Direct payments, spatial competition and farm survival in Norway

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Abstract: We argue that interdependencies between farms are crucial for assessing effects of direct payments on farmers exit decisions. Using spatially explicit farm level data for nearly all Norwegian farms, a binary choice model with spatially lagged explanatory variables is estimated in order to explain farm survival from 1999 to 2009. We show that ignoring spatial interactions between farm leads to a substantial overestimation of the effects of direct payments on farm survival. To our knowledge, this paper is the first attempt to empirically analyze the role of neighbor interactions for farm structural change in general and for an assessment of the effects of direct payments on farm survival in particular.

Keywords: spatial competition, land market, farm structural change, direct payments, policy assessment

JEL classification: C21, C25, Q12, Q13

1 Introduction

In Norway, as in many other industrial countries, direct payments are often legitimized as a way to maintain a vital agricultural sector and, in particular, to prevent the abandonment of farms. It is often argued that agricultural supports increase farm profitability and thus reduces farm exits. This argument is supported by Breustedt and Glauben (2007) in an regional level analysis for Western Europe in which they concluded to have found "[…] empirical evidence that the former EU's Common Agricultural Policy (CAP) has probably reduced the structural change in agriculture during the last decades of the last century via price support and subsidy payment programmes […] (p. 124)". Similarly, in a regional level analysis for the US Goetz and Debertin (2001) found that higher "[g]overnment payments reduce the odds that a country loses farms on net" but additionally that among the regions in which the number of farms decline "[…] higher payments accelerate the rate at which farmers exit (p.1020)". These studies analyze the effects of income support on net regional farm exit. These aggregate regional effects, however, might mask potential different reaction at the individual farm level. An additional drawback is that they need to rely on regional variation in payment levels or other farm characteristics for identification. This renders variable definition and interpretation more complicated.

Individual farm level studies, such as Key and Roberts (2006), on the other hand allow or more direct analysis of the effects of farm characteristics and payments. In their farm level analysis farm survival for US farms Key and Roberts (2006) found “a small but statistically significant positive effect [of payments] on farm business survival (p. 391)”. For an overall assessment of the effects of payments however an aggregation of the individual farm level effects is necessary. We argue that for such an aggregation it is crucial to consider the interdependence between farm behavior. Since so far this link is missing in farm level studies, Roberts and Key (2008 p. 628) argued in favor of regional level studies that: “[Farm level] studies [...] consider effects of payments on the growth or survival of individual farms, which cannot predict the effects of an increase in payments on aggregate farm structure. This is because studies of individual farms cannot account for how induced changes on one farm affect other, neighboring farms […].” In this paper we aim to consider these interactions between individual farms in the estimation and for an overall aggregation of the effects induced by a policy change. Particularly, the objective of this paper is to empirically analyze the effect of direct payments on farm exit rates controlling for spatial farm interaction using individual farm level data of nearly all Norwegian farms for 1999 and 2009. It is argued that ignoring the spatial interaction between farms in the aggregation of the results leads to an overestimation of the effects of direct payments on farm survival. To our knowledge this paper is the first attempt to analyze empirically the role of neighboring interaction for farm structural change in general and for an assessment of the effects of direct payments on farm survival in particular.

The importance of neighboring interaction is long recognized in the agent-based model literature. Balmann (1997) identifies spatial interdependence of farms, the immobility of land, and the location of farms in space as important assumptions (among others). In his model the spatial interdependence between farms are considered through interaction on the local land market. Here, farms compete for the limited resource land which is immobile and located at a specific point in space. The developed agent-based model is employed in further studies to analyze the importance of sunk cost (Balmann et al. 2006) and the effects of decoupling for structural change in Germany (Happe et al. 2006 and 2008).

Despite the recognition in the agent-based model literature, empirical studies concerned with spatial interaction in farm structural change are rare. An exception is Huettel and Margarian (2009) who analyze the effects of interactions on the land market for farm structural change. They consider different theoretical frameworks of strategic competition to characterize farm behavior on the land market leading to several hypotheses concerning the relationship between initial farm structure and farm growth which are then tested empirically. Even though their theoretical model is based on interaction on the land market their empirical model does not explicitly consider interaction between farms. Instead they model farm size developments as a Markov process in which transition probabilities between size classes are explained by regional or time varying variables. In contrast, our approach is based on individual farm data and does consider spatial dependence between farms explicitly.

Similar to our approach, Weiss (1999) analyzed farm survival and farm growth in Upper Austria using farm level data. He recognizes farm interdependence and the competition for land and labor; "Farm exits are a precondition for the farm sector to change its structure since land and labor are reallocated among remaining farms […] (p. 104)", but does not consider it in his empirical application.

In other areas such as land use/cover change, spatial dependencies and interactions on the land market are more widely recognized (see Irwin and Geoghegan 2001 and Verburg et al. 2004 for a review). Gellrich and Zimmermann (2007) focus is on drivers of land abandonment in the Swiss mountains. In some respect land abandonment is similar to farm structural change since the reasons to abandon land and to exit farming likely overlap. Their model is based on an economic framework taking off-farm employment opportunities, the share of part-time farmer and policy variables into account. Given their objective, however, their model looks at the regional scale and not at the individual farm level. Spatial correlation is thus considered between neighboring regions instead of individual farms.

One reason for the lack of empirical models analyzing spatial interactions between farms might be the scarcity of spatially explicit farm level data. The available data source for Norway thus provides a unique opportunity to analyze spatial aspects of farm structural change on the farm level empirically. We estimate a spatial binary choice model to explain farm survival using own as well as neighboring farm characteristics.

The remainder of the paper is structured as following. First, a theoretical model for farm size and interaction on the land market is derived. Based on this hypothesis about potential drivers of farm survival are discussed. In section 3 an overview on the available data base is given. The empirical model with the specification of the spatial weighting matrix as well as definition of dependent and explanatory variables is given in section 4. The regression results and the results of policy scenario simulations are presented in section 5 and 6. Section 7 concludes.

2 Theoretical model and Hypothesis

In order to discuss the spatial interaction on the land market and to guide the selection of explanatory variables a simple spatial competition model is developed. The model is inspired by a uniform delivery model (Graubner et al. 2011) and a Hotelling spatial competition model adapted to accommodate farm structural change. The general idea is that farms occupy that area for which their willingness to pay (WTP) per hectare, adjusted by transportation cost, is greater than zero and exceeds that of all competitors. As in the Hotelling spatial competition model we consider two farms $i = A, B$ located at both ends of a line with length one. All available agricultural area is of homogenous quality and spread equally along the line between the two farms.

Farm WTP α_i for one unit land is equal to the marginal value product of land i.e. the residual return to land after cost for all other production factors, including opportunity costs for labor and capital, are accounted for. Each unit of cultivated land ties labor and capital that could otherwise be employed or invested outside the farm, therefore, α_i can also be interpreted as the difference between the on-farm income per area unit and the forgone off-farm income induced by cultivating that area unit. In some cases α_i can also be larger than that difference (i.e. the marginal value product of land) if farmers derive non-pecuniary utility from being self employed or see farming as a “way of life” (Key and Roberts 2009). For a specific plot r on the line net WTP, $\pi_i(r)$, is determined as the difference between α_i and ‘transportation costs’ t which are assumed to be proportional to the distance between plot and farm. Net WTP for a specific plot is thus $\pi_A(r) = \alpha_A - tr$ and $\pi_B(r) = \alpha_B - t(1-r)$.

Both farms compete on the land market and occupy this area for which $\pi_i(r)$ is positive and exceeds that of the competitor (Figure 1). Farms are indifferent for plot r^*, characteristic by $\pi_A(r^*) = \pi_B(r^*)$, from which we can solve for the specific farm size equal to[1]

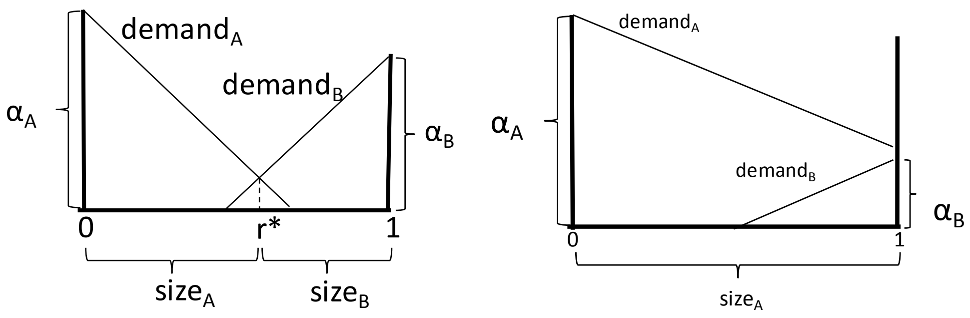
$$\begin{aligned} size_A &= r^* = \frac{\alpha_A - \alpha_B + t}{2t} \\ size_B &= (1 - r^*) = 1 - \frac{\alpha_A - \alpha_B + t}{2t}. \end{aligned} \tag{1}$$

Relevant for the objective of the paper, is a special case which arises when net WTP of one farm exceeds that of the competitor ($\alpha_A - t > \alpha_B$ exit of B or $\alpha_A + t < \alpha_B$ exit of A) for all available land. In this case one farm quits farming while the other takes over all agriculture land (Figure 1).

WTP for land differs between farms due to different characteristics of the farm business and the farm holder. Of particular interest with respect to the research question is the effect of direct payments on WTP and therefore finally on farm exit. Key and Roberts (2006 p. 391) found empirical evidence that government payments have significant positive effect on farm survival. He argued that this might be explained by the possibility to bid up prices on the land market and for other fixed resources. Payments might “relieve liquidity constraints allowing farms receiving more payments to achieve a more efficient scale and remain in business longer (p. 391).” Payments might also make “farming more profitable relative to alternative occupations, thereby reducing incentives to exit agriculture (p. 391)."

[1] We assume that for each plot there is always at least one farm with a positive net WTP such that no land falls fallow.

Figure 1: Farms competing on the land market, (1) sharing the available agricultural area, and (2) takeover of all area by one farm and exit of the other.



(1) (2)

Source: Own illustration

Based on these arguments we expect a positive influence of direct payments on α_i. It remains unclear, however, of whether the absolute amount of payments or measured in relative terms (e.g. on a per labor hour basis) is more relevant. This relates to the question of whether total farm income or the on-farm wage rate (i.e. total income over total labor requirement) is more important in determining α_i. With perfect labor markets we expect that α_i is primarily determined by the difference between the on- and off-farm wage rate with the total farm income being less important. Farms too small to generate a full income but with a relatively high on-farm wage rate per hour would take on an off-farm employment in order to fill the remaining income gap. With imperfect labor markets, however, this might not be possible and farmers might need to choose to either continue farming, without a full income, or to quit farming, taking on the alternative off-farm employment. In this case α_i is primarily determined by the difference between total on- and off-farm income, with the on-farm wage rate being less important. Accordingly, under fully functioning labor markets we expect that direct payments per labor input are more important than total direct payments in determining α_i while under imperfect labor markets we would expect the opposite.

On the other hand total farm income or total payments are a measure for the absolute size of a farm and it is argued by others that the absolute size of a farm is important in multiple aspects, beside than the ones discussed. For Norwegian milk farms, Flaten (2002) showed that, productivity increases with farm size particularly due to a more efficient use of labor. Weiss (1999 p. 105) considers the roll of technology and argued that "[e]ven if the technological advances are scale neutral […] their adoptions tends to favor larger farms since they may have more access to information and financing and may also have a larger set of management skills." Roberts and Key (2008 p. 630) argued that "[b]orrowing constraints could cause a farm's cost of capital to depend on its net worth" such that lager farms, having more collateral, face lower borrowing costs. With respect to government payments the authors further argued that they "[...] raise the net worth of a farm, making it less costly for a farmer to obtain financing to increase farm size. Similarly, anticipated payments may give farm operators more leverage with agricultural lenders (p.630)." To assess the relevancy of these arguments for α_i it is important to recognize that farm size can be approximated in multiple ways reflecting different dimensions of farm size. Total income or total payments for example reflect the economic size of farm while total cultivated area or the total labor input reflect the input side of production. In general, the different measures are expected to be highly correlated such that in principle the arguments apply similarly to all three measures. However, some of the arguments might match better to specific measures than other. Total area and total direct payments, for example, might be a more direct measure of farm collateral while total labor requirement might be more relevant to asses scale effects. Following from this we expect that all three measures are important in determining α_i with each representing slightly different effects.

Beside these factors that are of primary interest with respect to the research question there are plenty of others factors that might be important for determining farms WTP for land. To limit the discussion here, however, we restrict attention to those variables available in the empirical application. The productivity of a farm for example should have a positive influence on the on-farm income and hence on WTP. The farm share of lease to total land should, ceteris paribus, have a negative effect on farm net worth and hence increase capital cost and decrease α_i. Further difference in WTP can arise due to different farm specializations and the specific policy environments of that specialization. These might include different legal requirements for specific production types or specific policies for single specializations[2]. Equally important as characteristics of the farm business are personal characteristics of the farm holder (see among other Weiss 1999, Key and Roberts 2006). However, the age of the farm holder is the only variable available in the empirical application. Key and Roberts (2006) argued that "[a]ge may be correlated to knowledge about the firm's competitive abilities—with older owners able to acquire more information (p. 383)". Additionally, the financial liquidity of the farm holder might increase over time with older owner being able to "accumulate sufficient net worth to obtain a certain scale of production (p. 383)". On the other hand beyond a specific age farm development is strongly dependent on the availability of successor. Farms might increase their size before retirement if a successor is available or if not might decrease in size in order to prepare for an exit. The theoretical effect of age on farm growth and survival is thus unclear.

From (1) it follows that farms own size is positively related to own α_i but negatively related to neighboring α_i. In general we thus expect the effects of neighboring characteristic on own size to be the opposite as the effects of own characteristics. This means for total direct payments, for example, where we expect a positive influence on WTP that own size is positively related to own payments but negatively related to neighboring payments.

Farm growth and survival therefore depends on the relative difference between WTP, $\alpha_A - \alpha_B$, between farms, i.e. farms' occupy that area for which their difference between on and off-farm income exceeds that of their competitors, for both considering transportation costs. With respect to the payments, this implies that in a situation where changes in payments are the same for all farms also α_i changes by the same amount for all farms. Changes in payments could be the same in case of decoupled payments or coupled payments when farms production program are exactly the same. Since there is competition on the land

[2] Within the study period, for example, the government bought large quantities of milk quota rights which might have had an effect on milk farms but no direct effect on other.

market, a change in α_i by the same amount for all farms will not cause changes in farm size or farmers' survival decision since the relative difference in WTP between farms, $\alpha_A - \alpha_B$, stays unaffected. One can also think of the effect of a full capitalization of payments in land rents (Latruffe and Le Mouël 2009). In a situation in which farms do not receive the same amount of payments (e.g. due to different participating rates (Roberts and Key 2008 p. 630), different farm specializations or because per unit subsidy rates discriminate between land and herd sizes as is the case in Norway) the relative difference $\alpha_A - \alpha_B$ would change. Here, an increase in payments would lead to growth and an increase of the likelihood of survival for favored farms and a decline and an increasing likelihood of farm exit of the other. Payments should therefore either have no effect if they are the same for all farms or accelerate structural change if the changes differ between farms.

Finally, it is important to point out that the presented model only accounts for spatial interactions on the land market which are assumed to be important but which might not be the only way farm interact which each other. One other important type of interaction is technology adoption and knowledge transfer (Rogers 1995, Berger 2001). Case (1992), for example, found evidence that the probability of adopting a new technology increase with neighboring adoption. Consequently an active cooperate network raises technology diffusion and with it farm productivity. Neighboring farms are also important to maintain an active network of suppliers and processors. Overall, an active corporate network should thus increase farm profitability and hence WTP for land. For the background of the model presented above the effects of an active cooperate network on farm size should cancel out if all farms profit similarly (α_i would increase for all farms alike). However, larger farms are more likely to adopt a new technology (Feder and Slade 1984) and might also be more important in maintaining an active cooperate network of suppliers and processors. Therefore, small farms might benefit more from larger neighbors as large farm do from small ones. In this case, WTP of farms with larger neighbors' increases more compared to farms with smaller neighbors. Based on this reasoning neighboring size can also have a positive influence on own WTP and hence farm size and survival. Which effects dominate in the end, the negative due to competition on the land market or the positive due to an active cooperate network, remains an empirical question. In general all cases where we do not find the opposite sign of neighboring characteristics compared to own characteristics hints at interaction between farms other than the competition on the land market.

3 Data

The analysis is based on data from the Norwegian Direct Payment Register for the years 1999 and 2009. The register contains information about agricultural area by crop and number of animals by type of animal (126 different crop and animal activities are distinguished) for every farm that applies for direct payments. Eligibility for direct payments is subject to certain conditions, one of which is a minimum economic size of the farm (measured by turn-over) in order to prevent "hobby-farms" from receiving subsidies. As a consequence, the total numbers of acreage and/or animals may be somewhat underestimated when compared with other official sources such as slaughter statistics or the decennial total farm census.

Individuals and legal entities managing agricultural area or keeping animals eligible for direct payments may apply for subsidies by filling in data in the register. The register links the amount of acreage and animals with business identification and property numbers. Additionally, farmers' social security numbers are available containing the birth date.

As the unit of analysis we rely on the property number. Property units present in 1999, but not in 2009 are assumed to have left the sector. Some potential measurement errors arise from this choice: We disregard if farms split their activities in different business units. Small farms may incidentally have left the sector in 2009, but applied for subsidies in 2008 and 2010.

Table 1 shows the number of farms covered in the database for the two measures mentioned above and compared to the number of farms recorded in other statistics.

Table 1: Number of farms for various accounting measures

	1999	2009
Property number (NAA 2011)	66,892	45,460
Business number (NAA 2011)	66,832	45,420
Number of farms (Statistics Norway 2011)	70,740	47,688

Source: NAA 2011 and Statistics Norway 2011

Table 1 reveals that there are small differences between the measures to identify farms. For all practical purposes regarding the analysis, the number of properties and the number of businesses appears to be the same. Further, the numbers are somewhat lower than the number of farms provided by the Statistical Office (Statistics Norway) due to certain size limits regarding the eligibility of direct payments.

4 Empirical model and estimation

The paper aims to explore the effects of own and neighboring direct payments on farm survival. Therefore, we estimated a spatial probit model where we consider the exit decision between 1999 and 2009. The model can be interpreted as a latent utility model with the latent variable denoted as $\mathbf{y}^*$. The latent variable determines the outcome of the observed survival ($y_i = 1$ if $y_i^* > 0$) or exit decision ($y_i = 0$ if $y_i^* \leq 0$). In some sense it relates to the difference between own and neighboring WTP for land discussed in section 2. To reflect these difference and to estimated the effects of neighboring interaction, $\mathbf{y}^*$ is specified to be a linear function of own, $\mathbf{X}$, and neighboring characteristics , $\mathbf{WX}$ with $\mathbf{W}$ being a spatial weighting matrix defined below. For estimation two different model specification are considered, a spatially lagged explanatory variable model (SLX)

$$\begin{aligned} &\mathbf{y}^* = \mathbf{X\beta} + \mathbf{WX\theta} + \boldsymbol{\varepsilon} \\ &\varepsilon \sim N\left(\mathbf{0}, \sigma^2 \mathbf{I}\right) \end{aligned} \tag{2}$$

which assumes iid normal errors and a spatial Durbin error model (SDEM)

$$\begin{aligned} &\mathbf{y}^* = \mathbf{X\beta} + \mathbf{WX\theta} + \mathbf{u} \\ &\mathbf{u} = \rho \mathbf{Wu} + \boldsymbol{\varepsilon} \end{aligned} \tag{3}$$

which relaxes the assumptions of the SLX model by allowing for spatially autocorrelated errors (LeSage and Pace 2011 p. 22).

The SLX and SDEM specification are chosen over the more common spatial autoregressive model (SAR) of the form $\mathbf{y}^* = \rho \mathbf{Wy} + \mathbf{X\beta} + \boldsymbol{\varepsilon}$, since they allow greater flexibility with respect to the direct and indirect effects of explanatory variables. As shown by Pace and Zhu (2012), in the SAR model the indirect effects have the same signs as the direct effects and the ratio between indirect and directs effects is constant across variables. This is an undesirable property for our purpose since we expect in general the direct effects of own payments to differ from the indirect effects of neighboring payments (see section 2).

The SLX model is estimated using standard probit maximum likelihood estimation techniques. We then test for spatial error dependence using three different test principles appropriated for probit models that are discussed and compared in Amaral et al. (2012). Specifically, two different Lagrange Multiplier test proposed by Pinkse and Slade (1998) and Pinkse (2004) as well as a test based on a generalized version of the Moran's I statistics proposed by H. Kelejian and Prucha (2001) is applied. All three test statistics are asymptotic $\mathcal{X}^2(1)$ distributed. The test statistics are equal to 258.9, 204.9 and 192.7, respectively, and thus clearly lead to an rejection of the H_0-Hypothesis of no spatial autocorrelation. Since autocorrelation can lead to bias in the probit model the test results indicate that the SDEM model which considered the spatial autocorrelation in the errors might be more appropriated.

Estimation of a SDEM probit model for a sample of over 60,000 observations, however, is challenging from a computational perspective. Most existing estimation techniques such as McMillen (1992), Beron and Vijverberg (2004) or LeSage (2000) are only applicable for relatively small sample sizes of a couple of thousand observations (see Pace and LeSage 2011 for a more detailed comparison and a discussion of the limitations with respect to large samples). The major difference between a standard probit model and a probit model with spatially correlated errors (or the SLX and the SDEM model) is that the likelihood function is no longer based on univariate truncated normal distributions but, due to the dependence between observations, becomes a multivariate truncated normal distribution. This increases computational needs especially for large samples. Therefore, Pace and LeSage (2011) proposed a simulated maximum likelihood framework for probit models with spatially autocorrelated errors capable of handling large sample sizes. Their approach is based on the GHK (Geweke-Hajivassiliou-Keen) algorithm to approximate the intractable multivariate integral of the multivariate truncated normal distribution. The general idea of the GHK algorithm in this context is to replace the joint multivariate truncated normal density by a product of conditional densities. This product of condition densities has a sequential order in the sense that each conditional density only depends on prior variables in the sequence. Using specific realizations of the random variables allows calculating the sequence of conditional densities. By repeating the calculation R times, each time with a different realizations of the random variables, a numeric approximation of the multivariate truncated normal distribution can be obtained. One obstacle of the approach with respect to large samples is that the number of operations required for the GHK algorithm depends on the number of non-zeros in the Cholesky lower triangular matrix of the covariance matrix[3]. Pace and LeSage (2011) argued, however, that in most spatial application each observation might only depend on a limited number of neighbours such that the sparsity of the variance-covariance matrix can be exploited in order to reduce the computation burden of the GHK sampler. They further propose to adopted the GHK algorithm to rely on a Cholesky decomposition of the precision matrix (i.e. the inverse variance-covariance matrix) instead of the variance-covariance matrix since in many situations it has greater sparsity.

In our specific implementation for the SDEM model we also rely on the precision matrix being equal to[4]

$$\Psi = \left(\mathbf{I} - \rho\mathbf{W}\right)' \left(\mathbf{I} - \rho\mathbf{W}\right). \qquad (4)$$

As recommended by Pace and LeSage (2011) the sparsity of the precision matrix or variance-covariance matrix can be increases by an appropriate ordering of the observations. In our implementation we use the Matlab (Version R2013a) build in function *symamd*() for an symmetric approximate minimum degree permutation applied to the precision matrix to reorder the observations and to increase the sparsity of the precision matrix. For the GHK algorithm, we follow Pace and LeSage (2011) and employed a scrambled Halton sequences where we skipped the first 1,000 values and used only every 101st value (Matlab default). For each likelihood evaluation we used $R = 15$. Optimisation is performed with the Matlab

[3] For a dense variance-covariance matrix there are $n\left(n+1\right)/n$ non-zeros elements.

[4] The variance-covariance matrix is given by $Var\left(u\right) = \Gamma_{\rho}\Gamma'_{\rho}$ with $\Gamma = \left(\mathbf{I} - \rho\mathbf{W}\right)^{-1}$, see for example Beron and Vijverberg (2004 p. 170–173).

Optimization Toolbox using a constraint maximisation solver with an interior-point algorithm. Derivates are approximated numerically using forward differences. With our implementation it is possible to estimate the SDEM model with 64,488 observations in around 5.2h hours using Matlab Parallel Computing Toolbox with 12 workers on a Intel® Xeon® E5-2690 (2 processors) where we allow to parallelize the R repetitions of the GHK sampler.[5]

The dependent variable in the analysis represents farm survival in 2009 of all farm active in 1999 and is equal to one if a farm is still active in 2009, zero otherwise. We consider a farm as active if at least one production activity is observed for the farm in the payment data base. Because of missing observations due to mergers of municipalities it was necessary to exclude 11 municipalities from the analysis[6].

As explanatory variables we consider some that can be derived from the payment data base as well as from additional statistics such as the 1999 farm census. As discussed in section 2, with respect to the research objective to explain farm exit, the most important variables of interest are related to different types of farm income such as the total income, the on-farm wage rate and changes in the on-farm wage. Of particular interest is the roll of direct payments in this respect. In order to separate the influence of direct payments on farm survival we divide farm income into market returns and direct payments. It is important to note that what we call 'market returns' also substantially depends on policy decision since market prices are strongly affected by administrative prices. Since the actual market returns for each farm are unobserved we consider an average market return for each production activity. Therefore, market return rates are derived from the reference farms data collection (NILF 2000 and NILF 2009). It contains information of around 30 reference farms that are selected to represent the diversity of the Norwegian farm sector with respect to size,

[5] This is lower as the speed reported in Pace and LeSage (2011), who claim to estimate a sample of size 100.000 in around 4 min on a standard laptop computer without parallelization, but since our focus is on a single estimation no further improvements of the implementation is pursued.

[6] Municipality codes 529, 716, 718, 1154, 1214, 1418, 1514, 1569, 1572, 1576, and 1842.

specialization and location. Data is collected on an annual basis and each reference farm summarizes information from several farms within the Norwegian farm data accountancy system, comparable to the EU's Farm Accounting Data Network (FADN), to minimize farm specific variations. The reference farms are the basis for the annual negotiations for the adjustments of the market support and direct payments and thus are central in the design of Norwegian agricultural policy. Based on these reference farms information about the market return per unit of production activity is derived. A full cost accounting is applied considering fixed costs, depreciation and capital costs. Labor costs are excluded in order to derive the return to labor. The derived per unit rates are then multiplied by the production activity levels of each farm observed in the payments data base, resulting in the total market returns per farm. Due to data limitations it is not possible to distinguish market return rates with respect to different farm size or location. It is thus likely that the actual market return of a farm differs from the derived average market return. Nevertheless, we expect that the derived measures provide an appropriate approximation of the difference in farms market return that arise due to different production programs. Due to these limitations all income measures based on the market returns needs to be interpreted as the potential or expected income given a farmer's production program. In the following we will use the terms *income* or *on-farm wage* to describe this expected income of a farm.

The direct payments per farm are calculated using actual payment rates and eligibility rules. Most of the payments are based on current levels for animals and crops and differentiated by region and farm size. Using the observed production activities in the payment data base and considering the specific region and size of a farm the direct payments can be calculated rather accurately for each farm.

Total income is defined as the sum of total market returns and total direct payments. To derive farms' on-farm wage rate, the average labor requirement is calculated for each farm based on its actual production program using estimated labor input use coefficients. The potential wage rate of a particular farm is than obtained as the ratio of total direct payments or total market returns over total labor requirement. Additionally, we obtain a measure for the potential change in the on-farm wage rate if the farm would not have altered it size or production program. For the calculation we keep the production program constant to the 1999 level, even though we have observations on the actual production programs during the period.

The reasoning is that changes in the production program might already be the results of changes in income opportunities that we aim to measure. A more detailed description of the way the variables are derived is provided in Storm and Mittenzwei (2013).

As discussed in section 2 for a theoretical perspective it remains undeceive of whether the total income or the on-farm wage rate is more important for farmers WTP for land and hence farm survival. In the empirical application we thus include all the variable just discussed, namely the total direct payments in 1999 (*dpay99)* and the total market return in 1999 (*mReturn99*) as a measure of total farm income as well as the direct payment and market return per labor requirement in 1999 (*dpay99/reqLabo* and *mReturn99/reqLabo*) und the change in the latter two (*C.DPayLabo* and *C.mRetLabo*), as measures of the on-farm wage rate.

Additionally total agricultural area (*area*), total observed labor input in 1999 (*obsLabo99*) and estimated labor requirement for 1999 (*reqLabo99*)[7] are included. These three variables together with total income are all measures for the absolute size of the farm and therefore positively correlated (Table 2).

Table 2: Correlation coefficients between different measures of the absolute farm size

	area	obsLabo99	reqLabo99	dpay99
area	1	0.44	0.65	0.62
obsLabo99		1	0.78	0.70
reqLabo99			1	0.85
dpay99				1

Source: Own calculation.

[7] See Storm and Mittenzwei (2013) for detailed information about the estimation of the labor requirements.

Table 3: Descriptive statistics and definition of variable codes (n=64488).

	Codes	**Units**	**Mean**	**Median**	**Max.**	**Min.**	**Std. Dev.**
Age of farm holder	age	year	48.83	49.00	97.00	7.00	11.58
Farm area	area	daa*	153.50	121.00	3411.00	0.00	132.45
Agricultural labor input	obsLabo	hour	2215.46	1900.00	52330.00	0.00	1827.00
Estimated labor requirement	reqLabo	hour	1950.39	1454.92	44452.84	9.79	1719.36
Total direct payments	Dpay	1000 Nkr	167.02	128.47	1252.47	0.01	132.06
Total market return	mRet	1000 Nkr	-33.87	-24.20	1403.76	-2606.99	66.27
Ratio observed over estimated labor requirment	laboObs/Req	ratio	1.37	1.13	83.32	0.00	1.33
Ratio leased area over total area	landLease/Tot	ratio	0.27	0.13	1.50	0.00	0.33
Dummy if farm has milk cows	hasMilk	binary	0.33	0.00	1.00	0.00	0.47
Dummy if farm has sheep	hasSheep	binary	0.33	0.00	1.00	0.00	0.47
Dummy if farm has poultry	hasPoultry	binary	0.01	0.00	1.00	0.00	0.08
Dummy if farm has sows	hasSows	binary	0.05	0.00	1.00	0.00	0.22
Tot. market ret. per labor req. in 1999	mretrun/ reqLabo	1000 Nkr/hour	-0.01	-0.02	0.24	-0.58	0.03
Tot. direct pay. per labor req. in 1999	dpay/ reqLabo	1000 Nkr/hour	0.09	0.09	0.42	0.00	0.03
Change in market returns per labor 99-09 structure equal to 1999	C.mRetLabo	1000 Nkr/hour	-0.05	-0.04	0.29	-0.15	0.03
Change in direct pay. per labor 99-09 structure equal to 1999	C.DPayLabo	1000 Nkr/hour	0.10	0.09	0.28	-0.17	0.04

** daa = 1/10 ha.*

Further, in line with the discussion in section 2 the age of the farm holder[8] (*age*), a ratio of leased to total agricultural area (*landLease/Tot*) and a ratio between observed labor input and estimated labor requirements (*laboObs/Req*) as a measure of farm productivity is included. As a rough measure to reflect specialization specific policy environments dummy variables for indicating if a farm has milk cows (*hasMilk*), sheep (*hasSheep*), sows (*hasSows*) or poultry (*hasPoultry*) are considered. Descriptive statistics of all explanatory variables along with their variable codes, are provided in Table 3. In the regression analysis all variables are z-standardized by subtracting the mean and dividing by the standard error.

A requirement for the estimation of model (2) and (3) is to specify a spatial weighting matrix $\mathbf{W}$. The spatial weighting matrix should be constructed in order to closely approximate the neighboring relations between farms. This task is challenging in general and in particular for the background of the heterogeneous farming regions in Norway, varying from small scale berry production areas with high farm density to extensive sheep grazing regions with low farm density per unit area. We also expect that neighboring relations and the size of the local land market to differ between regions. In rather dense regions the distance between farms and the fields farmers compete for are likely smaller than in regions with only few farms. From the 1999 farm census, data about the driving distance to the furthest field is available and can be linked to the payment data base. We expect that these data carries some information about the regional structure of the farm sector, the distances farmers are willing to travel and hence the distance over which farms compete for land.

Using this data the median driving distance to the furthest field in each municipality is calculated. The median is used in order to eliminate the influence of potential outlier and zero observations that cannot be distinguished from missing observations. Neighbors of a farm are then defined as all farms that are within a radius of this median municipality driving distance. Additionally, the maximum number of neighbors is set to 20 (nearest neighbors) in order to prevent farms from having an unrealistically large number of neighbors. Finally, the farms

[8] For observations where age is missing in the data base we imputed the mean age. The age is missing for example for all farms where the owner is not a natural person. In total we have 495 or 0.77% missing observations for age.

identified as neighbors are weighted by their inverse distance, giving nearer neighbors a larger weight compared to neighbors further away.

One common criticism of spatial regression models is that the neighboring relations are defined in a rather arbitrary fashion and do not necessarily represent the true neighboring relation between farms. Even though we base our definition of the neighboring relationships on empirical data this criticism remains valid. However, as pointed out by LeSage and Pace (2011), in most cases the results of spatial regression models are less sensitive to the definition of the spatial weighting matrix as commonly believed. In order to explore the sensitivity of our results to the definition of the spatial weighting matrix we repeat estimation of the SLX model using two alternative definitions of neighboring relationships: First all farms within a fixed radius of 2km are considered as neighbors and, secondly, the 5 nearest farms are considered as neighbors. As can be seen in appendix A-1) , the results are largely unaffected by the definition of the neighboring relations.

5 Regression results

In the following the results for a model with and without the spatial interactions are presented. Distinguishing between the two models allows us to highlight how the conclusion regarding the effects of direct payments changes when ignoring spatial interactions. The regression results for the non-spatial model as well as the results for the spatial model using the SLX and SDEM model specification are reported in Table 6. It can be seen that the coefficients with respect to the non-spatially lagged variables differ only slightly between the three specifications. This allows us to discuss the non-spatial results first and to highlight the differences with respect to the spatial model in the following.

The non-spatial regression results are presented in the left part of Table 6. Except for the market return and its squared term, the dummy variable indicating if a farm has poultry (*hasPoultry*) and the squared term of the estimated labor requirement (reqLabo99^2) all explanatory variables are highly significant. The insignificant squared terms where dropped in from the model specification. Statistical significance is comparatively easy achieved with more than 60,000 observations, but says little regarding relevance. A measure of the explanatory power of the overall model is the percentage of correctly predicting the binary choice. With the non-spatial model we are able to correctly predict the exit/survival decision in 72.64% of the cases. Compared to the naive model, which correctly predicts survival in 62.72% of the cases, this is a total gain of 9.93 percentage points.

Table 4: Percentage of correct predictions of farm survival between 1999 and 2009 with different model specification of the non-spatial binary choice probit model with respect to the absolute size of a farm.

	Naive	All other non-spatial explanatory variables					Full Model
			and Area	and obs. Labor	and est.req Labor	and direct payments	
% Correct	62.72	67.58	71.82	71.48	71.85	72.49	72.59
Diff. to full M.	-9.88	-5.01	-0.78	-1.11	-0.75	-0.11	0.00

Source: Own estimation.

To assess the explanatory power of individual variables, we can explore how the percentage of correct prediction changes with or without the variable under consideration. Overall we found that the variables related to farm size (*area*, *obsLabo99*, *reqLabo99*, and *dpay99*) are most important explaining farmers' exit/survival decision (Table 4) with a positive relationship between farm size and survival. A model with all explanatory variables except these variables related to the absolute size would correctly predict farm exit/survival in 67.58% of the cases which is 4.86 percentage points more than the naive model and 5.01 percentage points less than the full model. Further, it is interesting to note that all variables related to the absolute size can explain more or less the same since the percentage of correct prediction with only one of the four variables is only slightly lower as the percentage of correct prediction with all four variables (Table 4).

The importance of the remaining variables is relatively evenly distributed with each variable adding only little to the overall explanatory power of the model. Of specific interest is the importance of the on-farm wage rate (*mreturn99/reqLabo* and *dpay99/reqLabo*) in 1999 and the change in on-farm wage rate from 1999 to 2009 (*C.DPayLabo* and *C.mRetLabo*). Both have a positive influence on farm survival but, individually and together, add only a little to the overall explanatory power of the model (Table 5).

Table 5: Percentage of correct predictions of farm survival between 1999 and 2009 with different model specification of the binary choice probit model with respect on-farm wage and changes in the on-farm wage

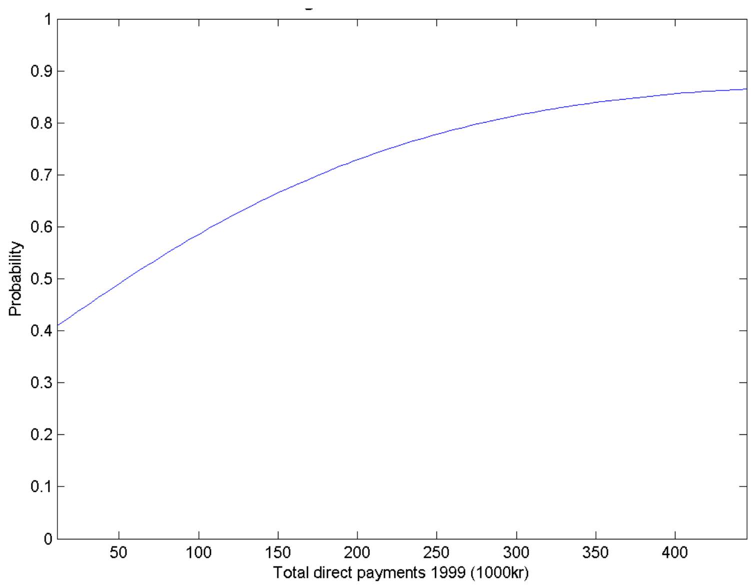
	Naive	All non-spatial explanatory variables except			Full Model
		on-farm wage	changes in on-farm wage	on-farm wage and changes in on-farm wage	
% Correct	62.72	72.53	72.34	72.17	72.59
Diff. to full M.	-9.88	-0.07	-0.26	-0.43	0.00

Source: Own estimation.

Taken together the results indicate that the absolute size of a farm is more important than the on-farm wage rate per hour or changes in this on-farm wage rate. As discussed in section 2 this might hind to potential imperfections on the labor market which render the potential on-farm income per person or family, as approximated by the absolute size of a farm, as more important than the on-farm wage rate per hour.

It is useful to analyze the effects of the absolute size and in particular the effects of direct payments on survival in more detail. Overall, all variables related to the absolute size of a farm show a positive influence (some with decreasing rate) between farm size and survival. To illustrate the relationship for direct payments, the survival probability is calculated based on the non-spatial regression results for an ‘average’ farm, keeping all other explanatory variables fixed at their means and vary only the total amount of direct payments. Figure 2 shows that direct payments have a larger effect for relatively small farms which is leveling out for larger farms. This indicates, as mentioned above, that farms need to have a sufficient size to provide for the family. Beyond that size, additional direct payments do not much increase the probability of survival anymore.

Figure 2: Probability for an 'average' farm to stay active between 1999 and 2009 for varying total direct payments. The x-axis represents the 2.5% to 97.5% quintile of the observed total direct payments.



Source: Own calculation.

From a policy perspective we could draw the conclusion from the non-spatial findings that increasing direct payments would be one approach to increase the survival probability of farms which do not have a sufficient income potential without them. In the following we explore how this conclusion is affected when considering spatial interaction between farms.

The spatial regression results for the SLX and SDEM model are reported in the right part of Table 6. For model specification we included all variables, except the squared terms, as spatially lagged variables[9]. The regression results for the SLX and SDEM model almost

[9] Since the spatially lagged variables show less variation we summarize variables that are highly correlated and measure related aspects. Specifically, the two variables for the on-farm wage rate *mReturn99/reqLabo* and *dpay99/reqLabo* are summarized to one variable *W_FarmWage99*. Similarly, the two variables for the change in on-farm wage rate *C.DPayLabo* and *C.mRetLabo* are summarized to one variable *W_C.inco99*. The spatially lagged observed labor input is excluded from the model specification because of a high correlation to the estimated

identical even so we found significant spatially autocorrelated errors with a $\rho = 0.12$ in the SDEM model. This finding implies that ignoring the spatially autocorrelation in the errors, as indicated by the significant ρ in the SDEM model and the test performed in section 4, does not result in a substantial bias of the SLX model estimates.

The results with respect to the non-spatial variables discussed before stays almost unaffected indicating the non-spatial results are robust with respect to the inclusion of spatial lagged explanatory variables. Overall the inclusion of the spatial lagged variables improves the percentage of correct prediction only slightly indicating that they have only little explanatory power for farmer's survival decision. Also the importance of different variables stays unaffected such that the findings discussed for the non-spatial model similarly hold for the spatial model.

Nevertheless, with respect to answering our research question considering the spatial effects is crucial. For the non-spatial findings we concluded that the absolute size of a farm is the most important factor in explaining farmer's survival decision and that, for the relevant range, the larger the absolute size the higher the survival probability, irrespective of how the absolute size is measured. This result also applies for the spatial model but the effect of the absolute size of neighboring farms is somewhat more complicated. When considering only one spatially lagged variable for the absolute size, we found a negative influence between neighboring size and own survival irrespectively which variable (*w_dpay99*, *w_uaar* or *w_laboreq99*) is used to measure the absolute size. As discussed above all three measures of the absolute size of the farm are highly correlated and the same holds for the spatially lagged absolute size measures. Nevertheless, the large sample size is sufficient to anyway identify different coefficients on the three variables (Table 6). Farms with larger neighbors in terms of area and labor use having a higher survival probability while farms with larger neighbors in terms of total direct payments having a lower survival probability.

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labor requirement that does not allow identifying both variables. The general model results and conclusions, however, are unaffected by the choice of which to exclude from the model.

Table 6: Regression results for the non-spatial probit, SLX and SDEM model to explaining farm survival. The dependent variable is equal to one if the farm stays active between 1999 and 2009 and zero otherwise. Spatially lagged variables are denoted with a leading “W_”.

	Non-spatial probit		SLX		SDEM	
Variable	Coef	p-value	Coef	p-value	Coef	p-value
const	0.3931	0.0000	0.3948	0.0000	0.3974	0.0000
age	0.5656	0.0000	0.5581	0.0000	0.5631	0.0000
age^2	-0.6596	0.0000	-0.6499	0.0000	-0.6548	0.0000
area	0.2533	0.0000	0.1920	0.0000	0.1886	0.0000
area^2	-0.1331	0.0000	-0.1190	0.0000	-0.1176	0.0000
obsLabo	0.2784	0.0000	0.2622	0.0000	0.2626	0.0000
obsLabo^2	-0.1174	0.0000	-0.1100	0.0000	-0.1103	0.0000
reqLabo	0.1411	0.0000	0.1291	0.0000	0.1334	0.0000
mRet	0.0043	0.7039	0.0090	0.4286	0.0107	0.3250
dpay	0.6197	0.0000	0.7421	0.0000	0.7507	0.0000
dpay^2	-0.3382	0.0000	-0.3477	0.0000	-0.3518	0.0000
laboObs/Req	-0.0425	0.0000	-0.0396	0.0000	-0.0394	0.0320
landLease/Tot	-0.0455	0.0000	-0.0441	0.0000	-0.0442	0.0287
mretrun/reqLabo	0.1141	0.0000	0.1006	0.0000	0.0972	0.0000
dpay/reqLabo	0.0629	0.0000	0.0723	0.0000	0.0738	0.0000
C.DPayLabo	0.1311	0.0000	0.0967	0.0000	0.0951	0.0000
C.mRetLabo	0.0780	0.0000	0.0638	0.0000	0.0586	0.0000
hasMilk	-0.1885	0.0000	-0.2254	0.0000	-0.2270	0.0000
hasPoultry	0.0071	0.2799	0.0061	0.3554	0.0067	0.5520
hasSheep	0.0220	0.0010	0.0209	0.0031	0.0205	0.0229
hasSows	0.0455	0.0000	0.0421	0.0000	0.0433	0.0084
W_mRet	---	---	-0.0179	0.0539	-0.0185	0.0665
W_dpay	---	---	-0.2708	0.0000	-0.2718	0.0000
W_area	---	---	0.0721	0.0000	0.0742	0.0003
W_reqLabo	---	---	0.0617	0.0000	0.0624	0.0188
W_landLease/Tot	---	---	-0.0371	0.0000	-0.0373	0.0520
W_FarmWage	---	---	0.0345	0.0015	0.0341	0.0186
W_C.inco	---	---	0.0498	0.0000	0.0509	0.0000
W_hasMilk	---	---	0.0774	0.0000	0.0761	0.0015
W_hasPoultry	---	---	0.0094	0.1084	0.0102	0.5515
W_hasSheep	---	---	0.0186	0.0090	0.0177	0.4407
W_hasSows	---	---	0.0144	0.0163	0.0130	0.5541
rho	---	---	---	---	0.1199	0.0000
n		*64488*		*64488*		*64488*
% Correct predictions Model		*72.59*		*72.63*		*72.64*
% Correct predictions Naive		*62.72*		*62.72*		*62.72*
Total Gain*		*9.88*		*9.91*		*9.92*

**Change in "% Correct" compared to naive specification.*

As discussed in section 2 a reason for this finding could be the multiple ways farm interact which each other. On the one hand farms gain from an active farming neighborhood and cooperative network due to technology diffusion or easier accesses to suppliers or processors. The larger the neighboring farms in terms of the cultivated area and/or the total labor use, the more likely it is that farms are situated in an active cooperative network with the positive effects that follow from this. On the other hand farms compete with their neighbors for the limited resource land on local land markets. Neighboring farms with a high willingness to pay for land should thus have a negative effect on farm survival since it increases the attractiveness for a farmer to give up and rent out his land or limit the possibilities for farm growth. Since direct payments are a major income source for Norwegian farms it can be expected that farms with higher direct payments (everything else equal) have a higher WTP for land. Hence, farms having neighbors with higher direct payments (everything else equal) are likely to face stronger competition on the land market which decreases survival probability.

From a political perspective these findings have important implication with respect to the effects of direct payments on farm survival. From the non-spatial results we concluded that increasing direct payments increases the survival probability of farms and that increasing direct payments for all farm can slow down farm structural change. However, from the spatial result we conclude, that increasing own direct payments increase the farms survival probability but negatively affects the survival of neighboring farms. The overall effects of a change in direct payments it thus more complicated and need to consider the actual neighboring relations between farms in the population. This issue is explored in more detailed in the next section.

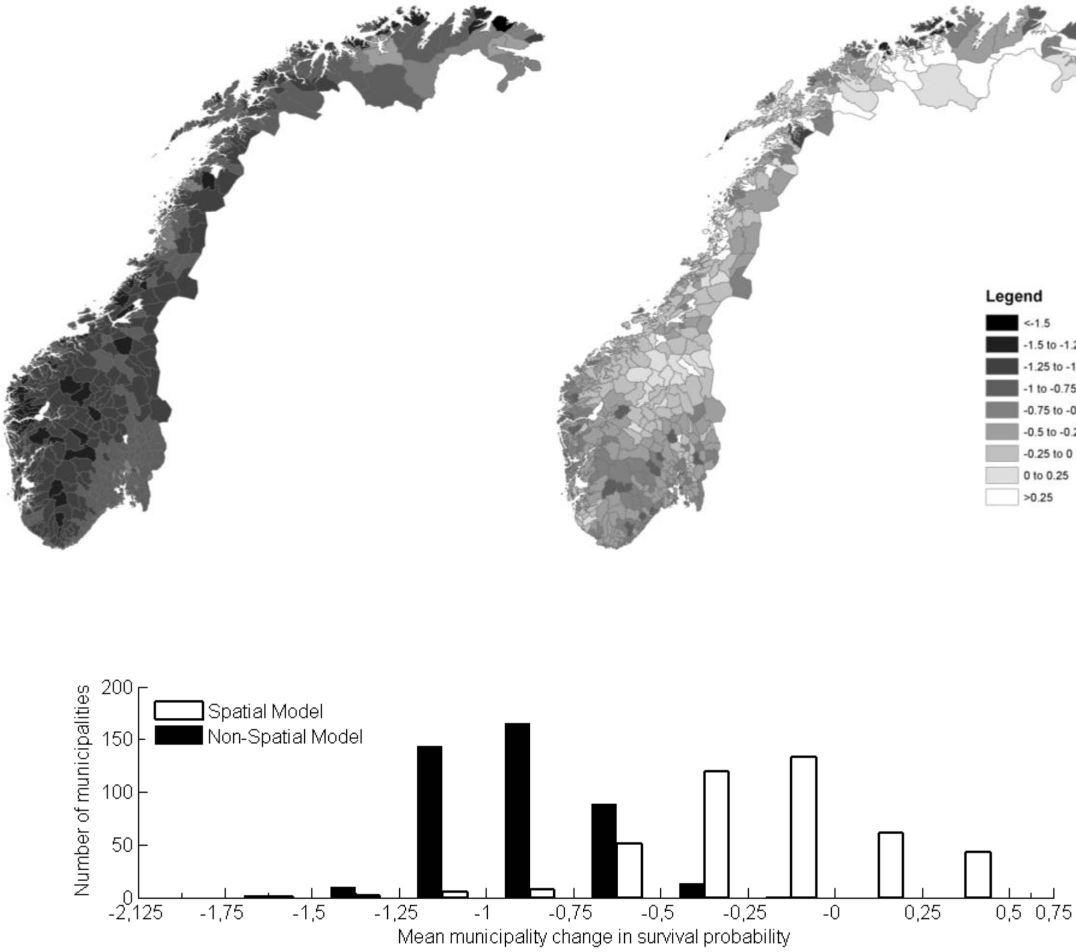
6 Policy Scenario simulation

In this section we aim to provide a more complete and meaningful picture on direct payments effects than are offered by the estimation results. We analyze the effect of particular changes in the policy regime on the entire population with a simulation experiment. For this, the following steps are applied; first, predicted survival probabilities are calculated for all farm given the observed data. Then, the total direct payments are calculated for each farm under the new policy regime and, based on those, new survival probabilities derived. Following, the difference between the new and the original survival probabilities are calculated. Finally, the results are aggregated at municipality level be calculating the mean change in survival probability in each region. In order to highlight the differences between the spatial and non-spatial model these steps are performed using the results of each model.

The entry approach is performed for two different policy scenarios. First, we consider a general reduction of all payment rates by 10%. In this scenario all farm types, farm sizes and regions are similarly affected from the reduction. Secondly, an elimination of the structural dimension of the payments is considered. In the current policy regime several support measures differentiate payments rates according to farm size, such that farmers receive more direct payments for the first compared with the last unit (animal head or area). Assuming constant rates equal to the lowest rates currently paid, this scenario implies an overall reduction of total direct payments by around 30% with small farms experiencing a higher reduction than large farms in relative terms. Figure 3 illustrates the results for the first scenario in which all payment rates are reduced by 10%. For the non-spatial results we found a rather modest reduction of the average survival probability of more than half a percentage point in almost all municipalities with most municipalities showing a reduction by more than one percentage point. Considering the spatial interactions weakens the effects of a reduction of direct payments. Now, in most municipalities the survival probability changes only slightly by less than one percentage point, with most municipalities showing a reduction be less than half a percentage point. In 61 municipalities (or 14%) the survival probability even increases. For the entire country, the mean decrease in survival probability is reduced from 1.04 percentage points for the non-spatial model to 0.26 percentage points for the spatial results. In terms of farm numbers we predict that a reduction of direct payments by 10% leads to an increase of farm exits in the ten year period by 964 farms for the non-spatial model. For a farm population of 64.488 farm in 1999 (40.445 in 2009) this effect appears rather modest. With the spatial model the increase in farm exits by 171 is even more moderate. Without the spatial interaction the predicted effects of a 10% decrease in direct payments on farm exits are already moderate but in comparison to the spatial model results they still exaggerate the effects substantially.

Figure 3: Mean municipality change in survival probability for a 10% reduction of all direct payment rates.

Non-Spatial model results *Spatial model results*

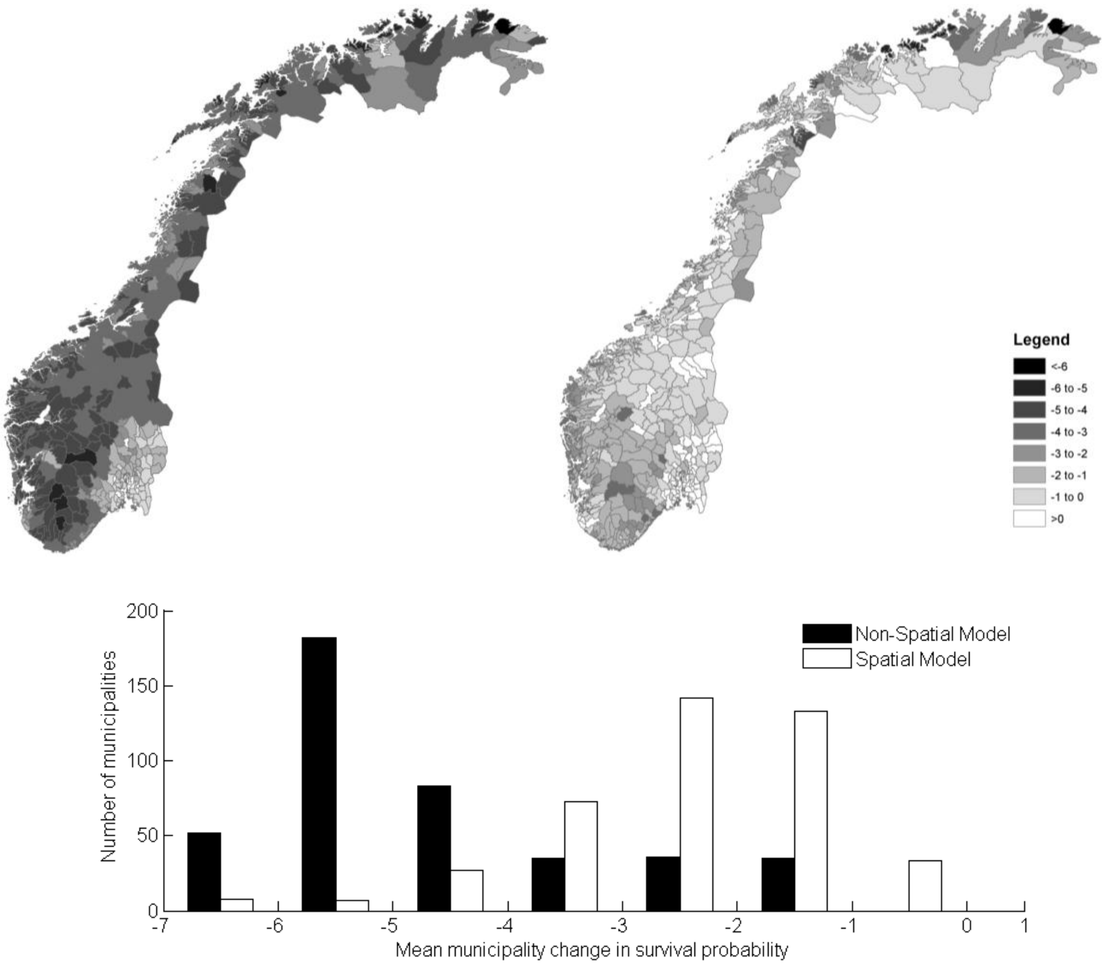


Source: Own illustrations. Shape files were derived from the GADM database (www.gadm.org), version 2.0.

In the second scenario in which the structural dimension of direct payments is abolished, average survival probability decreases by more than four percentage point in most of the municipalities and by at least one percentage point in all municipalities for the non-spatial model results. In 21 municipalities (or 4%) survival probability decreases by more than six percentage points. With the spatial results, in contrast, average survival probability decreases more moderate by less than four percentage points for most of the municipalities and by less than two percentage points in 50 municipalities (or 12%). For the entry country the mean decrease in survival probability is reduced from 4.00 percentage points for the non-spatial model to 1.60 percentage points for the spatial results. In absolute terms we predict in increase of farm exits by 4.046 farms for the non-spatial result compared to increase of 1.474 farms when considering the spatial model. Without considering the spatial interactions the prediction effects of a change in the policy regime are thus again substantially exaggerate compared to the case which considers the spatial interactions.

Figure 4: Mean municipality change in survival probability for a abolishment of the structural dimension of direct payments in which rates are set equal to the lowest rates currently paid.

Non-Spatial Model results *Spatial Model results*



Source: Own illustrations. Shape files were derived from the GADM database (www.gadm.org), version 2.0.

7 Conclusion

To our knowledge the paper is the first that considers farm level spatial interaction in an empirical analysis of farm structural change in general and for an assessment of the effects of direct payments on farm survival in particular. We found that higher direct payments of neighbors' decreases own survival probability. Ignoring this spatial interaction led to a substantial overestimation of the effects of direct payments on farm exits. An overall assessment of the effect of a change in the support regime can therefore not be based on the assumption of independent farm behavior when aggregating individual farm level results at regional level. Instead, changes can only be assessed for the entire farm population considering the spatial interactions capturing competition together with the actual characteristics and locations of farms in space.

In addition, we found that the total economic size of farm is more important than on-farm wage rates. Imperfect labor markets and family farm structures in Norway likely often lead to the requirement of farms being able to support a family or be abolished. This income potential depends mainly on initial farm size and to a lesser extent on the on-farm wage rate. Empirical results indicate that direct payments may somewhat help smaller farm across thresholds for survival, but the probability of survival of larger farms is basically unaffected.

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Appendix

A-1: Analysis of sensitivity of SLX regression results with respect to three different definition of the neighboring relationships. Neighbors defined as 1) all farms with a radius of 2km, 2) five nearest farms and 3) all farms within a radius of the regional median furthest driving distance to fields.

	All within 2km radius		5 Nearest Neigh		Median dist. to furthest fields	
Variable	Coef	p-value	Coef	p-value	Coef	p-value
const	0.3954	0.0000	0.3953	0.0000	0.3948	0.0000
age	0.5615	0.0000	0.5567	0.0000	0.5581	0.0000
age^2	-0.6516	0.0000	-0.6475	0.0000	-0.6499	0.0000
area	0.1408	0.0000	0.1504	0.0000	0.1920	0.0000
area^2	-0.1063	0.0000	-0.1105	0.0000	-0.1190	0.0000
obsLabo	0.2500	0.0000	0.2538	0.0000	0.2622	0.0000
obsLabo^2	-0.1055	0.0000	-0.1081	0.0000	-0.1100	0.0000
reqLabo	0.1244	0.0000	0.1291	0.0000	0.1291	0.0000
mRet	0.0107	0.3453	0.0090	0.4300	0.0090	0.4286
dpay	0.8222	0.0000	0.8086	0.0000	0.7421	0.0000
dpay^2	-0.3591	0.0000	-0.3588	0.0000	-0.3477	0.0000
laboObs/Req	-0.0382	0.0000	-0.0386	0.0000	-0.0396	0.0000
landLease/Tot	-0.0405	0.0000	-0.0420	0.0000	-0.0441	0.0000
mretrun/reqLabo	0.0894	0.0000	0.0926	0.0000	0.1006	0.0000
dpay/reqLabo	0.0829	0.0000	0.0813	0.0000	0.0723	0.0000
C.DPayLabo	0.0661	0.0000	0.0752	0.0000	0.0967	0.0000
C.mRetLabo	0.0525	0.0001	0.0574	0.0000	0.0638	0.0000
hasMilk	-0.2467	0.0000	-0.2449	0.0000	-0.2254	0.0000
hasPoultry	0.0058	0.3791	0.0055	0.4026	0.0061	0.3554
hasSheep	0.0307	0.0000	0.0290	0.0001	0.0209	0.0031
hasSows	0.0375	0.0000	0.0389	0.0000	0.0421	0.0000
W_mRet	-0.0223	0.0480	-0.0053	0.5805	-0.0179	0.0539
W_dpay	-0.3040	0.0000	-0.2653	0.0000	-0.2708	0.0000
W_area	0.0633	0.0000	0.0774	0.0000	0.0721	0.0000
W_reqLabo	0.0886	0.0000	0.0517	0.0004	0.0617	0.0000
W_landLease/Tot	-0.0441	0.0000	-0.0482	0.0000	-0.0371	0.0000
W_FarmWage	0.0490	0.0000	0.0272	0.0027	0.0345	0.0015
W_C.inco	0.0639	0.0000	0.0394	0.0000	0.0498	0.0000
W_hasMilk	0.0765	0.0000	0.0892	0.0000	0.0774	0.0000
W_hasPoultry	0.0059	0.3131	0.0034	0.5631	0.0094	0.1084
W_hasSheep	0.0018	0.8075	0.0043	0.5643	0.0186	0.0090
W_hasSows	0.0304	0.0000	0.0213	0.0004	0.0144	0.0163
n		64488		64488		64488
% Correct predictions Model		72.80		72.78		72.63
% Correct predictions Naive		62.72		62.72		62.72
Total Gain*		10.09		10.06		9.91

*Change in "% Correct" compared to naive specification