289.

Gebel, M., and Vossemer, J. (2014). The impact of employment transitions on health in Germany. A difference-in-differences propensity score matching approach. *Social science & medicine*, 108, 128-136.

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., and Vermeersch, C. M. (2016). *Impact evaluation in practice*. World Bank Publications.

Gude, A., Alvarez, I., Orea, L. (2018): "Heterogeneous spillovers among Spanish provinces: a generalized spatial stochastic frontier model", *Journal of Productivity Analysis*, 50: 155-173.

Hartvigsen, M. (2014): "Land reform and land fragmentation in Central and Eastern Europe", *Land Use Policy*, 36:330–341.

Imai, K., Kim, I.S. and Wang, E. (2018). Matching Methods for Causal Inference with Time-Series Cross-Section Data." Working Paper.

Manjunatha, A.V., Anik, A.R., Speelmand, S., Nuppenaua, E.A. (2013): "Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India", *Land Use Policy*, 31:397-405.

Miranda, D., Crecente, R., Alvarez, M.F (2006): "Land consolidation in inland rural Galicia, NW Spain, since 1950: An example of the formulation and use of questions, criteria and indicators for evaluation of rural development policies", *Land Use Policy*, 23:511-520.

Nilsson, P. (2018): "The Role of Land Use Consolidation in Improving Crop Yields among Farm Households in Rwanda", *The Journal of Development Studie*s, DOI: 10.1080/00220388.2018.1520217.

Orea, L., Álvarez, I. and Perez, J.A. (2020): "The impact of land consolidation on livestock production in Asturias´ parishes: a spatial production analysis", in Aparicio, J., Lovell, C.A.K., Pastor, J. and Zhu, J. (eds.) *Advances in Efficiency and Productivity II*, Springer Nature´s International Series in Operations Research & Management, Science: NY, pp. 239-259.

Orea, L., Pérez-Méndez, J.A., Roibás, D. (2015): "Evaluating the double effect of land fragmentation on technology choice and dairy farm productivity: A latent class model approach", *Land Use Policy*, 45:189-198.

Parrondo, F.F. (2006), El sector cárnico en Asturias, *Estudios Geográficos*, 67(260): 35-56.

Strezhnev, A. (2018). Semiparametric weighting estimators for multi-period difference-in-differences designs. In *Annual Conference of the American Political Science Association, August* (Vol. 30).

Wolfers, J. (2006). Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results," American Economic Review, 96(5), 1802-1820.

Wu, Z., Liu, M., Davis, J. (2005): "Land consolidation and productivity in Chinese household crop production", *China Economic Review*, 16:28-49.

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis*, 25(1), 57-76.

Yu, G., Feng, J., Che, Y., Lin, X., Hu, L., Yang, S. (2010): "The identification and assessment of ecological risks for land consolidation based on the anticipation of ecosystem stabilization: a case study in Hubei Province, China", *Land Use Policy,* 27:293–303.

Zhang, Z., Zhao, W., Gu, X. (2014): "Changes resulting from a land consolidation project (LCP) and its resource–environment effects: a case study in Tianmen City of Hubei Province, China", *Land Use Policy,* 40:74–82.

Zhou, Y, Guoc, L., Liu, Y. (2019): "Land consolidation boosting poverty alleviation in China: Theory and practice*", Land Use Policy,* 82:339–348.

Table 1. Descriptive Statistics

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
x	Total number of farms	4,964	23.26	18.39	0	153
	- Beef	4,964	15.35	11.95	0	80
	- Dairy	4,964	6.41	10.49	0	118
y	Total livestock	4,964	617.55	545.91	0	3586
	- Beef	4,964	333.93	337.96	0	3317
	- Dairy	4,964	283.61	454.34	0	2779
z	Livestock units / (Total bovine herd+1)	4,964	0.71	0.10	0	1
P	Population	4,964	329.51	668.74	3	7228
n	Number of LC processes	1,056	1.46	0.78	1	5
ΣI	Cumulative investment per hectare	1,056	10.27	5.51	0	38.82
ΣK	Cumulative age of LC processes	1,056	12.25	11.38	0	65

Table 2. Parameter estimates of parishes' production function.

Dep. Var.= lny_{it}	One-cohort model			Multi-cohort model		
Regressors	Coef.	Std. Err.	Robust-t	Coef.	Std. Err.	Robust-t
lnx	0.8975	0.0838	10.71	0.8999	0.0830	10.85
z	0.0085	0.0060	1.43	0.0083	0.0060	1.39
$1/2lnx^2$	-0.2807	0.0681	-4.12	-0.2783	0.0686	-4.05
$1/2z^2$	-0.0010	0.0002	-4.84	-0.0010	0.0002	-4.83
$lnx \cdot z$	0.0091	0.0027	3.37	0.0090	0.0027	3.34
n	-0.2514	0.0989	-2.54			
ΣD_{C_1}						
ΣD_{C_2}				0.0465	0.2867	0.16
ΣD_{C_3}				-0.1512	0.0726	-2.08
ΣI	0.0323	0.0125	2.59			
ΣI_{C_1}						
ΣI_{C_2}				-0.0070	0.0369	-0.19
ΣI_{C_3}				0.0149	0.0093	1.60
ΣK	0.0039	0.0036	1.07			
ΣK_{C_1}				0.0038	0.0047	0.81
ΣK_{C_2}				0.0026	0.0046	0.58
ΣK_{C_3}				0.0046	0.0070	0.65
$n \cdot z$	-0.0164	0.0097	-1.69	-0.0070	0.0078	-0.90
$\Sigma I \cdot z$	0.0025	0.0013	1.98	0.0012	0.0011	1.15
$\Sigma K \cdot z$	-0.0003	0.0004	-0.71	-0.0003	0.0004	-0.72
$n \cdot lnx$	0.3218	0.1272	2.53	0.2334	0.1230	1.90
$\Sigma I \cdot lnx$	-0.0467	0.0166	-2.80	-0.0338	0.0156	-2.17
$\Sigma K \cdot lnx$	-0.0077	0.0034	-2.31	-0.0070	0.0033	-2.12
Intercept	5.9606	0.0945	63.10	5.9545	0.0987	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 R-sq	0.7694			0.7689		
Between R-sq	0.8171			0.8201		
Overall R-sq	0.8087			0.8117		
Mean LC effect	-0.0484			-0.0023		

Table 3. Parameter estimates of parishes' number of farms function.

Dep. Var.= lnx_{it}	**One-cohort model**			**Multi-cohort model**		
Regressors	Coef.	Std. Err.	Robust-t	Coef.	Std. Err.	Robust-t
z	0.0069	0.0044	1.57	0.0069	0.0044	1.57
$1/2z^2$	-0.0003	0.0001	-2.77	-0.0003	0.0001	-2.77
n	0.0230	0.0589	0.39			
ΣD_{C_1}						
ΣD_{C_2}				0.2951	0.3216	0.92
ΣD_{C_3}				0.0477	0.0384	1.24
ΣI	-0.0063	0.0079	-0.79			
ΣI_{C_1}						
ΣI_{C_2}				-0.0461	0.0444	-1.04
ΣI_{C_3}				-0.0078	0.0055	-1.41
ΣK	0.0008	0.0031	0.26			
ΣK_{C_1}				0.0000	0.0057	0.00
ΣK_{C_2}				0.0046	0.0041	1.11
ΣK_{C_3}				-0.0068	0.0072	-0.95
$n \cdot z$	0.0133	0.0112	1.19	0.0129	0.0106	1.22
$\Sigma I \cdot z$	-0.0017	0.0015	-1.16	-0.0015	0.0014	-1.08
$\Sigma K \cdot z$	0.0003	0.0005	0.68	0.0003	0.0005	0.57
$n \cdot lnx$	3.3007	0.0568	58.16	3.3137	0.0610	54.28
$\Sigma I \cdot lnx$	0.0069	0.0044	1.57	0.0069	0.0044	1.57
$\Sigma K \cdot lnx$	-0.0003	0.0001	-2.77	-0.0003	0.0001	-2.77
Intercept	0.0230	0.0589	0.39			
Time dummies	Yes			Yes		
Municipality trends	Yes			Yes		
Fixed effects	Yes			Yes		
# Obs.	4964			4964		
# treated obs.	1056			1056		
# Parishes	292			292		
Within R-sq	0.6468			0.6476		
Between R-sq	0.2282			0.2386		
Overall R-sq	0.1921			0.1962		
Mean LC effect	0.0018			0.0048		

Table 4. Parameter estimates of parishes' population function.

Dep. Var.= lnP_{it}	With CSP assumption			With no CSP assumption		
Regressors	Coef.	Std. Err.	Robust-t	Coef.	Std. Err.	Robust-t
n	0.0709	0.0260	2.72			
D_1				0.1119	0.0183	6.10
D_2				0.0559	0.0551	1.01
D_3				0.0219	0.0340	0.64
ΣI	-0.0095	0.0038	-2.52			
I_1				-0.0182	0.0028	-6.44
I_2				-0.0051	0.0067	-0.75
I_3				0.0107	0.0057	1.88
ΣK	-0.0011	0.0013	-0.84			
K_1				-0.0015	0.0019	-0.78
K_2				0.0011	0.0041	0.28
K_3				-0.0109	0.0045	-2.41
Intercept	5.2547	0.0379	138.59	5.2512	0.0363	144.67
Time dummies	Yes			Yes		
Municipality trends	Yes			Yes		
Fixed effects	Yes			Yes		
# Obs.	4964			4964		
# treated obs.	1056			1056		
# Parishes	292			292		
Within R-sq	0.7547			0.7588		
Between R-sq	0.0449			0.0111		
Overall R-sq	0.0071			0.0068		
Mean LC effect	0.0014			-0.0023		

Table 5. Direct, Indirect, and total LC effects

Farms' size	Obs.	Mean	Std. Dev.	Min	Max
Parishes with internal LC processes					
Direct Effect	1,056	-0.0023	0.0823	-0.2716	0.4335
Indirect Effect	1,056	0.0103	0.0285	-0.2123	0.1027
Total Effect	1,056	0.0080	0.0841	-0.2947	0.4345
Parishes without internal LC processes					
Direct Effect	3,908	0	0	0	0
Indirect Effect	3,908	0.0117	0.0240	-0.0025	0.2496
Total Effect	3,908	0.0117	0.0240	-0.0025	0.2496

Number of farms	Obs.	Mean	Std. Dev.	Min	Max
Parishes with internal LC processes					
Direct Effect	1,056	0.0048	0.0754	-0.2462	0.3190
Indirect Effect	1,056	0.0429	0.0375	-0.0153	0.1966
Total Effect	1,056	0.0477	0.0821	-0.1825	0.3775
Parishes without internal LC processes					
Direct Effect	3,908	0	0	0	0
Indirect Effect	3,908	0.0164	0.0269	0.0000	0.2205
Total Effect	3,908	0.0164	0.0269	0.0000	0.2205

Population	Obs.	Mean	Std. Dev.	Min	Max
Parishes with internal LC processes					
Direct Effect	1,056	-0.0023	0.0613	-0.0606	0.2661
Indirect Effect	1,056	-0.0123	0.0323	-0.1865	0.0525
Total Effect	1,056	-0.0146	0.0637	-0.1827	0.2778
Parishes without internal LC processes					
Direct Effect	3,908	0	0	0	0
Indirect Effect	3,908	0	0.0027	-0.0246	0.0201
Total Effect	3,908	0	0.0027	-0.0246	0.0201

Table 6. Conditional and unconditional LC effects on livestock production

	Obs.	Mean	Std. Dev.	Min	Max
With no spatial spillovers					
Conditional Effect	1,056	-0.0023	0.0823	-0.2716	0.4335
Farm-induced Effect	1,056	0.0107	0.0486	-0.1237	0.2628
Unconditional Effect	1,056	0.0084	0.1034	-0.2998	0.6301
With spatial spillovers					
Conditional Effect	1,056	0.0080	0.0841	-0.2947	0.4345
Farm-induced Effect	1,056	0.0219	0.0610	-0.1280	0.4141
Unconditional Effect	1,056	0.0299	0.1080	-0.2718	0.7081

Appendix A. Testing the simplifying and identification assumptions

CSP assumption							
					Robustness analyses		
Null hypotheses		Production Function	Total number of farms	Population	Multi-output Distance Function	Dairy farms	Beef farms
$\gamma_{1n}=\gamma_{2n}=\gamma_{3n}$	F-test (a)	0.20	0.47	3.13	0.03	2.26	0.71
	P-value	0.816	0.627	0.045	0.967	0.106	0.493
$\gamma_{1n}=\gamma_{2n}=\gamma_{3n}$	F-test (b)	1.56	1.50	4.30	0.40	2.65	0.55
$\gamma_{1l}=\gamma_{2l}=\gamma_{3l}$	P-value	0.185	0.204	0.002	0.806	0.034	0.700
$\gamma_{1n}=\gamma_{2n}=\gamma_{3n}$	F-test (b)	0.25	0.88	3.94	0.28	1.83	1.02
$\gamma_{1K}=\gamma_{2K}=\gamma_{3K}$	P-value	0.912	0.474	0.004	0.891	0.124	0.400
$\gamma_{1n}=\gamma_{2n}=\gamma_{3n}$	F-test (c)	1.07	1.12	4.68	0.49	1.72	0.76
$\gamma_{1l}=\gamma_{2l}=\gamma_{3l}$	P-value	0.382	0.349	0.000	0.812	0.116	0.605
$\gamma_{1K}=\gamma_{2K}=\gamma_{3K}$							

Notes: a) degrees of freedom (2,291); b) degrees of freedom (4,291); c) degrees of freedom (6,291). Using clustered-robust covariance.

PT assumption							
					Robustness analyses		
Model		Production Function	Total number of farms	Population	Multi-output Distance Function	Dairy farms	Beef farms
Treated-specific time dummies	F-test [a]	1.66	1.69	1.77	1.81	1.17	1.40
	P-value	0.053	0.048	0.034	0.030	0.290	0.138
Treated-specific time trend	Coef.	-0.006	0.057	-0.001	0.002	-0.006	0.010
	F-test [b]	2.16	1.09	0.49	0.27	0.63	3.18
	P-value	0.143	0.297	0.484	0.604	0.428	0.076

Notes: a) degrees of freedom (16,291); b) degrees of freedom (1, 291). Using clustered robust covariance