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Institutions: University of Kiel

Published on: 01 Feb 2011 - Journal of Agricultural Economics (Blackwell Publishing Ltd)

Topics: Renting

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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2010: Ökonomie der Familie - Session: Panel Data Models, No. C15-V3

Provided in Cooperation with:
Verein für Socialpolitik / German Economic Association

The Incidence of EU Per-Hectare Payments on Farmland Rental Rates: A Spatial Econometric Analysis for German Farm-Level Data

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Summary

This article analyses determinants for 2001 farmland rental prices from 3,819 farms in Germany. Based on specification tests we estimate a general spatial model to account for both spatial relationships among rental prices of neighbouring farmers and spatially autocorrelated error terms. A € 1 per hectare higher rental price in a farmer's neighbourhood coincides with a € 0.72 higher rental price the farmer pays. The marginal incidence of EU per-hectare payments paid for eligible arable crop land amounts to € 0.38 for each additional € of premium payments. Regional livestock density, which is indirectly influenced by different policies, is also a major determinant for rental prices. Results are confirmed by sensitivity analyses. Consequently, German farmland rental rates are heavily influenced by agricultural policy instruments and therefore, these policies exhibit substantial distributional effects.

Key words: farmland rental price, per-hectare payment, spatial econometrics, subsidy incidence

1. Introduction

Between 1993 and 2004 approximately 160 billion € have been paid for arable crops as so-called per-hectare payments to farmers in the EU (European Commission, 2009). Who received this money in the end – farmers or landlords? Although farmers directly receive these payments, they may pass on a considerable share to landowners via increased farmland rental rates. The literature refers to this mechanism as 'incidence' (e.g., Kirwan, 2009). There are several econometric studies about the incidence of U.S. agricultural subsidies on farmland rental rates (Herriges *et al.*, 1992; Kirwan, 2009; Lence and Mishra, 2003; Roberts *et al.*, 2003).[1] However, only Fuchs (2002) provides an incidence estimate for EU per-hectare payments.[2] This offers little empirical basis for evaluating the distributional effects of 160 billion € paid by the European Commission. Thus, we aim to contribute an additional piece to the incidence puzzle of this agricultural subsidy in the EU.

In line with the literature, we estimate the marginal impact of subsidies on farmland rental rates as a measure of (marginal) incidence. More precisely, we regress farm-level rental prices on the per-hectare premium payments a farmer receives. Furthermore, we include farm-specific and regional economic and production characteristics, as well as personal attributes of the farmer. The farms are located in the German federal state of Lower Saxony. Rental prices are from 2001.

Our regression analysis is different from former analyses on incidence because we apply the so-called general spatial model (LeSage and Pace, 2009) from spatial econometrics. For our case, it turns out that a combined spatial lag and spatial error model – the general spatial model – is necessary to obtain consistent and efficient regression results. Lence and Mishra (2003), as well as Fuchs (2002), only account for spatially dependent errors. A second advantage of our analysis is the use of farm-level data on rental rates. Many analyses, including Fuchs' (2002) analysis of the EU per-hectare payments, use regional average data instead. Marginal impacts obtained from a regression of individual observations may differ substantially from marginal impacts based on average data regressions (Robinson, 1950; Orcutt *et al.*, 1968). Consequently, the latter impacts cannot be interpreted as "average behaviour" of individuals like the former.

The contribution of our study is two-fold. First, we estimate the determinants of farmland rental prices by means of a general spatial model accounting for both spatial lag and error effects simultaneously. This is new to the field of agricultural land markets. Second, we quantify – based on farm-level data – the (marginal) incidence of EU per-hectare payments on farmland rental prices before the decoupling of these subsidies from production in 2005.

In the remainder of this article, we first present a regression approach for spatially interrelated farmland rental prices. We then describe our data before we set out the regression strategy. Specification tests and estimation results are followed by conclusions.

[1] On the theory of subsidy incidence see Schultze, 1971; Schmitz and Just, 2002; and Kilian and Salhofer, 2008. Empirical evidence for the incidence on land values is given by e.g. Barnard *et al.*, 2001; Featherstone and Baker, 1988; Goodwin and Ortalo-Magne, 1992; Traill, 1979; and Weersink et al., 1999.

[2] Patton *et al.* (2008) mainly focus on the impact of livestock premiums (headage-based payments) on land rents in Northern Ireland based on data from 214 farms in an unbalanced panel from 1994 to 2002.

2. Economic Determinants for Rental Prices

2.1 Regression models for land rental prices

The above cited empirical analyses about rental prices are based on a standard regression model such as

$$r = X\beta + \varepsilon \tag{1}$$

with r being the rental price (per hectare), X the $n \times k$ matrix of k rental price determinants and control variables, β to be estimated, and ε the error term. Lence and Mishra (2003) (LM) derive (1) based on (expected) profit maximisation for their estimation of regional rental prices. LM assume that in "a relatively small geographical area … all farmers are alike …, and the total supply of tillable land is fixed at some level" (p. 754). Following standard microeconomic theory under perfect competition, LM conclude that the equilibrium land rental rate in an area is represented by r, and r equals the (expected) marginal profit for land (including subsidy payments). Consequently, most right-hand side variables in LM's and other empirical rental price analyses are supposed to proxy marginal profit of land. These variables include, e.g., revenues and government payments (LM), sales, variable costs, and proportion of irrigated and pasture land (Kirwan, 2009). In addition, LM assume implicitly that the equilibrium rental rates of different areas are independent of each other.

The assumptions of LM may be too restrictive for a specific data set . A more general empirical specification follows from adding a spatial lag ($\rho W_1 r$) to (1). Fingleton and Le Gallo (2008) suggest such a reduced form specification for a regression analysis of housing price determinants. The so-called spatial lag model (Anselin, 1988)[3] is then

$$r = \rho W_1 r + X\beta + \varepsilon \tag{2}$$

The spatial lag includes an $n \times n$ matrix W_1 of spatial weights that represents the spatial structure among all observations and the spatial lag parameter ρ, which is to be estimated. The ith element of the vector $W_1 r$ represents the weighted average of neighbouring rental prices for farmer i. Specification (1) is more restrictive than (2) because (1) follows from restricting $\rho = 0$ in (2). Such a restriction can be tested following, e.g., Anselin and Bera (1998) or Anselin *et al.* (1996).

[3] Anselin (1988) calls this specification mixed regressive, spatial autoregressive model, while LeSage and Pace (2009) call it spatial autoregressive (SAR) model.

For a house market analysis, Fingleton and LeGallo (2008) argue that the “spatial lag’s presence … is the outcome of interactions in the demand and supply functions” (Fingleton and Le Gallo, 2008, p. 323). They argue for the demand side “given that high prices reduce demand, high prices ‘nearby’ will reduce demand ‘nearby’, with the consequence that demand will be displaced from nearby places into *i* ['s place]”. An analogous reasoning may hold for the supply side, resulting in some influence ρ of the nearby prices on the price at *i*'s place (see (2)). It is an empirical question whether this specification is also useful for a specific land rental market analysis. In our view, there are good reasons to not preclude the more flexible regression specification (2) in favour of (1): farmers in a village may tend to increase their demand for land in a nearby village if the rental price in their home village is high. In addition, farming landlords may tend to quit farming and offer their own land on the local rental market when the neighbouring rental price is high. Consequently, the price at a given location may influence supply and demand nearby; thus, influencing the rental price at nearby locations. If this influence is not statistically significant, the more general specification (2) can be reduced to (1) by restricting ρ to zero.

Under standard assumptions ρ will turn out to be zero if land is demanded at all locations in the market by sufficiently many and sufficiently similar farmers.[4] Then, variables in X that proxy for the renting farmer’s (expected) marginal profit of land may suffice to determine rental rates. However, in economic reality, perfect markets are the exception rather than the rule. Therefore, rental rates may not equal (expected) marginal profit; consequently, additional rental rate determinants other than proxies for marginal profit must be taken into account. This can be done in two ways. In the first, the researcher adds observable variables to X that proxy for imperfect competition. Such variables may measure e.g. the concentration of farmers or landlords in an area (e.g., Kirwan, 2009). In the second, analogously to Fingleton and LeGallo (2008), the researcher may include averaged neighbour rental prices to proxy for the impact of (unobserved) imperfect competition on a specific farmer’s rental rate. As given above, the vector W_1r in (2) represents these averages.

But what may prevent land rental markets from being perfect? Kirwan (2009) mentions land market literature on custom (Young and Burke, 2001) and on long-term tenant-landlord relationships (Allen and Lueck, 2002, Sotomayer *et al.*, 2000) that both may limit

[4] Spatial patterns of rental rates being paid may coincide with spatial patterns of land rents being extracted from a land plot. Both Ricardo’s as well as von Thünen’s classical land rent models may exhibit such spatial patterns. The former depends on soil quality which, of course, exhibits a spatial pattern in most landscapes. The latter depends on a land plot’s distance to a market town. However, if such determinants are not incorporated among X their impact enters into the error term. A so-called spatial error model, as described in section 4.1, is then appropriate.

landowners' ability and incentives to extract the full marginal profit from a rental plot. Furthermore, by its very nature, the different locations of land plots violate the homogeneity assumption of a perfect market. A consequence of land markets' spatial dimension is thus that only those farmers located sufficiently close to a given plot actually compete for renting it. Other farmers may face high costs for reaching the plot to plough, sow, fertilize, harvest and so on. Consequently, in some (sufficiently small) areas the demand for land may be thin. In addition, farming families living together in the same village for generations are not necessarily perfectly competitive about renting land around their village.

Summarising, the above illustrations may call for testing regression models beyond those assuming perfect land rental markets. If some farmers behave as illustrated above rental rates may differ from marginal profits. Thus, more flexible specifications than (1) should be tested statistically.

We now describe policies that may influence rental prices in the EU and Germany.

2.2 Impact of selected policies on land rents

Previous studies include various determinants of land rents in X. In the following paragraph, we focus on two determinants, which are particularly important from a policy perspective. We first explain how per-hectare payments may influence land rents. Second, we turn to the impact of livestock density on farmland rental rates. Livestock density is affected by different policies, which may influence land rents indirectly.

In the literature, the impact of agricultural subsidies on land prices is referred to as incidence. We quantify the incidence of per-hectare payments – paid in the EU between 1993 and 2004 – on farmland rental rates. These EU payments were enacted in 1992 to compensate farmers for the reduction of price support: intervention prices for cereals were simplified to one intervention price for all and reduced by approximately one-third in three steps between 1993 and 1995; institutional prices for oilseeds and protein crops were abolished (European Commission, 1997). The per-hectare payments were paid for land cultivated with cereals, oilseeds, or protein crops, or land set aside. These payments were the product of a reference yield multiplied by a crop-specific institutional amount. Member states were responsible for developing regionalisation plans to define yield regions for each eligible crop. For each region, a reference yield was calculated as the 1986 - 1990 average, excluding the highest and lowest yields. Table 1 lists the premium payments for the different yield regions in Lower Saxony.[5]

Table 1. Per-hectare payments in Lower Saxony from 1995 - 2001

Yield region	Cereal payment (€/ha)	Oilseed payment (€/ha)	Set aside payment (€/ha)
1	318.02	560.38	402.90
2	389.60	560.38	493.40
3	331.83	560.38	420.79
4	256.16	560.38	324.67
5	226.50	560.38	286.83
6	303.20	560.38	383.98
7	254.62	560.38	322.63
8	228.55	560.38	289.39
9	274.56	560.38	347.68
10	295.02	629.91*	373.75

Source: European Commission (1997) and KTBL (1998). *The payment for oilseeds is uniform in Lower Saxony. Yield region 10 comprises only a single municipality, which did not belong to the federal state of Lower Saxony before 1993.

The incidence of subsidies on land rental rates depends on the specific type of subsidy and the competition on the land market. If subsidies are coupled to production, they generally exhibit production effects and may result in incomplete incidence if the subsidy is partly necessary to cover production costs (Roberts *et al.*, 2003). If subsidies do not impact production decisions, as is the case for truly decoupled payments, and the land market is highly competitive, theory predicts complete incidence as Patton *et al.* (2008) find for so-called less favoured area payments in the EU. These were paid for each hectare within specific regions irrespective of the hectare’s agricultural usage. If the payment levels are uncertain before the rental contracts are set, as in the United States, an incomplete incidence can be expected because a risk-averse renter demands a share of the expected subsidy as risk premium. Kirwan (2009), as well as Lence and Mishra (2003), provide empirical evidence for the incidence of various U.S. payments.

Furthermore, we include both the farm-level and regional livestock per hectare in our analysis, similar to Fuchs (2002) and Drescher and McNamara (2000). Livestock density may capture impacts of certain policy instruments on farmland rental rates. In Germany these may be manure spreading regulations, an extra tax burden for livestock farming above a certain animal density threshold, and investment aids for livestock farming. Their interplay is as

[5] We did not consider protein crops because they represent only 0.55 % of the eligible agricultural area in Lower Saxony in 2000 (MLELV, 2002).

follows: livestock operations may result in higher local demand for land due to manure spreading restrictions. If a farmer wants to keep livestock exceeding a certain threshold level (approximately two animal units per hectare, i.e. 1,000 kg live weight), he must either acquire additional acreage or give manure to farmers operating below this threshold. In addition, livestock operations with low animal density are privileged by German tax regulation. This additionally motivates farmers to rent more land to reduce their livestock density. Finally, investment aid for livestock operations, especially for stables and other buildings, amounted to € 564.6 million in Germany between 2000 and 2004 (Dirksmeyer *et al.*, 2006). This may induce higher livestock densities and may increase competition among livestock and arable farmers for land.

3. Data

We take our farm-level data from profit and loss statements of farms located in the German federal state of Lower Saxony. These data were collected by Landdata Ltd., the market leader of farm accountancy services in Germany. Additionally, we include county-level averages based on an agricultural census survey and additional official statistics provided by the Federal Statistical Office of Germany. We further use county-level climate variables from Germany's National Meteorological Service *Deutscher Wetterdienst* (DWD).

We base our estimations on 3,819 renting farms. For most variables, we use averages for the years 1999-2001 (see Table 2) to reduce the impact of volatile agricultural yields and prices. Our sample farms represent the typical range of farms in Lower Saxony. On average, the farmer is 48 years old and operates on 78 hectares (55% rented land). Most farms combine crop and livestock production.

Our endogenous variable, rent, represents a farm's total rental payments divided by rented land. On average, our farmers pay cash rents of € 253 per hectare in 2001. The variable does not distinguish between contracts set up among relatives and contracts set up at arm's length. In Germany, a considerable share of rent contracts is signed for several years (Swinnen *et al.*, 2008, p.54), so our variable includes contracts signed in different years. We take cash rent values from 2001 to cover rental decisions from a stable political environment after the introduction of EU payments in 1993.

Some details about our subsidy variable: we use the farm specific average premium payments received. This s_i average is calculated over the acreage of M eligible crops according to formula (3):

$$s_i = \frac{1}{A^*} \sum_{m=1}^{M} a_m * sr_m \qquad with\ A^* = \sum_{m=1}^{M} a_m \tag{3}$$

where a_m is the area of each eligible crop m in hectare and sr_m is the corresponding regional per–hectare payment given in table 1. $A*$ is the total eligible area in hectare and subscript i refers to a farm. On average, the sample farmers receive € 311 premium payments per hectare of eligible arable land.

Table 2. Variable definition and descriptive statistics

Variable	Definition	Mean	Std. Dev.	Min.	Max.
Rent	Annual cash rent per hectare in € (2001 farm average)	252.6	143.0	13.20	1495
Value added	Farm net value added minus wages paid and minus per-hectare payments (in € per hectare)	400.6	452.7	-7324	3735
Subsidy	Farm specific per-hectare payments (in € per hectare)	310.7	45.32	226.5	482.3
Animal density	Animal density in 500kg (= animal unit (AU)) per hectare	1.048	1.093	0	13.45
Animal density county	County mean of animal density	0.864	0.429	0.148	2.374
Pasturediff	Share of rented pasture land to total rented area multiplied with regional absolute difference between arable and pasture cash rent	21.55	26.07	0	197.2
Rentshare	Share of rented (including underlet) acreage to total operated acreage (rentshare can exceed 1 for farms that exhibit underlet)	0.545	0.258	0.00513	1.392
Sugarbeet	Land for sugar beets relative to arable land	0.0572	0.0828	0	0.470
Potato	Land for potatoes relative to arable land	0.0480	0.0993	0	0.830
Forage maize	Land for forage maize relative to arable land	0.0772	0.156	0	1
Soil	Farm average soil quality (*Ertragsmesszahl* / 100)	36.78	14.32	10	100
Farmsize	Farm size in hectares of total land	77.87	48.12	8.329	760.0
Family labour	Family workers per hectare	0.0229	0.0139	0.000118	0.245
Capital	Capital stock minus value of land, milk and sugar beet quota (1000 €/ha)	3.631	2.285	0.0196	35.85
Education	Education of farmer: (1) no education up to (5) university degree	1.717	1.032	1	5
Age	Age of farm manager	48.11	9.842	20	89
farmsize_cty	Average farm size on county level (ha)	41.00	6.542	24.35	65.20
Temperature	County annual average temperature (° C)	8.648	0.392	7.1	9.2
Precipitation	County annual average precipitation (mm)	707.1	70.77	545.2	973.8

Source: Own calculations from profit and loss statements (Landdata Ltd.), *Forschungsdatenzentrum* (Research Data Centre of the Federal Statistical Office of Germany), and climate data from Germany's National Meteorological Service DWD. If not stated differently, data represent 1999 to 2001 averages.

The variable farm net value added[6] (for short 'value added' in the remainder of the paper) does not necessarily correspond to the marginal profit from land. To account for economies of scale, we include the farm size measured in hectares, as well as the rented acreage relative to farm size. Because our value added does not only depend on arable farming but also on livestock keeping, we include additional farm-level variables: animal density, land share of forage maize, and a control for pasture land. The variable *pasturediff* is a farm's share of pasture land over total rented land multiplied by the absolute county difference between arable and pasture cash rents. We also control for the impact of high-value crops such as sugar beets and potatoes and highly fertile soils.[7] Note that sugar beets and potatoes face other market policies than grains: the former were not eligible for subsidy payments in the study period. Sugar beet production is restricted by a production-quota, and potato prices are much more volatile than grain or oilseed prices.

Further, we include a farm's capital stock to control for capital costs. Value added may differ from net profit for land for family farms relying on family labour force. These labour costs are supposed to be accounted for by the number of family workers per hectare.[8] We use a farmer's age and education such as Bierlen *et al.* (1999) to proxy bargaining abilities or impacts of a farmer's life-time working cycle. Regional climatic conditions are proxied by temperature and precipitation.

4. Regression strategy

We now illustrate the technical aspects for estimating the determinants of farmland rental rates in our sample.

4.1 Spatial Econometric Models

Basically, spatial dependencies are modelled as extensions of a standard linear regression model (Anselin, 1988, p.32; Anselin and Bera, 1998). The most general representation is as follows:

[6] Farm net value added is used following the EU Farm Accountancy Data Network's definition "Remuneration to the fixed factors of production (work, land and capital), whether they be external or family factors." (FADN)
[7] A quality index for soil ranges between 10 and 100 index points per hectare for low and high fertile soils, respectively.
[8] Wages paid to non-family workers are considered in our variable value added.

$$
\begin{aligned}
& r = \rho W_1 r + X\beta + \varepsilon \\
& \varepsilon = \lambda W_2 \varepsilon + \mu \\
& E\left[\mu_i^2\right] = \sigma^2 h(z_i) \\
& E\left[\mu_i \mu_j\right] = 0 \qquad \text{with } i \neq j
\end{aligned} \tag{4}
$$

It differs from (2) by more detailed specifications of the error term ε. The error ε consists of an error lag $W_2\varepsilon$ multiplied by the spatial error coefficient λ, which is to be estimated. W_2 is an $n \times n$ spatial weight matrix comparable to W_1. In line with most empirical analyses, we use the same spatial weight matrix W for W_1 and W_2. The disturbance μ is an $n \times 1$ vector of zero-mean error terms, allowing for heteroscedasticity depending on exogenous characteristics z_i of observation i. The standard homoskedastic situation follows from $h()=1$.

Special forms of this general spatial model can be derived by imposing restrictions on (4).[9]

$\rho = 0, \lambda = 0, h() = 1$	standard linear regression model such as (1)	(4a)
$\lambda = 0, h() = 1$	spatial lag model such as (2)	(4b)
$\rho = 0, h() = 1$	spatial error model	(4c)
$h = 1$	homoskedastic general spatial model	(4d)
no parameter restrictions	heteroscedastic general spatial model	(4e)

As we show above, if cash rent levels may be influenced by neighbouring cash rent levels the spatial lag model may be necessary ($\rho \neq 0$). Furthermore, unobserved effects that exhibit a spatial structure may lead to spatial dependence in the error term. For example, on the land market, different climate conditions or differences in the regional road infrastructure that we cannot fully include in our variables may call for a spatial error specification. To allow for both spatial components simultaneously we apply a general spatial model. Under homoskedasticity ($h() = 1$), the general spatial model can be consistently estimated by maximum likelihood (compare Anselin and Bera, 1998). In contrast, Kelejian and Prucha (2010) propose a method for estimating the general spatial model, which is robust against unknown heteroscedasticity. They apply a generalised method of moments to estimate λ; ρ and the coefficients for X are the so-called generalised spatial two-stage least square estimators (Kelejian and Prucha, 2010). They do not provide measures for the goodness of fit.

[9] See LeSage and Pace (2009) for details.

4.2 *Spatial weight matrix*

The weight matrix W_1 (W_2) contains the weights being used to calculate averages of nearby rental rates (error terms) for each observation. The *i*th row contains the weights for calculating the average of nearby rental rates (error terms) for observation *i*. We want close neighbours to have a higher weight than more distant farmers because the spatial relationship among rental rates and error terms is expected to decrease with distance following the first law of geography (Tobler, 1970). Therefore, we use (a function of) the inverse distance between observations as a weight, as is "often posited" (Bell and Bockstael, p. 73, 2000) in empirical analyses. In addition, we assume for our analysis that there is no spatial relationship between observations that are more than 10 kilometres away from each other. The economic rationale behind these assumptions is the cost for reaching the plot for ploughing, sowing, fertilizing, harvesting, and so on.[10] Consequently, the marginal profit of land decreases with distance from the farm and beyond some threshold a distant farmer is unlikely to compete effectively with local farmers for the land plot. As is common, we row-standardise W such that all weights in a row sum up to one.

Unfortunately, we do not know the exact location of our farms; we only know the municipality the farm belongs to. Thus, we use the distance between the municipalities where the farms are located. For this purpose we measure the air-line distance between the municipality's principal towns or villages.[11] A secondary effect is that we do not observe any distance measure for farms belonging to the same municipality. Instead, we assume a weight (before standardising) of 0.5.[12] (5) illustrates how we translate the distance d_{ij} between two observations i and j into the respective weight w_{ij}.[13]

$$w_{ij} = \begin{cases} 0 & \text{if } d_{ij} > 10 \\ \dfrac{w_{ij}^*}{\sum_{j=1}^{n} w_{ij}^*} \begin{cases} w_{ij}^* = d_{ij}^{-1} \\ w_{ij}^* = 0.5 \end{cases} & \begin{array}{l} \text{if } 0 < d_{ij} \leq 10 \\ \text{if } d_{ij} = 0 \end{array} \end{cases} \tag{5}$$

[10] A rough calculation shows that these costs reach about € 200 per plot for a plot-farm distance of ten kilometers: farmers in Lower Saxony must reach their plots by tractor between eight and twelve times per year. A ten kilometer distance then implies more than three hours of driving per year. (We further assume costs of € 50 per tractor hour and costs of € 20 per working hour).

[11] Note that a threshold (air-line) distance of ten kilometers between two municipalities allows for plot-farm distances well above ten kilometers because of the difference between air-line distance and road distance.

[12] Reducing those weights to 0.2 – assuming that the nearest neighbouring municipality is at least five kilometers away – does not change the results considerably. The 1022 municipalities in rural Lower Saxony commonly contain more than 5,000 inhabitants. They comprise a central town or village and several surrounding villages. Several municipalities form a county with more than 50,000 inhabitants.

[13] Note that the subscripts *i* and *j* do not refer to municipalities but rather farms.

The first row in (5) shows that the weight is set to zero for observations that are more than 10 kilometres away from each other. The second row shows the weight calculation if the (positive) distance is less than 10 kilometres: the distance is. In the third row we assume a pre-standardised weight of 0.5 for farms located in the same municipality. Finally, the weights are standardised such that they sum up to one for each *i*.

For sensitivity analyses we calculate weights differently than in (5). First, we calculate squared inverse distances by substituting δ_{ij}^{-1} in (5) by δ_{ij}^{-2}. These weights put more emphasis on close observations. Second, we calculate linearly decreasing (pre-standardised) weights based on

$$w_{ij}^{*} = \begin{cases} 0 & \text{if } d_{ij} > 10 \\ 10 - d_{ij} & \text{if } 0 < d_{ij} < 10 \\ 8 & \text{if } d_{ij} = 0 \end{cases}. \tag{5a}$$

In the three reported procedures, weights decrease with distance between observations: the assumption is – as described above – that the impact of more distant rental rates is less for a farmer than the rental rates paid by his nearby neighbours.[14]

4.3 Marginal effects

We now turn to the marginal effects of our cash rent determinants. The regression coefficients β in a spatial lag or in a general spatial model cannot be interpreted as marginal impacts of the respective exogenous variable as in ordinary least squares (OLS). In OLS, the value of the endogenous variable for a specific observation *i* changes by $\beta_k * \Delta x_{ki}$ irrespective of changes of x_k for other observations. This is different in models that include a spatial lag because of spill-over effects among neighbouring observations (see Easterly and Levine, 1998, for a descriptive explanation, as well as Case *et al.*, 1993). Analogously to former subsidy incidence analyses in the agricultural economics literature, we are interested in the (marginal) impact of a subsidy change that simultaneously applies for all sample farmers. Then the

[14] Habermann (2009) shows for our data – with other instrumentation – that additional rental rate observations in either the spatial lag or error exceeding the ten kilometre distance do not have a statistically significant impact on the rental rate.

marginal incidence of a subsidy change Δs, i.e. the share of the subsidy change Δs that translates into a rental rate change, becomes[15]

$$\frac{\Delta r}{\Delta s} = (1-\rho)^{-1}\beta_s \Delta s \tag{6}$$

We calculate the marginal effects of other variables, including county animal density and value added, analogously. Since the values of regression coefficients β are not very descriptive in a spatial lag model, we focus on the marginal effects in our regression results.[16]

4.4 Instrumentation of variables

In empirical analyses, potential farm-level determinants of rental prices may have to be instrumented because of endogeneity or expectation errors. Endogeneity may prevail because some right-hand side (RHS) variables and analysed rental rates may be jointly determined. Cash rent levels depend on farmers' expectations, which we cannot observe. Using present actual values as proxies may not be appropriate due to measurement error (Kirwan, 2009). Both problems may be overcome by means of instrument variables (IV). Lence and Mishra (2003), as well as Patton *et al.* (2008), instrument their RHS variables with values from the previous year(s). Kirwan (2009) uses 1997 fixed government payments as leads to instrument 1992 subsidy payments.

For our case, a heteroscedasticity-robust test (Wooldridge, 1995) reveals significant endogeneity for some of our RHS variables.[17] Hence, we instrument these RHS variables. The endogenous variables have been regressed on the following 22 variables: the 1996 values for the eleven endogenous variables;[18] soil, education, age, animal density at county level, farm size at county level, temperature, and precipitation from Table 2. To improve the instruments' quality for the endogenous variables value added and family labour, we further added the

[15] Kim, Phipps, and Anselin (2003, p. 35) provide a derivation of (6). Their assumptions that W is row-standardised, $\rho < 1$, and that the direct effect, i.e. without any spill-over effects, of the subsidy is equal for all observations hold for our analysis. Patton and McErlean (2004) describe that the latter assumption does not hold for log-log specifications.

[16] However, it must be noted that our marginal effects (6) do not refer to a rental rate difference between two farms following from e.g. different farm sizes. Such a marginal effect of farm size difference is not in line with our assumption of a simultaneous change in size for all farms in the sample. However, both kinds of marginal effects have the same sign in our analysis.

[17] These variables include value added, animal density, subsidy, *pasturediff*, rentshare, sugarbeet, potato, forage maize, farmsize, capital, and family labour.

[18] We assume the 1996 values as being not contemporaneously correlated with our error term (compare Lence and Mishra, 2003).

county-level variables per-capita income, unemployment rate, population change between 1995 and 2005 as well as population density. Appendix 1 shows the instruments' quality:[19] the smallest value for Shea's R^2 amounts to 0.21 for value added, which is in line with Kirwan's (2009) values of 0.22 and 0.15 for instrumenting subsidy.[20] Our instruments do not cause any problems of overidentification following a heteroscedasticity-robust test (Wooldridge, 1995).

5. Results and Discussion

There are several candidate models (4a) to (4e) that might be appropriate for our analysis – as we have outlined in section 4.1. We must test for heteroscedasticity and for the existence and form of spatial dependencies. As a natural starting point, we estimate the least restrictive model (4.e), called 'heteroscedastic general spatial model', and test for heteroscedasticity as well as for the spatial lag and spatial error coefficient being different from zero. A Breusch-Pagan test reveals significant heteroscedasticity in μ; thus, the homoscedastic general spatial model (4d) is not appropriate.

Testing for the appropriate spatial specification is more complex because we must test for a spatial error conditioned on a spatial lag (or vice versa). Because such tests proposed by Anselin and Bera (1998) need homoscedasticity[21] we refer to Kelejian and Prucha's (2010) robust approach. Their procedures not only allow for estimating the coefficients for model (4e), but also to draw inference about the coefficients, including λ and ρ.[22] The upper two rows in Table 3 display the estimates for the spatial coefficients $\rho = 0.72$ and $\lambda = -0.60$ as well as the coefficients' significance levels that are below 0.01. The latter indicate that it is not appropriate to omit either one or both of the coefficients. Furthermore, the coefficients are in the parameter space commonly assumed for spatial models, i.e. $-1 < \lambda \leq 0$ and $-1 < \rho < 1$. The first inequality implies that the spatial error "fades out" in space, whereas the latter ensures spatial stationarity. Consequently, the heteroscedastic general spatial model (4e) is more

[19] The null hypothesis of a test proposed by Stock and Yogo (2005) that these instruments are weak is rejected. Our test statistic amounts to 62.6 which is well above the tabulated values in Stock and Yogo (2005). However, this test assumes homoscedasticity. To our knowledge, there are not any tests yet for several endogenous variables under heteroscedasticity. Alternative instrumentation led to either overidentification or lower values for Shea's R^2.

[20] E.g. Foster *et al.* (2008) report smaller values than 0.21 for three separate estimations with a single endogenous variable.

[21] We get a test statistic of 518.8 (when ignoring the heteroscedasticity), which is well above the corresponding χ^2 value for one degree of freedom.

[22] Based on Monte Carlo simulations, Arraiz et al. (2010) show that Kelejian and Prucha's (2010) estimators behave well in samples smaller than ours. In particular, the rejection rates for either λ or ρ equalling zero do not differ considerably from the nominal level chosen in the simulations.

appropriate from a statistical point of view than the alternatives (4a) to (4d), which would be biased or inefficient for our data.

The first economic result for our data set is thus that the spatial lag should be integrated in the estimation of land rental prices.[23] The estimate of 0.72 for ρ indicates that an increase of the average neighbouring cash rent by one € per hectare raises farmer i's cash rent by 72 cents per hectare.

Table 3: Estimation results for cash rent determinants (3,819 farms)

	heteroscedastic general spatial model (4e)			
Spatial lag and error coefficient	Coefficient	Probability (rounded)	Marginal effect	Probability (rounded)
ρ	0.715 ***	0.00		
λ	-0.604 ***	0.00		
Rental rate determinants				
value added	0.065 ***	0.00	0.228 ***	0.00
subsidy	0.109 **	0.05	0.383 **	0.03
animal density	1.018	0.73	3.57	0.74
animal density county	38.461 ***	0.00	134.77 ***	0.00
pasturediff	-0.685 ***	0.00	-2.40 ***	0.00
rentshare	35.321 ***	0.00	123.767 ***	0.00
sugarbeet	131.991 ***	0.00	462.49 ***	0.00
potato	21.822	0.33	76.46	0.33
forage maize	54.085 ***	0.01	189.52 **	0.01
soil	0.765 ***	0.00	2.68 ***	0.00
farmsize	-0.110 *	0.07	-0.389 *	0.07
family labour	-521.562 **	0.04	- *	0.06
capital	-2.267 *	0.09	-7.94 *	0.10
education	1.913	0.30	6.70	0.30
age	-0.067	0.74	-0.24	0.74
farmsize_county	-0.594 **	0.04	-2.08 **	0.05
temperature	-1.282	0.77	-4.49	0.77
precipitation	-0.142 ***	0.00	-0.50 ***	0.00
constant	154.90 **	0.04		

Source: own calculations. *, **, *** significantly different from zero at the 10, 5 and 1 % level, respectively. Marginal effects are calculated according to (6). Standard errors are calculated according to the delta method (Greene, 2003, p.913).

[23] The statistics of the classical Moran's I test on spatial dependence (Moran, 1950) for OLS regressions with and without additional county dummies are 13.3. and 9.6, respectively. Consequently, we must reject the test's null of no spatial dependence for both specifications. Hence, even county fixed effects do not sufficiently control for spatial dependence. We do not include county dummies in our main estimation because they are correlated to both the subsidy variable (through the yield regions described in 2.2) and the county-level variables such as county average animal density.

We now turn to the estimates for the determinants of rental rates, starting in the third row of Table 3. Note that we do not refer to the regression coefficients for the determinants in the first column but to marginal effects in the third column instead. The latter are more descriptive and comparable to results in the literature using regressions without a spatial lag.

Given the selection of variables, value added is the closest proxy for a farmer's profit on land. The marginal effect of our value added variable on farmland rental rates amounts to 23 cents for each additional € per hectare. These values are comparable to former studies. For the EU, Patton *et al.* (2008) yield a coefficient of 0.31 for dairy net market returns. Lence and Mishra (2003) obtain values between 0.3 and 0.45 for U.S. corn and soybean revenues, while Kirwan (2009) obtains coefficients between 0.31 (-0.02) and 0.44 (-0.05) for his sales (variable costs) variables in different model specifications. Only Fuchs (2002) reports a substantially lower coefficient of 0.1 for his variable of farm net value added without per-hectare payments. Additional proxies for marginal profit, e.g., soil quality and share of high value crops are discussed at the end of this section.

The marginal impact of subsidy payments on farmland rental rates amounts to 0.38 for each additional € of our subsidy variable. Patton *et al.* (2008) find that some EU payments – the so-called less favoured area payments – have even been fully capitalized into cash rents in Northern Ireland. These payments are decoupled from production, in contrast to our subsidy payments. Thus, they have minor or no impact on production and may yield higher incidence levels. Compared to U.S payments, our incidence levels are similar or higher. Roberts *et al.* (2003) obtain incidence levels between 34 and 41 cents for an additional dollar in U.S. government payments. Kirwan (2009) reports a marginal incidence level of around one-quarter for U.S. direct government payments net of Conservation Reserve Program payments. Herriges *et al.* (1992) quantify the implicit value of corn base acreage eligible to the U.S. commodity program between \$ 11 and \$ 13. This corresponds to a land rent increase of roughly 11 to 14 %. Although Lence and Mishra (2003) yield an incidence of 13 % for the sum of different government payments, the coefficients for separate payments from different programs are between – 0.23 and 0.86.

The only empirical analysis about the EU arable premium payments conducted by Fuchs (2002) yields a 7 cent incidence for each additional €. This low incidence may be explained by the time period (1989-1999) he uses. The per-hectare payments were introduced in three steps between 1993 and 1995. However, according to Swinnen *et al.* (2008), in the majority of Fuchs' (2002) regions (e.g., Belgium, France, Germany, Netherlands, Scotland) rental contracts are long-term, and thus only a few rental contracts are renegotiated each year.

Hence, it takes time for the influence of EU payments to become visible in the regional farmland rental price. As a result, a subsidy incidence based on a panel from 1989 to 1999 is probably underestimated.

We now turn to the impact of animal density. An increase of one animal unit per hectare in all county leads to a cash rent increase of € 135. The estimate for regional livestock density shows the importance of local competition for land. Drescher and McNamara (2000), as well as Fuchs (2002), also find a positive impact of regional livestock density. The impact of animal density is important for policymakers deciding on investment aid for new animal operations. Though such subsidies may support incomes of livestock farmers to a certain degree, they also increase cash rents for all tenants in that county (in the long-run). Hence, the overall effect on farmers' incomes may be negative. At the farm level, we find no significant impact of livestock keeping on farmland rental rates.

Other farm characteristics also contribute to the explanation of cash rents. In line with Bierlen *et al.* (1999), as well as Drescher and McNamara (2000), we find a significant positive impact of the soil quality. An increase in soil quality by one point comes with 2.7 €/ha higher rental rates. Further on, cash rents increase with higher shares of sugar beets in the cropping pattern. Farmers that exhibit a 10 percentage point higher share of beets pay 46 €/ha higher rental rates. Our control for pasture land (*pasturediff*) also yields the expected negative sign.

We finish with the results of sensitivity analyses with two alternative spatial weight matrices. Our weight matrix W is determined exogenously (see section 4.2). However, different functional relationships between distance and weights have only a minor impact on exemplary results (see Appendix 2). The marginal incidence of a subsidy is a little higher than the 0.38 reported in table 3; it is 0.45 for weights equalling the (standardised) inverse squared distance and 0.41 for linearly with distance-decreasing weights. In addition, the marginal effects for value added become 0.19 and 0.22, respectively, confirming the 0.22 in table 3. The full set of regression results for the sensitivity analyses can be obtained upon request.

6. Conclusions

This article analyses determinants of 2001 farmland rental prices from 3,819 farms in the German Federal State of Lower Saxony. We consider several farm-level economic, socio-economic, and agronomic characteristics, as well as regional variables on agricultural and demographic structure to estimate the incidence of former EU subsidies paid for arable crop acreage. Based on specification tests we estimate a heteroscedastic general spatial model to account for both spatial relationships among rental prices of neighbouring farmers and spatially autocorrelated error terms. Non-spatial models, spatial error or spatial lag models are biased or yield inefficient standard errors for our data.

Our results show that a € 1 per hectare higher rental price in a farmer's neighbourhood coincides with a € 0.72 higher rental price the farmer must pay (everything else equal). This neighbour effect on local rental markets has not been examined in the literature yet. We find empirical evidence for the incidence of EU agricultural subsidies paid for eligible arable crop land between 1993 and 2004. Our estimate for the marginal incidence amounts to € 0.38, 0.41, and 0.45 per additional Euro of these per-hectare payments – depending on the weight matrices applied in the regression. Consequently, a considerable share of subsidy payments passes farmers' pockets and ends up with landlords. Finally, rental prices per hectare are € 135 higher if livestock density in all counties increases by one animal unit (equals 500 kilogram live weight) per hectare. Consequently, subsidies for livestock farming (e.g., investment aid) may support incomes of livestock farmers, but they also increase cash rents for all tenants in that county. Hence, the overall effect on farmers' incomes may be negative.

We conclude that German farmland rental rates are heavily influenced by EU and national agricultural policy instruments. Hence, these policies exhibit substantial distributional effects and their income effect may be high not only for farmers but also for landowners.

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Appendix 1: Quality of instruments

endogenous variable	**Shea's adjusted partial R^2**	**adjusted R^2**
value added	0.209	0.418
animal density	0.577	0.783
subsidy	0.631	0.805
pasturediff	0.607	0.681
rentshare	0.628	0.720
sugarbeet	0.797	0.922
potato	0.768	0.869
forage maize	0.397	0.590
farmsize	0.677	0.880
family labour	0.446	0.630
capital	0.496	0.644

Source: Own calculations.

Appendix 2: Marginal effects of subsidy and value added for different weight matricesx *W*

	Specification of weights in *W*		
	Inverse distances (from table 2)	Squared inverse distances	Linearly decreasing with distance
subsidy	0.383 **	0.453 ***	0.409 **
value added	0.228 ***	0.193 ***	0.220 ***

Source: Own calculations. *, **, *** significantly different from zero at the 10, 5 and 1 % level, respectively. Marginal effects are calculated according to (6). Standard errors are calculated according to the delta method (Greene, 2003, p. 913).