DEPARTMENT OF ECONOMICS
JOHANNES KEPLER UNIVERSITY OF LINZ

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Working Paper No. 2209
June 2022

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Farm exits and competition on the land market: Evidence from spatially explicit data*

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June 24, 2022

Abstract

In this article, we analyze competition for agricultural land as an important, scarce and immobile input. The cost of cultivating a parcel of land depends strongly on the distance from the farmer to the plot, leading to spatially small land markets. To investigate this issue, we are able to use extremely rich datasets, and combine information on both farms and their cultivated plots (including their exact locations) for virtually all farms in Austria for a five-year period. When analyzing the takeover of parcels from farms leaving the market, we find that the distance between an exiting farm's plot and the closest parcel of a prospective buyer farm is an important determinant of which buyer will prevail on the land market. In addition, the proximity between the farmsteads of the exiting farm and a prospective buyer farm is also important. The results suggest (i) that agricultural land markets are indeed very small and (ii) that information frictions are important in this market.

Keywords: spatial competition, land market, farm exit, spatial data

JEL Classification: L13, L25, Q12, R14

*This work was supported by the Austrian National Bank (OeNB) Anniversary Fund (Project-Number: 17658). The Austrian National Bank did not interfere in any stage of the research.

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1 Introduction

The agricultural sector has experienced sizable efficiency gains over the last decades. The optimal farm size to reach an efficient scale of production has increased continuously, provoking structural change in this industry. Expanding farm business has proved to be the most successful way to remain profitable and to survive in this market. The scope for farm growth, which we understand as an increase in a farm's area under cultivation, is, however, limited due to peculiarities of the production technology: agricultural land, a crucial input factor for most crops, is immobile and scarce (as noted, among others, by Huettel and Margarian, 2009).

The purpose of this article is to evaluate spatial aspects of competition on the agricultural land market. Two stylized facts guide our empirical analysis: First, in most densely populated European countries converting raw to arable land is not a large-scale option. New plots entering the agricultural land market are scarce and quantitatively unimportant, and neighboring farms thus have to compete in the local land market for a quasi-fixed supply of this factor of production. Second, the process of how farms exit the market is characterized by a constant area under cultivation in the years prior to market exit: farms do not continuously become smaller, but exit abruptly. Therefore, rival farms usually cannot acquire individual plots of land, even if they have a high willingness-to-pay (WTP). Rather, they must wait until a farm exits the market altogether (a decision that competing farms have little ability to influence) to have a chance to compete on the land market for the exiting farm's plots. Farm exits are thus a precondition for the remaining farms to grow in size (Weiss, 1999; Storm et al., 2015).

To analyze local competition on the land market, we are able to use and to combine extremely rich data sets, including information on both farms as well as their cultivated plots for virtually all farms in Austria for the period between 2015 and 2019. All plots are geo-referenced and can be linked over time and with the farms cultivating these plots. Farm-level information includes the exact locations of all farmsteads and comprehensive data on farm and farmer characteristics. We can therefore take the perspective of single plots of farms leaving the market, and assess which characteristics influence a rival farm's probabilities of taking over the respective plots.

Our work is thus related to the literature on farm growth and farm survival. While farms interact with other farms also through a number of other channels, such as social and network effects or technology diffusion,[1] the interaction due to competition on the land market is likely to be the most important single issue of spatial interdependence among neighboring farms. While this channel has been widely recognized (see, e.g., Balmann, 1997; Weiss, 1999; Huettel and Margarian, 2009; Happe et al., 2008), econometric evidence

[1]Spatial interdependence due to knowledge transfer and technology adoption as investigated by Berger (2001), for example.

incorporating interactions via competition on the land market is extremely scarce.[2] Only a few articles draw on geo-reference plot data in their empirical analyses. Plogmann et al. (2020) use these data to analyze spatial aspects of plot takeovers, but are interested in the relationship between land concentration and farm growth rather than investigating competition on the land market. Cotteleer et al. (2008), on the other hand, explore whether transaction prices are influenced by market power, i.e. by the number of potential buyers in the vicinity, rather than on the relationship between distance and takeover probabilities.

This article is most closely related to Storm et al. (2015), who explicitly account for spatial spillover effects when analyzing the effects of subsidies (direct payments) on farm exits. The authors find that subsidies have a positive (direct) effect on the survival probabilities of the recipient farms, but negative (spillover) effects on neighboring farms' survival rates, because keeping farms in the market (due to subsidies) impedes other neighboring farms from growing (because the total area of agricultural land is fixed) and therefore increases neighboring farms' exit probabilities. Disregarding these spillover effects ultimately leads to an overestimation of the impact of direct payments on farm survival rates. While Storm et al. (2015) document negative spillover effects of farm survival, they can only discuss potential channels how these interdependencies may arise, due to data limitations.

We contribute to this literature by isolating the spatial interactions that occur through the land market. We find that the distance between an exiting farm's plot and the prospective buyer farm's closest plot is an important determinant of which buyer will prevail on the land market. This distance thus affects the buyer farm's WTP, because proximity is associated with lower production costs (costs of cultivating this plot). The distance between the exiting farm's plot and the buyer farm's farmstead, on the other hand, does not contribute to explaining this transaction. Interestingly, the distance between the farmsteads of the exiting farm and the buyer farm is found to be of key importance. This finding indicates information frictions on the agricultural land market, because a shorter distance between the two farms makes personal or social ties between the farmers more likely, while this distance is not related to the production costs of the buyer farm. Farm and farmer characteristics have a similar impact on takeover probabilities as on farm growth, as expected. We also document that the spatial scope of spillover effects is very

[2]While empirical evidence is scarce, a number of articles analyzes spatial interdependence between farms in competition for arable land by agent-based simulation models (Balmann, 1997; Freeman et al., 2009; Happe et al., 2008, 2009). A somewhat related literature investigates land use and land use change. This literature is interested in modeling the spatial and temporal patterns of land conversion or land cover. See e.g. Irwin and Geoghegan (2001) for advances of spatially explicit economic land-use models. The use of spatial-econometric techniques is not uncommon in this area of research, as applied for examples in contributions analyzing vegetation change in Tanzania (Pelkey et al., 2000), deforestation (Nelson, 2002), or water quality (Robertson et al., 2006). This literature is interested in questions of (or related to) land use, but does not focus on who (i.e. which economic agent) uses the land.

narrow, suggesting that agricultural land markets are indeed spatially very small. Policy interventions that increase particular farms' survival probabilities (e. g., due to subsidies) reduce other farms' possibilities to expand their business, but these negative spillover effects influence rival farms only in the immediate proximity.

The remainder of the article is organized as follows. The empirical strategy and the various data sources are described in Section 2. The main empirical results are presented and discussed in Section 3, while Section 4 provides sensitivity analyses. Section 5 concludes.

2 Empirical strategy and data

2.1 Empirical strategy

The research design of modeling the competition on the land market can be captured by a conditional logit (CL) model (McFadden, 1974). We evaluate only plots i of farm e if (i) farm e leaves the market in year $(t-1)$ and (ii) plot i is taken over in year t, i.e. cultivated by a farm in year t that was already in the market in year $(t-1)$. In this framework, the probability that plot i of *exiting* farm e is taken over by (the prospective *buyer*) farm b in year t, $p_{iebt} = Pr[plot_{iebt} = 1]$, is given by:[3]

$$p_{iebt} \equiv Pr[plot_{iebt} = 1 | \boldsymbol{dist}_{ieb,t-1}, \boldsymbol{X}_{b,t-1}] = \frac{\exp(\boldsymbol{dist}'_{ieb,t-1}\boldsymbol{\alpha} + \boldsymbol{X}'_{b,t-1}\boldsymbol{\beta})}{\sum_{f \in F^i} \exp(\boldsymbol{dist}'_{ief,t-1}\boldsymbol{\alpha} + \boldsymbol{X}'_{f,t-1}\boldsymbol{\beta})} \quad (1)$$

This probability depends on the prospective buyer farm's characteristics $\boldsymbol{X}_{b,t-1}$ in the year prior to the takeover, as well as on a vector of distances $\boldsymbol{dist}_{ieb,t-1}$. This vector comprises three variables, indicating (i) the distance between plot i and the prospective buyer farm's farmstead ($dist_{ieb}^{plot \rightarrow farm}$), (ii) the distance between plot i and the buyer farm's plot located most closely to plot i ($dist_{ieb,t-1}^{plot \rightarrow plot}$), and (iii) the distance between the farmsteads of the exiting farm and the prospective buyer farm ($dist_{eb}^{farm \rightarrow farm}$). $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the parameter vectors to be estimated. We restrict the set of rival farms competing for plot i, F^i, to all farms located in a distance of at most 5 kilometers to the respective plot (i.e. to farms where $dist_{if}^{plot \rightarrow farm} \leq 5\,\text{km}$).

By applying a CL model, we estimate the probability of acquiring a given plot assuming taht a transaction takes place. By conditioning on a transaction we control for all effects that do not vary over alternatives, i.e. all plot and exiting farm characteristics (like soil quality, size of the exiting farm, age of the exiting farmer, ...).

[3] We refer to all farms active in both years $(t-1)$ and t as *prospective buyer farms* and the farm that takes over a particular plot as the *buyer farm*, even if that farm only leases that parcel. We will discuss this issue in more detail later.

Given the large number of observations (more than 80,000 transactions and on average 150 prospective buyer farms in the vicinity), estimating Equation (1) is computationally challenging, a common problem with non-linear estimation techniques and a large number of observations. We circumvent this issue in the following way: One restriction inherent to the conditional logit model is the so-called independence of irrelevant alternatives (IIA) assumption, stating that the ratio of choice probabilities between two alternatives (i.e. between two potential buyer farms) depends only on the characteristics of these two farms, but not on the number or characteristics of others. A violation of this assumption would render the CL model invalid. This assumption seems very plausible in the present application, as economic theory suggests that the farm with the highest WTP will take over the plot (i.e. the buyer farm has to have a higher WTP than all other farms). If the IIA assumption holds, however, the parameters can be consistently estimated when the number of non-chosen alternatives is reduced (see Train, 2009, p. 48 f.). This allows us to consistently estimate the parameter vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, even if we reduce the set of potential buyers F^i to the buyer farm and a constant number of (randomly selected) non-buyer farms, which reduces the computational cost substantially.[4] We will include five randomly selected non-buyer farms in the main specification of the empirical analysis, but show that the results are robust when the size of the control groups is changed.

2.2 Data

To analyze competition on the land market, a number of excellent micro data sets covering the agricultural sector in Austria are available. The Federal Ministry of Agriculture, Forestry, Environment and Water Management (BMLFUW) promotes empirical research by offering access to data as an in kind support.[5] To conduct our empirical analysis, data is available at two levels of aggregation, namely at the plot (parcels of agricultural land) and at the farm level. The datasets are comprehensive, both in scope (as they cover almost all farms and plots) and in detail. Plots as well as farms (farmsteads) are geo-coded and can thus be linked across space.

Plot data

Information on plots of agricultural land is provided by the "Integrated Administration and Control System" (IACS). This is an information system developed by the EU to administer agricultural subsidies. IACS is maintained by national bodies (in Austria by "Agrarmarkt Austria") and is a core element of the Common Agricultural Policy (CAP). This data base includes information on virtually the entire population of more than 1.7

[4] The downside of this approach is that the parameters are less precisely estimated due to a smaller number of observations. Given the large number of transactions, this problem is only of minor importance.

[5] Data can be used for scientific purposes, but researchers must not disclose individual data and are obliged to make their findings publicly available.

million parcels of land used for agriculture in Austria.[6] Each plot is linked to the farm cultivating this parcel of land in that particular year by a unique farm ID. Each plot is characterized by its size and spatially identified by its geo-coded location, which is made accessible via maps. All plots cultivated by one farm are numbered consecutively and are linked over time by its size and location (see Appendix A for details). Data are available annually for the 2015-2019 CAP funding cycle.[7]

The spatial distribution of the agricultural plots available for our analysis is illustrated by a series of maps in Figure 1 and contrasted with satellite images of the same map section. The maps suggest that the geo-spatial data are very accurate and comprehensive.

The plots are classified according to their major type of use into three main groups, namely cropland, pastures, and miscellaneous agricultural areas. The latter category comprises for example vineyards, special cultures, forests, and pond areas. Additionally, data on the legal ownership status of the plots are provided by the BMLFUW, containing information on whether a plot is owned or leased. If a plot is owned by more than one farm (or more than one natural or legal person), the ownership status is assigned to the largest owner.[8] Descriptive Statistics on plot-level data is provided in Table 1.

Farm data

Two major sources of micro data at the farm level are used for the empirical analysis of this article. First, we use data of the Farm Structure Surveys (FSS), providing information for the entire population of Austrian farms ("agricultural holdings"), conducted in 2010. Second, the Farm Accountancy Data Network (FADN) provides access to book keeping data of a sample of approximately 2,400 representative farms annually. Both data sets can be linked by a unique farm identification number.

The Farm Structure Survey (FSS) provides micro data at the farm level of excellent quality. As agricultural policy is a common EU policy, the European Commission (EC) imposes high standards on the amount and the quality of data on agriculture that has to be collected and published in a homogeneous manner throughout EU Member States.[9] The data are collected by the national statistical offices of the Member States, which is the

[6] IACS contains only information of farms receiving EU farm payments. A small number of farms (e.g. those owned by municipalities or federal states) does not receive EU transfers. Consequently, they are – along with their cultivated plots – not covered by IACS.

[7] A detailed description of all variables in this data set can be found in https://gruenerbericht.at/cm4/jdownload/send/47-datenpoolbeschreibung/1770-invekos-datenpool-2017.

[8] The plots cultivated by the farms and the parcels registered in the land registry are not congruent. Therefore, a farmer can be both owner and lessee of (parts of) one plot. In most cases (between 81 % and 85 % throughout the observation period), the entire area of one plot is either leased or owned by one farmer. In ambiguous cases, ownership was assigned to the owner of the largest share of the respective plot.

[9] Note that agricultural policy is the second biggest expenditure of the EU budget (420 bn Euro during the multiannual financial framework period 2014-2020 of which approximately 1.7 bn are spent in Austria per year; see BMLFUW, 2016, Tables 5.1.4 and 7.1.4).

Table 1: Agricultural plots by type of land use and ownership

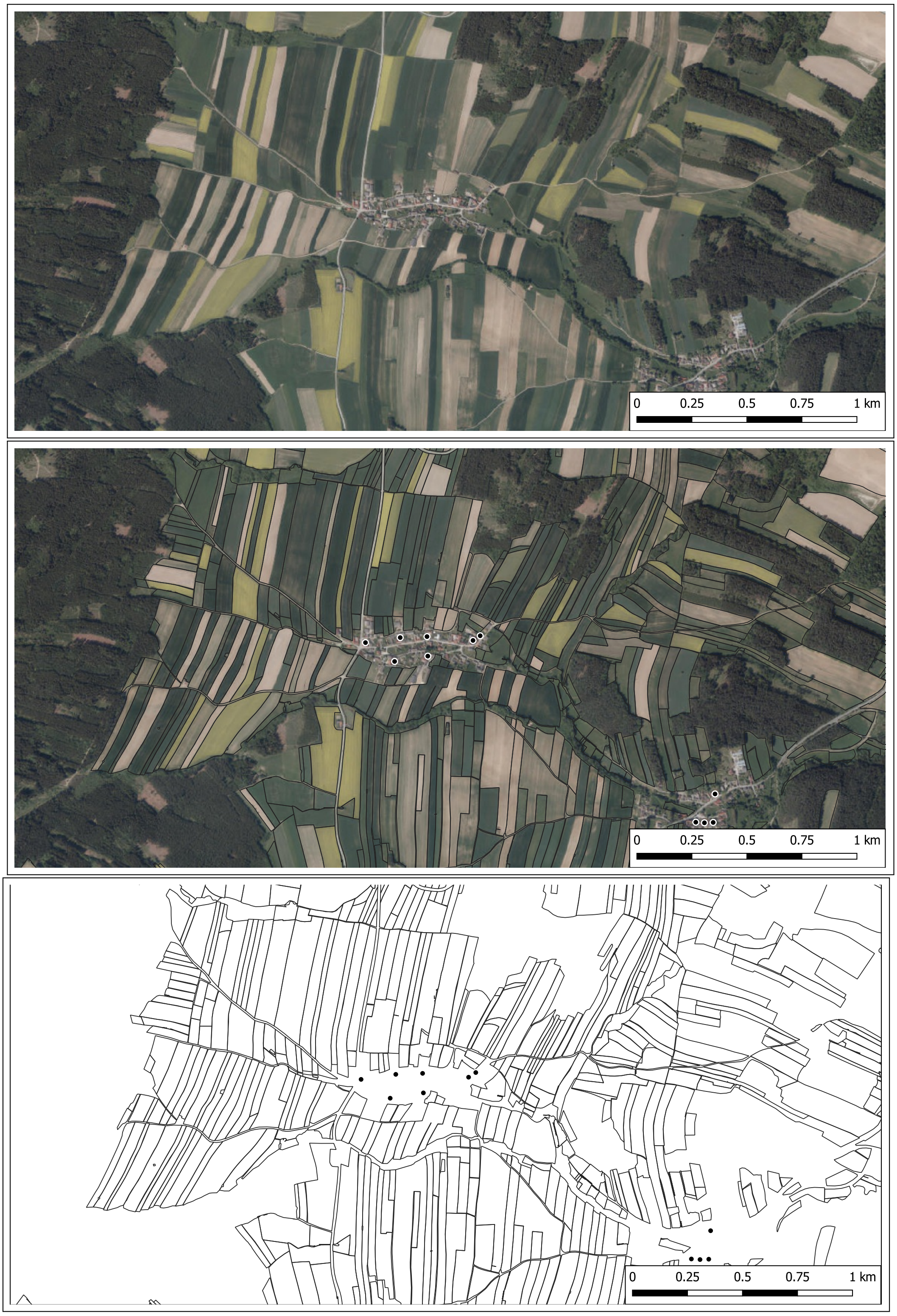
	2015	2016	2017	2018	2019
Total number of plots	1,652,414	1,640,791	1,629,202	1,621,922	1,612,320
Type of land use					
Cropland	813,588	797,954	786,049	779,271	772,456
Pastures	744,318	746,788	745,761	744,125	741,136
Miscellaneous use	94,508	96,049	97,392	98,526	98,728
Ownership status					
Owned	1,125,466	1,105,953	1,084,817	1,043,317	1,050,310
Leased	525,644	534,693	543,796	517,845	561,518
Status unknown	1,304	145	589	60,670	492
Total agricultural area	31,939	32,219	32,172	32,092	31,991
Type of land use					
Cropland	13,461	13,384	13,329	13,313	13,283
Pastures	17,921	18,259	18,252	18,182	18,110
Miscellaneous use	557	575	590	597	598
Ownership status					
Owned	25,314	25,375	25,123	24,449	24,653
Leased	6,600	6,838	7,038	6,755	7,331
Status unknown	24	5	10	887	6

Notes: Areas are given in km^2.

Austrian Statistical Office ("Statistics Austria") in our case. A general census is conducted about every ten years. We use the latest census before our observation period, conducted in 2010.[10] The census includes detailed information on the owner and the manager of the farm, on farm labor force (employees in per capita and full-time equivalents), cultivated land and livestock. Descriptive statistics on the variables are provided in Table 2. Farm-level data were supplemented with geo-referenced farmstead locations, provided annually by the BMLFUW, covering more than 99 % of all active the farms in the sample.

[10] An overview of agricultural censuses in Austria since 1951 is provided in Reindl et al. (2016), and details on more recent surveys are available at the website of Statistics Austria (see http://www.statistik.at/web_de/statistiken/wirtschaft/land_und_forstwirtschaft/agrarstruktur_flaechen_ertraege/arbeitskraefte/index.html).

Figure 1: Spatial distribution of agricultural plots and farmsteads



Notes: The maps show the spatial distribution of agricultural plots and farmsteads based on satellite images (top panel), the geo-coded data of the plots and farmsteads used for the analysis (bottom panel), or both (middle panel).

The Farm Accountancy Data Network (FADN Data) provides accounting data from a sample of approximately 2,400 farms, collected annually between 2010 to 2017. The data are organized as a rotating panel, with some farms dropping out of the sample every year. For 3,089 farms, data are collected at least once during the observation period. These data include information on the size of agricultural land cultivated, owned and leased by the farm, similar to the IACS data. Additionally, these data include depreciation on buildings and machinery, as an indicator for the long-run (building) and short-run (machinery) capital stock. Other variables indicating the size of a farm include the farm's yield (in Euros), livestock, as well as a standardized input measure. Equity ratios are calculated based on the farms' debts and assets. Summary statistics for the variables based on accounting data are also included in Table 2.

Distances

To investigate the competition in the agricultural land market, we propose three different measures of distance between the exiting farm and the prospective buyer farms. Prospective buyer farms subsume the buyer farm, as well as other farms that can be considered as rival farms on the land market. All distances are calculated as Euclidean distances. For distances involving the plots of farms, we use the respective centroids (calculated so that they are within the polygon of the plots) as starting or ending points. Three different types of distances are calculated:

First, the distance between plots of exiting farms and farmsteads of prospective buyer farms, $dist_{ieb}^{plot \rightarrow farm}$. This measure is an indicator of production costs, as a shorter distance from the farmstead of the buyer farm should be associated with lower costs of farming the plot. Therefore, a shorter distance is leads to a higher WTP and a higher probability of buying the plot in question.

Second, the distance between plots of exiting farms and the closest plots of prospective buyer farms, $dist_{ieb,t-1}^{plot \rightarrow plot}$. To derive this measure, we calculate the distances between the respective plot of the exiting farm and all plots of a prospective buyer farm, and select the smallest of these distances. Again, a shorter distance is associated with lower production costs and a higher WTP. In an alternative variant, we calculate this distance under the condition that the type of use of the two plots is the same. We therefore take the smallest distance to a plot of the prospective buyer farm with the same type of use.

Third, the distance between the farmsteads of the exiting farm and prospective buyer farms, $dist_{ieb}^{farm \rightarrow farm}$. This distance should not influence production costs and thus the WTP for plots of the exiting farms. However, a shorter distance between two farms implies a higher probability of a personal relationship between the managers or the owners of the two farms. An effect of farmstead distance on the transaction can thus be interpreted as evidence of information frictions in the agricultural land market.

The construction of these three distance measures is illustrated in Figure 2. Descrip-

Table 2: Summary statistics on farm level data

	N	Mean	S. D.	Min	Max
Integrated Administration and Control System (IACS)					
Number of plots under cultivation	558,796	14.66	17.88	1.00	1,283.00
Area under cultivation (in ha)	558,796	29.31	78.69	0.01	13,200.24
Share cropland (in %)	558,796	36.48	39.74	0.00	100.00
Share pastures (in %)	558,796	59.05	41.35	0.00	100.00
Share miscellaneous (in %)	558,796	4.47	18.85	0.00	100.00
Farm Structure Survey (FSS)					
Age[1]	173,317	49.09	11.96	16.00	99.00
Female[1]	173,317	0.66	0.47	0.00	1.00
Practical education only[1]	173,317	0.55	0.50	0.00	1.00
Basic education[1]	173,317	0.21	0.41	0.00	1.00
Advanced education[1]	173,317	0.23	0.42	0.00	1.00
Recent qualification[1]	173,317	0.19	0.39	0.00	1.00
Workforce (FTE)	173,317	0.98	1.67	0.13	222.32
Share owner (in %)	173,317	66.03	28.61	0.00	100.00
Share spouse (in %)	173,317	15.34	20.54	0.00	100.00
Share child (in %)	173,317	6.10	15.00	0.00	100.00
Share other family (in %)	173,317	6.24	15.34	0.00	100.00
Share non-family (in %)	173,317	6.29	18.66	0.00	100.00
Farm Accountancy Data Network (FADN)					
Area cultivated (in ha)	19,391	39.30	36.64	0.00	424.77
Area owned (in ha)	19,391	23.17	23.11	0.00	358.42
Area leased (in ha)	19,391	13.61	20.88	0.00	220.98
Depreciation					
buildings (in 1 ,000 Euro)	19,391	7.17	5.67	−3.29	78.36
machinery (in 1,000 Euro)	19,391	10.94	8.36	0.00	95.12
Yield (in 1,000 Euro)	19,391	138.87	118.57	−265.73	1,698.67
Input (standard., in 1,000 Euro)[2]	19,391	86.08	77.37	0.00	954.58
Livestock (large livestock units)[3]	19,391	26.85	28.52	0.00	397.61
Equity ratio	18,743	89.47	19.98	−186.16	100.00

Notes: IACS data are available between 2015 and 2019 at the plot level and are aggregated at the farm level. FSS data are provided for 2010 and FADN data are available between 2010 and 2017.

[1] Farmer characteristics refer the characteristics of the farm manager.

[2] The standardized input weights different input categories (cultivated area, livestock) by the average yield (of these inputs) multiplied by producer prices.

[3] Livestock is calculated by weighting the various animals according to their typical weight. A weight of one corresponds to about 500 kg.

tive statistics on all distance measures are summarized in Table 3. The distance measures are calculated for all farms with farmsteads within 5 km distance to the corresponding plot and are reported separately for buyer and non-buyer farms. We observe about 50,000 transactions. The distance $dist_{ieb}^{plot \to farm}$ is limited to 5 km by the sample selection. The other distances $dist_{ieb,t-1}^{plot \to plot}$ and $dist_{ieb,t-1}^{plot \to plot}$ can take larger values, although this is uncommon.

Figure 2: Construction of distance measures

Notes: The maps show the spatial distribution of agricultural plots (gray shading) and farmstead (triangle) of an exiting farm, and the parcels (checkered areas) and farmstead (diamond) of a prospective buyer farm. The plots and farmsteads of other farms are left blank or indicated by black dots, respectively. For a given parcel of the exiting farm, the arrows show the distance to the nearest plot of the prospective buyer ($dist_{ieb,t-1}^{plot \to plot}$), the distance to the prospective buyer's farmstead ($dist_{ieb}^{plot \to farm}$), and the distance between the two farmsteads ($dist_{ieb}^{farm \to farm}$).

Table 3: Summary statistics on distances

Variable name	Group	N	Mean	S. D.	Min	Max
Distance between plot and farmstead						
$dist_{ieb}^{plot \rightarrow farm}$	$plot_{iebt} = 1$	49,129	1.70	1.22	0.02	5.00
$dist_{ieb}^{plot \rightarrow farm}$	$plot_{iebt} = 0$	7,596,063	3.27	1.20	0.02	5.00
Distance between plot and plot (irrespective of type of use)						
$dist_{ieb,t-1}^{plot \rightarrow plot}$	$plot_{iebt} = 1$	49,129	0.66	0.90	0.01	24.22
$dist_{ieb,t-1}^{plot \rightarrow plot}$	$plot_{iebt} = 0$	7,596,063	2.59	3.33	0.00	494.74
Distance between plot and plot (same type of use)						
$dist_{ieb,t-1}^{plot \rightarrow plot}$	$plot_{iebt} = 1$	47,988	0.73	1.00	0.01	42.90
$dist_{ieb,t-1}^{plot \rightarrow plot}$	$plot_{iebt} = 0$	6,825,469	2.65	2.22	0.00	441.30
Distance between farmstead and farmstead						
$dist_{ieb,t-1}^{plot \rightarrow plot}$	$plot_{iebt} = 1$	49,114	1.75	11.57	0.00	798.92
$dist_{ieb,t-1}^{plot \rightarrow plot}$	$plot_{iebt} = 0$	7,594,322	3.68	9.74	0.00	805.19

Notes: Figures indicate distances (in kilometers) between the plots or the farmsteads of an exiting farm to plots or farmsteads of farms with farmsteads within 5 km distance (i.e. with $dist_{ieb}^{plot \rightarrow farm} \leq 5\,\text{km}$). Summary statistics are reported separately for buying farms ($plot_{iebt} = 1$) and for non-buying farms ($plot_{iebt} = 0$). The number of observations is smaller for the distance between plots of the same type of use, because this distance cannot be calculated if the prospective buying farm does not cultivate a plot with the same type of use in year $(t-1)$.

3 Results

3.1 Stylized facts

As stated in the introduction, two stylized facts guide our empirical analysis. First, converting raw to arable land is not a large-scale option, and farms thus have to rely on rival farms leaving the market to grow in size. Table 4 contrasts the agricultural area under cultivation in Austria (both in size and the number of plots) with the area re-allocated due to farm exits. About 1.3 % of all plots (corresponding to about 1 % of the agricultural land) are re-allocated every year due to farms leaving the market.[11] Compared to the plots of the exiting farms, the new plots in our sample are significantly smaller in number (about 1/4) and size (about 1/8). There are a number of reasons why plots appear as new parcels in our data: The land may have been fallow since the beginning of our observation period, or the farms may have participated in CAP subsidies only after 2015. Furthermore, parcels are also classified as new plots if more than half of the parcel has been converted to non-agricultural uses.[12] Actual new plots (i.e. land converted to agricultural land) is therefore only a (potentially small) subsample of the plots that appear as new parcels in our data and are therefore quantitatively of minor importance. Thus, farms must exit in order for the remaining farms to grow.

Table 4: Agricultural plots of exiting farms

	2015	2016	2017	2018	2019
Total number of plots	1,652,414	1,640,791	1,629,202	1,621,922	1,612,320
Plots of exiting farms	19,659	21,838	19,691	19,760	–
New plots in sample	–	5,658	5,230	5,172	8,676
Total agricultural area	31,939	32,219	32,172	32,092	31,991
Area of exiting farms	286	331	322	308	–
Area new plots in sample	–	37	39	28	52

Notes: Areas are given in km^2. Information on the cultivated area of exiting farms are given for the year prior to market exit. All plots are classified as *new plots*, if they appear in the sample the first time since 2015.

The second stylized fact is related to the process of how farms exit the market. This process is characterized by a relatively constant area under cultivation in the years prior to market exit. This hypothesis is supported by a regression of the growth rates of farms leaving the market before they exit, as reported in Table 5. The first regression shows that exiting farms reduce their area under cultivation by 1.4 %, 2.1 % and 4.5 % in the

[11]Gross exit rates of farms are higher (about 2 % per year), because exiting farms are smaller on average.

[12]If parts of a parcel are rezoned and the remaining plot is less than half the size of the original parcel, that parcel is considered a new plot. See Appendix A for details.

three years before they leave the market. Focusing on the farms that exit in 2018 (i.e. between 2018 and 2019), where we are able to observe growth rates for all three years prior to market exit, gives very similar results. Thus, farms do not continuously become smaller, but reduce their area under cultivation only marginally and exit in an abrupt way.

Table 5: Growth rates of exiting farms prior to market exit

	entire sample	farms exiting in 2018
1 year before exit	-0.045^{***}	-0.040^{***}
	(0.002)	(0.004)
2 years before exit	-0.021^{***}	-0.022^{***}
	(0.003)	(0.004)
3 year before exit	-0.014^{***}	-0.014^{***}
	(0.004)	(0.004)
Observations	12,313	6,036
R^2	0.032	0.023

Notes: Regressions estimate growth rates of farms that exit between 2015 and 2019 (first column) or in 2019 (second column). Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

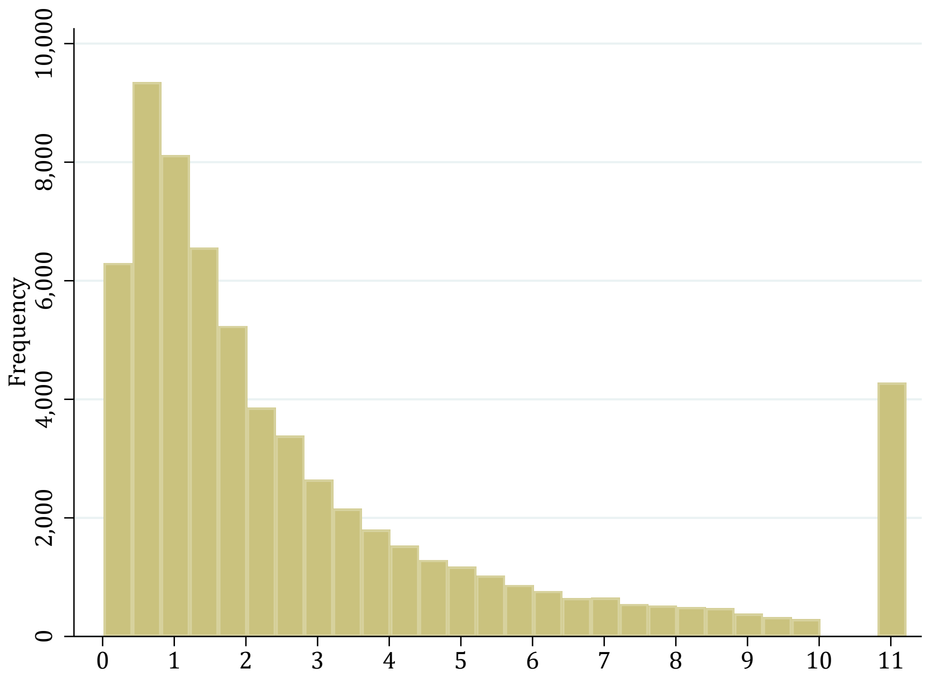
3.2 Descriptive evidence

In most cases, the plots of exiting farms are taken over by farms in the immediate vicinity. The distribution of the distances between these plots and the buyer farms' farmsteads, $dist_{ieb}^{plot \rightarrow farm}$, are illustrated in Figure 3 and show that in more than 81 % of all transactions the distances are below 5 km. We thus restrict the analysis to plots with a distance $dist_{ieb}^{plot \rightarrow farm}$ of up to 5 km to the buyer farm for computational reasons. All farms within a radius of 5 km from the respective plot are considered as prospective buyer farms.

The distribution of distances of non-buyer farms (among prospective buyers) is contrasted with the distances of buyer farms in Figure 4. The number of non-buyer farms increases with distance from the plots of exiting farms, since the area where farms could be located increases with distance,[13] except at the very end (due to data truncation). The density function of the buyer farms' distances is strikingly different, peaking at a distance of less than 1 km. About two thirds of the buyer farms are located within 2 km distance of the respective plots. This descriptive evidence suggests that proximity is a key determinant in evaluating which farm will prevail on the land market.

[13]This is the main reason for restricting the prospective buyer farms to a distance of up to 5 km. If we double the distance to 10 km, the number of prospective buyer farms would quadruple.

Figure 3: Distances between plots of exiting farms and buyer farms



Notes: The histogram shows the distribution of distances (in kilometers) between plots of exiting farms and farmsteads of buying farms ($dist_{ieb}^{plot \to farm}$). Distances larger than 10 km are set to 11.

3.3 Main results

The main results of conditional logit models on the determinants of takeovers are reported in Table 6. The first specification includes only the three distance variables, namely the distance between the plot of the exiting farm and the farmstead of the prospective buyer farm, $dist_{ieb}^{plot \to farm}$, the distance between the plot of the exiting farmer and the closest plot of the prospective buyer, $dist_{ieb,t-1}^{plot \to plot}$, and the distance between the exiting and the prospective buyer's farmsteads, $dist_{ieb}^{farm \to farm}$. Model (2) includes additional variables on farm and farmer characteristics, as well as information on workforce composition. In specification (3), the variable $dist_{ieb,t-1}^{plot \to plot}$ measures the distance to the potential buyer's closest plot with the same land use type as the exiting farm's plot.

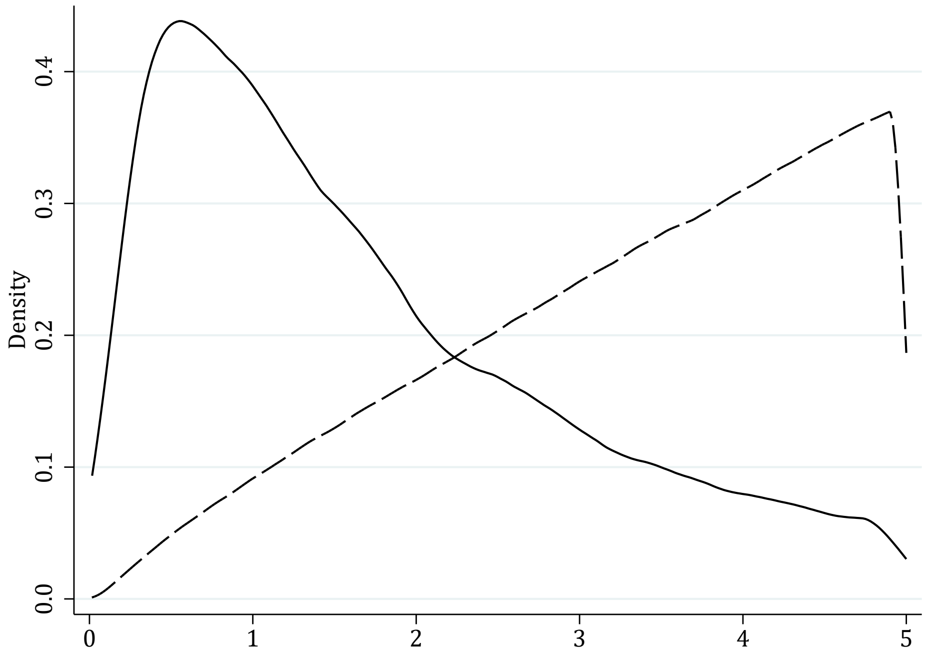
The distance between the plot of the exiting farmer and the closest plot of the prospective buyer, $dist_{ieb,t-1}^{plot \to plot}$, has a large and statistically significant negative influence on the farm takeover probabilities. In contrast, the parameter estimates on the distance between the plot of the exiting farm and the farmstead of the prospective buyer farm, $dist_{ieb}^{plot \to farm}$, are much smaller (in absolute terms) and even have a positive sign in the sparse Model (1). It appears that distance to the nearest prospective buyer's plot is a much better indicator of a farmer's cost of farming the plot than the distance to the prospective buyer's farmstead. Proximity between the exiting and the prospective buyer farm's farmsteads, $dist_{ieb}^{farm \to farm}$, also turns out to be an important determinant. The magnitude of the estimated parameters is quite large (although somewhat smaller compared to the effects

Table 6: Regression results on takeover

	Model (1)	Model (2)	Model (3)
Distances			
$dist_{ieb}^{plot \to farm}$ (in log)	0.095***	−0.119***	−0.197***
	(0.016)	(0.018)	(0.019)
$dist_{ieb,t-1}^{plot \to plot}$ (in log)	−1.085***	−0.929***	−0.889***
	(0.009)	(0.010)	(0.011)
$dist_{eb}^{farm \to farm}$ (in log)	−0.668***	−0.658***	−0.645***
	(0.008)	(0.009)	(0.010)
Farm characteristics			
# of plots		0.013***	0.014***
		(0.000)	(0.000)
Area (in km^2)		0.113***	0.129***
		(0.020)	(0.020)
Share area same use		0.801***	0.724***
		(0.040)	(0.047)
Farmer characteristics			
Age		−0.022***	−0.023***
		(0.001)	(0.001)
Female		−0.010	−0.016
		(0.018)	(0.019)
Basic education		0.329***	0.321***
		(0.022)	(0.022)
Advanced education		0.319***	0.307***
		(0.022)	(0.022)
Recent qualification		0.162***	0.173***
		(0.017)	(0.018)
Workforce (reference: owner)			
Workforce (FTE)		0.045***	0.055***
		(0.005)	(0.005)
Share spouse		−0.037	−0.023
		(0.045)	(0.046)
Share child		0.904***	0.867***
		(0.052)	(0.053)
Share other family member		−0.966***	−0.981***
		(0.065)	(0.066)
Share non-family		−0.097*	−0.103*
		(0.054)	(0.057)
N	284,692	254,020	230,912

Notes: The table reports reports parameter estimates of a conditional logit model on the takeover of a plot. Standard errors are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1% level. Distance $dist_{ieb,t-1}^{plot \to plot}$ in Model (3) is calculated as the distance to the closest plot of farm b with the same type of use as plot i.

Figure 4: Distances of buyer farms and non-buyer farm in the vicinity



Notes: The figure shows kernel density estimates on the distribution of distances (in kilometers) between plots of exiting farms and farmsteads of prospective buyer farms ($dist_{ieb}^{plot\to farm}$), separately for buyer farms (solid line) and non-buyer farms (dashed line). The graphs are based on an Epanechnikov kernel function.

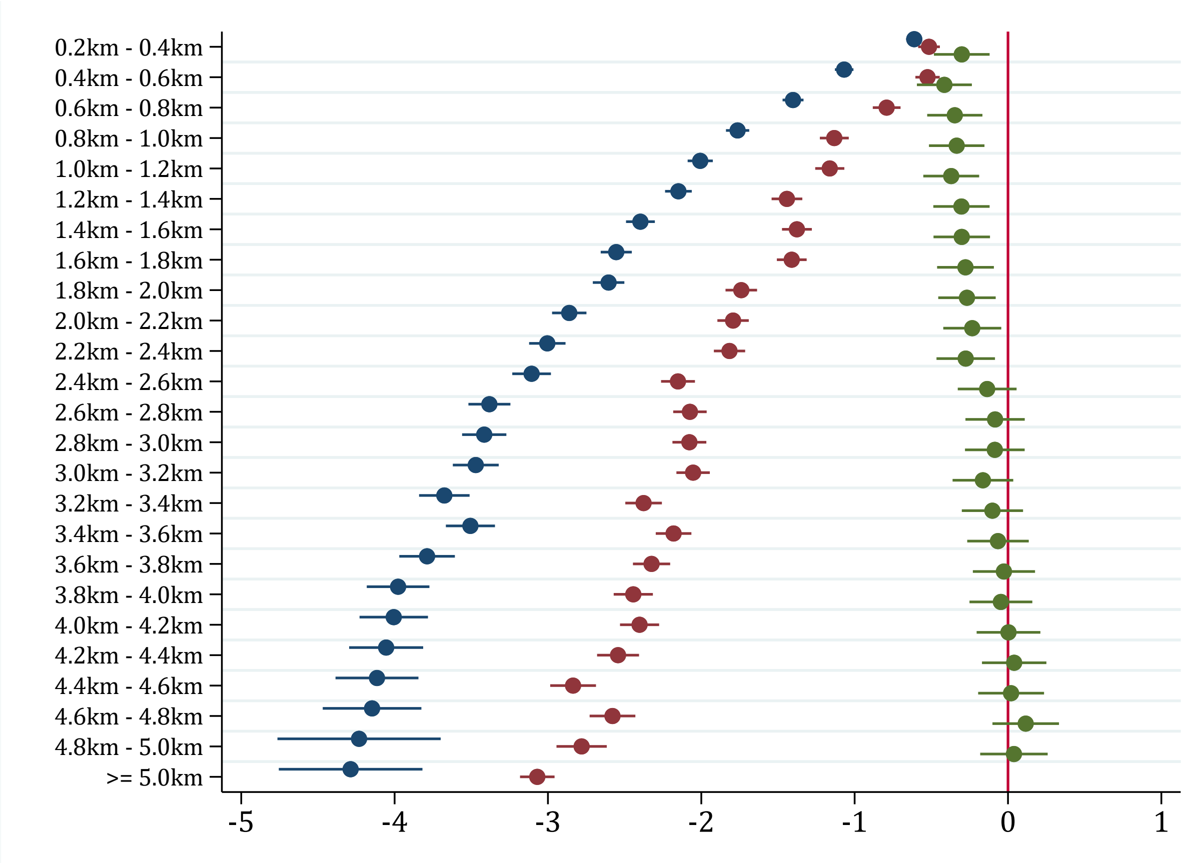
of $dist_{ieb,t-1}^{plot\to plot}$) and significantly negative in all specifications.

The parameter estimates for farm and farmer characteristics have the expected signs. In general, larger farm (as measured by the number of cultivated plots and the total acreage) are more likely to buy a particular plot. If the prospective buyer farm has a larger share of cultivated area with the same type of use as the corresponding plot of the exiting farm, takeovers are also more likely. The probability of takeovers increases if a farmer (i.e., farm manager) of the prospective buyer is younger, better educated (basic or advanced education compared to the reference category of only practical farming experience), and has received an additional qualification within the last year. The gender of the farmer has no significant influence on the transaction.

With respect to the composition of the farm workforce, we again find that larger farms (in this case, measured in terms of the number of full-time equivalent workers) are more likely to prevail on the land market. A larger share of the spouse, other family members, and non-family labor in the workforce (compared to the farmer as the reference category) tends to reduce the probability of taking over the plot in question (although not all parameter estimates are significantly different from zero). In contrast, a large labor force composed of the farmer's children makes takeovers more likely. This is a plausible result, as a child of the farmer working on the farm is an indicator of a potential successor within a family farm.

To investigate the relationship between takeover probabilities and distance more closely, we re-estimate a similar regression as Model (2), but relax the restrictions on the functional form of the distance variables. The distance variables $dist_{ieb}^{plot \rightarrow farm}$, $dist_{ieb,t-1}^{plot \rightarrow plot}$, and $dist_{ieb}^{farm \rightarrow farm}$ are translated into dummy variables for each 200 m bin. The parameter estimates on these dummy variables (along with the 95 % confidence intervals) are illustrated in Figure 5. The reference categories are distances below 200 m. The parameter estimates on the dummy variables confirm the results reported in Table 6: The distance between the plot under consideration and the closest plot of the prospective buyer farm, $dist_{ieb,t-1}^{plot \rightarrow plot}$, has the strongest (negative) influence on takeover probabilities. In contrast, the estimated coefficients for $dist_{ieb}^{plot \rightarrow farm}$ are small, and significantly different from zero for some dummy variables only. The effect of a larger distance between the farmsteads, $dist_{ieb}^{farm \rightarrow farm}$, is again significantly negative, but a bit smaller (in absolute terms) compared to the influence of $dist_{ieb,t-1}^{plot \rightarrow plot}$.

Figure 5: Effect of distances on farms' takover probabilities



Notes: The figure shows the parameter estimates of the dummy variables for the distance variables, along with the 95 % confidence intervals. Distances are discretized in 200 m bins. Green dots indicate the parameter estimate on the distance between the plot of the exiting farm and the farmstead of the potential buyer farm ($dist_{ieb}^{plot \rightarrow farm}$). Blue dots denote the effects of distance between the plot of the exiting farm and the closest plot of the prospective buyer farm ($dist_{ieb,t-1}^{plot \rightarrow plot}$), and red dots indicate the coefficients of the distance between the farmsteads of both farms ($dist_{eb}^{farm \rightarrow farm}$).

4 Sensitivity analysis

We provide a series of sensitivity analyses to show that our results are not driven by the way we select our sample, to investigate sub-samples of all observed transactions, and to analyze the effects of additional control variables. In general, the results of these robustness checks support the findings of the main specifications, reported and discussed in Section 3.3.

In Table 7, we report regression results with a different number non-buyer farms in the sample and contrast the results with our main regression Model (2), where we include five non-buyer farms. In Model (4), we include less (only one) non-buyer farms, and in specification (5) we include more, namely ten.[14] With only one non-buyer farm in the sample, the results are quite similar, although $dist_{eb}^{farm \rightarrow farm}$ increases somewhat at the expense of $dist_{ieb}^{plot \rightarrow farm}$ (in absolute terms). The standard errors increase due to a smaller number of observations, and the parameters are thus less precisely estimated. In Model (5), where we include a larger number of non-buyer farms, the standard errors are a bit smaller, while the parameter estimates are very similar compared to Model (2). Very similar parameter estimates, irrespective of the size of the non-chosen alternatives (i.e. non-buyer farms), suggests that the independence of irrelevant alternatives (IIA) assumption holds in our application. Consequently, conditional logit regressions yield consistent parameter estimates, even when we restrict the number of non-buyer farms in the sample, justifying our approach.

In the main specification, we include only farms with farmsteads within a 5 km distance to the plot of an exiting farm (i.e., $dist_{ieb}^{plot \rightarrow farm} \leq 5\,\text{km}$). In specification (6), we start with the sample of our main Model (2), but exclude all the farms where any of the other distance measures $dist_{ieb,t-1}^{plot \rightarrow plot}$ or $dist_{eb}^{farm \rightarrow farm}$ is larger than 5 km. Again, the results are hardly affected by this modification, as reported in the final specification in Table 7.

In Table 8, we distinguish whether the farm exiting the market was the owner or the tenant of the respective plot, and whether the farm taking over the plot buys or leases the parcel. The results are not sensitive to whether the exiting farm was the owner (Model (7)) or the tenant of the plot (Model (8)). In contrast, the distance to the nearest plot of the farm taking over the parcel, $dist_{ieb,t-1}^{plot \rightarrow plot}$, is more important if the respective farmer buys the land. If the new farmer buys the land, the results are very similar, irrespective of restricting the sample to exiting farms owning the land (Model (11)) or not (specification (9)). The parameter estimate for $dist_{ieb,t-1}^{plot \rightarrow plot}$ is substantially smaller if the farm takes over the parcel as a tenant (Model (10)). Low production costs are therefore more important for (long-term) decisions to purchase agricultural land than for (short-term) decisions to lease land.

[14]We select the non-buyer farms randomly, but ensure that for each transaction the group of non-buyer farms do not overlap in the different specifications reported in Table 7.

Table 7: Regression results on takeover with alternative size of control group

	Model (2)	Model (4)	Model (5)	Model (6)
Distances				
$dist_{ieb}^{plot\rightarrow farm}$ (in log)	-0.119^{***}	-0.062^{*}	-0.143^{***}	-0.081^{***}
	(0.018)	(0.033)	(0.015)	(0.019)
$dist_{ieb,t-1}^{plot\rightarrow plot}$ (in log)	-0.929^{***}	-0.948^{***}	-0.914^{***}	-0.915^{***}
	(0.010)	(0.019)	(0.008)	(0.011)
$dist_{eb}^{farm\rightarrow farm}$ (in log)	-0.658^{***}	-0.742^{***}	-0.627^{***}	-0.656^{***}
	(0.009)	(0.019)	(0.008)	(0.010)
Farm characteristics				
# of plots	0.013^{***}	0.016^{***}	0.012^{***}	0.014^{***}
	(0.000)	(0.001)	(0.000)	(0.000)
Area (in km^2)	0.113^{***}	0.031	0.011	0.171^{***}
	(0.020)	(0.032)	(0.013)	(0.023)
Share area same use	0.801^{***}	1.024^{***}	0.811^{***}	0.753^{***}
	(0.040)	(0.066)	(0.034)	(0.042)
Farmer characteristics				
Age	-0.022^{***}	-0.017^{***}	-0.023^{***}	-0.023^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Female	-0.010	-0.058^{*}	0.011	-0.003
	(0.018)	(0.031)	(0.016)	(0.019)
Basic education	0.329^{***}	0.255^{***}	0.343^{***}	0.324^{***}
	(0.022)	(0.036)	(0.019)	(0.023)
Advanced education	0.319^{***}	0.329^{***}	0.359^{***}	0.319^{***}
	(0.022)	(0.036)	(0.019)	(0.023)
Recent qualification	0.162^{***}	0.135^{***}	0.159^{***}	0.157^{***}
	(0.017)	(0.030)	(0.015)	(0.018)
Workforce (reference: owner)				
Workforce (FTE)	0.045^{***}	0.048^{***}	0.049^{***}	0.051^{***}
	(0.005)	(0.009)	(0.003)	(0.005)
Share spouse	-0.037	0.062	0.097^{**}	0.017
	(0.045)	(0.076)	(0.039)	(0.047)
Share child	0.904^{***}	0.823^{***}	0.891^{***}	0.927^{***}
	(0.052)	(0.090)	(0.043)	(0.055)
Share other family member	-0.966^{***}	-0.833^{***}	-0.855^{***}	-0.950^{***}
	(0.065)	(0.106)	(0.056)	(0.067)
Share non-family	-0.097^{*}	-0.041	-0.060	-0.119^{**}
	(0.054)	(0.091)	(0.046)	(0.058)
Number of observations (N)	254,020	83,982	463,947	219,509
Number of transactions	41,991	43,870	43,863	40,897

Notes: The table reports reports parameter estimates of a conditional logit model on the takeover of a plot. Standard errors are reported in parentheses. * significant at 10 %, ** significant at 5 %, *** significant at 1 % level. Control group of non buying farms is restricted to five in Model (2), to one in Model (4) and to ten in Model (5). In Model (6), the group of prospective buyers comprises also five non-buyer farms, but farms with a distance $dist_{ieb,t-1}^{plot\rightarrow plot} > 5\,\mathrm{km}$ or $dist_{eb}^{farm\rightarrow farm} > 5\,\mathrm{km}$ are excluded from the analysis.

Table 8: Regression results on takeover depending on ownership status

	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)
Distances					
$dist_{ieb}^{plot\rightarrow farm}$ (in log)	−0.087***	−0.265***	−0.019	−0.108***	−0.032
	(0.022)	(0.033)	(0.048)	(0.023)	(0.055)
$dist_{ieb,t-1}^{plot\rightarrow plot}$ (in log)	−0.960***	−0.862***	−1.257***	−0.868***	−1.222***
	(0.012)	(0.019)	(0.028)	(0.013)	(0.031)
$dist_{eb}^{farm\rightarrow farm}$ (in log)	−0.621***	−0.728***	−0.674***	−0.667***	−0.632***
	(0.012)	(0.015)	(0.024)	(0.012)	(0.028)
Farm characteristics					
# of plots	0.015***	0.011***	0.005***	0.014***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Area (in km^2)	0.169***	0.084**	0.071	0.146***	0.082
	(0.025)	(0.033)	(0.051)	(0.026)	(0.060)
Share area same use	0.745***	0.952***	0.617***	0.929***	0.540***
	(0.046)	(0.079)	(0.106)	(0.051)	(0.117)
Farmer characteristics					
Age	−0.024***	−0.015***	−0.011***	−0.023***	−0.013***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
Female	−0.013	−0.013	−0.176***	0.048**	−0.230***
	(0.022)	(0.037)	(0.050)	(0.023)	(0.056)
Basic education	0.292***	0.430***	0.477***	0.290***	0.495***
	(0.026)	(0.043)	(0.061)	(0.028)	(0.068)
Advanced education	0.327***	0.289***	0.522***	0.259***	0.530***
	(0.026)	(0.043)	(0.061)	(0.027)	(0.068)
Recent qualification	0.146***	0.179***	0.261***	0.111***	0.225***
	(0.020)	(0.034)	(0.049)	(0.022)	(0.054)
Workforce (reference: owner)					
Workforce (FTE)	0.051***	0.023**	0.029*	0.045***	0.026
	(0.006)	(0.011)	(0.016)	(0.006)	(0.017)
Share spouse	−0.026	−0.109	−0.138	−0.000	−0.304**
	(0.053)	(0.090)	(0.127)	(0.057)	(0.142)
Share child	0.942***	0.745***	0.933***	0.925***	1.048***
	(0.061)	(0.103)	(0.144)	(0.065)	(0.160)
Share other family member	−1.061***	−0.591***	−0.885***	−0.928***	−0.816***
	(0.076)	(0.128)	(0.179)	(0.082)	(0.196)
Share non-family	−0.146**	−0.032	0.158	0.076	0.193
	(0.065)	(0.101)	(0.147)	(0.067)	(0.166)
N	186,611	65,570	48,873	149,154	38,400
Ownership status					
Seller	owner	tenant	both	both	owner
Buyer	both	both	owner	tenant	owner

Notes: The table reports reports parameter estimates of a conditional logit model on the takeover of a plot. Standard errors are reported in parentheses. * significant at 10 %, ** significant at 5 %, *** significant at 1 % level.

In about half of all transactions, all plots of an exiting farm are taken over by a single farm. In the next sensitivity analysis we thus distinguish between these full takeovers (see Model (12) in Table 9) and transactions in which a farm takes over only a strict subset of all the parcels of the exiting farm (Model (13)). When a farm takes over all plots, the proximity between the farmsteads of the two farms' is more important. It seems plausible that personal and social ties (indicated by $dist_{eb}^{farm \to farm}$) are more important in the case of complete takeovers.

In the final sensitivity analysis, we include information from the accounting data. We have to restrict the observations to transactions (i) where the buyer farm and (ii) at least one non-buyer farms are covered by the FADN data. This reduces the size of the sample to 2,178 transactions with 12,317 prospective buyer farms. We first re-estimate the main Specification (see Model (2) in Table 6) with the reduced sample, as reported in the first column of Table 10. The parameter estimates for the distance variables $dist_{ieb,t-1}^{plot \to plot}$ and $dist_{eb}^{farm \to farm}$, for the number of plots cultivated by the prospective buyer farm and its share of the plot area with the same type of use have the same signs and are similar in magnitude to those in the main specification. Interestingly, the area under cultivation is not significantly different from zero, while the distance between the plot in question and the prospective buyer farm's farmstead is significantly positive.

When variables based on accounting data are included, as in Model (15), we control for the same farm and farmer characteristics considered in previous regressions, except for the number of plots and the total area under cultivation (as there are similar variables in the FADN data). The coefficients on variables included in both regressions are very similar. Accounting data indicating the size of a prospective buyer farm (area under cultivation, aggregated inputs) again suggest that larger farms are more likely to takeover plots of exiting farms. Coefficients on livestock and yield, on the other hand, are not significantly different from zero. Depreciation of buildings has a positive impact on the probability of takeover, while depreciation of machinery has no influence. These results suggest that high capital stock is important, but only capital stock of long-term investments (in buildings).

The area leased by the farmer has no effect on takeover probabilities, while the parameter estimate for the area owned by the prospective farmer is significantly negative. Two reasons can be given for this result. First, the area owned by the prospective buyer includes not only cultivated plots, but also parcels leased to other farmers. When controlling for leased farmland and total acreage (as done in Model (15)), owned farmland is an indicator for plots leased to other farmers. Second, in most transactions (54 %), the transaction is characterized by the retiring farmer owning the parcel while the farmer takes over the cultivation of the parcel as a tenant.[15] In about 41 % of transactions, the old and new farmer have the same legal status, so the owner either sells the parcel to the

[15]We do not observe the owner of the parcel in this case. Most likely, the owner of the exiting farm retains ownership of the parcel.

Table 9: Regression results on full vs. partial takeover of farms

	Model (12)	Model (13)
Distances		
$dist^{plot \rightarrow farm}_{ieb}$ (in log)	0.108***	−0.279***
	(0.029)	(0.024)
$dist^{plot \rightarrow plot}_{ieb,t-1}$ (in log)	−0.930***	−0.929***
	(0.016)	(0.013)
$dist^{farm \rightarrow farm}_{eb}$ (in log)	−0.792***	−0.581***
	(0.016)	(0.012)
Farm characteristics		
# of plots	0.015***	0.012***
	(0.001)	(0.001)
Area (in km^2)	0.102***	0.124***
	(0.031)	(0.026)
Share area same use	0.718***	0.898***
	(0.056)	(0.056)
Farmer characteristics		
Age	−0.021***	−0.023***
	(0.001)	(0.001)
Female	−0.043	0.016
	(0.027)	(0.025)
Basic education	0.333***	0.323***
	(0.032)	(0.030)
Advanced education	0.351***	0.289***
	(0.032)	(0.030)
Recent qualification	0.105***	0.207***
	(0.026)	(0.023)
Workforce (reference: owner)		
Workforce (FTE)	0.043***	0.047***
	(0.007)	(0.006)
Share spouse	−0.141**	0.059
	(0.067)	(0.061)
Share child	0.931***	0.885***
	(0.076)	(0.072)
Share other family member	−0.802***	−1.144***
	(0.092)	(0.093)
Share non-family	0.112	−0.252***
	(0.080)	(0.073)
N	112,774	141,246

Notes: The table reports reports parameter estimates of a conditional logit model on the takeover of a plot. Standard errors are reported in parentheses. * significant at 10 %, ** significant at 5 %, *** significant at 1 % level. Model (12) restricts the sample to plots where all plots of the exiting farm are taken over by one farm. Model (13) restricts the sample to plots where the plots of the exiting farm are taken over by (at least two) different farms.

buyer farm or both farms cultivate the land as tenants in consecutive years.[16] Thus, farm growth is usually accompanied by an increasing share of leased land. This explanation is also consistent with the finding that farms with a higher equity ratio are less likely to take over land from exiting farms.

5 Conclusions

In this article, we investigate competition on the agricultural land market. Arable land is a scarce and immobile input, and the costs of cultivating land depends on the distance of the farmer to the corresponding plot. We are able to utilize extremely rich data on both farms and plots, and can therefore investigate transactions of plots of farms that leave the market entirely. Two stylized facts guide our analysis: Converting raw to arable land is not a large-scale option, and farms leave the market in an abrupt way (i.e. they cultivate a rather stable area prior to market exit). Since farms remaining in the market have little ability to influence competing farms' decisions to exit, farm exits can be viewed as relatively exogenous events. These exogenous shocks give farms an opportunity to increase their acreage, and consequently farm exits are an important precondition for farms to grow.

Larger farms that cultivate a higher share of land with the same type of use and are managed by younger and better educated farmers have a better chance of succeeding in the land market. Most importantly for our analysis, a short distance between the plot in question and the prospective buyer farm is of key importance. Two findings are particularly interesting: First, the distance between the plot under consideration and the closest parcel of the prospective buyer farm is an important determinant, while the distance between the plot and the farmstead of the prospective buyer is less relevant. This result suggests that the distance to the closest plot of the farm taking over the parcel is a good indicator of the cost of farming this plot, while the distance to the farmstead is less important. Farmers therefore strive to farm as compact an area as possible (rather than scattered plots). Second, the distance between the farmsteads of the exiting farm and the prospective buyer is also important. This variable does not influence production costs, but a short distance between the farmsteads makes personal or social ties between the two farmers more likely. The effect of this variable on the takeover probability can be interpreted as an indication of information frictions in the agricultural land market.

A limitation of the present analysis is that we have no information on transaction prices (rents or land prices). We thus cannot evaluate whether the seller or the buyer benefits from these information frictions. Furthermore, we interpret proximity between the farmsteads of two farms as an indicator of personal or social ties. It would be inter-

[16] In only 5 % of all transaction, the new farmer owns the plot that the exiting farmer cultivated as a tenant.

Table 10: Regression results on takeover with accounting data

	Model (14)	Model (15)
Distances		
$dist_{ieb}^{plot \to farm}$ (in log)	0.648***	0.617***
	(0.074)	(0.082)
$dist_{ieb,t-1}^{plot \to plot}$ (in log)	−0.903***	−0.901***
	(0.042)	(0.044)
$dist_{eb}^{farm \to farm}$ (in log)	−0.810***	−0.822***
	(0.042)	(0.046)
Farm characteristics		
# of plots	0.013***	
	(0.003)	
Area (in km^2)	0.009	
	(0.174)	
Share area same use	0.864***	0.397*
	(0.191)	(0.220)
Farm characteristics (based on accounting data)		
Area cultivated (in log)		0.559***
		(0.169)
Area owned (in log)		−0.232**
		(0.105)
Area leased (in log)		0.034
		(0.076)
Depreciation buildings (in log)		0.223***
		(0.066)
Depreciation machinery (in log)		−0.050
		(0.073)
Yield (in Euro, in log)		0.101
		(0.128)
Input (standardized, in log)		0.378***
		(0.100)
Livestock (standardized, in log)		0.026
		(0.032)
Equity ratio		−0.006***
		(0.002)
Farmer characteristics	yes	yes
Workforce	yes	yes
Number of observations (N)	12,317	12,317
Number of transactions	2,178	2,178

Notes: The table reports reports parameter estimates of a conditional logit model on the takeover of a plot. Standard errors are reported in parentheses. * significant at 10 %, ** significant at 5 %, *** significant at 1 % level. The sample is restricted to observations for which accounting data are available. Besides sample size, Model (14) is identical to the main Model (2), reported in Table 6. Model (15) includes dummy variables for the case when accounting data are only available for a previous year (depending on the time lag). If the variable values (in levels) in Model (15) are zero, the logarithmized values are set to zero and a corresponding dummy variable is included.

esting to incorporate data on actual contacts between farmers, like family ties or joint memberships in agricultural associations. However, these issues must be left to future research.

References

Balmann, A. (1997). Farm-based modelling of regional structural change: A cellular automata approach. *European Review of Agricultural Economics*, 24(1):85 – 108.

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.

BMLFUW (2016). Grüner Bericht 2015. Technical report, Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft.

Cotteleer, G., Gardebroek, C., and Luijt, J. (2008). Market power in a gis-based hedonic price model of local farmland markets. *Land Economics*, 84(4):573–592.

Freeman, T., Nolan, J., and Schoney, R. (2009). An agent-based simulation model of structural change in Canadian prairie agriculture, 1960-2000. *Canadian Journal of Agricultural Economics*, 57(4):537 – 554.

Happe, K., Balmann, A., Kellermann, K., and Sahrbacher, C. (2008). Does structure matter? The impact of switching the agricultural policy regime on farm structures. *Journal of Economic Behavior and Organization*, 67(2):431 – 444.

Happe, K., Schnicke, H., Sahrbacher, C., and Kellermann, K. (2009). Will they stay or will they go? Simulating the dynamics of single-holder farms in a dualistic farm structure in Slovakia. *Canadian Journal of Agricultural Economics*, 57(4):497 – 511.

Huettel, S. and Margarian, A. (2009). Structural change in the West German agricultural sector. *Agricultural Economics*, 40:759 – 772.

Irwin, E. G. and Geoghegan, J. (2001). Data, methods: Developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment*, 85(1 - 3):7 – 24.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., editor, *Frontiers in Econometrics*, chapter 4, pages 105–142. Academic Press, New York.

Nelson, G. C. (2002). Introduction to the special issue on spatial analysis for agricultural economists. *Agricultural Economics*, 27(3):197 – 200.

Pelkey, N., Stoner, C., and Caro, T. (2000). Vegetation in Tanzania: Assessing long term trends and effects of protection using satellite imagery. *Biological Conservation*, 94(3):297 – 309.

Plogmann, J., Mußhoff, O., Odenig, M., and Ritter, M. (2020). Farm growth and land concentration. *FORLand - Working Paper 24*.

Reindl, A., Resl, T., and Triebl, C. (2016). Entwicklung der Anzahl land- und forstwirtschaftlicher Betriebe in Österreich über die Zeit. In *Grüner Bericht 2016*, volume 57, pages 60–61. BMLFUW (Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft).

Robertson, D. M., Saad, D. A., and Heisey, D. M. (2006). A regional classification scheme for estimating reference water quality in streams using land-use-adjusted spatial regression-tree analysis. *Environmental Managemen*, 37(2):209 – 229.

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.

Train, K. E. (2009). *Discrete Choice Methods with Simulation.* Cambridge University Press, New York, second edition.

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.

Appendix A Linking plots over time

There are two challenges with linking plots over time. First, there is no time-invariant plot ID; instead, each plot ID is composed of the (unique and time-invariant) farm ID and a sequential number of all plots of the respective farm. Therefore, plot IDs may change over time, and this is certainly the case if the farmer cultivating the plot changes. Second, the geographical shape of the parcel may change. We use geo-referenced data, available as maps, to identify the plots over time in order to create a panel. Linking the plots was done by intersecting the geo-referenced plots over consecutive years, as explained below. All calculations were performed with the program *R* and, more specifically, with the package *sf* (version 0.9.4).

In a first step, the centers (central points) of the plots are calculated. These centers differ from the centroids to ensure that the centers are always within the polygon of the plot (*R function: sf::st_point_on_surface*). In a second step, the centers of one year are intersected with the polygons of the plots of the following year. Similarly, the centers of the plots of the following year were intersected with the polygons of the plots of the year under investigation. Finally, we compare the size of the plots that were linked in some way by this procedure. By intersecting the data in both directions in time, several possible relationships between the plots can be identified, depending on the number of matches and the size of the plots. Each plot can thus be classified into 7 mutually exclusive categories:

1. There is a one-to-one relationship between the plots in consecutive years, and the plots are of the same size (i.e. the difference in the size of the plots is less than 5 % of the original size of the plot).

2. There is a one-to-one relationship between the plots according to their locations, but the size of the plots has changed by more than 5 % (but less than 50 %).

3. The plot has been combined with other parcels to form a larger plot, and the aggregated size of the individual plots is the same as the size of the combined plot (i.e. the difference is less than 5 %).

4. The plot has been divided into two or more smaller plots, and the size of the original plot is the same as the aggregated size of the divided plots (i.e. the difference is less than 5 %).

5. There is no clear relationship between the plots in consecutive years (e. g. three plots have been combined and split in a different way at the same time).

6. The plot lies fallow for at least a year and does not show up in the data at a later date (or with a more than 50 % change in size).

7. The area lies fallow for at least a year, but reappears in the data later (with a change in size of less than 50 %).

The number of plots in each category are reported in Table A1. This table shows that we are able to find a one-to-one relationship (category 1) for about 93 % of all plots over the entire sample period. For nearly 98 % of all plots (category 1-3) we are able to unambiguously identify which farmer cultivates the plot in the consecutive year. We therefore use all plots in the categories 1-3 for the empirical analysis.

Table A1: Number of plots in each category

Category	2015-2016		2016-2017		2017-2018		2018-2019	
	plots	perc.	plots	perc.	plots	perc.	plots	perc.
1	1,499,706	90.76	1,529,760	93.23	1,535,392	94.24	1,517,763	93.58
2	73,696	4.46	39,906	2.43	36,600	2.25	41,441	2.56
3	26,833	1.62	32,702	1.99	23,782	1.46	26,788	1.65
4	7,487	0.45	8,397	0.51	7,560	0.46	7,911	0.49
5	28,619	1.73	16,726	1.02	14,278	0.88	15,381	0.95
6	12,894	0.78	11,652	0.71	10,669	0.65	12,638	0.78
7	3,179	0.19	1,648	0.10	921	0.06	0	0.00
Total	1,652,414	100	1,640,791	100	1,629,202	100	1,621,922	100