What drives competition on the farmland market? A case study in Brittany (France)

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Abstract

We investigate factors which may drive the number of agents who compete for a specific piece of agricultural land by fitting count data models on data originating from a local committee, the CDOA, which is responsible for agricultural guidance of the prefect in delivering the necessary 'authorizations to farm'. We notably find that the size of the offered land positively contributes to the competitor number, and that new entrants face less competition. The seemingly counterintuitive result that a locally denser farmer population yields fewer competitors is given a line of potential explanation pertaining to the likely role of farmer unions.

Keywords: farmland market, competition, count data models, France

JEL Code: Q15, D40, C21

1. Introduction

Most papers aiming at studying the functioning of agricultural land markets are primarily concerned with price formation and the drivers which may influence it. Ay and Latruffe (2016), Latruffe *et al.* (2013), Letort and Temesgen (2014) provide such recent examples for France and even for the particular regional French context we are interested in, namely Brittany. The references therein nonetheless provide an extensive list of works in other national contexts and time periods.

Among these drivers, the number of agents competing for the offered land is rarely a central issue, if at all. This possibly happens because, most of the time, a relevant information on this number is simply not available. But it is sometimes, and papers which rely on auction data seem to do have such information at their disposal in general. Yet is this information not systematically used: for example, Chang and Lin (2015), who use administrative foreclosure auction data for agricultural land in Taiwan, are interested in the impact on the sales price of a particular policy, the minimum lot size program, but do not control for the number of bidders. When they do account for the number of bidders, studies are again primarily interested in quantifying its impact on the resulting land price. For example, Ooi *et al.* (2006) find a positive impact of the number of bidders on the sales price in urban land auctions in Singapore, a result which is consistent with the auction theory (McAfee and McMillan, 1987). Wen *et al.* (2018) find the same result for residential land market data in the city of Hangzhou (China) and, in an agricultural land market context, Huettel *et al.* (2014) also mention that an increase in the number of bidders may induce a positive price effect, with Huettel *et al.* (2013) indeed finding such an impact. In a more general way, Iftekhar *et al.* (2014) study the impact of the number of bidders on the auction efficiency for a number of iterative auction designs with the help of an agent-based model. Curtiss *et al.* (2013) go a little step further by investigating the role of agents' heterogeneity and not just competitors number. But while they discuss the potential role of bidders heterogeneity, they actually study the impact of buyers heterogeneity, that is, heterogeneity across agents who uniquely win a particular land auction and not across the whole set of agents who participated to the auction. Finally, though they do not use auction data, Latruffe *et al.* (2013) also control for the buyers quality, simply distinguishing between farmer and non-farmers buyers.

It is thus clear from this preceding literature that, while the impact of the number of bidders on the market price has been under scrutiny, none of these studies have investigated the question of what actually drives the intensity of competition so far, as measured by the number of agents demanding the same land. Here, we intend to fill this gap by studying the potential factors which contribute to increase or decrease the number of farmers with known interest in using an offered piece of land (most of the time through purchase or farm lease contract) but eventually may not make the deal. Thanks to its high degree of farmland market regulation, one of the highest among European Union member states (Swinnen *et al.*, 2013), France offers a chance to do so thanks to a direct observation of how fierce this competition is.

Indeed, when a farmer wants to use a new piece of land, not only does he/she need to rent it or buy it but he/she simultaneously has to get an 'authorization to farm' from the local prefect. When several farmers concurrently apply as potentially interested to rent or acquire the same land, the prefect grounds his/her decision on the advice of a particular body, the CDOA (standing for 'Commission Départementale d'Orientation Agricole', namely 'Departmental Committee on Agricultural Guidance'). These local committees are responsible for agricultural guidance at the NUTS3 level (the French 'départements'), and mainly consist of local farmer representatives, local ministry of agriculture officers, and managers of the local SAFER (standing for 'Société d'Aménagement Foncier et d'Etablissement Rural', namely 'Land Development and Rural Establishment Company', another body in charge of the regulation of farmland in France, see Latruffe and Le Mouël, 2006; Latruffe *et al.*, 2008; Piet *et al.*, 2012). In case of rented farmland, legal rules state that the application procedure shall not take into account the landowner's preference for a particular applicant but shall be focused on the regional guidelines (enacted by the State administration after dialogue with farmer unions). Broadly speaking, while priorities may vary locally, the role of these committees is to favour the settlement of new farmers, to help consolidate the smallest farms, to impede 'excessive' farmland concentration and to promote sustainable agriculture oriented production systems.

Even if it ends up to the local prefect at the regional level to decide which competitor the land should be directed to, the CDOA's advice is of primary importance as it is usually followed. Therefore, in order for the CDOA to do its job and achieve its orientation objectives, farmers who want to buy or rent land have to apply for an authorization to farm by filling a form which describes the land they intend to acquire, their own farm before including the new land, their farm as it would become if the new land were included, and the purpose of the land acquisition project. This includes data on the location and size of the desired land, whether the project is a new farm settlement, the enlargement of an existing farm or the merger of several agricultural companies, the legal status, size and main agricultural products of the pre-existing farm in the latter case, etc.

We could have access to such a database for two regions in Brittany (France) for a time period ranging from January 2016 to May 2018 and were able to fit econometric models in the count data model family in order to investigate the statistical contributions of several potential drivers to the number of competitors applying for given pieces of land.

The remaining of the paper is structured as follows. Section 2 presents the four modelling frameworks that were used, while section 3 introduces the data to which these models were applied. Section 4 then reports the estimation results obtained, before section 5 concludes by discussing one line of potential explanation for one specific result we find which seems counterintuitive at first glance, thus providing guidance for future research.

2. Model

The number of agents, here farmers, competing for a given piece of agricultural land is obviously discrete and can only be strictly non-negative. Moreover, as will be exemplified in the applied section of this paper, empirical observation shows that this number appears to be limited in practice, rarely exceeding a dozen or at most twenty. Taken together, such rare events characteristics advocate to turn to the family of count data models as a suitable tool to study the phenomenon and its drivers. Another justification for doing so is to view the number of competitors as the realization of a counting process where the observed events are the occurrences of applications arriving between the time the land availability is revealed and the time application possibilities close.

Consider therefore that the number of competitors is modelled as a random variable Y which can take on non-negative discrete values $y = 1,2, \ldots$ The basic count data model consists in assuming that these counts are Poisson distributed, that is that the probability that $Y = y$ is given by (Cameron and Trivedi, 2013):

$$\Pr[Y = y] = \frac{e^{-\mu}\mu^{y}}{y!} \text{ with } y = 0,1,2, \ldots$$

where $\mu > 0$ is the intensity parameter. Under this model, the mean and variance of Y are both equal to μ, which is referred to in the literature as the equidispersion property of the Poisson distribution (Cameron and Trivedi, 2013). It is however not unusual that real-life processes violate this property, with data rather exhibiting overdispersion, that is $\mathrm{Var}[Y] > \mathrm{E}[Y]$.[1] A standard way to account for this feature is to turn to models which allow overdispersion of the counts, such as the negative binomial model. Because it is robust to distributional misspecifications, Cameron and Trivedi (2013) advocate to prefer the negative binomial specification where $\mathrm{Var}[Y]$ is complemented with a term proportionate to the square of the mean, $\mathrm{E}[Y] = \mu$, that is $\mathrm{Var}[Y] = \mu + \alpha\mu^2$, with $\alpha \geq 0$. This corresponds to the NB2 specification in Cameron and Trivedi's terminology, and reduces to Poisson if $\alpha = 0$. Under this specification, the distribution of Y is given by:

$$\Pr[Y = y] = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(y + 1)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}}\left(\frac{y}{\alpha^{-1} + \mu}\right)^{y}$$

where $\Gamma(.)$ denotes the Gamma function, defined as $\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt$ for all $x > 0$ (Johnson *et al.*, 2005).

Still, taking overdispersion into account in this way may not be sufficient to address another common characteristic of real-life count data, the excess-of-zeros issue. In this case, too many counts of a specific value, namely zero, are observed with respect to what is expected from the model. Since it can be demonstrated that this (as well as overdispersion) may reveal unobserved heterogeneity (Mullahy, 1997), one way to tackle it consists in specifying that the data generating

[1] Authors agree that, if underdispersion (*i.e.*, $\mathrm{Var}[Y] < \mathrm{E}[Y]$) may actually exist, it is rare in practice.

process is actually a discrete mixture of two different ones, with two possible and slightly different approaches.

In the first approach, the so-called hurdle model (Mullahy, 1986; Cameron and Trivedi, 2013), zero counts are assumed to be generated by one process, while strictly positive counts are assumed to be generated by another. The probability distribution of counts is thus given by:

$$\Pr[Y = y] = \begin{cases} f_1(0) & \text{if } y = 0 \\ \dfrac{1 - f_1(0)}{1 - f_2(0)} f_2(y) & \text{if } y > 0 \end{cases}$$

where $f_1(.)$ is the probability distribution function (pdf) of the zero-count generating process, and $f_2(.)$ is the pdf of the strictly-positive-count generating process. In the following, as is common practice (Cameron and Trivedi, 2013), we chose a logit specification for f_1 and a truncated negative binomial specification for f_2.

Alternatively, the second approach considers that zero counts may be generated by two distinct processes, one which produces only zeros, and another which may produce any non-negative count. This is the so-called zero-inflated strategy, for which the probability distribution writes:

$$\Pr[Y = y] = \begin{cases} g_1(0) + \big(1 - g(0)\big) g_2(0) & \text{if } y = 0 \\ \big(1 - g_1(0)\big) g_2(y) & \text{if } y > 0 \end{cases}$$

where $g_1(.)$ is the probability distribution function (pdf) of the zero-count generating process, and $g_2(.)$ is the pdf of the non-negative-count generating process. There also, we retained a logit specification for g_1 and a negative binomial specification for g_2.

For each of the four models, we adopted the so-called exponential mean function specification for the intensity parameter μ which consists in setting $\mu = \exp(\mathbf{x}'\boldsymbol{\beta})$, where $\mathbf{x}$ is a vector of k regressors (including a constant) and $\boldsymbol{\beta}$ is the k-dimensional vector of the corresponding parameters to be estimated. The overdispersion parameter α was estimated as a scalar and specified as $a = \ln(\alpha)$ to ensure positivity. Finally, whenever relevant, the logit model was specified as $\exp(\mathbf{z}'\boldsymbol{\delta})/(1 + \exp(\mathbf{z}'\boldsymbol{\delta}))$, where $\mathbf{z}$ is a vector of l regressors (including a constant), and $\boldsymbol{\delta}$ is the l-dimensional vector of the corresponding parameters to be estimated.

The four models just introduced were estimated thanks to likelihood maximisation techniques in order to determine which one best fits our data. Since this is beyond the scope of this paper, we invite the interested reader to refer to Cameron and Trivedi (2013) for a thorough exposition of the properties of these models and corresponding estimation strategies.

3. Data

We could have access to a database which gathered the information of CDOA applicants' forms for two NUTS3 regions in Brittany (France)[2], namely the Côtes d'Armor and Morbihan 'départements', for a time period ranging from January 2016 to May 2018. These two cases are interesting as they altogether account, from year to year, for more than 50% of the number of authorization-to-farm applications in Brittany, which on its own represents one sixth of the national

[2] The Nomenclature of Territorial Units for Statistics (NUTS) provides a single uniform breakdown of territorial units for the production of regional statistics for the European Union (Source: http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction).

figure while representing less than 10% of the total number of farms and cultivated hectares (table 1).

Table 1. 2010 Census figures on the number of farms and the total utilized agricultural area (UAA) and 2012, 2013 and 2014 numbers of authorization-to-farm applications

	2010 Census		2012	2013	2014
	Farms	UAA (10^3 ha)			
France	489,990	26,963.3	28,647	29,175	28,233
… of which Brittany	34,450	1,638.2	4,292	4,744	4,717
as of France (%)	*7%*	*6%*	*15%*	*16%*	*17%*
… of which Côtes d'Armor	9,470	438.3	1,517	1,451	1,399
as of Brittany (%)	*27%*	*27%*	*35%*	*31%*	*30%*
Morbihan	7,560	368.2	1,309	1,070	1,005
as of Brittany (%)	*22%*	*22%*	*31%*	*23%*	*21%*

Source: 2010 Agricultural Census and French ministry of Agriculture.

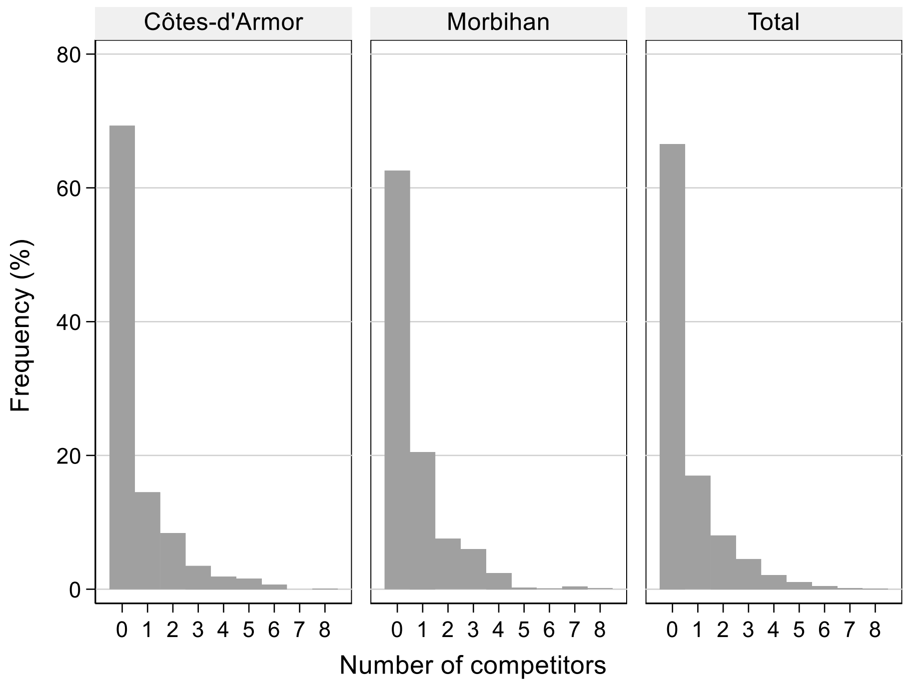
The database consisted of 1,814 authorization-to-farm applications, 1,031 of which (57%) were located in Côtes-d'Armor and 783 (43%) in Morbihan. From this, we had to remove 111 observations which seemed inconsistent since the demanded area was larger than the offered one. We therefore ended up with 1,703 observations and a slightly different breakdown between Côtes-d'Armor (1,000 applications, or 59%) and Morbihan (703 applications, or 41%).

In the database, an observation consisted in one application, that is in one specific farmer applying for one specific piece of land. A piece of land therefore appeared several times in the database, which corresponds to cases where competition exists. But farmers also appeared several times as they may apply for more than one piece of land at the same time. It thus happened that the 1,703 observations corresponded to 1,417 different farmers who applied for 1 (in 1,196 cases, or 84.4%) to more than 4 (in 13 cases, or 0.9%) pieces of land, with a maximum of 7.

From this database, we defined our dependent competition variable as the number of competitors each farmer faced on a specific piece of land, and not as the total number of farmers applying for a specific piece of land. Had we done so, counts would have started from 1 since the database does not inform on potentially offered land for which no one would apply; actually, while this may occur elsewhere in France, it seems unlikely to us that such a situation exists in Brittany. With our definition, counts therefore start from 0, which depicts situations where only one farmer is applying, that is, situations with no competition. This is also advantageous in the sense that it allows to include variables characterizing applicants in the list of the model's regressors.

Under this definition, it appeared that the number of competitors ranged from 0 to 8 and that, overall, two-thirds of the observations exhibited no competitors, 18% a unique competitor, 8% two competitors and the remaining 9% three competitors or more (figure 1). Regions differed only slightly, with a bit more no-competition situations in Côtes-d'Armor and more situations with a single competitor in Morbihan. The average number of competitors was 0.654 with a standard deviation of 1.185, and was not statistically different across regions. As the ratio of the standard deviation to the mean appeared well above 1 (1.81), such figures led to the intuition that overdispersion exists which may not be completely removed by simply including regressors in the model, as Cameron and Trivedi state that "[i]*f the sample variance is more than twice the sample* *mean, then data are likely to remain overdispersed after the inclusion of regressors.*" (Cameron and Trivedi, 2013: 89). This was a motivation for testing the hurdle and zero-inflated models.

Figure 1. Observed competition counts frequencies



Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018).*

The database also comprised a set of variables which could be used as potential regressors in the implemented models. Descriptive statistics are reported in table 2. Apart from the regional indicator variable (*DEPART*) already discussed above, a first subset of these variables allowed to characterise the demanding agent on several grounds. The demanded area (*DAREA*) ranged from very small plots (less than 1 hectare) to large pieces of land (over 100 hectares) and was 11 hectares on average, which is more or less equivalent to two to three average plots in Brittany according to Latruffe and Piet (2014: table 4) and on fifth of the average farm size in Brittany (Agreste Bretagne, 2018). More than three fourth of the applicant farmers were engaged or intended to engage in livestock farming (*SPEC*.Livestock modality), which is consistent with Brittany's overall agricultural specialization (Agreste Bretagne, 2018). Rather, almost 94% of the applicants were involved or about to involve in incorporated farms (*STATUS*.Incorporated), a much higher share than the overall regional figure of 54% (Agreste Bretagne, 2018). This may nonetheless be consistent with the observation that, over the last decades in France, the number of individual farms declines while that of incorporated farms increases (Piet and Saint-Cyr, 2018). As regards the reason why farmers legally had to apply for an authorization to farm (*DREASON*), the vast majority of applications (93%) were motivated by the fact that the resulting farm would cross the legal area threshold which makes application compulsory (*DREASON*.Threshold). The remaining motivations were mainly that the farmer could not justify the adequate education level (*DREASON*.Diploma, 3%), that he/she had another activity outside agriculture (*DREASON*.Pluriactive, 2%) or that he/she would become involved in two or more farms

(*DREASON*.Multiple, 1.5%). Finally, as regards the finality of the project motivating the demand (*PROJECT*), 81% of the applications were motivated by farm enlargement (*PROJECT*.Enlarge) while 16% were intended for the settlement of a new farmer (*PROJECT*.NewSet), the remaining 3% corresponding to other projects such as the transmission of a farm inside a couple (*PROJECT*.TakeOver) or the reinstallation of a farmer on a new farm (*PROJECT*.Reinstall).

Table 2. Descriptive statistics

	N	Mean	Std. dev.	P1	P99
DEPART.Morbihan	1,703	0.587	0.492	0	1
DEPART.Côtes-d'Armor	1,703	0.413	0.492	0	1
DAREA (ha)	1,703	11.37	14.21	0.28	67.13
SPEC.Livestock	1,703	0.755	0.430	0	1
SPEC.Crops	1,703	0.245	0.430	0	1
STATUS.Individual	1,703	0.065	0.246	0	1
STATUS.Incorporated	1,703	0.935	0.246	0	1
DREASON.Threshold	1,703	0.934	0.248	0	1
DREASON.Education	1,703	0.031	0.172	0	1
DREASON.Pluriactive	1,703	0.018	0.134	0	1
DREASON.Multiple	1,703	0.015	0.120	0	1
DREASON.Other	1,703	0.002	0.048	0	1
PROJECT.Enlarge	1,703	0.810	0.392	0	1
PROJECT.NewSet	1,703	0.156	0.363	0	1
PROJECT.TakeOver	1,703	0.015	0.123	0	1
PROJECT.Reinstall	1,703	0.012	0.108	0	1
PROJECT.Other	1,703	0.006	0.080	0	1
OTUAA (ha)	1,703	51.83	40.15	0.95	192.00
OREASON.Retirement	1,703	0.342	0.474	0	1
OREASON.Exit	1,703	0.233	0.423	0	1
OREASON.Reduction	1,703	0.112	0.315	0	1
OREASON.Reorganize	1,703	0.085	0.279	0	1
OREASON.Family	1,703	0.012	0.108	0	1
OREASON.Other	1,703	0.217	0.413	0	1
FRAG_NPLOT	1,703	19.13	5.84	10.61	37.47
FRAG_SHAPE	1,703	5.42	0.31	4.90	6.31
FRAG_AVPLS (ha)	1,703	4.60	1.60	1.86	8.74
FRAG_MAXDP (km)	1,703	4.09	1.00	2.26	7.83
FRAG_AVNND (km)	1,703	0.39	0.07	0.25	0.64
LOCAL_NFARMS	1,703	45.0	26.3	4	123

Note: P1 and P99 stand for the 1st and 99th percentiles, respectively.

Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018)*

A second subset of variables allowed to characterise the offering agent in two respects. The total utilized agricultural area of the offering agent's farm (*OTUAA*) was consistent with regional figures, with an average of 52 hectares when the figure for all farms in Brittany was 47 in 2010 (Agreste Bretagne, 2018) and values ranging from less than a hectare to more than 300 hectares, an interval similar to that observed in 2007 for commercial farms (Latruffe and Piet, 2014: table 2). The reason why the offering agent released part or all of his/her land was mainly retirement (*OREASON*.Retirement, 34%), before stopping (*OREASON*.Exit, 23%) or reducing (*OREASON*.Reduction, 11%) his/her activity, internally re-organizing the operations (*OREASON*.Reorganize, 8.5%) or because of a family motive (*OREASON*.Family, 1.2%) such as the transmission of the farm among partners inside a couple. Altogether, these five main modalities thus represented almost 80% of all motives.

Unfortunately, due to the database vacuity or incompleteness on these issues, it was not possible to characterize the offered land in itself directly from variables available inside the database, for instance as regards its soil quality, its distance from the farmsteads of the offering and demanding agents, the shape of the corresponding plot(s) or the number of neighbouring, hence potentially interested, farmers, etc. To approximate some of these dimensions, we used the information we had regarding the location of the offered pieces of land at the municipality level to complement the database with a third set of variables. On the one hand, we used the work by Cariou and Piet (2014) to characterize the degree of farmland fragmentation in the municipality where the offered land lied with respect to five indicators depicting: (i) the average number of plots by farm (*FRAG_NPLOT*); (ii) the average shape of the plots (*FRAG_SHAPE*); (iii) their average size in hectares (*FRAG_AVPLS*); (iv) their maximum distance to the farmstead (*FRAG_MAXDP*) and; (v) the average distance to their nearest neighbour (*FRAG_AVNND*).[3] On the other hand, we extracted from the 2010 Agricultural Census for France the number of farms in the municipality where the offered pieces of land were located (*LOCAL_NFARMS*). It appears that, for the six additional variables considered, our sample exhibits descriptive statistics which are very close to that derived from Cariou and Piet (2014) for Brittany as a whole.

4. Results

The four models presented in section 2 were estimated from the data. The whole set of variables described in table 2 were included as the **x** vector of regressors in the Poisson model and negative binomial (NB) model, in the truncated negative binomial part (f_2) of the hurdle (HNB) model and in the negative binomial part (g_2) of the zero-inflated (ZINB) model.[4] For the logit parts, respectively f_1 and g_1, of the HNB and ZINB models, the **z** vector of regressors were selected among **x** thanks to a stepwise-forward selection process.

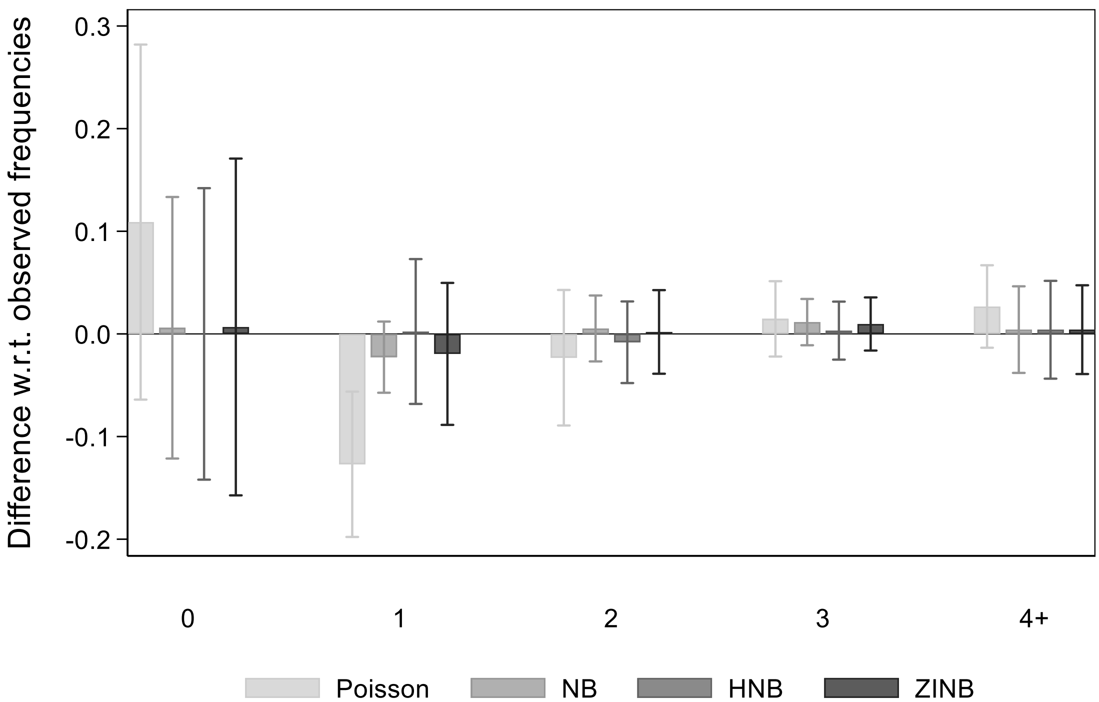
Before commenting on the regressors, we start by assessing and comparing the four models in order to determine whether they are appropriate or not and which one of them should be preferred. To do so, figure 2 provides a visual inspection of the differences between the predicted count probabilities and the actually observed frequencies for the four models, and table 3 reports the results of the corresponding Pearson chi-square statistic calculations. First, both the visual inspection and the goodness-of-fit test lead to reject the simple Poisson model. This result confirms our first intuition that the equidispersion assumption does not hold for our data and that overdispersion should be accounted for. Second, the NB model yields a fairly acceptable visual result but is nonetheless slightly rejected on the grounds of the formal test. However, the estimated value for α ($\hat{\alpha} = 1.39$, see table 4) confirms that overdispersion is present. The result of the

[3] The interested reader is invited to refer to Encadré 1 in Piet and Cariou (2014) for a formal definition of these fragmentation indicators and a discussion of their interpretation.

[4] Poisson specifications for f_2 and g_2 proved to yield poorer fit than with the negative binomial approach, so that we do not report the corresponding results here.

Pearson test therefore indicates that the negative binomial specification is just sufficient to address the overdispersion issue but advocates for testing more elaborate models. This is confirmed by the results obtained with the HNB and ZINB models. Both pass visual inspection and the goodness-of-fit test, the HNB model performing slightly better than the ZINB in this matter. However, the Akaike information criterion (AIC) favours the ZINB model rather than the HNB, being smaller for the former than the latter thanks to a higher log-likelihood (table 4). Overdispersion is also confirmed with these more elaborate models, the estimated α being significantly different from zero for both the HNB model ($\hat{\alpha} = 0.22$) and the ZINB model ($\hat{\alpha} = 1.05$), even if it is significantly lower than the value found with the NB model in both cases.

Figure 2. Models ability to predict the observed competitor count frequencies



Note: Capped spikes represent 1-standard deviation intervals.

Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018)*

Table 3. Goodness-of-fit test statistics

Model	Pearson χ^2 test statistics
Poisson	270.99
NB	15.92
HNB	2.85
ZINB	10.97
Critical value	15.51

Note: The critical value corresponds to the χ^2 statistic for 8 (9 count categories minus 1) degrees of freedom at the 5% significance level.

Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018)*

Table 4. Estimation results for the four models considered

Model	Poisson	NB	HNB	ZINB
DEPART.Morbihan	-0.0146 (0.0875)	-0.0052 (0.0932)	-0.1073 (0.1087)	-0.0362 (0.0912)
DAREA	0.0159 (0.0026)***	0.0218 (0.0031)***	0.0162 (0.0037)***	0.0145 (0.0031)***
SPEC.Crops	-0.0641 (0.1073)	-0.0148 (0.1058)	-0.0316 (0.1151)	0.0404 (0.1057)
STATUS.Incorporated	0.2144 (0.1933)	0.1291 (0.1913)	0.1658 (0.2441)	0.1850 (0.1921)
DREASON.Education	-0.5095 (0.3569)	-0.4612 (0.4118)	-0.4554 (0.5596)	-0.4464 (0.3733)
DREASON.Pluriactive	0.1116 (0.2658)	-0.0630 (0.2650)	-0.0157 (0.2384)	0.1913 (0.2865)
DREASON.Multiple	0.7681 (0.2212)***	0.9441 (0.2550)***	-0.2755 (0.2911)	0.7989 (0.2559)***
DREASON.Other	0.6637 (0.7188)	0.4597 (0.7156)	1.3660 (0.1957)***	1.6615 (0.1665)***
PROJECT.NewSet	-0.2937 (0.1359)**	-0.2537 (0.1310)*	-0.1590 (0.1464)	-0.2394 (0.1317)*
PROJECT.TakeOver	-1.0213 (0.4782)**	-1.0923 (0.5752)*	-1.6309 (1.0583)	-0.9465 (0.5313)*
PROJECT.Reinstall	-1.6515 (0.7957)**	-1.4434 (0.8248)*	-0.5459 (0.6430)	-0.3307 (0.8553)
PROJECT.Other	0.1034 (0.4462)	0.5487 (0.6329)	0.0805 (0.4085)	0.3719 (0.6143)
OTUAA	0.0060 (0.0010)***	0.0067 (0.0011)***	0.0046 (0.0015)***	0.0078 (0.0014)***
OREASON.Exit	0.1134 (0.1025)	0.1102 (0.1030)	0.1539 (0.1121)	0.1017 (0.1064)
OREASON.Reduction	-0.8280 (0.1802)***	-0.7966 (0.1747)***	-0.4377 (0.2352)*	-0.4892 (0.1850)***
OREASON.Reorganize	-0.4254 (0.1720)**	-0.4683 (0.1874)**	-0.0888 (0.2251)	-0.3684 (0.1874)**
OREASON.Family	-0.7026 (0.5899)	-0.4911 (0.6162)	-0.7180 (0.9017)	-0.3659 (0.5673)
OREASON.Other	-0.1501 (0.1193)	-0.1583 (0.1155)	0.1292 (0.1507)	-0.0973 (0.1199)
FRAG_NPLOT	-0.0261 (0.0128)**	-0.0280 (0.0111)**	-0.0144 (0.0126)	-0.0096 (0.0106)
FRAG_SHAPE	-0.7276 (0.1582)***	-0.8456 (0.1811)***	-0.2297 (0.1977)	-0.8934 (0.1858)***
FRAG_AVPLS	0.0005 (0.0421)	0.0074 (0.0432)	-0.1274 (0.0530)**	-0.0297 (0.0454)
FRAG_MAXDP	-0.1262 (0.0537)**	-0.1476 (0.0500)***	-0.1963 (0.0629)***	-0.1323 (0.0488)***
FRAG_AVNND	-0.1542 (0.7744)	-0.0422 (0.7828)	0.8923 (0.8897)	0.4097 (0.7543)
LOCAL_NFARMS	-0.0061 (0.0018)***	-0.0062 (0.0017)***	-0.0089 (0.0021)***	-0.0060 (0.0017)***
CONSTANT	4.2401 (0.9559)***	4.8631 (1.0421)***	2.5493 (1.1557)**	4.7752 (1.0577)***
alpha		1.3873 (0.1277)***	0.2238 (0.1028)***	1.0516 (0.1215)***
DAREA			-0.0200 (0.0040)***	-0.9646 (0.3684)***
DREASON.Education			0.5102 (0.4194)	-1.5259 (1.9047)
DREASON.Pluriactive			-0.0153 (0.4094)	6.0553 (3.0174)**
DREASON.Multiple			-2.0949 (0.5087)***	-24.9418 (2.0741)***
DREASON.Other			0.1521 (1.2007)	14.0933 (5.4692)**
PROJECT.NewSet			0.3593 (0.1654)**	0.7635 (1.2350)
PROJECT.TakeOver			0.9936 (0.5742)*	10.7462 (4.5087)**
PROJECT.Reinstall			1.7365 (0.7922)**	17.2213 (7.2151)**
PROJECT.Other			-0.3067 (0.6359)	-21.2504 (3.1587)***
OTUAA			-0.0064 (0.0014)***	0.0160 (0.0106)
OREASON.Exit			-0.0564 (0.1403)	0.0664 (1.0202)
OREASON.Reduction			0.8378 (0.2093)***	4.2294 (1.9399)**
OREASON.Reorganize			0.5304 (0.2284)**	0.8822 (1.0191)
OREASON.Family			0.4101 (0.6385)	-0.9541 (1.9378)
OREASON.Other			0.3087 (0.1492)**	1.5568 (1.0607)
FRAG_SHAPE			1.0691 (0.1963)***	-0.7123 (2.0140)
FRAG_AVPLS			-0.1684 (0.0365)***	-2.5615 (0.9824)***
CONSTANT			-3.9784 (1.0171)***	12.0273 (11.7334)
N	1703	1703	1703	1703
LL	-1928.4154	-1762.1713	-1730.7493	-1712.2304
AIC	3,906.83	3,576.34	3,547.50	3,512.46

*Note: *, ** and *** indicate significance at 10 per cent, 5 per cent and 1 per cent levels, respectively.*

Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018)*

It can be derived from the HNB model and a t-test at the 1% level that $\widehat{f_1}(0) > \widehat{f_2}(0)$, that is, the probability of a zero count as predicted by the logit part of the model is strictly and significantly higher than the probability of a zero count as it would be predicted by the negative binomial if it were not truncated. In other words, this confirms the presence of excess-zeros. The result holds also for the ZINB model since the zero-inflation probability estimate $\widehat{g_1}(0)$ is significantly different from zero at the 1% level. Under the HNB specification, this zero-inflation probability may be computed as $\widehat{f_1}(0) - \widehat{f_2}(0) = 0.263$, whereas for the ZINB model, we find $\widehat{g_1}(0) = 0.142$. Recalling that the zero-inflation probability reflects the process where no competition could ever happen and noting that the overall zero-count probability is $\widehat{f_1}(0) = 0.655$ under the HNB model and $\widehat{g_1}(0) + \widehat{g_2}(0) = 0.659$ under the ZINB model, such results mean that the HNB model predicts almost twice more no-competition-ever situations ($0.263/0.655 = 40\%$) than the ZINB model ($0.142/0.659 = 22\%$) or, conversely, much less situations where competition could have happened but did not ($100 - 40 = 60\%$ for the HNB model to be compared to $100 - 22 = 78\%$ for the ZINB model).

We now turn to the analysis of regressors, focusing on the results of the ZINB model (last column of table 4) since this model appears as an appropriate one according to the Pearson chi-square goodness-of-fit test and happens to be the preferred model according to the Akaike information criterion. Moreover, most coefficient signs, magnitudes and significance levels are robust across the four models.

The first 25 rows of table 4, *i.e.*, until α, report the estimated β coefficients for the intensity parameter μ of the models. For continuous variables, these coefficients may be directly interpreted as semi-elasticities, that is, as the proportionate change in the conditional mean of the dependent variable, $\mathrm{E}(y|\mathbf{x})$, induced by a one-unit change in the regressor (Cameron and Trivedi, 2013). For indicator variables, the contribution to the conditional mean is $\exp(\beta)$ and not simply $1 + \beta$ (Cameron and Trivedi, 2013). We first note that there is no difference among the two studied 'départements', the coefficient for *DEPART*.Morbihan being not significantly different from zero. Both the demanded area (*DAREA*) and the total UAA of the offering agent (*OTUAA*) are positive and very significant (at 1%), the contribution of the former being almost twice as large as that of the latter: a 1-hectare larger piece of land will attract 1.45% more competitors on average, while a 1-hectare larger releasing farm will generate only 0.78% more demands. As for the 'départements', results indicate no significantly different behaviours whatever the production specialization or legal status of the demanding agent. Coefficients associated with *DREASON*.Multiple and *DREASON*.Other are highly significant and quite large in absolute terms, but should be interpreted with care since they correspond to only a few observed cases in the database (1.5% or less, see table 1); the same caveat holds for *PROJECT*.TakeOver. Even if only significant at the 10% level, the coefficient associated with *PROJECT*.NewSet is certainly more meaningful since more such situations were represented in the database (almost 16%, see table 1). It then appears that demanding agents who apply for land in the frame of a new settlement face on average $\exp(-0.2394) = 0.787$ less competitors than those who do so for enlargement projects. Said differently, when an enlarging applicant faces 5 competitors, a new farmer will only face 4. Releasing land because of a complete activity termination (*OREASON*.Exit) does not yield a significantly different number of competitors than when it is because of retirement. At reverse, when the release of land corresponds to a partial disposal or internal reorganization (*OREASON*.Reduction and *OREASON*.Reorganize, respectively), the number of competitors is significantly reduced, by a factor of $\exp(-0.4892) = 0.613$ in the first case, and $\exp(-0.3684) = 0.692$ in the second case. Only two of the five fragmentation variables appear to have a significant contribution, *FRAG_SHAPE* and *FRAG_MAXDP*, both in the direction of reducing the number of competitors, which is consistent with intuition: the more irregularly shaped or remote the plots in the vicinity, the fewer the candidates. A likely irregular shape has the stronger effect, almost removing any competition (-89%), that of a likely 1-km farther plot being less important (-13%). Finally, the number of farmers in the neighbourhood (*LOCAL_NFARMS*) is highly significant but limited in absolute value (-0.6% for each supplementary farm in the municipality). Yet it is quite counterintuitive: being negative, the coefficient means that the more numerous the neighbours, the less fierce the competition. We provide a line of potential explanation in the discussion section.

The second set of coefficients (*i.e.*, after α) report the estimated δ coefficients for the zero-inflation logit equation, for regressors which were selected on the grounds of a stepwise-forward selection process. They thus only show for the relevant specifications, namely the HNB and ZINB models. This time, as is usual for any logistic regression (Green, 2018), the reported coefficients are not directly interpretable, only the signs are meaningful at this stage. As noted before for the intensity equation, the coefficients associated with many of the binary regressors (*DREASON*.Multiple, *DREASON*.Other, *PROJECT*.Pluriactive, *PROJECT*.TakeOver, *PROJECT*.Reinstall and *PROJECT*.Other) should be interpreted with due care even though significant and very large in absolute values. The negative sign associated with *DAREA* suggests that, consistent with the previous finding, a larger offered piece of land reduces the probability of excess zeros, that is, increases the probability of potential competition. This time, the same holds significantly for the average plots size in the neighbourhood (*FRAG_AVPLS*). Reciprocally, and also consistent with the intensity equation's result, offering land as part of a partial disposal project (*OREASON*.Reduction) significantly increases the probability of excess zeros, that is, reduces the probability of competition, with respect to retirement situations.

For the HNB model and specifically the preferred ZINB model, overall contributions of the regressors to the average number of competitors faced by each applicant has to take both the intensity and zero-inflation equations into account, and are thus best presented as marginal effects for continuous variables and treatment effects for indicator variables. These are numerically reported in table 5 for the ZINB model, which also includes derived elasticities for continuous variables, and graphically displayed in figure 3 for visual assessment as suggested by Jann (2014). Note that, as argued by Cameron and Trivedi (2013), we report the average marginal and treatment effects rather than the marginal and treatment effects at the means.[5] For continuous variables, marginal effects report the change in the expected mean of competitors for a one-unit change of the regressor, and elasticities report the relative change induced by a one-percent change. For indicator variables, treatment effects report the change in the expected mean when the regressor is unity rather than zero and should be therefore interpreted relative to the base modality.

Results not only confirm previous separate findings but allow for a direct and consolidated comparison of regressors contributions. Namely, while the contribution of a 1-hectare increase in the offered area (*DAREA*) on the number of competitors appears more than seven times that of a 1-hectare increase in the total UAA of the offering agent (*OTUAA*), both effects are much closer in relative terms, a 1-percent increase in the former implying a 0.40% increase in the number of competitors while the same relative increase in the latter implies an increase of almost 0.25%, or a factor of "only" 1.6. Of course, this is because one supplementary hectare represents a much lower relative increase for the total area of the offering agent than for the offered area. Notwithstanding,

[5] It appears that both are actually very close for most of the considered regressors.

both results suggest that a larger supply induces more competition on average. As for the variable indicating the new settlement nature of the demanding agent's project, *PROJECT*.NewSet, the negative sign in the intensity equation and the positive sign in the zero-inflation equation reinforce each other to yield a significant overall negative effect, a farmer seeking land when entering business facing on average 0.17 competitors less than a farmer aiming at farm enlargement. The same applies when the offering agent's reason for releasing land is UAA contraction through a partial land disposal (*OREASON*.Reduction), but with a more than double magnitude (–0.37).

Table 5. Average marginal (for continuous regressors) and treatment (for indicator regressors) effects and elasticities (for continuous regressors) for the ZINB model

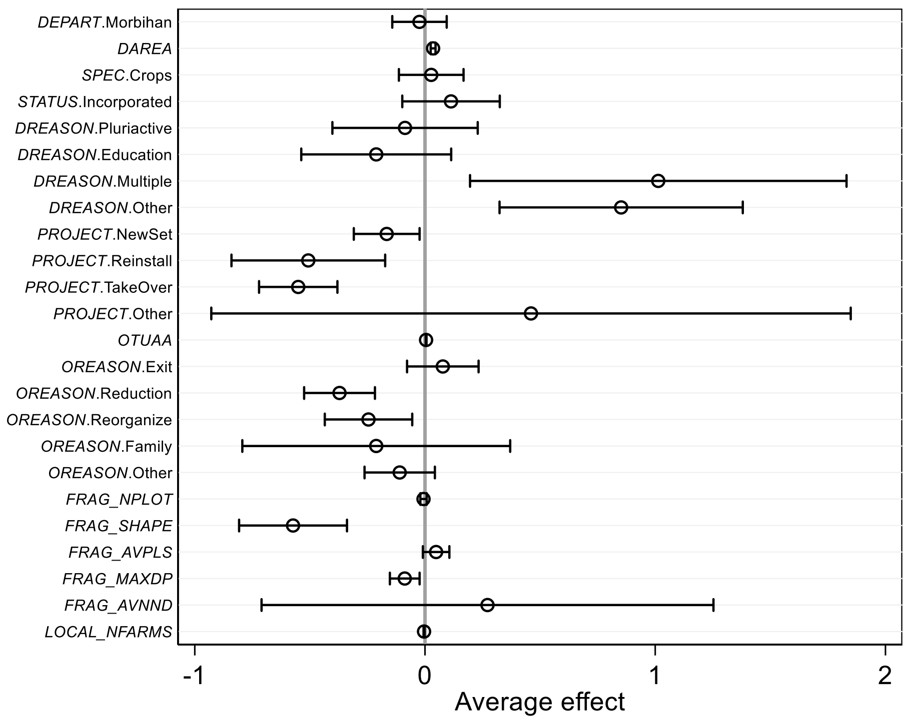
	Average effect	Std. err.	Z	P>|z|	Sign. level	Elasticity
DEPART.Morbihan	-0.0240	0.0603	-0.40	0.691		
DAREA	0.0352	0.0054	6.58	0.000	***	0.400
SPEC.Crops	0.0270	0.0716	0.38	0.706		
STATUS.Incorporated	0.1131	0.1080	1.05	0.295		
DREASON.Pluriactive	-0.0866	0.1610	-0.54	0.591		
DREASON.Education	-0.2118	0.1661	-1.27	0.202		
DREASON.Multiple	1.0132	0.4172	2.43	0.015	**	
DREASON.Other	0.8520	0.2695	3.16	0.002	***	
PROJECT.NewSet	-0.1664	0.0729	-2.28	0.022	**	
PROJECT.Reinstall	-0.5068	0.1703	-2.98	0.003	***	
PROJECT.TakeOver	-0.5506	0.0868	-6.34	0.000	***	
PROJECT.Other	0.4604	0.7085	0.65	0.516		
OTUAA	0.0048	0.0009	5.38	0.000	***	0.247
OREASON.Exit	0.0774	0.0792	0.98	0.329		
OREASON.Reduction	-0.3712	0.0785	-4.73	0.000	***	
OREASON.Reorganize	-0.2454	0.0969	-2.53	0.011	**	
OREASON.Family	-0.2117	0.2968	-0.71	0.476		
OREASON.Other	-0.1099	0.0779	-1.41	0.159		
FRAG_NPLOT	-0.0064	0.0070	-0.90	0.366		-0.122
FRAG_SHAPE	-0.5731	0.1195	-4.79	0.000	***	-3.108
FRAG_AVPLS	0.0483	0.0294	1.64	0.100		0.222
FRAG_MAXDP	-0.0880	0.0329	-2.67	0.008	***	-0.360
FRAG_AVNND	0.2715	0.5008	0.54	0.588		0.105
LOCAL_NFARMS	-0.0040	0.0012	-3.36	0.001	***	-0.180

*Notes: For indicator variables, treatment effects represent the variation of the dependent variable induced by a discrete change from the base level; Elasticities are only calculated for continuous variables; *, ** and *** indicate significance at 10 per cent, 5 per cent and 1 per cent levels, respectively.*

Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018)*

The significant contributions of 'ambient' fragmentation indicators *FRAG_SHAPE* and *FRAG_MAXDP* as well as that of the potential competition variable (*LOCAL_NFARMS*) are also confirmed. The coefficient associated with *FRAG_AVPLS*, which was significant in the zero-inflation equation but not in the intensity equation, is globally at the edge of significance but does not reach the desired minimum level of 10%. The negative sign for *FRAG_SHAPE* and *FRAG_MAXDP* was expected, the shape of plots in the vicinity proving to have the largest relative effect in absolute value, with an elasticity suggesting that 1-percent more irregularly shaped local conditions lead to a 3% decrease in the number of competitors. With an elasticity of –0.36, the contribution of the local average maximum distance of plots lies in absolute terms in-between that of the offered area and total UAA of the offering agent, but in an opposite direction. Finally, with an elasticity of –0.18, the contribution of the average local number of farms (*LOCAL_NFARMS*) is twice less important in relative terms and remains logically negative since it was not selected in the zero-inflation equation. Yet is this negative contribution still unexpectedly negative.

Figure 3. Average marginal (for continuous regressors) and treatment (for indicator variables) effects for the ZINB model



Notes: Capped spikes represent 95%-confidence intervals.

Source: authors' calculations based on the Côtes-d'Armor *and* Morbihan *CDOA applications database (2016-2018)*

5. Discussion

Most of our results conform to intuition and appear to be robust across the four tested models, even though only the two more elaborate ones, the HNB and ZINB models, should be regarded as appropriate. These results are three-fold. First, the relevance of controlling for overdispersion and zero-inflation indicates that unobserved heterogeneity is present among the data, the HNB and ZINB models appearing as appropriate approaches to addressing the issue. Second, some regressors are found as contributing to increase competition. They converge in indicating that large land releases logically attract more competitors. Nonetheless, the corresponding incentive remains small: a detailed inspection of marginal effects suggests that the offered piece of land has to be at least 50 hectares to be predicted as significantly attracting one more competitor; offered plots of that size represent less than 3% in the database. The same proportion of situations holds for the total UAA of the offering agent, a threshold of 150 hectares being necessary to significantly attract one more competitor. Third, some other regressors tend to be associated with a decreasing competition. They are of three kinds: (i) one pertaining to the type of project the demanding agent is bearing, with new entrants being less likely to be confronted to competitors than farmers who seek to enlarge their farm; (ii) one pertaining to the likely appropriateness of the offered land to develop farming operations as measured by the degree of ambient farmland fragmentation, and; (iii) one pertaining to the likely local competition level as measured by the average number of farms in the neighbourhood. As already mentioned in the previous section, this last result seems counterintuitive at first glance since it could be expected that more neighbours would imply fiercer competition.

As a potential line of explanation for this unexpected result, we hypothesize that this could be linked with the local role of farmers unions. Indeed, the implication of union representatives is essential in the functioning of CDOA committees (Bernardi and Boinon, 2009), and expert knowledge from the field tends to indicate that, upstream to the CDOA, farmers unions are active at the local level to lower competition among neighbours as much as possible. The intensity of these informal mediations may therefore vary in relation to the involvement of unionists and the existence of a strong union activity at the local level. Then, it is likely that more farmers in a municipality could be associated with a stronger local union activity, hence explaining a seemingly counterintuitive result. Still this would be consistent with our other results, especially that related to the project's nature of the demanding agent: generation renewal being not only an official priority for CDOAs but also a topical professional concern, a stronger local union activity could also favour new settlement projects by lowering the risk of having to compete with an already installed, enlargement-seeking, colleague. This could also explain why, even if non zero, factors incentivizing competition are found as having to reach high levels before having a significant effect, even if, in the same time, legal changes in the application procedure have facilitated the access to publicly available information about farmland releases on the market and fostered applications that escape from union watch. In turn, this would be a supporting argument for our finding that larger offered plots attract more competitors, a result which seems inconsistent with Brorsen *et al.* (2015) who state that, according to auction theory and because of financial constraints and risk aversion, the number of bidders is likely to decrease with parcel size. Finally, this could definitely be the rationale behind zero-inflation, competitive applications accruing to the CDOA then appearing as remaining situations where preliminary negotiations have failed for some reason.

This is why we plan to complement our regressors list, especially that of the zero-inflation equation, with a proxy of the local intensity in unions' activity as a direction for future research. The observed participation rate during the latest professional representative elections could be an interesting candidate, provided it can be gathered at an infra-'département' scale rather than the officially published figures, without which it would be no more than redundant with our fixed effect 'département' dummy.

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