Farmland sales under return and price uncertainty

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Abstract

This paper seeks to explain liquidity in farmland markets. Focusing on supply, we adopt a real options model that determines the value of the opportunity to sell farmland. A proportional hazard model is applied to estimate the duration between land sales in Germany. We find that the influence of the correlation between land prices and returns and their drift rates are in line with theoretical expectations; the effect of volatility is ambiguous. This implies that if owning and renting land are not perfect substitutes, higher liquidation values are required to trigger land sales, which amplifies the sluggishness of farmland markets.

Keywords: farmland supply; land market liquidity; land price uncertainty; real options model; duration model

JEL classification: C41; G12; Q15

1 Introduction

It is well-known that agricultural land markets are thin. In Europe, less than one percent of the farmland was sold each year in most Member States between 2005 and 2015 (Loughrey et al., 2020). Likewise, in the US the amount of farmland transferred between 2015 and 2019 is expected to be ten percent, yet less than one percent per year is expected to be sold between non-relatives (USDA-NASS, 2015). Poor liquidity is a characteristic of many real estate markets and is related to immobility and extreme heterogeneity of this asset class, causing high search and transaction costs (Bigelow et al., 2020; Delbecq et al., 2014; Lence, 2001). While these figures are rather stable at the aggregated level, it is noteworthy that land market liquidity exhibits considerable spatial and temporal variability at the local level (Kionka et al., 2021). Figure 1 shows temporal variability by illustrating that the likelihood to observe a transaction in Germany is 1.4 times higher in 2008 compared to 2018. This begs the question whether the heterogeneity of local land markets' liquidity is purely random or whether it can be explained by economic factors. Figure 1 shows a negative relation between land prices and land turnover: While prices increased significantly in the last decade, less farmland has been sold. This observation is in contrast to findings from real estate markets that postulate a positive price-volume relation (Stein, 1995; Wheaton, 1990).

Why is liquidity of farmland markets a relevant issue? In general, market liquidity is closely related to market efficiency: It describes the ability of market participants to realise desired buy or sell transactions without a time delay. In thin markets, sellers and buyers face the risk of either selling for a price lower than the "fundamental" value or paying a premium on top of it. Moreover, in thin markets, less information about current prices or values is available (Bigelow et al., 2020). Seifert et al. (2021) argue that market thinness entails bargaining power for market participants when negotiating about the sharing of land rents. As a result, land prices can deviate from competitive prices and may, in turn, convey incorrect information about the profitability of land. Thus, in thinly traded markets, prices may not fulfill their price discovery function (Adämmer et al., 2016). Moreover, from the viewpoint of expanding farms as well as financial investors, it would be desirable to understand when and where the supply of agricultural land is large and the chances of land acquisition are high. In fact, the availability of land is one of the most important drivers of structural change in agriculture (Saint-Cyr et al., 2019).

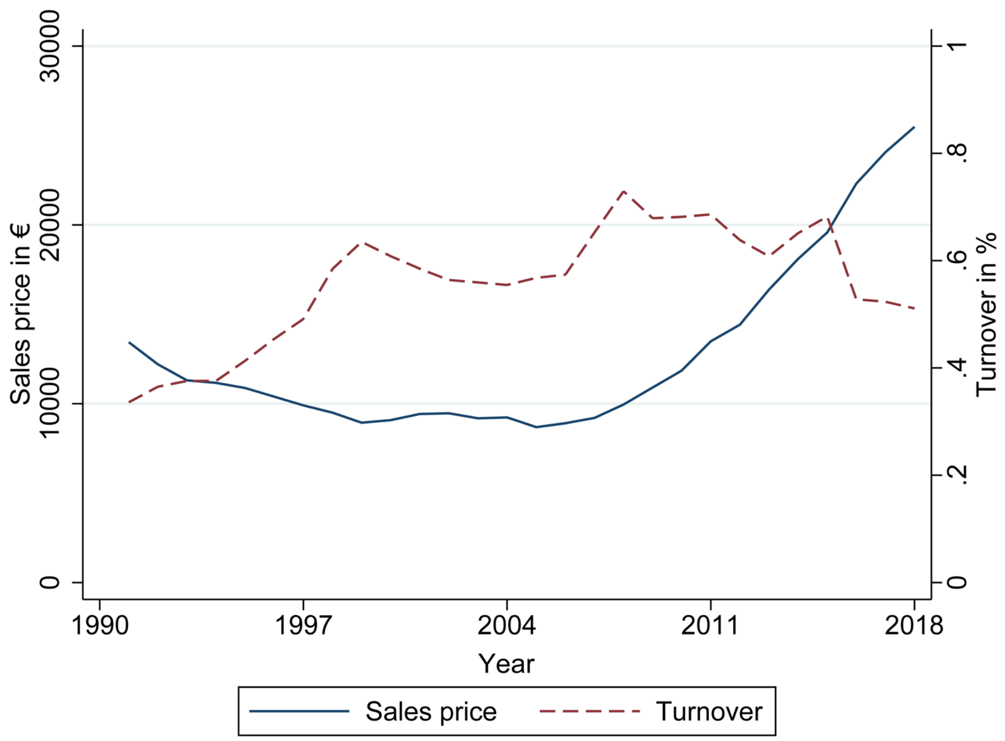

Figure 1. Sales prices and turnover (1991–2018) of agricultural land in Germany

Given its relevance, it is not surprising that land market activity has been analyzed theoretically and empirically. Nevertheless, the existing literature focuses on price formation rather than transaction volume or frequency. Transactions in land markets imply a match of potential buyers' willingness to pay and landowners' willingness to accept. A key for predicting the occurrence of land market transactions is thus the understanding of factors that determine the willingness of landowners to sell their land. From an economic perspective, landowners should sell if the liquidation value, i.e., the current land price, exceeds the present value of future returns of holding land, including land rents, returns from production and land appreciation.

The implementation of this simple rule, however, is challenging because it involves expectation formation and appropriate discounting (Goodwin et al., 2003). Observed land prices are often perceived as "too high" compared with the outcome of simple present value models (Falk, 1991; Moss, 1997). Moreover, it is puzzling why landowners are reluctant to sell land. Several proposals have been made in the literature to rationalise such behaviour. Adelaja et al. (2010) provide evidence for land hoarding in the U.S., i.e. landowners retain land for future sales and explain this phenomenon by land values appreciating faster than the riskless rate of return. Brown and Brown (1984) show that heterogeneous expectations on farmland prices increase the reservation prices of landowners because of the possibility of finding a buyer who is more optimistic about future values than the present owner. Just and Miranowski (1993), Shiha and Chavas (1995) and Lence and Miller (1999) emphasise the role of transaction costs in farmland markets: Large costs of conferring property can drive a wedge between land prices and returns to land and cause a range of inaction in which land prices can vary without triggering sales.

An alternative approach for understanding inertia in land markets is to consider the opportunity to buy or sell land as a real option. Uncertainty about land prices and returns of owning land together with sunk costs and the flexibility to postpone the (dis)investment decision create a value of waiting that rationalises the reluctance to buy or sell land even though simple present value models may suggest this. Turvey (2003) estimates that for farmland in Ontario, the options value is 1.5 times higher than the present value of land returns and that actual market prices are close to the real options value. From the viewpoint of a seller, this implies that land prices should exceed the "fundamental value" considerably before a sale is triggered. The real options approach has also been used to value the opportunity to develop agricultural land for non-agricultural purposes. Focusing on the duration until development, Towe et al. (2008) show that the presence of a real option to preserve farmland delays the decision to develop farmland by about six years. Plantinga et al. (2002) estimate that development options values amount to 10 percent of land prices in the U.S. on average.

In this paper, we adopt the real options perspective to explain the reservation prices of landowners for selling their land. The contribution of our paper to the literature is twofold. First, we offer a microeconomic explanation of market liquidity, focusing on the supply side of the market. The real estate literature argues that the distribution of reservation prices in real estate markets evolves differently for potential buyers and sellers (Fisher et al., 2003, 2004; Mei, 2018). As a result, it is conjectured that market transactions occur more frequently in booming markets. However, assumptions about the shape and evolution of reservation prices are ad hoc and lack a microeconomic underpinning. In our paper, we model the decision to sell land explicitly and show how this disinvestment decision is related to land prices and price uncertainty. Our second contribution is the proposal of an empirical approach that allows tests of hypotheses that are derived from our theoretical model. Usually, empirical testing of real options models is based on observed (dis)investment decisions, which are explained by logit or probit models (e.g., Pieralli et al., 2017). In this paper, we use a duration model to predict the time until a stochastic rent-price ratio falls below a disinvestment trigger. Estimating first passage time is rather novel in the context of empirical real options models. It has the advantage that it is closely related to a market liquidity indicator, i.e., duration (Ametefe et al., 2016).

The remainder of this article is structured as follows: First, we present the theoretical framework applied to explain disinvestment behaviour of landowners. Subsequently, the empirical strategy explains the empirical implementation of the theoretical model. Lastly, the results of the empirical and theoretical model are discussed before drawing conclusions concerning the political implications of this paper.

2 Theoretical background: A real options model of farmland sales

Our theoretical framework is a real options model that considers the timing of land sales from the viewpoint of a landowner. The focus on landowners may appear restrictive because land transactions indicate a match of sellers' willingness to accept and buyers' willingness to pay and thus understanding land market liquidity requires the analysis of both sides of the market. In agricultural land markets, however, the number of potential buyers often exceeds the number of suppliers. Analysing 9,684 land transactions in eastern Germany, Croonenbroeck et al. (2020) report that an average of four bids are submitted in public land tenders and realised prices in public land tenders are above average. Likewise, Hobe and Musshoff (2021) find that bids in restricted land auctions exceed displayed reservation prices. The fact that land can be sold without discount on listing prices indicates that land markets are rather a seller's market.

Taking an investor perspective, we consider land as a financial asset and focus on profitability as the main determinant of land market transactions while other motives for holding land, such as recreational value or tradition, are ignored. We abstract from tract size and consider a unit sized land plot although in practice large plots are traded less frequently due to liquidity constraints of potential buyers. Moreover, we assume that land is homogeneous and traded at a unique price. This assumption is unrealistic given marked heterogeneity of this production factor, but it is not detrimental to our analysis because we do not strive for an analysis of price determinants. Relevant features of our model that capture important aspects of land market transactions are irreversibility of the sales decision, flexibility to determine the disinvestment time and uncertainty about future land returns and farmland values.

The model's objective is to determine option-based disinvestment triggers for landowners – farmers and other non-agricultural landowners– who face the choice of keeping or selling land. Keeping land generates a stochastic gross margin or a land rent R, while selling land yields a stochastic liquidation value L, i.e., the current land price.[1] Liquidation values and land returns are linked through arbitrage processes and are thus correlated; however, they are different entities because liquidation values incorporate transaction costs and present values of land rents are influenced by firm specific factors, such as production efficiency. Hence, we have to set up a real options model with two stochastic processes. Specifically, we assume that land rents R and liquidation values L follow geometric Brownian motions:

$$\frac{dR}{R} = \alpha_R dt + \sigma_R dz_R \tag{1}$$

and

$$\frac{dL}{L} = \alpha_L dt + \sigma_L dz_L \tag{2}$$

where α_R and α_L are the drift rates of the stochastic processes, σ_R and σ_L are their volatilities, dz_R and dz_L are the increments of a Wiener process and

$$E(dz_R^2)= dt, \qquad E(dz_L^2)=dt, \qquad E(dz_L dz_R)= \rho\, dt \tag{3}$$

with ρ denoting their correlation. Hence, both processes are assumed to be stochastically dependent. This stylized model is able to mimic basic empirical characteristics of land markets, such as non-stationarity of land prices and cash rents, however, it cannot entirely capture the complex relationship between both variables that has been discussed in the literature (Clark et al., 1993; Gutierrez et al., 2007; Plogmann et al., 2020).

At each instant, landlords decide whether to continue land operation or to sell the land irreversibly. The value of the option to disinvest F is a function of L and R. The disinvestment option is kept alive when either L is low or R is high and it is exercised when either R is sufficiently low for a given L or when L is sufficiently high for a given R. The Bellman equation for this optimal stopping problem is (Dixit, 1989):

$$F(R,L) = \max\left\{L, R + \frac{1}{1+r}\mathcal{E}[dF(R,L)]\right\} \tag{4}$$

where r denotes the risk adjusted discount rate. We assume that r exceeds the drift rate α_R to ensure a positive and finite present value of land returns. The abandonment option value F satisfies the Hamilton-Jacobi-Bellman equation:

$$RF_R\alpha_R + LF_L\alpha_L + \frac{1}{2}(F_{RR}\sigma_R^2R^2 + 2\rho\sigma_L\sigma_R F_{RL}RL + F_{LL}\sigma_L^2L^2) - rF + R = 0 \tag{5}$$

Eq. (5) is a partial differential equation that depends on both R and L and the optimal stopping region is defined by a free boundary. To reduce the dimension of the problem and to arrive at an analytical solution, we follow McDonald and Siegel (1986) and consider the ratio of returns and liquidation value, i.e., the rent-price ratio. When doing so, we take advantage of the natural homogeneity of the problem: Doubling the current values of R and L will double the value of

[1] Land prices are not only related to returns from agricultural land use but also to non-agricultural use, particularly in the urban fringe (Borchers et al., 2014; Capozza & Helsley, 1989). The switch from agricultural to non-agricultural land use can be considered as a development option, which is not the focus of this paper.

the option and the liquidation value. Thus, the optimal stopping problem depends on the ratio of both stochastic processes $D = R/L$. The value of the option $F(R, L)$ can be stated as a homogeneous function of degree 1:

$$F(R, L) = Lf(D). \tag{6}$$

Taking the partial derivatives of Eq. (6) and substituting them into the partial differential Eq. (5) yields an ordinary differential equation for the unknown function $f(D)$. This heterogeneous differential equation can be solved by ruling out speculative bubbles and imposing value matching and smooth pasting as boundary conditions.[2] The resulting disinvestment trigger D^* for the rent-price ratio is:

$$D^* = (r - \alpha_R)\left(\frac{\beta_2}{\beta_2 - 1}\right), \tag{7}$$

where β_2 is the negative root of the fundamental quadratic equation (see Appendix A.1 for a derivation).[3]

Eq. (7) shows that the disinvestment trigger D^* is the difference between the interest rate r and the drift rate of returns α_R, which is, in contrast to the classical Gordon growth model, multiplied by the option multiple $\left(\frac{\beta_2}{\beta_2-1}\right)$. The option multiple is smaller than one due to the assumption $r > \alpha_L$. Comparative statics show how these parameters affect the disinvestment trigger D^* (see appendix A.2). The drift rates of the stochastic processes, α_L and α_R, have a negative effect on the disinvestment trigger D^*. In case of a high drift rate α_R, landowners expect increasing returns from owning land and are thus willing to accept a lower rent-price ratio D. Likewise, for a higher drift rate α_L, waiting is reasonable because landowners expect higher liquidation values in the future. The volatility of the liquidation value, σ_L, and the volatility of the return process, σ_R, have a negative influence on the disinvestment trigger because it is more likely for lower ratios of D to recover. Higher correlations, ρ, between R and L, however, increase the disinvestment trigger since the uncertainty of the ratio D is reduced. The comparative statics outlined here provide the basis for the hypotheses specified in Section 3.

3 Empirical strategy

Testing predictions from the outlined disinvestment model is not straightforward because disinvestment triggers are unobservable and relate to individual sale decisions for which data are rarely available. In the following, we explain how we overcome these challenges by applying a duration model to aggregated farmland sales.

Regarding the modeling approach, structural and reduced-form models have been used to empirically estimate dynamic stochastic decision models. Structural models attempt at estimating "deep" parameters, such as parameters of the stochastic process or the discount rate, directly from the Bellman equation of the optimal stopping problem. Structural estimation is

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[2] Speculative bubbles may be present in agricultural land markets (Olsen & Stokes, 2015; Power & Turvey, 2010) and may constitute a motive for land hoarding. However, for the particular market situation that is analyzed in our empirical application there is no evidence for the existence of bubbles (Tietz & Forstner, 2014).

[3] Note that our disinvestment model can be easily translated into an investment model by reinterpreting the variables (McDonald & Siegel, 1986). In that case, a potential buyer has to pay a stochastic land price and yields a stochastic return from operating or leasing out land.

computationally demanding because it involves solving a dynamic decision model at each iteration of the estimation procedure (cf. Rust, 1994). Reduced-form models instead are indirectly derived from the optimality conditions of the dynamic decision problem. They approximate the latent disinvestment trigger by usually presuming a linear relationship between model parameters (e.g., drift rates and volatilities) and the observed (dis)investment decision.

Provencher (1997) finds that the discrepancy between structural and reduced-form models can be made fairly small by an appropriate approximation of the value function. In our empirical analysis, we opt for a reduced-form estimation.

Three different types of reduced-form models have been proposed in the literature for the estimation of real options models: Binary choice models, count data models and duration models. Binary choice models focus on the occurrence of a single (dis)investment and allow the deduction of how this event is affected by parameters of the underlying stochastic price process (Belderbos & Zou, 2009; Moel & Tufano, 2002; Pieralli et al., 2017; Pietola et al., 2003). Count data models, in contrast, analyze how the number of sale transactions is influenced by the parameters of the underlying stochastic price process (e.g. Schwartz & Torous, 2007). Third, duration models have been used to estimate the expected time until stochastic prices cross the (dis)investment trigger, i.e., the first passage time (Dunne & Mu, 2010; Hurn & Wright, 1994; Kellogg, 2014; Towe et al., 2008). By their nature, count data models and binary choice models neglect the timing of transactions and thus relevant information about land market liquidity. Therefore, we prefer to estimate a duration model, which covers this aspect by estimating the likelihood of a land sale in a specific time period. More precisely, we use a Cox proportional hazards model (Cox, 1972; Kleinbaum & Klein, 2012), which is specified as follows:

$$h_{ij}(t) = h_0(t) e^{\boldsymbol{X}_{ij}\boldsymbol{\beta}'}. \tag{8}$$

For subject i and disinvestment j, the hazard $h_{ij}(t)$ to disinvest at any given time t is modelled as a function of explanatory variables $\boldsymbol{X}_{ij}$ and the baseline hazard $h_0(t)$. An advantage of the Cox model is its parsimony in the sense that it requires no assumptions on the parametric form of the baseline hazard.

For positive (negative) coefficients $\boldsymbol{\beta}$ and hence a hazard ratio $\exp(\beta)$ above (below) one, the likelihood of disinvestment is higher (lower) and the duration between disinvestments is shorter (longer). This allows inference about the unobserved disinvestment trigger: a shorter (longer) duration implies that the landowner's unobserved disinvestment trigger is comparatively high (low), denoting that landowners are less (more) willing to tolerate lower rent-price ratios R/L.

The vector $\boldsymbol{X}_{ij}$ is comprised of determinants of the disinvestment trigger D^* according to the real options model. Eq. (7) shows how D^* is influenced by the parameters of the stochastic processes, namely the drift rate and volatility of the return (α_R and σ_R) and the liquidation value (α_L and σ_L) as well as the correlation between both processes (ρ). However, it remains unclear how the associated observed duration is affected because the first passage time depends on two factors: the boundary and dynamics of the stochastic process, both of which depend on the model's parameters. Dixit (1993, p. 57) derives the time until a Brownian motion hits a boundary, in our case the disinvestment trigger D^*. An increase in the drift rates reduces the boundary and hence increases the duration. Likewise, a stochastic process with a higher drift hits the boundary later, so that both effects enhance each other. For the volatility, however, both effects counteract. On the one hand, increasing volatility reduces the disinvestment trigger, delaying the time until disinvestment. On the other hand, a more volatile stochastic process decreases the first passage time to the disinvestment trigger. The net effect depends on the specific parameter values and a clear hypothesis regarding the effect of the volatilities cannot be derived. In contrast, a clear hypothesis can be stated with respect to the correlation ρ: increasing correlation decreases the time until disinvestment.

We include further determinants of the hazard into the set of explanatory variables that are not directly related to the real options model, namely the farm exit rate and share of farmers among land sellers. Since a farm exit often leads to the farmer selling land, a higher regional farm exit rate might lead to more land disinvestments and hence increases the disinvestment hazard. Moreover, the farm exit rate as variable may account for county demographics, such as farmers' age. Including the share of farmers among land sellers accounts for the so-called 'clientele effect' (Amihud et al., 2006). Given their interest in land not solely for financial investment purposes, farmers are assumed to hold land longer than non-agricultural landowners. A higher share of farmers as sellers per county should thus decrease the hazard for disinvestment.

The real options model described in Section 2 refers to individual disinvestment decisions of landowners. Ideally, we would estimate the duration model based on individual holding periods of land. Data on individual holding periods, however, are not available and we have to switch to an aggregated level, the county level. This begs the question of whether the predictions from our theoretical model are also valid at the aggregate level. If we assume that all individuals in one county face the same stochastic processes, their disinvestment decisions follow the same rule, i.e., if one individual disinvests reacting to a change in the rent-price ratio after a specific number of days, then other individuals in that county should disinvest after the same number of days. However, this is not what is observed in the land market because each landowner is subject to additional factors of sales decisions, e.g., binding rental contracts, subsidy programs tied to the area or different product distribution channels. Hence, disinvestment decisions of individuals in one county are staggered. Nevertheless, we expect the same comparative statics to hold at the aggregate as they would for an individual disinvestment decision: if an individual's optimal timing of a land sale will change in response to a change of the disinvestment trigger, the aggregated disinvestment decisions of other individuals in the same county will behave accordingly, i.e., longer individual holding periods of land translate into longer times between disinvestments per county. Moving from an individual to an aggregate level also has repercussions for the stochastic process of prices (cf. Leahy, 1993). In the aggregate setting, prices are no longer exogenous and follow regulated Brownian motions. However, Leahy (1993) asserts that the optimal individual decision rule is unaffected, i.e., individual landowners may act myopically and disregard competitive behaviour.

The use of county-level data has a further implication: Since individual disinvestment decisions are staggered and aggregated land supply at a county level evolves continuously, we have to define events for which durations can be measured and explained with the Cox model. At this point, we resort to volume durations, i.e., the time until a specific amount of land has been sold within a county. Since counties which enter the empirical analysis have different sizes, we define volume durations as a percentage of sold arable land relative to a county's arable land.

Our strategy to identify the effects of return and land price uncertainty on the optimal timing of land sales rests on a search for variation of the explanatory variables and encompasses three elements. First, we strive for spatial variability of land prices and returns by including all counties of our study region Lower Saxony into the analysis. Yang et al. (2017) found pronounced heterogeneity of land price dynamics in Lower Saxony. Likewise, Kionka et al. (2021) report that liquidity of regional land markets varies considerably within this state. Thus, drift rates and volatilities of land prices and returns as well as their correlation can be expected to vary sufficiently. Note that exploiting temporal variability is not feasible because the length of the study period does not allow for the derivation of reliable time varying volatilities, e.g., by estimating Generalized Autoregressive Conditional Heteroscedasticity (GARCH) processes for price and return series. Second, to control for other factors that may have an impact on land sale decisions beyond real options effects, we include further observable variables into the duration model. Third, we expect unobserved heterogeneity among counties to play a role. Potential sources of heterogeneity are farming conditions, such as varying soil qualities, weather conditions and farming structures, e.g., differing livestock intensities. Moreover, socioeconomic factors, such as the median age of the farmer or regional employment opportunities, differ across counties. To cope with the problem of unobserved heterogeneity, we include random effects into the standard Cox proportional hazard model (Eq. (8)).

4 Study Region and Data

Our empirical study is conducted for one of the most relevant German federal states in terms of agriculture, Lower Saxony. As of 2020, Lower Saxony consists of 37 counties and eight district-free cities. Covered to 60% with agricultural land, it accounts for one-fifth of the total agricultural gross value added in Germany (Destatis, 2019; ML-Niedersachsen, 2020). Furthermore, among the federal states in Germany, the largest amount of land was sold in Lower Saxony in 2019 (Destatis, 2020), which renders Lower Saxony an especially interesting study region for the field of liquidity. Due to its heterogeneity, it has been the subject of several empirical analyses (Breustedt & Habermann, 2011; Schaak & Mußhoff, 2020; Yang et al., 2019).

The empirical analysis involves several datasets. The durations between transactions are included in a dataset provided by the committee of land valuation experts in Lower Saxony (*Oberer Gutachterausschuss für Grundstückswerte in Niedersachsen, OGA*). It contains sale transactions of arable land in Lower Saxony between 2005 and 2018. We remove all district-free cities as well as the county Wesermarsch from the analysis due to its small amount of arable land. Each transaction comprises information on the price, size, seller, buyer, date of transaction and location. The date and size of a transaction allow the derivation of volume durations, i.e., the number of days until a specific percentage of land per county has been sold. At this point, we choose 1% as the volume to be transacted. To show the robustness of our results with regard to this volume, we also consider durations of 0.5% and 1.5%. Table 1 contains the descriptive statistics for the duration until 1% of the arable land is sold at the county level (see Table A2 for durations of 0.5% and 1.5%). Each duration is measured either from the beginning of the study period or from the end of the preceding duration in the respective county. Hereby, transactions at the end of the study period that do not sum up to 1% (0.5% and 1.5%) of arable land are censored. The mean duration amounts to 624 days, i.e., it takes far more than one year until 1% of arable land is sold. The variability of duration, however, is high and ranges from 210 days to 1,752 days. Figure 2 depicts the empirical distribution (Kaplan-Meier estimate) of the waiting times.

Table 1. Descriptive Statistics

	Mean	St. Dev.	Min.	Max.
Duration until 1% of arable land is sold in days	623.76	217.71	210	1752
α_R in %	0.54	0.77	–1.35	2.39
α_L in %	5.04	1.47	2.15	8.71
σ_R in %	25.20	5.48	18.02	42.76
σ_L in %	16.13	6.41	8.48	36.79
ρ in %	55.42	15.26	15.69	78.73
Farm exit rate in %	3.05	1.64	0.73	7.69
Share of farmers in %	50.07	27.90	0	100

To estimate the parameters of the stochastic process of the liquidation value, we use yearly average land sales prices per county from official statistics (Landesamt für Statistik, 2020b) from 1990 to 2018. For estimation of the stochastic process of land returns, rental price data could be used as a proxy, at least for non-agricultural landowners. Rental price data on a county level, however, are only available for three years (1991, 1999 and 2010), rendering a reliable estimation of a stochastic process impossible. Hence, we compute a return proxy by means of the production structure, the average attained yields per crops produced and the respective crop prices, levelled to available rental prices.[4] This approximation reflects the decision faced by landlords operating their own land. The drift rates (α_R, α_L), volatilities (σ_R, σ_L) and correlation ρ are calculated as the mean, standard deviation and Pearson correlation coefficient of relative changes of returns and land prices, respectively.

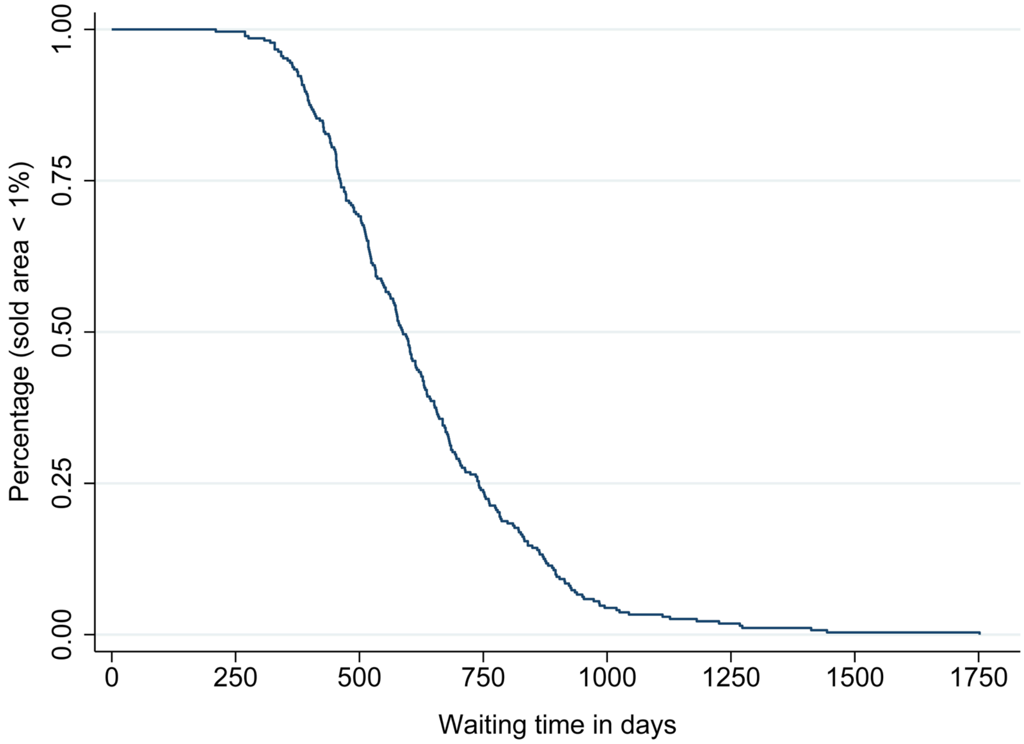

Figure 2. Empirical Kaplan-Meier survival curve (1%)

According to the descriptive statistics in Table 1 (a more detailed overview is provided in Table A4 in the appendix), the mean drift rate α_R of the return process is with 0.54% smaller than the mean drift rate α_L of the liquidation value process (5.04%). The drift rate α_R of the return process is negative in a few counties (e.g., –1.35% in Verden) and reaches a maximum of 2.39% in Celle. The drift rate α_L of the liquidation value process ranges from 2.15% (Hameln-Pyrmont) to 8.71% (Leer). The mean volatility σ_R of the return process is 25.20%. In contrast, this is larger than the volatility σ_L of the liquidation value process (16.13%). The correlation ρ between both processes amounts to a mean of 55.42%. Even though the geographical extent of the study region is rather small, the figures show distinct variability (Table 1, second column). This is in line with findings from previous studies about the agricultural land market in Lower Saxony. Yang et al. (2017) , for example, identify three clusters of counties in Lower Saxony

[4] The production structure and average yield are provided by the Landesamt für Statistik (2020a). Yearly crop prices (in dt/ha) for Germany are provided by the Food and Agriculture Organization of the United Nations (2020).The production structure is available only for the years 1991, 1999, 2010 and 2016. To fill the missing years, we assume constant production shares between the years. We consider the area covered by all main crops, namely potatoes, rape, maize, wheat, triticale, rye, barley and oat. The production shares are then multiplied by the respective yearly yields in each county and the corresponding yearly crop prices.

showing different land price dynamics. Likewise, Schaak and Mußhoff (2020) find that the rent-price ratio of arable land varies regionally in Lower Saxony and is affected by locally varying factors.

The farm exit rate is adjusted for each duration, i.e., we compute the annual farm exit rate from official statistics and weigh it by means of the turnover in the respective years in case the duration covers more than one calendar year. Finally, the share of farmers among sellers is calculated based on the transaction dataset provided by the OGA that contains information about the seller being a farmer or not. The transaction volume is used as weight when aggregating this information to the county level. In case data on whether the seller is a farmer was missing, we replaced this information by spatial interpolation.

5 Results

Before we turn to the estimation results, we provide further specification details of the Cox proportional hazards model. First, because we expect unobserved heterogeneity among counties, we use the mixed proportional hazard model introduced by Lancaster (1979) as an extension of the Cox proportional hazards model. It includes random effects v_i that control for unobserved heterogeneity and enter the basic model in Eq. (8) as an additional factor:

$$h_{ij}(t) = h_0(t) v_i e^{\boldsymbol{X}_{ij}\boldsymbol{\beta}'}. \tag{9}$$

Identification of the model requires for the distribution of random effects v_i that $E(v_i) < \infty$ (van den Berg, 2001). This is ensured by using a gamma distribution with mean one and variance θ. A likelihood ratio test indicates that the parameter θ is statistically significantly different from zero, affirming that unobserved heterogeneity is present. The parameter θ differs slightly for different turnovers: While in the 1% and 1.5% case, we find a within-county correlation of about 0.4, θ reduces to 0.29 in the 0.5% case.

Moreover, we test the proportional hazards assumption, which implies that the multiplicative effects of the covariates on the hazard rate should be constant over time. To this end, we apply a Schoenfeld test, which checks for each covariate whether or not the set of Schoenfeld residuals is time dependent (Schoenfeld, 1982). Additionally, we perform this test globally. It turns out that the null hypothesis of temporal independence is rejected at a 5% significance level. Allison (2010) notes that the proportional hazards assumption rarely holds in real world applications. Yet, we set up an alternative model that is able to account for a violation of the proportional hazards assumption. We estimate a stratified Cox proportional hazards model with standard errors clustered by county. Stratifying over time allows the baseline hazard to vary over the years k of disinvestment (i.e., $h_0(t)$ in Eq. (8) changes to $h_{0k}(t)$):

$$h_{ij}(t) = h_{0k}(t) e^{\boldsymbol{X}_{ij}\boldsymbol{\beta}'}. \tag{10}$$

Table 2 depicts the results for the mixed proportional hazards model and the stratified Cox proportional hazards model for the duration until 1% of a county's land is sold. The results for the mixed proportional hazards model with volumes of 0.5% and 1.5% are depicted in Table A3 in the appendix. The fit of these models can be assessed by means of Harrell's C, a concordance measure, which compares the predicted likelihood of disinvestment with the actual time until disinvestment occurs for any pair of counties. It amounts to 0.637 for the mixed proportional hazards model and to 0.646 for the stratified model – for an interpretation of this figure, one has to recall that a random ordering of pairs yields a C-value of 0.5. Overall, the models have a modest fit, which can be ascribed to the lack of seller-specific information or non-monetary motives of selling or holding land, e.g., intrinsic or emotional values, that are not captured in our model.

Table 2. Results of the mixed proportional hazards model and the stratified Cox proportional hazards model

	Mixed proportional hazards model (1%)			Stratified Cox proportional hazards model (1%)		
	Hazard ratio		St. error	Hazard ratio		St. error
α_R	0.704	*	0.143	0.741	*	0.124
α_L	0.830		0.112	0.811	**	0.078
σ_R	1.009		0.031	1.016		0.022
σ_L	1.026		0.032	1.048	**	0.020
ρ	1.019	*	0.011	1.020	***	0.007
Farm exit rate	1.180	***	0.048	1.295	**	0.147
Share of farmers	0.996		0.003	0.995		0.004
Harrell's C	0.637			0.646		

Note: The reported hazard ratios correspond to $\exp(\beta)$, the exponential of the estimated coefficients. The asterisks ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

The results of the duration models provide empirical evidence for the validity of the real options approach to farmland sales. We reject the null hypothesis of no influence for the hazard ratios for both drift rates, α_R and α_L, in the mixed proportional hazards models (except α_L for a turnover of 1%) and the stratified Cox proportional hazards model at a significance level of 5%. For both drift rates, we find hazard ratios smaller than 1. Hence, higher drift rates of returns and land prices decrease the likelihood of land transaction. An estimated hazard ratio of 0.704 for the drift rate α_R (see Table 2) indicates that an increase of the drift rate from the sample minimum to the sample maximum (i.e., by 3.74 percentage points) implies that the likelihood of land transactions reduces to approximately a third ($0.704^{3.74} = 0.27$). Hence our hypothesis that an increase in the drift rates of land prices and rental prices increases the duration until a specific amount of land is supplied cannot be rejected. Given that significance and effect size vary only slightly among all models, this finding appears robust. It provides a theoretical explanation of the negative relationship between land prices and turnover depicted in Figure 1. In contrast to the conjecture of Fisher et al. (2004), our real options model predicts that in booming land markets, the distribution of reservation prices of landowners shifts to the right. *Ceteris paribus*, this shift renders a match with a potential buyer less likely. This view challenges the hypothesis of a positive relation between prices and turnover that has been derived from search friction models for housing markets (Berkovec & Goodman, 1996).

For the volatilities σ_R and σ_L, we find positive hazard ratios, i.e., increasing risk reduces the duration. In the mixed proportional hazards models, this effect is not significant for both volatilities. In the stratified Cox proportional hazards model, we can reject the null hypothesis of no influence for σ_L at the 5% level. At first glance, these results seem to contradict the "(dis)investment-reluctance-hypothesis" propagated in the real options literature. However, as noted earlier, a change in price and return volatility has two counteracting effects on the first passage time and thus the resulting net effect is unclear. It should also be noted that the effect sizes of the volatilities are small.

The estimation results for the correlation ρ between land price and return processes are similar for both model variants and robust against changes of the transaction volume. The hazard ratio for this variable amounts to 1.019 (1.020) and the null hypothesis can be rejected at the 1% significance level. An increase of the correlation by the range observed in the sample (63 percentage points) increases the hazard ratio by a factor of 3.27. This result is in line with our hypotheses and states that stochastic dependency among rental and sale prices reduces the incentive to postpone land sales. This finding may be relevant to evaluate one-sided policy interventions in land markets that affect either sales or rental markets, which, in turn, will change the correlation between sales and rental prices.

Regarding the farm exit rate, we find a positive and statistically significant effect on the hazard for land sales. With a hazard ratio of 1.180 (see Table 2), the likelihood of a land transaction is around three times higher if the farm exit rate increases from its sample minimum to its sample maximum (i.e., by 6.69 percentage points). The results again differ only slightly between all models and confirm our hypothesis. In contrast, we cannot find strong evidence for the hypothesised 'clientele effect' in our data: The hazard ratios for the share of farmers among sellers are below one, implying that a higher share of farmers increases the holding period for this asset and thus the sluggishness of the land supply. However, the null hypothesis cannot be rejected at a significance level of 10%, which may be due to the heterogeneity of the group of non-agricultural sellers as well as spatial interpolation, which may have introduced some uncertainty into the data.

The impact of a change in the covariates on waiting times can be illustrated by means of survival curves. Figure 3 depicts the estimated survival curves for the mixed proportional hazards model at the sample mean of all variables and at the sample extreme values (minima and maxima) of the explanatory variables. The plots depict the probability that less than 1% of a county's land area is sold as a function of time. "Time" is the number of days since the last event occurrence. The survival curve evaluated at the mean values of the explanatory variables shows that the probability of realising a land turnover of 1% in less than 400 days is virtually zero. The survival rate reduces to 0.5 after just over 600 days and approaches zero after about 1,000 days. If the drift rate of the returns α_R takes on its sample minimum (maximum), it lasts about 510 (680) days until 1% of the land is sold with a probability of 0.5 (cf. Figure 3a). Hence, a delay of about 170 days is predicted. For the range of the drift rate of land prices α_L, the change of duration is similar. Hence, a variation of the drift rates α_R and α_L induces delays of about half a year between counties with lower and higher drift rates.

The impact of volatilities σ_R and σ_L and correlation ρ is depicted in Figure 3b irrespective of their statistical significance. For the correlation ρ, the waiting time is expected to be about 160 days longer at the sample minimum compared to the sample maximum at a probability level of 0.5. For the volatility σ_R, the waiting time difference between its sample minimum and sample maximum is comparatively small and amounts to approximately 30 days. For the volatility σ_L, the waiting time difference is larger with about 90 days.

Finally, Figure 3c portrays the estimated change in the duration resulting from a change in the farm exit rate and the share of farmers among sellers. While the farm exit rate has a significant influence and shifts the waiting time by about 140 days when switching from the sample minimum to the maximum with a probability of 0.5, the effect of the farmers' share is less pronounced (approximately 40 days).

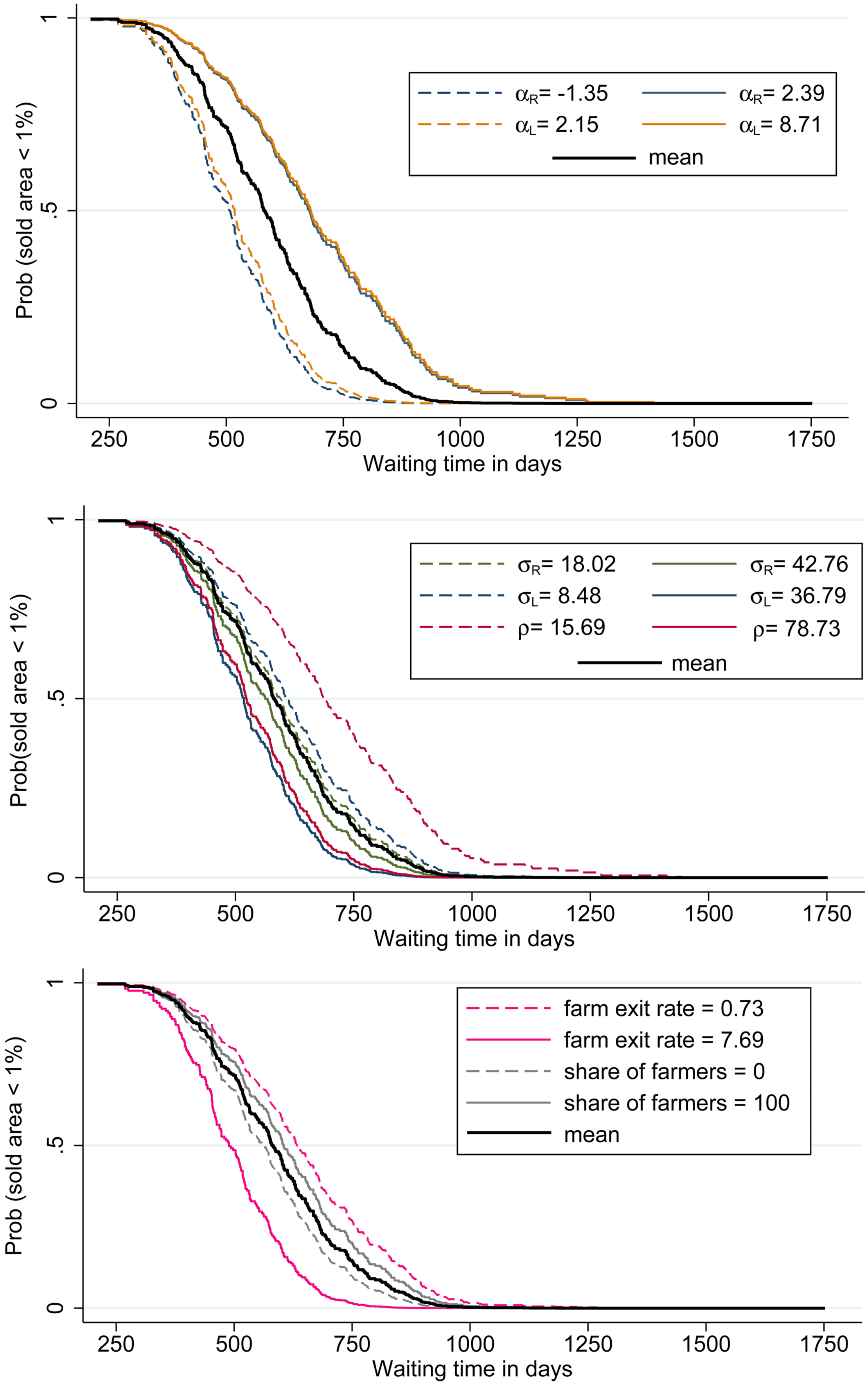

Figure 3. Survival curves at the minimum and maximum values of a) the drift rates α_R and α_L; b) the volatilities σ_R and σ_L and correlation ρ; and c) the farm exit rate and share of farmers.

6 Discussion and Conclusions

This paper seeks to explain observed heterogeneity of liquidity in agricultural land markets from a microeconomic perspective. Focusing on the supply side, we adopt a real options model that determines the value of the opportunity to sell for landowners who earn a return from renting out or operating land. This view makes sense if land returns and sale prices are both stochastic and are not perfectly correlated – otherwise, renting and owning land would be perfect substitutes. In this setting, landowners disinvest if the rent-price ratio falls below a threshold that depends on the parameters of both stochastic processes. In line with standard results, we find that uncertainty in conjunction with flexibility to defer disinvestments creates an incentive to wait, which might explain observed disinvestment reluctance in agricultural land markets. Specifically, the theoretical model predicts that higher volatilities and drift rates of both stochastic processes decrease the optimal disinvestment trigger, while a higher correlation leads to an increase.

To test these hypotheses empirically, we employ a duration model that estimates the likelihood of land sales as a function of time and option specific variables. In contrast to the majority of empirical real options models, we do not explain just the occurrence of (dis)investments, but rather the first passage time until a prespecified amount of land is sold. The model is applied to a large set of land transactions in Western Germany. We find that the influence of the drift rates and the correlation between both stochastic processes are in line with theoretical expectations, while the effect of return and price volatilities is ambiguous. This is due to the fact that uncertainty not only affects the disinvestment threshold, but also the likelihood of matching the threshold, and both effects counteract (Musshoff et al., 2013). In fact, the ambivalent role of uncertainty constitutes a caveat for the empirical testing of the real options model because volatility is the key variable that distinguishes real options models from classical investment models. Thus, it would be desirable to carve out the net effect of this factor on observable variables, such as (dis)investments or first passage times. Another limitation of our empirical analysis is rooted in the use of aggregated county-level data, which may mask the effects of options-related variables and individual land sale decisions. Ideally, one would track the holding period of land plots using transaction specific data that also provide information about the characteristics of sellers and buyers as well as the terms of rental contracts, which have an impact on keeping or selling farmland.

Nevertheless, our empirical results are helpful in understanding some stylised facts about land market liquidity. It appears that liquidity does not follow (absolute) land prices which is in contrast to findings on other real estate markets (Stein, 1995). Our model emphasises the rent-price ratio and predicts that in boom phases, i.e., in times of higher drift rates of sale and rental prices, landowners are more reluctant to sell their land. Unsurprisingly, we find that farm exits constitute a positive supply shock and increase liquidity in a regional land market. In contrast, we did not find evidence that agricultural and non-agricultural landowners differ in their willingness to sell land, although it is often conjectured that financial investors have shorter holding periods for their assets compared with farmers.

Our results have some practical implications. First, from the perspective of potential sellers, our model rationalises a larger range of inaction than classical investment models do. The imperfect correlation between sales and rental prices implies that owning and renting land are not perfect substitutes and that a higher liquidation value is required in exchange for a stochastic return from operating land. This effect amplifies the sluggishness of farmland markets that is caused by high transaction costs. Second, our results contribute to the ongoing discussion of land market regulations that has been triggered by the sharp increase of land prices in the last decade. In fact, many countries in the EU have instruments in place that target the capping of land prices or contemplate the introduction of price caps (Odening, M., Hüttel, S., 2021; Swinnen et al., 2016). Our model, however, questions the effectiveness of these regulations. Capping farmland prices will most likely increase the rent-price ratio and thus discourage landowners from selling land. In turn, land supply will be reduced, which causes further price pressure in land markets.

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Appendix

A.1 Derivation of the disinvestment trigger

Taking the partial derivatives of Eq. (6) and substituting them into the partial differential Eq. (5) yields an ordinary differential equation for the unknown function $f(D)$:

$$\frac{1}{2}f''(D)D^2(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2) + (\alpha_R - \alpha_L)Df'(D) + (\alpha_L - r)f(D) + D = 0. \quad \text{(A1)}$$

The value matching condition becomes:

$$f(D) = 1. \quad \text{(A2)}$$

The two smooth pasting conditions become:

$$f'(D) = 0 \quad \text{(A3)}$$

and
$$f(D) - Df'(D) = 1. \quad \text{(A4)}$$

The general solution for the differential equation A1 is $f(D) = B_1D^{\beta_1} + B_2D^{\beta_2}$. In our case, the likelihood of disinvestment becomes very small when D nears infinity, so the value of the option should go to zero as D becomes very large. Hence, B_1 corresponding to the positive root β_1 is zero and the first term vanishes.

The value of the option for the active firm thus equals:

$$f(D) = B_2D^{\beta_2} + \frac{D}{r - \alpha_R} \quad \text{(A5)}$$

if

$$\beta_2 = \frac{1}{2} - \frac{(\alpha_R - \alpha_L)}{(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2)} \quad \text{(A6)}$$

$$- \frac{\left\{(\alpha_R - \alpha_L)^2 - (\alpha_R - \alpha_L)(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2) + \frac{(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2)^2}{4} - 2(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2)(\alpha_L - r)\right\}^{1/2}}{(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2)}$$

is the negative root of the following fundamental quadratic equation:

$$Q(\beta) = \tfrac{1}{2}\beta(\beta - 1)(\sigma_R^2 - 2\rho\sigma_L\sigma_R + \sigma_L^2) + \beta(\alpha_R - \alpha_L) + (\alpha_L - r) = 0. \quad \text{(A7)}$$

By means of the value matching condition and the first smooth pasting condition, a solution for the disinvestment trigger D^* is obtained:

$$D^* = (r - \alpha_R)\left(\frac{\beta_2}{(\beta_2 - 1)}\right). \tag{A8}$$

A.2 Comparative statics

Comparative statics can show how the option multiple and hence the disinvestment trigger D^* changes with β_2. First, we differentiate the quadratic equation (A9) totally, evaluating all derivatives at the negative root β_2. For the variable α_R, this produces the following total derivative (see Table A1):

$$\frac{\partial Q}{\partial \beta}\frac{\partial \beta_2}{\partial \alpha_R} + \frac{\partial Q}{\partial \alpha_R} = 0. \tag{A9}$$

The first partial derivatives $\frac{\partial Q}{\partial \beta}$ and $\frac{\partial Q}{\partial \alpha_R}$ of the quadratic expression are derived under the assumption that $\beta_2 < 0$. It follows that $\frac{\partial Q}{\partial \beta} < 0$ and $\frac{\partial Q}{\partial \alpha_R} > 0$. For the total derivative to equal zero, it must hold that $\frac{\partial Q}{\partial \alpha_R} > 0$. For the remaining variables, refer to Table A1.

Table A1. Comparative statics

x	Total derivative	$\frac{\partial Q}{\partial \beta}$	$\frac{\partial Q}{\partial x}$	$\frac{\partial \beta_2}{\partial x}$
α_R	$\frac{\partial Q}{\partial \beta}\frac{\partial \beta_2}{\partial \alpha_R} + \frac{\partial Q}{\partial \alpha_R} = 0$	$\frac{\partial Q}{\partial \beta} < 0$	$\frac{\partial Q}{\partial \alpha_R} = \beta < 0$	$\frac{\partial \beta_2}{\partial \alpha_R} < 0$
α_L	$\frac{\partial Q}{\partial \beta}\frac{\partial \beta_2}{\partial \alpha_L} + \frac{\partial Q}{\partial \alpha_L} = 0$	$\frac{\partial Q}{\partial \beta} < 0$	$\frac{\partial Q}{\partial \alpha_L} = -\beta + 1 > 0$	$\frac{\partial \beta_2}{\partial \alpha_L} > 0$
σ_R	$\frac{\partial Q}{\partial \beta}\frac{\partial \beta_2}{\partial \sigma_R} + \frac{\partial Q}{\partial \sigma_R} = 0$	$\frac{\partial Q}{\partial \beta} < 0$	$\frac{\partial Q}{\partial \sigma_R} = \beta(\beta - 1)(\sigma_R - \rho_c\sigma_L) > 0$	$\frac{\partial \beta_2}{\partial \sigma_R} > 0$
σ_L	$\frac{\partial Q}{\partial \beta}\frac{\partial \beta_2}{\partial \sigma_L} + \frac{\partial Q}{\partial \sigma_L} = 0$	$\frac{\partial Q}{\partial \beta} < 0$	$\frac{\partial Q}{\partial \sigma_L} = \beta(\beta - 1)(-\rho_c\sigma_R + \sigma_L) > 0$	$\frac{\partial \beta_2}{\partial \sigma_L} > 0$
ρ	$\frac{\partial Q}{\partial \beta}\frac{\partial \beta_2}{\partial \rho} + \frac{\partial Q}{\partial \rho} = 0$	$\frac{\partial Q}{\partial \beta} < 0$	$\frac{\partial Q}{\partial \rho} = \frac{1}{2}\beta(\beta - 1)(-2\sigma_R\sigma_L) < 0$	$\frac{\partial \beta_2}{\partial \rho} < 0$

A.3 Additional Tables

Table A2. Descriptive Statistics (0.5% and 1.5% of the arable land in the county is sold)

	Mean		Std. Dev.		Min.		Max.	
	0.5%	1.5%	0.5%	1.5%	0.5%	1.5%	0.5%	1.5%
Duration in days	316.12	927.82	131.05	306.87	59	415	1041	2461
α_R in %	0.54	0.53	0.77	0.78	-1.35	-1.35	2.39	2.39
α_L in %	5.02	5.04	1.45	1.43	2.15	2.15	8.71	8.71
σ_R in %	25.26	25.34	5.47	5.53	18.02	18.02	42.76	42.76
σ_L in %	16.13	16.09	6.35	6.27	8.48	8.48	36.79	36.79
ρ in %	55.26	55.39	15.27	15.32	15.69	15.69	78.73	78.73
Farm exit rate in %	3.00	3.09	1.74	1.56	0.72	0.74	7.95	7.28
Share of farmers in %	50.50	49.96	30.66	26.05	0	0.16	100	100

Table A3. Results of the mixed proportional hazards model (0.5% and 1.5% of the arable land in the county is sold)

	Mixed proportional hazards model (0.5%)		Mixed proportional hazards model (1.5%)	
	Hazard ratio	St. error	Hazard ratio	St. error
α_R	0.735 **	0.118	0.693 *	0.157
α_L	0.823 *	0.087	0.767 *	0.112
σ_R	1.007	0.024	1.021	0.034
σ_L	1.029	0.025	1.039	0.036
ρ_c	1.019 **	0.008	1.023 *	0.012
exit %	1.122 ***	0.029	1.150 **	0.063
farm %	0.999	0.002	0.996	0.004
Harrell's C	0.620		0.655	

Note: The reported hazard ratios correspond to $\exp(\beta)$, the exponential of the estimated coefficients. The asterisks ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.1 level, respectively.

Table A4. Descriptive statistics for all counties in Lower Saxony, 2005–2018

County	Duration (in days)	α_R	α_L	σ_R	σ_L	ρ	Farm exit rate (in %)	Share of farmers (in %)
Ammerland	553.56	0.92	5.8	26.22	18.42	73.21	3.64	52.20
Aurich	456.64	0.56	4.57	23.2	13.9	68.5	3.29	25.72
Celle	660.43	2.39	5.47	28.82	19.21	66.23	3.03	59.42
Cloppenburg	703.14	1.06	5.81	25.28	10.54	60.26	2.8	64.55
Cuxhaven	472.7	0.05	4.58	24.34	13.01	52.18	2.94	52.85
Diepholz	541.56	1.08	5.01	23.96	8.82	78.73	3.75	33.86
Emsland	847.83	0.99	6.13	28.67	9.01	65.56	3.35	69.97
Friesland	726.17	0.08	4.62	37.76	20.36	62.76	2.32	61.34
Gifhorn	477.7	1.65	5.29	27.31	12.59	59.96	2.93	71.85
Goslar	687.17	0.20	5.81	22.11	22.32	20.58	2.29	39.66
Göttingen	459.18	0.30	2.88	19.47	14.02	53.04	2.86	5.99
Grafschaft Bentheim	1,142.25	0.05	4.98	32.31	10.25	57.73	2.97	81.12
Hameln-Pyrmont	688.43	0.75	2.15	19.62	10.04	57.43	2.43	26.08
Harburg	630.14	1.28	5.5	21.36	13.56	68.56	3.2	75.45
Heidekreis	723.71	0.65	4.36	22.87	14.15	63.54	2.74	40.85
Helmstedt	704.71	0.13	7.54	21.38	30.62	15.69	2.36	77.15
Hildesheim	646.43	0.10	3.68	21.18	14.68	16.90	3.06	34.46
Holzminden	589.38	0.62	3.4	23.91	18.69	45.46	3.01	44.24
Leer	680.43	1.77	8.71	22.88	36.79	66.12	2.85	42.07
Lüchow-Dannenberg	574.75	1.16	5.97	26.74	24.64	62.65	3.02	42.96
Lüneburg	556.86	0.52	4.92	26.53	16.74	54.06	2.98	71.66
Nienburg (Weser)	494.44	0.629	4.41	22.36	11.63	72.54	3.78	43.17
Northeim	743.33	0.64	3.77	24.03	15.53	59.19	2.82	19.22
Oldenburg	550.22	0.58	5.63	21.95	13.15	74.62	3.09	42.10
Osnabrück	1004.6	1.44	6.23	18.02	8.48	69.33	3.42	68.83
Osterholz	564.75	-0.42	4.35	32.01	22.25	40.24	2.81	33.57
Peine	726.29	1.03	4.28	20	14.34	45.32	3.06	65.18
Region Hannover	725.83	0.66	3.85	19.48	12.87	28.71	2.86	35.81
Rotenburg (Wümme)	617.25	-0.07	5.31	22.58	14.51	62.54	3.19	59.34
Schaumburg	508.1	0.463	2.19	23.45	9.32	47.82	3.09	90.11
Stade	666.43	0.5	5.19	30.79	11.41	49.7	3.33	67.84
Uelzen	778.2	1.42	5.18	31.76	18.78	56.43	2.79	75.19
Vechta	922	0.3	5.29	19.97	10.02	64.83	2.34	63.17
Verden	573.63	-1.35	5.02	25.59	13.24	46.71	3.51	27.34
Wittmund	414.25	-1.29	8.4	42.76	28.31	52.10	3.81	30.90
Wolfenbüttel	825.33	0.03	5.76	21.26	20.89	34.96	2.44	76.78

Note: The parameters α_R, α_L, σ_R, σ_L and ρ are estimated for the time period 1991–2018. The values in column (1), (7) and (8) are average values over all durations.