Local and regional spatial interactions in the analysis of Norwegian farm growth

Hugo Storm and Thomas Heckelei

Institute for Food and Resource Economics (ILR), University of Bonn, Germany

Contact: hugo.storm@ilr.uni-bonn.de

Paper prepared for presentation at the 150th EAAE Seminar

'The spatial dimension in analysing the linkages between agriculture, rural development and the environment'

Preliminary version, please do not quote without permission

Edinburgh, UK, October 22-23, 2015

Copyright 2015 by Hugo Storm and Thomas Heckelei. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Local and regional spatial interactions in the analysis of Norwegian farm growth

Hugo Storm and Thomas Heckelei

Abstract We analyse the importance of farm level spatial interaction for farm growth. We hypothesize that farms compete on local land markets and interact through knowledge transfer leading to positive and negative feedbacks, respectively. One of the main challenges in the analysis of farm level interaction is to distinguish between actual interactions from the effects of spatially correlated omitted variables. We approach this challenge be estimating a spatially lagged explanatory model (SLX) employing two spatial weighting matrix differentiating between a local and regional neighbourhood. Using a spatially explicit dataset for nearly all Norwegian farms in 1999 and 2009, we found that neighbouring effects differ substantially between local and regional neighbourhood. Our results indicate that the behaviour of directly neighbouring farms is indeed important for farm growth decisions.

Keywords: farm growth, direct payments, land market, spatial competition, spatial interaction

JEL classification: C10, C21, Q12, Q18

1 Introduction

Individual farms interact which each other in multiple ways. Due to the specific characteristics of the farm sector most of these interactions are spatial in nature. Storm et al. (2015) analysed how these farm level spatial interactions affect farm survival and change the aggregate impact of direct payments. Here we generalize their study by considering farm growth in terms of arable land instead of just farm survival. The central objective is to analyse how spatial interdependence affects farm growth and the impact of direct payments on growth. The hypothesis is that competition on the land market leads to negative spatial feedback while network effects lead to positive spatial feedback. Assuming there are positive effects of direct payments on the individual level; at the aggregate, negative spatial feedbacks would reduce these individual farm level effects while positive spatial feedback would amplify it.

In order to identify spatial interdependencies we employ a spatial regression approach with two different spatial weighting matrixes. One criticism of spatial regression methods is the arbitrary definition of the spatial weighting matrix (Bell and Dalton, 2007; Holloway and Lapar, Ma. Lucila A., 2007)[1]. Additionally Gibbons and Overman (2012) argue in a paper provocatively entitled "Mostly Pointless Spatial Econometrics?" that the classical, widely used spatial lag dependent variable (SAR) model suffers from an identification problem that is not appropriately addressed in the applied literature.

Both points will be central for our research design. In order to avoid the identification problem of the SAR model we employ a spatially lagged explanatory variable (SLX) that is proposed as an suitable alternative in Gibbons and Overman (2012). With respect to the spatial weight matrix we systematically analyse how our estimation results depend on different definitions of neighbouring relationships. Additionally we work with a model including two spatial weight matrices. The possibility to consider more than one spatial weighting matrix is an additional advantage of the SLX model compared to the SAR model where this is not easily possible (LeSage and Pace, 2011). With these two weighting matrices we aim to distinguish between local and regional spatial interdependencies. With local interdependencies we aim to capture effect of directly neighbouring farm while regional

[1] LeSage and Pace 2011) on the other hand argued that the results of spatial regression models are less sensitive to the definition of the spatial weighting matrix in most cases.

interdependence are defined more broadly including farms in a larger area around the farm. The reasoning for this differentiation is that we assume that local spatial interdependencies are more strongly driven by actual interaction between farms (on the land market or through knowledge diffusion) that we aim to identify. Regional interdependencies, on the other hand, might arise through unobserved, omitted, spatially correlated variables that affect both farm growth and neighbouring characterizes. The differentiation is obviously not clear cut, but nevertheless we consider it a valuable approach in the direction to distinguish these two different effects which is novel to the literature.

In the next section the importance of spatial interaction for farm growth are discussed from a theoretical point of view. The methodical challenges for the identification of spatial interaction and our approach to cope with them are discussed in section 3, followed by empirical results in section 4. The final section concludes.

2 Theoretical Framework

In a non-spatial context the analysis of farm growth is extensively studied (see Zimmermann et al., 2009 for a review). Zimmermann and Heckelei (2012) and Akimowicz et al. (2013) categorize the determinations of farm growth along with their theoretical underpinning. The selection of control variables included in the growth model will be guided by these theoretical considerations. Here we limit the discussion to own and neighbouring farm size and direct payments as the main explanatory variables of interest. Since one of the main hypotheses is that farms interact with each other on the land market, we define farm size in terms of arable land. We do not consider non-arable land because we assume that it is not easily transferred to arable land such that there is no direct substitution between the two.

One of the main determinants of farm growth is technological innovation and economies of scale (Cochrane, 1958; Harrington and Reinsel, 1995; Hallam, 1991). Technological innovation reduces per unit costs and with it output prices, driving out farms not willing or able to innovate. Innovative farms can grow by picking up the resources released by the leaving farms. Due to better access to information and financing, larger farms tend to be more capable to innovate leading to a positive impact of size on farm growth (Weiss, 1999). With increasing farm size it might also be possible to realize scale effects due to a better utilization of input factors. These factors would contribute to a positive impact of farm size on farm growth. In the specific case of Norway, however, there are also several policies that differentiate payments by farm size, such that small farms receive relatively more subsidies than large farms (Knutsen, 2007p. 28). Additionally there exist several upper limits on livestock production[2]. These size discriminating policies might limit the relative growth potential of farms that are already large. The final relationship between farm growth and own size is thus ambiguous.

Analogously, the theoretical effects of neighbouring farm size on own growth is also ambiguous. On the one hand, farms compete on the land market for the limited available arable land. Consequently, we expect to find an effect of neighbouring size opposite to the effect of size on own growth. Specifically, if own size positively affects own growth due to scale effects and a higher rate of innovation we expect a negative effect of neighbouring size on own growth due to competition on the land market. In reverse, is the growth potential lower for large farm due to size discriminating policies, we expect positive effects of neighbouring size due to lower competition on the land market. Beside interaction on the land market, however, farmers are also part of a corporate network with other farmers important

[2] For example, for joint dairy operations the total milk quota is limited or concession limits exist for poultry and pig production (Knutsen (2007)).

for technology adoption and knowledge transfer (Case, 1992; Rogers, 1995; Berger, 2001; Holloway et al., 2002; Gezelius, 2014; Padel, 2001; Lewis et al., 2011; Schmidtner et al., 2012; Lapple and Kelley, 2015; Schmidtner et al., 2015). Under the assumption that larger farms are more innovative, these cooperation effects should lead to a positive effect of neighbouring size on own growth. Similarly, larger neighbouring farms might also be fostering growth by maintaining a corporate network of suppliers, wholesalers and processors (Mosnier and Wieck, 2010). Further, Gezelius (2014) highlighted the importance of exchanges in labour and machinery between neighbouring farms in Norway.

Another driver of farm growth discussed in the literature is the relation between on- and off-farm wages (Hallam, 1991). Direct payments increase this ratio which might encourage farmers to increase farm labour input. Similarly, higher direct payments increase the return to land and with it farmer's willingness to pay (WTP) for land and consequently encourage farm growth. Following the same logic, neighbouring direct payments on the other hand should increase competition on the land market and limit the possibilities for own growth. This is a similar argument as in Storm et al. (2015) with respect to farm survival. The relevance shows in the evidence of government payments capitalizing into the land price. Several recent studies (Breustedt and Habermann, 2011; Feichtinger and Salhofer, 2014; Guastella et al., 2014) analyse this question empirically by using a spatial lag dependent variable (SAR) model to explain prices with several land characteristics as well as spatially lagged prices.

3 Methodology

In order to identify spatial interactions between farms we employ a spatial econometric approach. The use of spatial econometrics has become widespread (Holloway et al., 2007; Bell and Dalton, 2007). However, several authors such Pinkse and Slade (2010), McMillen (2010), Carrión-Flores and Irwin (2010) but most forcefully Gibbons and Overman (2012) argue that the classical, widely used spatial lag dependent variable (SAR) model suffers from an identification problem that is not appropriately addressed in the applied literature. Vega and Elhorst (2015) deepened the discussion. Intuitively, Gibbons and Overman (2012p. 178) describe the identification problem as follows: “How can you distinguish between something unobserved and spatially correlated driving spatial correlation in y from the situation where y is spatially correlated because of direct interaction between outcomes? Further, how can you tell whether an individual is affected by the behaviour of their group, or by the characteristics of their group when group behaviour depends on the characteristics of the group?”. As a way forward Gibbons and Overman (2012) proposed to use either natural experiments that enable identification in the SAR model or the use the spatially lagged explanatory variable (SLX) model as an alternative. We choose the second approach estimating an SLX model similarly as in Storm et al. (2015) and also proposed in Vega and Elhorst (2015).

The SLX model is specified as $\mathbf{y} = \mathbf{X\beta} + \mathbf{WX\theta} + \boldsymbol{\varepsilon}$, where $\mathbf{y}$ is a vector of the dependent variable with size N and $\mathbf{X}$ is a $(N \times K)$ matrix of explanatory variables, $\mathbf{W}$ is a row standardized $(N \times N)$ spatial weighting matrix, $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are vectors of size K to be estimated and $\boldsymbol{\varepsilon} \sim N\left(\mathbf{0}, \sigma^2 \mathbf{I}\right)$ with $\mathbf{I}$ being an identity matrix of size N. The SLX model avoids the identification problems of the SAR model to distinguishing between direct and indirect spatial interaction effects. Instead “only” an overall interaction effect is estimated which is - as argued by Gibbons and Overman (2012p. 184) - in many cases “simply more credible”. Additionally, the overall effect is often of interest from a policy perspective and theory can be used to argue about the most likely channels of interaction.

Nevertheless, also the SLX model might lead to biased estimates in cases where unobserved, spatially correlated variables cause correlation in both explanatory variables as well as outcomes. To counter this problem we estimate the SLX model including two spatial weighting matrixes, $\mathbf{y} = \mathbf{X\beta} + \mathbf{W}_L\mathbf{X\theta} + \mathbf{W}_R\mathbf{X\lambda} + \boldsymbol{\varepsilon}$. The possibility to consider more than one spatial weighting matrices is an additional advantage of the SLX model compared to the SAR model where this is not easily possible (LeSage and Pace, 2011). With these two weighting matrices we aim to distinguish between local, $\mathbf{W}_L\mathbf{X}$, and regional, $\mathbf{W}_R\mathbf{X}$, spatial interdependencies. As an illustration consider the effect of direct payments. Given the discussion above, we expect a positive effect of own payments on farm growth and due to competition on the land market a negative effect of neighbouring payments. However, the level of neighbouring direct payments might be correlated with unobserved characteristics of the region. For example, given that direct payments in Norway are coupled payments per area or head, (average) neighbouring direct payments could reflect the intensity of production or the farm structure in a region. These regional characteristics might be correlated to farm growth, leading to an omitted variable bias with respect to the effects of neighbouring direct payment. In our model we aim to distinguish between these two effects by including local and regional lags of direct payments. The local lags of direct payment, for example, are intended to capture the actual interaction on the land market while the regional lag is intended to capture the effects of unobserved regional characteristics.

For the regional spatial weighting matrix, $\mathbf{W}_R$, we define neighbours as all farms within a ring from radius 30 km to 60 km around the farm. This distance is set arbitrarily but we assume that it is substantially larger than the distance relevant for competition on the land market or (space dependent) knowledge spillovers. For the local spatial weighting matrix, $\mathbf{W}_L$, we vary the radius in order to analyse the sensitivity of the final estimation results ranging from 500 m to 30 km, $\mathbf{W}_L^{0.5km},...,\mathbf{W}_L^{30km}$. In both cases neighbouring definitions are defined as a binary variable with no distance weighting applied. Both weighting matrices are row standardized. Appendix 7.1 visualises the neighbouring relationships for one exemplary observation.

4 Empirical Results

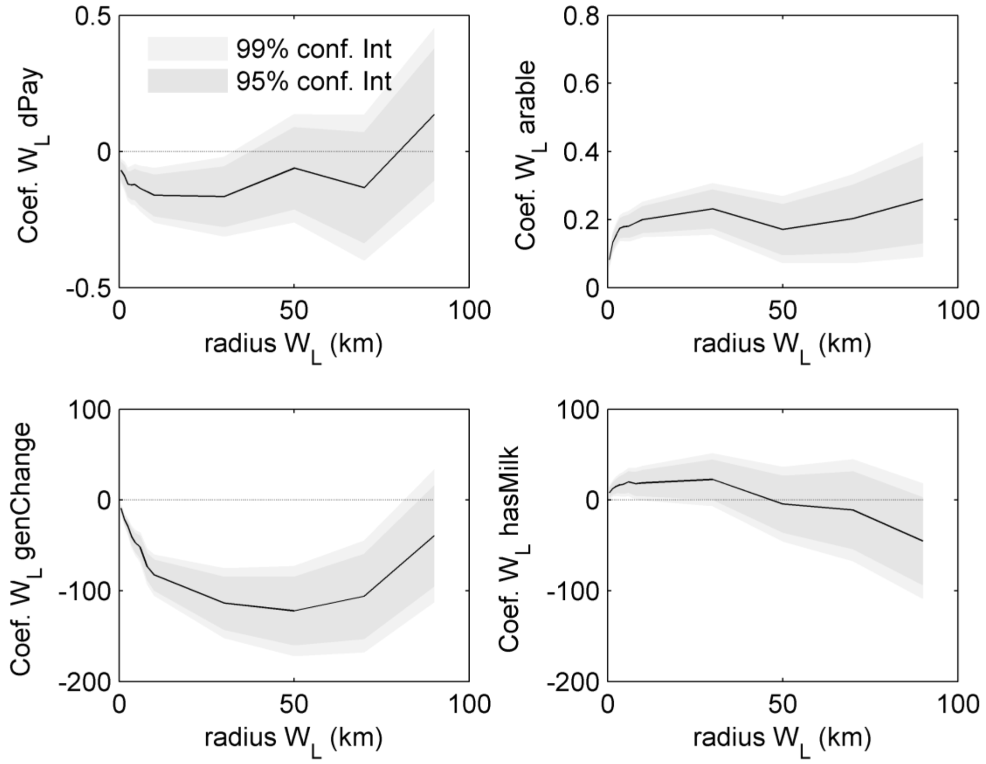
In our empirical model we aim to explain farm growth in terms of arable land between 1999 and 2009 (defined in daa = 1/10ha). For the analysis we use a Norwegian data set providing individual farm-level data of nearly all Norwegian farms in 1999 and 2009. Descriptive statistics for the dependent and the full set of explanatory variables, along with the variables codes, are provided in the appendix 7.3. For model specification, we start with a full model including all explanatory variables. Some insignificant variables are then excluded in cases they are not relevant for the research question.

4.1 *Sensitivity analysis with one single spatial matrix*

Before presenting the estimation results for our model including two spatial weighting matrices we start with a "classical" SLX specification including only one spatial weighting matrix. For this model we vary the radius used for the neighbouring definitions from 500 m to 90 km. The results of the model provide a reference for comparison and helps illustrating the advantages of considering two spatial weighting matrices.

Figure 1 show the estimated coefficients for four selected spatial lagged variables for varying radii of the neighbouring relationships. We observe that the effects of neighbouring characteristics change quite substantially with changes in the definition of $\mathbf{W}$. For direct payments ($W_L dPay$) and the share of farms having milk cows ($W_L hasMilk$) we find a significant effect up to a radius of around 30km. Further increases in the radius lead to a change in the sign of the coefficient change (even though not significantly different from zero). For the share of farms with a generational transfer during the considered period ($W_L genChange$), the coefficient remains negative and significant but nevertheless changes substantially following a U-shape. Only for arable land ($W_L arable$) the effect remains rather stable. Based on our discussion above, one explanation for the changes in estimated coefficients may be that our spatial lagged variables capture two different effects with different strength at different radii. First, the local interaction on the land market or via knowledge spillovers and second, the regional effect due to confounding variables that affect growth of all farms in the region and cause spatial correlation in our explanatory variables.

Figure 1 Estimated coefficients for the spatial lagged explanatory variables for varying neighbouring definitions based on a radius from 0.5 to 90km.



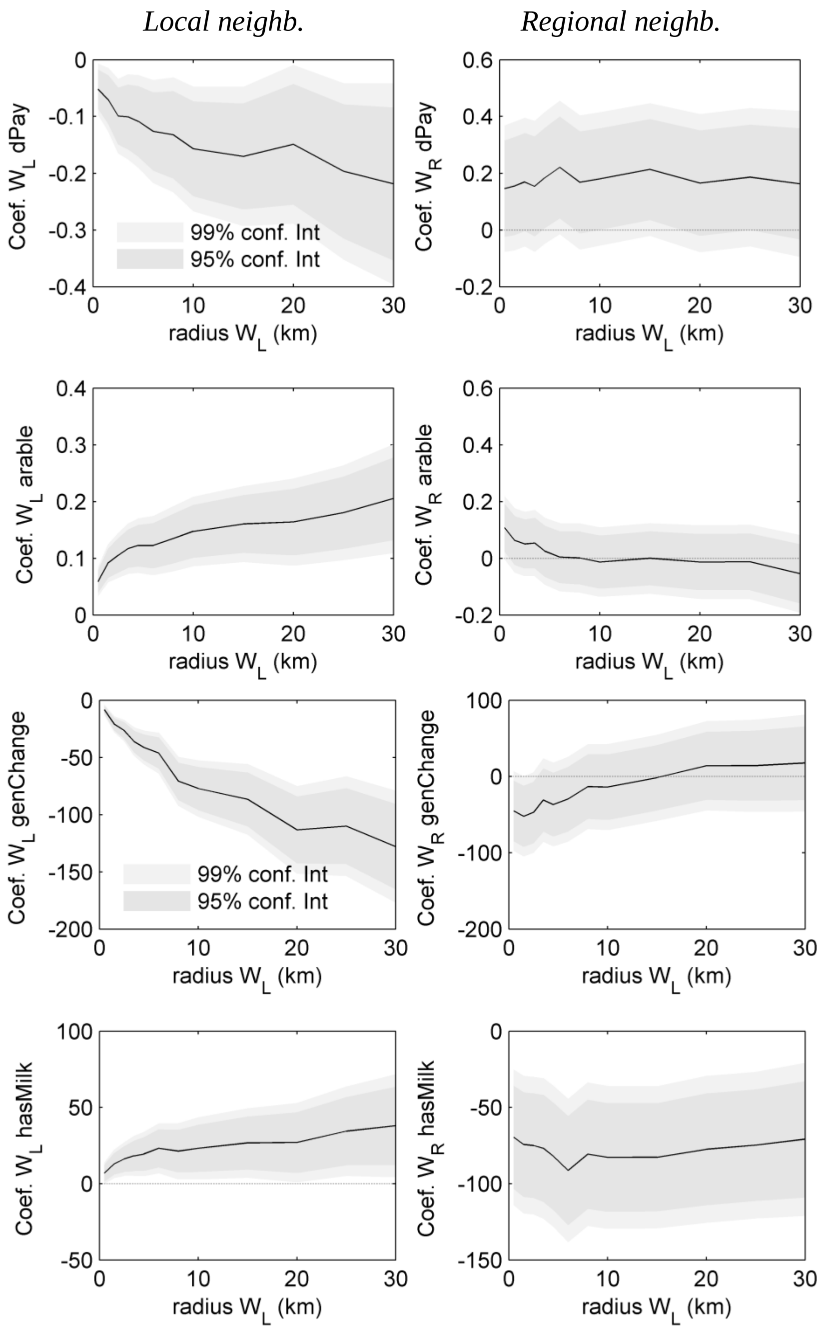
Variable codes: W_LdPay = average neighbouring direct payment; $W_L$arable = average neighbouring arable land; $W_L$genChange = share of neighbours that had a generational transfer between 1999 and 2009; $W_L$hasMilk = share of neighbours that had milk cows in 1999)

4.2 *Sensitivity analysis of two spatial weighting matrices*

In order to distinguish the two effects we separate two different neighbourhoods as discussed above. In order to investigate the hypothesis that explanatory variables are spatially correlated the correlation of different neighbouring characteristics between the local and regional neighbourhood is calculated. Appendix 7.2 shows that neighbouring characteristics between local and regional neighbourhoods become increasingly positively correlated with increasing radius of the local neighbourhood. With a local radius of 30 km the correlation coefficient is around 0.9. This finding supports the hypothesis that explanatory variables are indeed spatially correlated.

Figure 2 shows the estimated coefficient of selected variables for the local and regional neighbourhood (the regression output for three radii of the local weighting matrix are provided in the appendix 7.4) . The effects of the local neighbourhood largely follow the neighbouring effects for the range 0.5 to 30 km for just one spatial weighting matrix (compare figure 1). However, the effects between the local and regional neighbourhood differ substantially despite their high spatial correlation. For example, consider the effect of neighbouring direct payments on farm growth ($W_L dPay$). We find that neighbouring payments are highly correlated between the local and regional neighbourhood (for local 30km area: correl. coef. = 0.89; see appendix 7.2). Nevertheless, in figure 2 we find a fundamentally different effect of local ($W_L dPay$) and regional neighbouring payments ($W_R dPay$). In the local neighbourhood increasing direct payments significantly reduce farm growth while in the regional neighbourhood increasing direct payments increase farm growth. We find a similar pattern for the milk cow share, with a significant positive effect in the local neighbourhood ($W_L hasMilk$) and a significant negative effect in the regional neighbourhood ($W_R hasMilk$). For average neighbouring arable land ($W_L arable$) and the generational transfer share ($W_L genChange$) we found significant effects for the local neighbourhood only.

Figure 2 Estimated coefficients for the spatial lagged explanatory variables for varying neighbouring definitions based on a radius from 0.5 to 30 km



Note: The left column is the spatially lagged variable with the direct neighborhood (radius from 500m to 30km). The right column is the spatially lagged variables of all farms within a ring between a radius of 30 to 60km.

These substantial and significant differences between local and regional neighbourhoods for some variables despite high correlation between the two, strongly support the hypothesis of two different effects being captured with the spatial lagged variables. The negative effect of local direct payments, for example, supports the hypothesis that farm growth is negatively affected by competition on the land market that intensives as neighbouring farms receive higher direct payment. The fact that the regional direct payments show an opposite effect might indicate[3] that the variable picks up regional characteristics which are associated with a higher consolidation and hence growth rate in the region. These characteristics could be, for example, the intensity of production or the productivity in a region. These opposite effect of direct payments between local and regional neighbourhood together with the high correlation of the two is a strong indication that farms in the direct neighbourhood indeed have a substantially different effect on farm growth, perhaps indicating more at direct interaction effects.

5 Conclusion

In this paper we have analysed the importance of farm level spatial interaction for farm growth. One of the main challenges in the analysis of spatial interaction is to distinguish between direct and indirect interaction as well as spatial correlation arising due to spatial correlation of omitted variables affecting both outcomes and explanatory variable. We approached this challenge by estimating an SLX model with two different spatial weighting matrices in order to distinguish between local and regional interaction effects. Additionally, we systematically analysed the sensitivity of our results with respect to varying neighbouring definitions. Our empirical application, using a Norwegian dataset, indicates that despite high

[3] Note that lower bound of the 95% confidence interval is close to zero for all radii of the local neighbourhood indicating that the effect is weakly supported by the data. However, considering the high correlation between local and regional direct payments this is not surprising and the difference between the two effects is nevertheless rather substantive.

spatial correlation in the explanatory variables the neighbouring effects of the explanatory variables differ substantially between local and regional neighbourhood. This result provides strong empirical support for the hypothesis that individual farm growth depends substantially on the behaviour of directly neighbouring farms i.e. that direct interaction occurs. Given that we found a negative effect of the amount of direct payments farms receive in the direct neighbourhood, while the effect in the regional neighbourhood was positive, indicates that farms compete on the local land market in order to grow. This finding contributes to the literature where empirical results concerning spatial farm level interaction and their roll for farm growth are lacking.

6 References

Akimowicz, M., Magrini, M.-B., Ridier, A., Bergez, J.-E. and Requier-Desjardins, D. (2013). What Influences Farm Size Growth? An Illustration in Southwestern France. *Applied Economic Perspectives and Policy* 35(2):242–269.

Bell, K.P. and Dalton, T. J. (2007). Spatial Economic Analysis in Data-Rich Environments. *Journal of Agricultural Economics* 58(3):487–501.

Berger, T. (2001). Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics* 25(2-3):245–260.

Breustedt, G. and Habermann, H. (2011). The Incidence of EU Per-Hectare Payments on Farmland Rental Rates: A Spatial Econometric Analysis of German Farm-Level Data. *Journal of Agricultural Economics* 62(1):225–243.

Carrión-Flores, C. and Irwin, E. G. (2010). Identifying spatial interactions in the presence of spatial error autocorrelation: An application to land use spillovers. *Resource and Energy Economics* 32(2):135–153.

Case, A. (1992). Neighborhood influence and technological change. *Regional Science and Urban Economics - Special Issue Space and Applied Econometrics* 22(3):491–508.

Cochrane, W. (1958). Farm Prices: Myth and Reality. University of Minnesota Press, Minneapolis.

Feichtinger, P. and Salhofer, K. (2014). The common agricultural policy of the EU and agricultural land prices - a spatial econometric approach for Bavaria. Paper presented at the 2014 EAAE International Congress, August 26-29, 2014, Ljubljana, Slovenia.

Gezelius, S.S. (2014). Exchange and Social Structure in Norwegian Agricultural Communities: How Farmers Acquire Labour and Capital. *Sociologia Ruralis* 54(2):206–226.

Gibbons, S. and Overman, H. G. (2012). Mostly Pointless Spatial Econometrics? *Journal of Regional Science* 52(2):172–191.

Guastella, G., Moro, D., Sckokai, P. and Veneziani, M. (2014). The capitalization of fixed per hectare payment into land rental prices: a spatial econometric analysis of regions in EU. Paper presented at the 2014 EAAE International Congress, August 26-29, 2014, Ljubljana, Slovenia.

Hallam, A. (1991). Economies of Size and Scale in Agriculture: An Interpretive Review of Empirical Measurement. *Review of Agricultural Economics* 13(1):155–172.

Harrington, D.H. and Reinsel, R. D. (1995). A Synthesis of Forces Driving Structural Change. *Canadian Journal of Agricultural Economics* 43:3–14.

Holloway, G., Lacombe, D. and LeSage, J. P. (2007). Spatial Econometric Issues for Bio-Economic and Land-Use Modelling. *Journal of Agricultural Economics* 58(3):549–588.

Holloway, G. and Lapar, Ma. Lucila A. (2007). How Big is Your Neighbourhood? Spatial Implications of Market Participation Among Filipino Smallholders. *Journal of Agricultural Economics* 58(1):37–60.

Holloway, G., Shankar, B. and Rahmanb, S. (2002). Bayesian spatial probit estimation: a primer and an application to HYV rice adoption. *Agricultural Economics* 27(3):383–402.

Knutsen, H. (2007). Norwegian Agriculture - Status and Trends 2007. Norwegian Agricultural Economics Research Institute (NILF), OLSO.

Lapple, D. and Kelley, H. (2015). Spatial dependence in the adoption of organic drystock farming in Ireland. *European Review of Agricultural Economics* 42(2):315–337.

LeSage, J.P. and Pace, R. K. (2011). Pitfalls in Higher Order Model Extensions of Basic Spatial Regression Methodology. *The Review of Regional Studies* 41(1):13–26.

Lewis, D.J., Barham, B. L. and Robinson, B. (2011). Are There Spatial Spillovers in the Adoption of Clean Technology? The Case of Organic Dairy Farming. *Land Economics* 87(2):250–267.

McMillen, D.P. (2010). Issues in Spatial Data Analysis. *Journal of Regional Science* 50(1):119–141.

Mosnier, C. and Wieck, C. (2010). Determinants of spatial dynamics of dairy production: a review. Discussion Paper 2010:2, Institute for Food and Resource Economics, University of Bonn.

Padel, S. (2001). Conversion to Organic Farming: A Typical Example of the Diffusion of an Innovation? *Sociologia Ruralis* 41(1):40–61.

Pinkse, J. and Slade, M. E. (2010). The Future Of Spatial Econometrics. *Journal of Regional Science* 50(1):103–117.

Rogers, E.M. (1995). Diffusion of innovations, 4th ed. Free Press, New York, NY.

Schmidtner, E., Lippert, C. and Dabbert, S. (2015). Does Spatial Dependence Depend on Spatial Resolution? – An Empirical Analysis of Organic Farming in Southern Germany. *German Journal of Agricultural Economics* 64(3):175–191.

Schmidtner, E., Lippert, C., Engler, B., Haring, A. M., Aurbacher, J. and Dabbert, S. (2012). Spatial distribution of organic farming in Germany: does neighbourhood matter? *European Review of Agricultural Economics* 39(4):661–683.

Storm, H., Mittenzwei, K. and Heckelei, T. (2015). Direct Payments, Spatial Competition, and Farm Survival in Norway. *American Journal of Agricultural Economics* 97(4):1192–1205.

Vega, S.H. and Elhorst, J. P. (2015). The SLX Model. *Journal of Regional Science* 55(3):339–363.

Weiss, C.R. (1999). Farm Growth and Survival: Econometric Evidence for Individual Farms in Upper Austria. *American Journal of Agricultural Economics* 81(1):103–116.

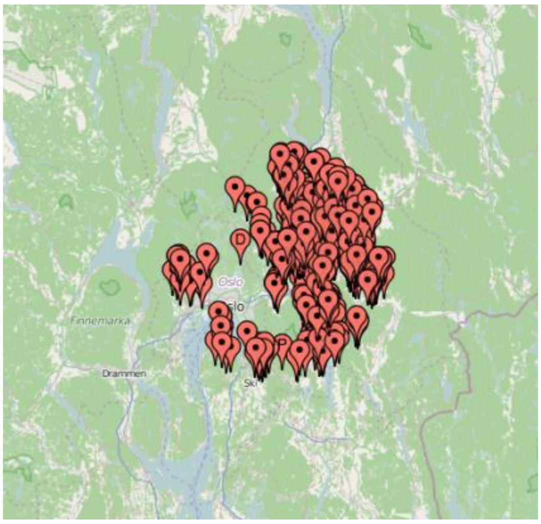
Zimmermann, A. and Heckelei, T. (2012). Structural Change of European Dairy Farms - A Cross-Regional Analysis. *Journal of Agricultural Economics* 63(3):576–603.

Zimmermann, A., Heckelei, T. and Domínguez, I. P. (2009). Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants. *Environmental Science & Policy* 12(5):601–618.

7 Appendix

7.1 *Appendix: Local and regional neighbouring farms for one exemplifying observation (point A).*

Local neighbourhood, $\mathbf{W}_L^{30km}$



Regional neighbourhood, $\mathbf{W}_R$ (ring 30 to 60km)

Note: Only a random sample of 500 neighboring farms are shown per maps. The total number of neighboring farms is 1540 and 5122 for the local and regional neighborhood, respectively. Source Maps: http://gpso.de/maps/ Map Data: 2015 OpenStreetMap.

7.2 *Appendix: Correlation coefficients between spatially lagged variables in the direct neighbourhood (radius 500m to 30km) and the farm in a ring between a radius of 30 to 60km.*

Radius of direct Neighbourhood	**dPay**	**genChange**	**hasMilk**	**arable**
500 m	0.3054	0.2529	0.3526	0.3056
2 km	0.5020	0.4762	0.5056	0.6063
3 km	0.5990	0.5893	0.5780	0.6832
4 km	0.6519	0.6690	0.6215	0.7239
5 km	0.6886	0.7261	0.6525	0.7492
6 km	0.7247	0.7794	0.6841	0.7745
8 km	0.7566	0.8281	0.7133	0.7952
10 km	0.7794	0.8588	0.7370	0.8113
15 km	0.8218	0.8960	0.7797	0.8377
20 km	0.8509	0.9194	0.8097	0.8579
25 km	0.8736	0.9337	0.8362	0.8776
30 km	0.8941	0.9450	0.8623	0.8980

Note: See Appendix 7.3 for variable codes.

7.3 *Appendix: Descriptive statistics, variable definition and variable codes*

	Code	Unit	Mean	Median	min	max	std
Change in Arable land 1999 to 2009	delArable	daaa	32.34	3.00	-1247.00	5061.00	122.01
Age of the farm holder	age	year	48.20	48.00	7.00	90.00	10.99
Arable land	arable	daa[a]	158.19	125.00	0.01	2994.00	136.11
Observed labor input	obsLabo	hour	2642.67	2500.00	8.00	52330.00	1881.48
Estimated labor requirement	reqLabo	hour	2391.60	2107.97	17.42	42873.53	1805.32
Total direct payments	dPay	1000 Nkr	204.95	195.71	0.00	1252.47	133.23
Total market return	mRet	1000 Nkr	-40.45	-37.41	-2168.29	1403.76	72.81
Ratio observed over estimated labor requirement	laboObs/Req	ratio	1.28	1.11	0.00	65.77	0.95
Dummy if farm has milk cows	hasMilk	binary	0.42	0.00	0.00	1.00	0.49
… has sheep	hasSheep	binary	0.33	0.00	0.00	1.00	0.47
… has sows	hasSows	binary	0.06	0.00	0.00	1.00	0.24
… has poultry	hasPoultry	binary	0.01	0.00	0.00	1.00	0.09
Tot. Direct pay. per total farm area	dPayUaar	1000 Nkr / daa[a]	1.28	1.28	0.00	40.74	0.80
Dummy if a generational transfer took place	genChange	binary	0.30	0.00	0.00	1.00	0.46
Regional dummy[b] for "Other regions in Eastern Norway"	argR12	binary	0.19	0.00	0.00	1.00	0.39
… "Jæren"	argR21	binary	0.04	0.00	0.00	1.00	0.21
… "Other regions in the counties of Agder and Rogaland"	argR22	binary	0.09	0.00	0.00	1.00	0.28
… "Western Norway"	argR32	binary	0.21	0.00	0.00	1.00	0.41
… "Lowlands in Trøndelag"	argR41	binary	0.08	0.00	0.00	1.00	0.27
… "Other regions in Trøndelag"	argR42	binary	0.08	0.00	0.00	1.00	0.27
… "Northern Norway"	argR52	binary	0.09	0.00	0.00	1.00	0.28

[a]daa = 1/10 ha. [b] reference region is "Lowlands in Eastern Norway"

7.4 *Appendix: Regression results for 3 radii and selected variables*

	W_km2		**W_km15**		**W_km30**	
Variable	**Coef**	**p-value**	**Coef**	**p-value**	**Coef**	**p-value**
const	-12.0208	0.7892	-49.2241	0.3143	-133.0330	0.0123
age	-3.7846	0.0000	-3.8478	0.0000	-3.6980	0.0000
age^2	0.0314	0.0000	0.0318	0.0000	0.0303	0.0000
arable	-0.1023	0.0000	-0.1095	0.0000	-0.1062	0.0000
obsLabo	0.0007	0.2995	0.0011	0.1251	0.0007	0.3173
reqLabo	0.0043	0.0000	0.0034	0.0006	0.0039	0.0001
dPay	0.1079	0.0000	0.1234	0.0000	0.1142	0.0000
mRet	-0.0266	0.0704	-0.0200	0.1816	-0.0211	0.1637
laboObs/Req	1.7885	0.0730	1.3245	0.1923	1.4585	0.1565
hasMilk	-13.5959	0.0000	-14.8646	0.0000	-14.1124	0.0000
hasSheep	-2.8446	0.0159	-2.9212	0.0139	-3.5480	0.0029
dPayUaar	4.2981	0.0002	4.1535	0.0004	4.4307	0.0002
genChange	18.0979	0.0000	17.7511	0.0000	18.6507	0.0000
….						
W_dPay	-0.0699	0.0013	-0.1703	0.0003	-0.2188	0.0015
W_arable	0.0914	0.0000	0.1606	0.0000	0.2052	0.0000
W_reqLabo	-0.0027	0.0378	-0.0001	0.9741	0.0015	0.6638
W_hasMilk	13.0465	0.0003	26.7595	0.0025	38.0301	0.0037
W_age	0.3176	0.0000	1.4735	0.0005	3.4780	0.0000
W_genChange	-20.7696	0.0000	-86.5704	0.0000	-127.8734	0.0000
….						
Wring_dPay	0.1553	0.0771	0.2136	0.0185	0.1627	0.1028
Wring_arable	0.0628	0.1524	0.0003	0.9954	-0.0543	0.3074
Wring_reqLabo	0.0072	0.1519	0.0086	0.1020	0.0130	0.0246
Wregion_hasMilk	-74.2748	0.0000	-82.6139	0.0000	-70.8047	0.0003
Wring_age	2.0835	0.0261	1.7189	0.0815	1.4931	0.1459
Wring_genChange	-52.1622	0.0105	-1.4572	0.9468	17.7892	0.4705
….						
n	32043	---	30940	---	30257	---
AIC	8.5897	---	8.6248	---	8.6472	---
rsqr	0.0512	---	0.0522	---	0.0516	---
rbar	0.0501	---	0.0510	---	0.0504	---