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Microeconometric analysis of the impacts of climate change on German agriculture: applications and extensions of the Ricardian approach

Cumulative dissertation

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Abbreviations, acronyms, and initialisms

A-K	Anselin-Kelejian
°C	Degree Celsius
CO_2	Carbon dioxide
Eq.	Equation
Esri ArcGIS	Esri's Geographic Information System
FADN	Farm Accountancy Data Network
FAO	Food and Agriculture Organization
FDZ	Forschungsdatenzentrum der Statistischen Landesämter / Research Data Center of the Federal Statistical Office and the Statistical Offices of the Länder
FSS	Farm Structure Survey
H_0	Null hypothesis
ha	Hectare
i.i.d.	Independently and identically distributed
IIA	Independence of irrelevant alternatives
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental variables
km	Kilometer
LFA	Less favored area
LM	Lagrange multiplier
m	Meter
mm	Millimeter
N	Number (of population)
n	Number (of sample)
OLS	Ordinary least squares
REMO	Max Planck Institute’s Regional Model
RESET	Regression equation specification error test
RHS	Right-hand-side
R^2_{cor}	Squared correlation
R^2_{var}	Variance ratio
SAR	Spatial-autoregressive

Abbreviations, acronyms, and initialisms (cont'd)

SD	Standard deviation
SER	Spatial-autoregressive error
Stata	StataCorp's statistical software for data analysis
S2SLS	Spatial two-stage least squares
UAA	Utilized agricultural area
VIF	Variance inflation factor
WebWerdis	Web-based Weather Request and Distribution System
WFD	Water Framework Directive
WTP	Willingness to pay
χ^2	Chi-square distribution
2SLS	Two-stage least squares

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CHAPTER 1

Introduction

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This chapter provides a succinct introduction to the dissertation. Section 1.1 opens up the concept of valuation of the economic impacts of climate change on agriculture. Section 1.2 outlines the overall aim and objectives of the thesis. Section 1.3 is devoted to the impact assessment employed herein, the so-called Ricardian approach, with an emphasis on theoretical and methodological issues. These are followed by the delineation of subsecutive research topics in section 1.4. An overview of the data utilized, the analytical methods employed, and the software used is provided in section 1.5. An outline of the main body is given in section 1.6.

1.1 General introduction

The valuation of the economic impacts of climate change is a well-honored subject in economics and policy analysis. This "honor" stems from the controversy that surrounds the very nonmarket nature of climate: since an established pricing system for climatic attributes does not exist, the value of the latter has to be imputed from goods that are explicitly traded. The agricultural land market offers an excellent example in which case the differentiated product being traded is land for farming. Suppose, for instance, that two farms are virtually similar in any respect except that one is characterized by higher average temperatures than the other. Standard microeconomic theory makes it possible to utilize land prices or farm profits to infer the willingness to pay (WTP) to meet or avoid the difference in temperature (Kolstad, 2000: 317).

The latest IPCC report leaves no room for doubt: climate change is unequivocal (IPCC, 2007). However, extracting information of economic nature on climate from the agricultural land market is an equivocal issue. If climatic attributes were actually priced, a profit-maximizing landlord would equate the offer price for each attribute to the corresponding market price, and a price for climate would be included into the price of land. This behavior is intuitive because lower offers would lead to foregone profits for the landlord, and higher offers would be difficult to match a potential bid by the tenant (Palmquist, 1989). But since neither have climatic attributes an actual market price nor can their levels be administered, they bear a set of implicit (unobserved) prices that are exclusively demand-determined (Palmquist, 1989).

Agriculture is inextricably linked with weather and its long-term counterpart, climate. Climate affects farmland prices through a twofold impact on farm profits: it affects total revenues by altering yield levels, and total costs by altering the quantity and productivity of inputs. In this context, the process of profit maximization dictates a continuous adjustment to local climatic conditions, broadly referred to as adaptation (Mendelsohn, 2000: 585). Exploring how adaptation occurs is becoming increasingly important in the scientific community as the capacity and potential to adapt may differ *across* countries and even across regions *within* a country. Few empirical studies have been carried out to explore the extent to which climate affects specific choices in the production environment. Recent examples include the choice between crops (Seo and Mendelsohn, 2008a; Wang *et al.*, 2010), the choice between livestock species (Seo and Mendelsohn, 2008b), and the reliance on irrigation (Kurukulasuriya *et al.*, 2011). Comprehensive literature reviews of the general toolkit of adaptation tactics can be found in Smit and Skinner (2002) and Kurukulasuriya and Rosenthal (2003), among others.

A plethora of approaches and methods have emerged to study the impacts of climate change on agriculture. The basic toolkit comprises–but is not limited to–crop simulation models (*e.g.*, FAO's CropWat), farm management models (*e.g.*, Adams *et al.*, 1995), market equilibrium models (*e.g.*, Zhai *et al.*, 2009), and the Ricardian approach (*e.g.*, Mendelsohn *et al.*, 1994). Not surprisingly, what is perceived as limitation of one approach is frequently regarded as an asset of another approach (Mendelsohn, 2007). For example, whereas the Ricardian approach is the only one that captures actual adaptation, it misses the effects of price changes or CO_2 fertilization, which can be accounted for in other approaches. Since no approach is holistic or free of caveats, two lines of research can generally be distinguished: the coupling of approaches into hybrid models (*e.g.*, Aurbacher *et al.*, 2013), and the sporadic imposition of more detailed structure on existing approaches. This dissertation follows the latter avenue, and takes up the challenge of improving the Ricardian approach.

The somewhat deceptive name of the approach was not assigned by the classical economist David Ricardo (1772–1823) himself, but was indeed inspired by his seminal theory of economic rent. The approach was conceptualized and popularized by Mendelsohn *et al.* (1994; 1996) in a seemingly eccentric attempt to determine the implicit value of climate change in US agriculture from a cross section of farmland prices. In the last two decades, the approach has merited numerous applications for over 30 countries. Extensive reviews of applications for African, Asian, South American, and US regions can be found in Mendelsohn and Dinar (2009: chapters 7–10). A handful of studies covering European regions are somewhat recent (Maddison, 2000; Lang, 2007; Lippert *et al.*, 2009; Garciaa and Viladrich-Grau, 2009; Van Passel *et al.*, 2012; De Salvo *et al.*, 2013). Overall, under moderate warming, the Ricardian approach tends to show damages for low-latitude regions and benefits for temperate and polar countries (Massetti and Mendelsohn, 2011a).

In a nutshell, the intuition of the Ricardian approach is as follows: if future climate conditions in area A were to resemble current climate conditions in area B, then the future behavior of farmers in A would resemble the current behavior of farmers in B, *ceteris paribus*. In essence, climate is assumed to alter the distribution of crops and livestock species in space, which implies a redistribution in the expected behavior of farms. This notion of redistribution, which is traced back to Aristotle's (384–322 BCE) era[1], is at the crux of establishing any causal relationship between climate and farm behavior. From an economic perspective, it seems intriguing to overlap spatial variation in steady-state farm profitability with spatial variation in historical climate. This association can be translated into a meaningful equation where land prices or farm profits are regressed against climatic and other (control) land and site characteristics. In the case of asset or rental prices, the Ricardian function gives the equilibrium price schedule in a given agricultural land market–that is, a set of prices for the various attributes of land that are assumed to lead to market clearing.

Several methodological issues pertaining to the overall reliability of the Ricardian approach have been exposed in the literature. The original study generated an abnormal amount of criticism in the 1990s (*e.g.*, Cline, 1996; Quiggin and Horowitz, 1997; Kaufmann, 1998; Fischer and Hannemann, 1998; Darwin, 1999, among others), and some aspects have

[1] In his book *Meteorologica* (I, 14), the Greek philosopher states: *"(...) places that once enjoyed beneficial climate now deteriorate and grow dry. This has happened to the land of Argos and Mycenae in Greece. During the Trojan War, the land in Argos was marshy, unproductive, and able to support only few inhabitants, whereas that in Mycenae was productive and, therefore, more popular. Now the opposite is the case; Mycenae has become unproductive and completely dry, whereas Argos is under cultivation. What has happened in this small district must be happening in larger districts and whole countries"* (own translation; see also Neumann, 1985).

been recently taken into account. Yet, conceptual, methodological, and analytical issues of paramount importance have merited limited or no empirical investigation. This dissertation takes up the challenge to improve specific aspects of the approach in order to render it a more realistic impact assessment tool. We pursue our assessment with empirical illustrations for agriculture in Germany. Due to the involvement of individual and potentially confidential farm data from the census, the studies presented herein were carried out on the basis of remote data analysis with the Research Data Center (FDZ) (see section 1.5 for details).

1.2 Overall aim and objectives

The purpose of this dissertation is to propose distinct methodological extensions that improve the conceptual and analytical fidelity of the Ricardian approach. The proposition of extensions finds its roots in specific limitations of the approach. In particular, we are concerned with two main objectives: a more efficient treatment of the variables that proxy climate (applicable in specific situations), and the endogenous treatment of two long-run adaptation strategies, namely the occurrence of the farm type[2] and irrigated acreage (applicable to all situations).

We illustrate the aforementioned extensions by means of empirical applications for agriculture in Germany. Thus, a sub-objective of the studies carried out herein is to serve as continuing work to two previous Ricardian studies for Germany (Lang, 2007; Lippert *et al.*, 2009). Those studies aimed to answer what the impacts of historical climate in Germany looked like (*i*) at the very aggregate scale of districts, (*ii*) with minimal and somewhat outdated farm and climate data, and (*iii*) without explicitly quantifying adaptation. This dissertation builds on that work in a more rigorous way: we utilize detailed and up-to-date farm and climate data at substantially lower spatial scales, and also attempt to open the "black box" of adaptation.

1.3 The Ricardian approach: state of the art

This section provides a succinct discussion of an otherwise wide range of issues that are evoked in empirical applications of the Ricardian approach. Section 1.3.1 offers a brief treatment of the microeconomic backdrop. Sections 1.3.2 and 1.3.3 deal with estimation

[2] The following types are considered in this thesis: arable-crop farms, forage farms, livestock-fattening farms, permanent-crop farms, horticultural-crop farms, and mixed farms.

issues applicable both in the usual version of the approach as well as in a recent variant. The main attractive features and limitations of the approach are listed in sections 1.3.4 and 1.3.5.

There has been a thorough review of applications of the Ricardian approach previously (Mendelsohn and Dinar, 2009). This section differs in that it places greater emphasis on critical theoretical and methodological aspects. Therefore, it is intended to serve as a complementary update to the work presented and reviewed in Mendelsohn and Dinar (2009).

1.3.1 Microeconomic backdrop

According to Ricardo's seminal Law of Rent, the economic rent of a parcel represents the economic advantage retrieved by using that parcel in its most productive use. Climate comes into play by assuming that, in the long run, the most profitable faming activity at any particular location is dependent on local climate (Polsky, 2004). The driving premise is what is often referred to as efficient adaptation: farmers maximize profits by strategically contemplating past climate and past profitability. This presumption leads to the assumption that local climatic trends are "visible" to landlords and tenants. Hence, climate enters into their utility functions, impacts their bids, and contributes to the determination of the equilibrium rental price schedule.

Before establishing a formal link between climate and farm profitability, it is important to consider the extent of realism of the assumption that such a link exists. In other words, how realistic is it to assume that climate contributes in the configuration of the optimal use of agricultural land? An overcited real-world example is that wheat generally prefers cooler settings whereas fruits are more productive in warmer environments (*e.g.*, Mendelsohn, 2000). Let us generalize this example to the case of farm types, and inspect the spatial distribution of arable and permanent crops in Germany in 2010. Own estimations based on FDZ (2011) and DWD (2013) do reveal a pattern: given an overall historical mean of 8.6 °C for spring temperature, about 66% of all arable-crop farms are located in colder states (<8.6 °C), whereas about 82% of all permanent-crop farms are found along the Rhine and Neckar valleys in the warmer states of Rheinland-Pfalz, Hessen, and Baden Württemberg (>8.6 °C). A general climate-response pattern can also be identified for another farm type and another climatic attribute: more than half of all forage farms (53%) are located in the southern tier (Bayern and Baden Württemberg) where average historical precipitation in spring and summer is substantially higher (662 mm) than the overall mean (461 mm). The conceptual backdrop of the Ricardian approach becomes now evident: the choice of the farm type may reflect long-term adaptation to local climate.

Let us move to an algebraic formalization of the link between climate and farm profitability. The point of departure is the assumption that farms at a specific location are assumed to maximize the value of a profit function (π):

$$max \;\; \pi = p_i\, q_i(z_c, z_{nc}) - c_i(z_c, z_{nc}) - P_L L_i(z_c, z_{nc}) \tag{1}$$

where p_i, q_i, and c_i are the price, quantity, and cost of production of good i. Land devoted to the production of i, L_i, is assumed to be heterogeneous with an annual cost (or rent) of P_L. It is convenient to distinguish between a vector of land and site attributes whose levels can be controlled (z_c), and another vector of attributes whose levels cannot be controlled (z_{nc}). In chapter 4, for instance, z_c covers the occurrence of the farm type and irrigated acreage, whereas z_{nc} comprises climatic and topographical factors. The usual assumptions that approximate the concept of perfect competition are assumed to hold, and the selection of optimal levels of the attributes subsumed in z_c, q_i and L_i, given z_{nc}, are assumed to lead to the farm structure that maximizes profit (Mendelsohn *et al.*, 1996).

The aforedescribed backdrop may lead to various analytical variants that are conceptually equivalent. The first accrues from setting $\pi = 0$ in Eq. (1)[3], then solving the resulting equation with respect to P_L, and then discounting P_L to infinity (see Mendelsohn *et al.*, 1996). This leads to the market (asset) value of land, V_L:

$$V_L = \int_0^{\infty} P_L\, \mathrm{e}^{-rt}\, dt = \int_0^{\infty} \frac{\left(p_i q_i(z_c, z_{nc}) - c_i(z_c, z_{nc})\right)\mathrm{e}^{-rt}}{L_i(z_c, z_{nc})}\, dt \tag{2}$$

where e^{-rt} is the discount factor. The second path accrues from changing the interval of integration of P_L from ∞ to a fixed contract period, say T, which leads to the value of land during the contract. The analyst is generally interested in expressing a farm-profitability indicator as a function of the land and site attributes. Thus, the above paths may lead to a regression of the asset or rental price of land against against z. A third path that avoids the zero-profit assumption, and is thus typically followed in developing-country applications, is a

[3] Although farms in a perfectly competitive land market may earn positive or negative profits in the short run, zero economic profits will prevail in the long run. Breaking even is a condition of the long-run equilibrium framework because of the willingness to enter and to leave the sector in response to the possibility of making excess returns (Nicholson and Snyder, 2012: 425f.).

direct regression of revenue measures against *z*. In any case, the interest lies in the derivation of an implicit price (or WTP) for the consecutive land attributes (Palmquist, 2005).

1.3.2 Estimating the traditional Ricardian model

The traditional version of approach regresses an indicator of farm profitability against farmland characteristics. Farm data for these studies typically come from official censuses for developed-country applications, and from estimates through surveys for developing-country applications. Climate data are available from meteorological networks as measurements from ground stations or satellites. Additional data may vary by context. While the focus remains on the climate variables, the use of relevant control variables is necessary to achieve model completeness, and may also serve as mousetrap for undesirable specification and estimation pitfalls such as omitted-variable bias. Unless the data are readily available from previous applications, often tremendous amounts of data have to be processed (see section 1.5).

The first decision when estimating the Ricardian model relates to the choice of the regressand. The first empirical application (Mendelsohn *et al.*, 1994) infers the value of climate from the asset price of farmland. In some contexts, however, the market price of land no longer conveys accurate information about land costs, and thus farmers' decisions will no longer reflect true opportunity costs of land. Typical examples that may lead to misallocation of resources are unclear property rights (*e.g.*, Behnin, 2008), policy interventions (*e.g.*, Fleischer *et al.*, 2008), and subsistence farming (*e.g.*, African countries). Since in such cases economic profits are inaccurately reflected in reported farmland prices, the value of climate has been inferred from revenue-based measures. A detailed exposition of the shortcomings from doing so is given in Mendelsohn and Dinar (2009: 59–62). In this context, a panel-based intertemporal net-revenue approach (Deschênes and Greenstone, 2007) that captures short-term weather adaptation is an attractive, albeit rarely used, alternative.

A second set of issues when estimating the Ricardian model relates to the operationalization, parameterization, decomposition, and formularization of climate. To start with, historical averages have remained a conceptually elegant and estimably easy right-hand-side (RHS) operationalization of climate in cross-sectional setting. As such, climatological normal (*i.e.*, 30-year means) are typically used to de-escalate the time-varying nature of climate to static. This operationalization assumes invariant higher moments, an assumption we relax in chapter 4. Parameterization boils down to the choice of the climatic attributes. The literature draws mostly on temperature and precipitation measures because they are relatively straightforward to obtain, albeit by no means bounding (*e.g.*, sunshine duration was used in

Maddison, 2000). Decomposition of the measures of climate can be monthly (*e.g.*, Mendelsohn and Reinsborough, 2007), seasonal (*e.g.*, Massetti and Mendelsohn, 2011b) or annual (*e.g.*, De Salvo *et al.*, 2013), and generally depends on data availability. Finally, formularization of climate relates to the way that expected nonlinearities are accounted for, and is discussed below.

The functional form choice is an empirical matter. Following Darwin's (1999) broader critique on the Ricardian approach, the literature has shown tendency toward logarithmic and Box-Cox transforms. The log-transformation is dictated by the fact that property-value measures are positive and usually exhibit high skewness, whereas Box-Cox variants (*e.g.*, Lang, 2007; De Salvo *et al.*, 2013) may be motivated by the interdependency of environmental characteristics (Maddison *et al.*, 2006). From a purely practical viewpoint, the advantage of the log-transformation is that it is easier to interpret and handle *post hoc* than the Box-Cox, especially if additional specification issues (*e.g.*, spatial autocorrelation) are to be accounted for. A tractable path to choose the functional form is to come up with an R^2 measure that is comparable between y and $logy$ (*e.g.*, Wooldridge, 2002: 203)[4], or to assess the Box-Cox parameter estimate after a Box-Cox test.

Irrespective of the functional form for y, it has remained as panacea to introduce polynomials to formularize nonlinearity in the RHS variables that proxy climate. The use of second-degree polynomials adjoins Quiggin and Horowitz's (2003) concept of the "climatic optimum": the direction and amount of change in crop-specific yields or profits at a location depend on the theoretically optimal configuration of climate relative to its current and future levels. Climate change will be beneficial (damaging) if, on average, climate moves closer to (further away from) the optimum. Thus, a positive first-order partial derivative of y with respect to temperature ($\vartheta y/\vartheta z_{temp} > 0$) suggests an increase, whereas a negative partial derivative ($\vartheta y/\vartheta z_{temp} < 0$) suggests a decrease in land prices or farm profits due to a temperature increase of 1 °C, *ceteris paribus*. Whether concavity ($y'' < 0$) or convexity ($y'' > 0$) will be portrayed is generally a question of the scale of analysis, the size of the study area, and the decomposition of climate. For example, it would be difficult to uncover a nonlinear response of profits (and even yields) to temperature under a narrow temperature spectrum. An attractive feature of the quadratic formularization is its accordance with the standard hedonic

[4] Misguiding justification has been given in a previous study (Massetti and Mendelsohn, 2011a), where the comparison between y and *logy* was (erroneously) done on the basis of adjusted R^2 measures. Since different dependent variables are fitted, different functional forms for y lead *a priori* to different amounts of explained variation (Wooldridge, 2002: 195).

framework in that nonlinearity in the environmental variables and thus, varying marginal WTP by the point of evaluation, are expected *a priori* (see Freeman, 2003). An example for Germany can be identified in Lippert *et al.* (2012), where the partial effect of mean annual temperature on maize shares is lower for counties that already experience beneficial temperature levels (*e.g.*, Karlsrühe) and higher for counties farther away from the empirical optimum (*e.g.*, Lörrach) of 9.85 °C (own estimation, based on their Table 2).

Additional specification and estimation pitfalls (*e.g.*, collinearity across months or seasons, endogeneity, omitted-variable bias, simultaneous-equation bias, measurement errors in the climate variables, spatial autocorrelation) may also arise. These issues are dealt with extensively in chapters 2–4.

1.3.3 Structural Ricardian models

Structural Ricardian models are the natural extension of the traditional Ricardian model. The recent spur in those models is attributed to the fact that they offer an estimably simple starting point to open the "black box" of adaptation: an observed on-farm decision is parameterized in the first step, and economic impacts are then conditionally quantified. For example, Seo (2010) examined the climate-dependent choice between crop, livestock, and mixed farm types in Africa with a polycategorical model, and the total effect of climate on each farm type with three conditional net-revenue regressions. Published empirical work of the structural Ricardian approach has also covered irrigation (Kurukulasuriya *et al.*, 2011), since the climate-induced behavior of irrigated farms is expected to differ from that of rainfed farms. Overall, structural Ricardian studies have found that the effect of climate on farm-type and irrigation choices can be captured, and that adaptation strategies do merit further investigation in the approach. However, the endogeneity of adaptation to climate has not yet been explicitly modeled. We build on this aspect to delineate a research topic in section 1.4.3.

1.3.4 Attractive features

A first attractive feature of the Ricardian approach is that it draws on empirical evidence across large landscapes. This is a major advantage over controlled experiments or crop simulation models, which extrapolate from smaller areas (or few farms) to larger areas. Furthermore, whereas crop simulation models typically model specific crops, the Ricardian approach can effectively consider the entire spectrum of crops or farm types.

The most widely cited premise of the Ricardian approach is the incorporation of implicit adaptation. The term "implicit" refers to the fact that the total effect of climate can be monetarily quantified by looking directly at the farm-profitability indicator. Thus, the traditional version of the approach looks at the consequences of actual adaptation *without* explicitly modeling how that adaptation has occurred. This might be seen either as an advantage in terms of cost-effectiveness (*e.g.*, agroeconomic models are more data- and personnel-intensive) or as a disadvantage in terms of structural comprehensiveness (*e.g.*, crop-simulation models model biophysical impacts in detail). Finally, note that the term "endogenous" has often been used in place of the term "implicit" when characterizing the treatment of adaptation. Albeit common, this choice of words is erroneous because the term "endogenous" relates to endogenous estimation in the world of applied statistics–what has been ignored in previous Ricardian studies but is dealt with in this dissertation (chapter 4).

Another conceptual advantage is that of efficient adaptation. Farms are assumed to have engaged in a trial-and-error process while searching for the optimal production mix (Lippert *et al.*, 2009). This point is not accounted for in controlled-laboratory experiments, in which adaptation is brought into the simulations by the expert builder (Mendelsohn, 2007). The efficient treatment of adaptation implies that the costs of various choices at farm level are all incorporated into the impact estimates. However, those costs are not explicitly quantified.

1.3.5 Limitations

This section provides a brief list of commonly cited limitations of the Ricardian approach. Those limitations that were taken as the points of departure for our specific research topics are presented separately in section 1.4.

To begin with, the Ricardian approach assumes that farmers are clairvoyants: they identify climate change, know when and how to adapt, react similarly and instantaneously as if they were long-adjusted to farming, and alter farming activities to maximize profits. Clearly, this mechanism prescribes inexpensive (optimistic) adaptation.

In essence, the comparative static nature of the Ricardian approach is tantamount to the concept of ergodicity (see Schneider *et al.*, 2000) in many respects. First, cross-sectional spatial differences in climate serve as a proxy for what is a dynamic phenomenon. This may limit the fidelity of the approach to reproduce actual adaptation, which is also dynamic. In addition to that, the approach assumes perfect substitutability across space at the same time. This point is particularly important when considering the roles of technology and irrigation in shaping the adaptation potential (*e.g.*, Kumar, 2011). For example, though sufficient water availability is assumed at any particular location to undertake the appropriate adaptation measures, this might not be the case in reality. In chapter 4, we offer the first attempt to explicitly model the endogeneity of irrigation to climate in the Ricardian model without conditional regressions.

The effect of factors that do not vary systematically across space is not considered in the Ricardian approach. For example, since CO_2 concentrations are effectively the same in a pure cross section, the extent to which changes in CO_2 levels lead to yield enhancement or to more efficient water use is not considered. In general, the effect of CO_2 might be detected by looking at productivity over time. However, it would be difficult to empirically isolate that effect from confounding phenomena such as technical changes (Mendelsohn *et al.*, 2009).

A crucial assumption is the constancy of input and output prices, supply, and demand (Cline, 1996; Darwin, 1999). This is a strict constraint because these factors *affect* and *are affected* by farm-level adaptation. It has been asserted that the bias stemming from the assumption of constant prices is likely to be small (see Mendelsohn and Nordhaus, 1996).

The increase in the frequency or intensity of extreme weather events (*e.g.*, droughts, floods) affects farm profitability. Sophisticated methods that could glean the analogous probabilistic information do exist *(e.g.*, for an introduction to Monte-Carlo-type weather generators, see World Bank, 2010: 21), but taking this empirically into account seems to generally be a difficult task. In chapter 4, we consider the effect of extreme climate through the inclusion of an arbitrarily developed indicator variable.

The *modus operandi* of the approach allows for an assessment of the potential impacts of future climate through simulation exercises. This is accomplished by substituting the base climate data by future projections. This operation has at least two shortcomings. First, it is often objectionable that the use of past (observed) climate variation is a well-serving proxy for future (unobserved) climate change (Stern, 2008). This point renders questionable the usefulness of simulation exercises for the very long run, say for 2100 (Auffhammer and Schlenker, 2013). In this context, simulations for the near decades are better trusted because (*i*) climate variation in the near future is closer to the baseline, and (*ii*) nonmarginal impacts are likely closer to the marginal estimates, which are what such models value by nature. And second, simulation exercises add uncertainty (*e.g.*, due to climate model misspecification, climate scenario uncertainty) to an approach that already includes uncertainty in many ways (*e.g.*, Ricardian model misspecification, interpolation errors). This point does not imply that simulation exercises cannot be deemed informative, but does call for a great deal of consciousness in the interpretation of simulation results.

We close this section with a methodological note. The literature recognizes the necessity to obtain consistent and unbiased estimates of the independent influence of climate variables on the farm-profitability indicator. Analytically speaking, the requirement of orthogonality between the climatic variables and the disturbances may not be fulfilled due to measurement errors, omitted variables, endogenous variables, and simultaneously determined variables. Overall, the extent of the bias depends on the ability of the econometric analysis to identify what leads to correlated disturbances, and to deal with potential confounders. For example, an instrumental variables (IV) perspective to correct for endogeneity due to potential errors in the interpolated variables is taken in chapters 2 and 3, and spatial lags that can protect against omitted variables are used in chapter 4.

1.4 Research topics

This section introduces our research topics. The topics are presented in chronological order (from the one that was dealt with first, to the one that was dealt with last), which coincides with their structural complexity (from the least to the most complex).

1.4.1 Errors in the interpolated variables

This topic is dealt with in chapter 2. It is shaped by the following research questions.

Are there any reasons to expect that the variables that proxy climate contain errors?

There usually exists a mismatch between the spatial support of the climatic measures, which are collected at a finite set of monitoring stations, and the farm data, which are collected at the farm. This mismatch necessitates a spatial interpolation operation for the climatic measures. Various deterministic and probabilistic alternatives are possible, the choice among which is typically done on the basis of cross-validation. However, any interpolation scheme is subject to prediction errors. The variance of such errors cannot be completely eliminated; it may only be reduced upon choosing of the "best" scheme. This aspect has been long disregarded in Ricardian studies, where interpolated climate is typically treated as "true" climate without errors.

What kinds of errors are expected in the interpolated climate variables?

In this application, we define as errors any discrepancy between interpolated (used but unobserved), actual (unobserved or missing), and perceived climate. From an errors-in-variables perspective, we demonstrate that interpolated temperature and precipitation measures are likely to be correlated with the disturbance term of the Ricardian model. This would degrade the exogeneity of the interpolated variable(s) leading to biased and inconsistent ordinary least squares (OLS) estimates.

How to cope with such errors?

Inspired by a recent application that focuses on air quality measures (Anselin and Lozano-Gracia, 2008), we address the issue of correlated errors explicitly into the estimation process by treating interpolated climate as endogenous. We implement a *post hoc* trend surface analysis through IV estimation, where interpolated climate is instrumented by regionalized variables.

1.4.2 A structural Ricardian analysis of farm types in Germany

This theme is dealt with in chapter 3. It comprises the following research directions.

Application of a structural Ricardian analysis of farm types

A recent trend pertains to the imposition of formal structure on adaptation in the form of conditional regressions. The classification of farms into various farm types by the German statistical office has resulted into readily available data that can be utilized for that purpose. Those data enable us to investigate (*i*) the extent to which the decision to opt for certain farm types is driven by climate, and (*ii*) the influence of climate on the profitability associated with each farm type. We accomplish the first aim with the estimation of a multinomial model for the occurrence of six farm types (cash crops, forage, livestock fattening, permanent crops, horticulture, and mixed), and the second aim with the estimation of six land-rental-price models conditional on the farm type.

Modifications from the usual setup

In our context, three distinct modifications from previous studies are made. First, published studies rely on data on sampled individual farms. In our case, data on all farms are available. However, the unknown absolute location of individual farms poses an impediment to spatially interpolate the measures of climate. Therefore, we aggregated the data at the administrative level that is as close as possible to the farm level, using the relative location of farms. Second, as the dependent variable in the multinomial model is nominal and refers to a group of farms, we examine the most frequent farm type at the community level instead of the actual type of individual farms. In order to deal with uneven aggregate units, probability-weighting is used. Third, in addition to probability-weighting, we implement the errors-in-variables "correction" (section 1.4.1) in all models.

1.4.3 Endogenous adaptation and spatial effects

This theme is dealt with in chapter 4. It is driven by the following research topics.

Implicit vs. endogenous adaptation

The traditional version of the approach assumes implicit adaptation–that is, regressing land prices or farm profits against climatic attributes enables the calculation of the total monetary effect of climate without formally modeling how long-run adaptation has occured. The structural version of the approach assumes implicit adaptation but conditional on the farm type–that is, regressing land prices or farm profits of farms of a certain type against climatic attributes enables the calculation of the total monetary effect of climate on that farm type. This happens in the framework of J conditional regressions, where J is the number of farm types, and substitution among the farm types is not accounted for. We propose an alternative way which explicitly allows for endogenous substitutions among the various farm types. The proposed modeling framework can be generalized to account for any adaptation strategy that might be of interest.

How to explicitly account for the endogeneity of any adaptation measure?

We are the first to model the endogenous nature of adaptation explicitly. We develop and estimate a land-rental-price model with the choice of the farm type and irrigation treated as endogenous. In this new version of the Ricardian approach, the latter choices are simultaneously determined *by* climate and determine farm profitability *along* with climate. We use the nonlinear projections of the endogenous variables and the spatial lags of those projections as instruments. We take an IV perspective that allows for the decomposition of the effects of climate into direct (the unmediated effect of climate on farm profitability) and indirect (the effect of climate that is mediated by the farm-type and irrigation variables).

Spatial autocorrelation

In addition, we take an explicit spatial econometric perspective and account for spatial autocorrelation, which is a statistical phenomenon often inherent in cross-sectional data. This leads to the first application of a Ricardian model that couples both types of endogeneity (*i.e.*, spatial and aspatial) and separates the effect of the spatial multiplier in the computation of marginal impacts.

1.5 Overview of data, methods, and software

In what follows, we present a brief description of the data utilized, the methods employed, and the software used in our studies. Operational information and sources are described in detail in the consecutive articles (chapters 2–4).

All data utilized in our applications are secondary. For ease of notation, we can group the data into five categories: farm-specific, climatic, topographical, geographical, and spatial characteristics. Farm data come from the census, and refer to records from the years 1999 and 2010. Access to these data was obtained through a contract with FDZ. Base climate data cover the 1961–2009 period. Parts of these data (1961–1990) that had been readily available from a previous study (Lippert *et al.*, 2009) are utilized in chapters 2 and 3; more recent data (1980–2009) that were obtained from WebWerdis are exclusively utilized in chapter 4. Rest data come from various sources.

Spatial interpolation of the 1980–2009 climate data was carried out by coupling Stata/SE 11 with the Esri ArcGIS Geostatistical Analyst extension. The data were integrated, aggregated, geocoded, and zonally rearranged with Stata and the Esri ArcGIS Spatial Analyst extension, and were spatially matched at various administrative levels.

For the estimation of the traditional Ricardian models, we employ cross-sectional microeconometrics. We rely on IV estimation to correct for warranted-by-the-data endogeneities, and we couple the IV models with spatial econometric counterparts. For the structural Ricardian models, we take a limited dependent-variable perspective to account for the nominal nature of adaptation choices. Care is taken in model specification, estimation, testing, and prediction.

Due to data privacy restrictions by the Federal Statistical Office, the empirical applications presented herein were pursued on the basis of remote data analysis *(kontrollierte Datenfernverarbeitung*). This enabled us to remotely access individual farm data from our home institution (Hohenheim). First, programming codes and external data were sent to FDZ/Kiel. Those codes merged our data with the farm data from the census. Second, the FDZ had to make sure that the codes run without syntax and compatibility errors. Third, upon fixing such errors, the output of our analysis was inspected to make sure that confidential data are not revealed. Fourth, only the results were emailed to us. These four steps were repeated about 35 times in order to generate publishable results of satisfactory quality. Parts of the analysis for chapter 2 were performed in the guest scientist workstation of FDZ/Stuttgart. In all, neither were we allowed to obtain any data in hand nor to develop maps that would help us visualize the results.

1.6 Outline of dissertation

The remainder of the dissertation is organized as follows. The main body comprises three empirical studies that deal with the research topics presented in section 1.4.

The first article, entitled "Errors in variables in Ricardian models of climate change", is presented in chapter 2. It applies the traditional version of the Ricardian approach on land rental prices at the district level (*Kreise*; N = 439), and aims at a more efficient treatment of the interpolated climate variables through IV estimation.

The second article, entitled "Adaptation and climate change impacts: a structural Ricardian analysis of farm types in Germany", is presented in chapter 3. In this article, we develop a variant of the structural Ricardian approach at the community level (*Gemeinde*; n = 9,684) that investigates the climate-induced choice between six farm types, and related economics impacts per farm type.

The third article, entitled "Endogenous farm-type selection, endogenous irrigation, and spatial effects in Ricardian models of climate change", is presented in chapter 4. It proposes a new version that can explicitly recognize the endogeneity (to climate) of any adaptation strategy into the land-value model. Our empirical example considers the incidence of farm types and irrigated acreage at the level of community associations (*Gemeindeverbände*; n = 3,515), and takes those factors into account simultaneously with spatial autocorrelation.

Chapter 5 concludes the dissertation by stapling the outlined articles together in order to delineate their limitations, highlight their contributions, and draw overall conclusions. The dissertation concludes with a propagation of avenues that merit promising future research.

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CHAPTER 2

Errors in variables in Ricardian models of climate change[5]

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Abstract

In the so-called Ricardian models, climate variables have been typically treated as nonstochastic. However, if climate variables are the result of spatial interpolation, their exogeneity degrades. In this article, we assess the extent to which errors in the interpolated measures of climate may affect the corresponding empirical marginal implicit prices. Upon using cost-effective instruments that can account for such errors, we treat interpolated climatological normals as endogenous with a *post hoc* IV-based trend surface analysis. We further account for spatial autocorrelation to correct for other cross-sectional data inefficiencies. Drawing on farm census data for Germany, our results suggest that the bias in the price estimates for (interpolated) climate may be severe, but the bias in the overall welfare may not be. Projected temperature and precipitation changes seem to benefit agriculture in Germany in the upcoming decades.

Keywords

Climate change; Ricardian analysis; errors in variables; instrumental variables

JEL classifications

O13, Q51, Q54, R32

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[5] This chapter is an unpublished manuscript.

2.1 Introduction

In the absence of an explicit market for climate change, political interest boils down to providing credible implicit price signals on this phenomenon's attributes. Ideally, such signals would play the key role of proactive measures in environmental policy design. However, making the impact of climate "visible" in agricultural policy decisions has long remained a daunting challenge for the scientific community. Interestingly, this challenge has led to a continuous search for methodological strategies that seek to explore the association of climate with farm profitability in greater detail.

In doing so, the Ricardian approach has become a popular procedure. In essence, this approach explores the role of climatic attributes in the determination of the value of land under the presumption of efficient adaptation. Analytically, this relationship is materialized by regressing a farm-profitability indicator against the attributes of the land and the site. The interest lies in climatological averages (*i.e.*, 30-year means), which constitute a conceptually elegant and estimably simple RHS operationalization of climate. Parameterization of climate can be done in various ways (Mendelsohn and Dinar, 2009: chapter 4) and typically depends on data availability.

Owing to its overall cost-effectiveness when being compared to classic agroeconomic programming models, the Ricardian approach tends to be the preferred impact assessment of agricultural and environmental economists. The pioneering work of Mendelsohn *et al.* (1994) might have generated an abnormal amount of criticism (*e.g.*, Cline, 1996; Quiggin and Horowitz, 1997; Kauffmann, 1998; Fischer and Hannemann, 1998; Darwin, 1999, among others), but the seemingly eccentric idea to estimate the impacts of climate change on agriculture from a cross section has led to a voluminous literature with applications for countries all over the world. Extensive reviews and advances can be found in Mendelsohn and Dinar (2009). Theoretical perspectives are offered in Mendelsohn (*et al.*, 1996; 2000).

In Hanemann (2000), several methodological issues pertaining to the descriptive and simulative reliability of Ricardian models were exposed. Among other things, the editorial comment included a discussion on possible measurement errors and their sources. An important source of errors relates to the interpolation of climate data that originate from ground meteorological stations. This aspect has been disregarded in a bulk of studies that relied on interpolation procedures (*e.g.*, Polsky and Easterling, 2001; Weber and Hauer, 2003; Kurukulasuriya and Ajwad, 2007; Lippert *et al.*, 2009; Molua, 2009; Seo *et al.*, 2009). The lack of scientific interest in improving the quality of climate variables whose values are not observed at every location is a rather surprising element of climate impact assessment.

In this article, we focus on measurement errors that may accrue from the discrepancy between interpolated ("observed") and the true (unobserved or missing) values for a climate variable. This is a new methodological aspect with respect to the Ricardian approach, which typically treats interpolated climate as "true" climate without errors. From an errors-in-variables perspective, we demonstrate that interpolated temperature and precipitation are likely to be correlated with the disturbance term of the Ricardian model. The exogeneity of the interpolated variable(s) then degrades, and the corresponding OLS estimates are biased and inconsistent.

The scope of this article is to examine the extent of that potential bias in the marginal implicit price estimates for climatological normals. Our empirical assessment draws on census data covering all rent transactions that took place in Germany in 1999, and is pursued by means of a series of regressions at the district level (*Landkreis;* $N = 439$).

In stark contrast to previous applications, errors in variables are herein sought to be addressed explicitly in the estimation process by treating interpolated climate as endogenous. In doing so, we employ cost-effective natural instruments that proxy climate as a three-dimensional trend. In environmental sciences, implementation of this procedure in an *ad hoc* manner is often referred to as trend surface analysis (*e.g.*, Unwin, 1978), and is one among several methods available to perform spatial interpolation. In this application, we perform this procedure *post hoc* to improve the interpolated estimates. We further account for spatial autocorrelation, which is expected due to a number of reasons. This IV procedure is principally extensible to structural (*e.g.*, Seo and Mendelsohn, 2008) or panel-data-based Ricardian models (*e.g.*, Masetti and Mendelsohn, 2011).

The analysis underlying this article differs from the Ricardian analysis for Germany in Lippert *et al.* (2009) in many aspects. First, the current dataset contains no missing values, and includes four new important explanatory variables. Second, we rely on a different weighting scheme for the dependent variable as well as on another functional form. Third, expected heteroskedasticity is now taken into account. And fourth, though interpolated climate data are virtually the same, climate variables are now further estimated endogenously. Our overall result might be in accordance with the conclusion in Lippert *et al.* (2009) in the sense that climate will likely benefit agriculture in Germany in the upcoming decades, but it will be made evident that we arrive at this conclusion through another mechanism.

The remainder of the article is sketched as follows. First, we present theoretical background that relates to errors in variables in Ricardian analyses (section 2.2). Then, a brief discussion of data sources and variables is given (section 2.3). The next section introduces the modeling framework along with a discussion on the instruments (section 2.4). In the subsequent sections we review our regression results (section 2.5) and, following the *modus operandi* of the approach, we present a marginal impact analysis and a simulation exercise based on future climate projections (section 2.6). Section 2.7 concludes.

2.2 Theoretical framework

Ricardian valuation models are typically estimated using climate data that originate from satellites or ground meteorological stations. In particular, although temperature data series may come from either source, precipitation data originate exclusively from ground stations, since satellites can only measure soil moisture. Though empirical applications depend on data availability, the combined use of satellite measurements for temperature and ground station data for precipitation has been recommended (Mendelsohn *et al.*, 2007). In the absence of satellite data, in this article we rely on interpolated ground station data for both climatic attributes. We elaborate on an idea delineated in Anselin (2001; 2002) where it was argued that the exogenous treatment of interpolated measures of environmental quality is likely to create complications in the form of errors in variables (Anzelin and Lozano-Gracia, 2008).

Weather stations are often dispersed across the landscape. In obtaining a measure of a climatic attribute for a certain location, one typically resorts to spatial interpolation procedures (*e.g.*, inverse-distance weighting, kriging, splines). The interpolated data then, as if they were true and observed measurements, constitute RHS variables in the Ricardian model, with which the effect of climate indicators of farm profitability is estimated. However, any interpolation procedure is subject to prediction errors, which might follow (spatial) patterns of known or unknown nature. For example, increasing errors are expected with greater distance to the meteorological stations (Anselin, 2002). Moreover, since climate operates at a larger scale than individual farms, the presence of positive spatial autocorrelation is to be expected[6].

[6] *"Everything is related to everything else, but near things are more related than distant things"* (Tobler, 1979).

Using traditional notation, consider the standard cross-sectional version of the Ricardian model with a dependent variable $\mathbf{y}$ that represents a land-value or farm-profitability indicator, and k nonstochastic regressors, $\mathbf{X}_k^*$:

$$\mathbf{y} = \beta_0 + \beta_1\mathbf{X}_1^* + \ldots + \beta_k\mathbf{X}_k + \mathbf{u} \tag{3}$$

If the actual values of a climatic attribute, say $\mathbf{X}_1^*$, were observed, the model parameters could be estimated consistently by OLS regression with i.i.d. $[0, \sigma_{\mathbf{u}}^2]$ disturbances. Since true climate is not measured at every location, Eq. (3) is estimated by substituting the values of $\mathbf{X}_1^*$ with its interpolated items. The interpolated regressor, $\mathbf{X}_1$, measures true climate with a prediction error ε $[0, \sigma_\varepsilon^2]$:

$$\mathbf{X}_1 = \mathbf{X}_1^* + \boldsymbol{\varepsilon} \tag{4}$$

This decomposition of $\mathbf{X}_1$ might lead to two further assumptions. If one is to accept that $\boldsymbol{\varepsilon}$ is uncorrelated with $\mathbf{X}_1$, it is implied that $Cov(\boldsymbol{\varepsilon}, \mathbf{X}_1^*) = -\sigma_\varepsilon^2$ (assumption 1). In this case, OLS preserves its consistency with an inflated disturbance variance notwithstanding (Wooldridge, 2003: chapter 15). Alternatively, assuming that $\boldsymbol{\varepsilon}$ is uncorrelated with $\mathbf{X}_1^*$ leads to $Cov(\boldsymbol{\varepsilon}, \mathbf{X}_1) = \sigma_\varepsilon^2$ (assumption 2). To understand why this nonzero covariance might be problematic, we can substitute Eq. (4) into Eq. (3):

$$\mathbf{y} = \beta_0 + \beta_1(\mathbf{X}_1 - \boldsymbol{\varepsilon}) + \ldots + \beta_k\mathbf{X}_k + \mathbf{u} \tag{5.1}$$

$$\mathbf{y} = \beta_0 + \beta_1\mathbf{X}_1 + \ldots + \beta_k\mathbf{X}_k + \mathbf{u} - \beta_1\boldsymbol{\varepsilon} \tag{5.2}$$

$$\mathbf{y} = \beta_0 + \beta_1\mathbf{X}_1 + \ldots + \beta_k\mathbf{X}_k + \mathbf{u}^* \tag{5.3}$$

where $\mathbf{u}^*$ is the new composite disturbance, $[0, \sigma_{\boldsymbol{u}}^2 + \beta_1^2\sigma_\varepsilon^2]$. Thus, although the assumption that $\mathbf{u}$ is uncorrelated with $\mathbf{X}_1$ (or $\mathbf{X}_1^*$) is retained, we have $Cov(\mathbf{u}^*, \mathbf{X}_1) = -\beta_1\sigma_\varepsilon^2$. Unless the variance of $\boldsymbol{\varepsilon}$ is somehow forced to zero, accepting the second assumption renders the OLS estimates biased and inconsistent due to errors in variables (Greene, 2002: chapter 5). As the variance of $\boldsymbol{\varepsilon}$ depends on the interpolation scheme, choosing of the "best" scheme among competing ones might merely reduce the bias, not eliminate it completely.

When may the above assumptions be of relevance? To understand when assumption 1 may arise, note that our farm-profitability indicator is the land rental price (see section 2.3). The equilibrium rental price schedule in the agricultural land market is demand-determined for climatic attributes (Palmquist, 1989). The driving presumption of the Ricardian approach is that of efficient adaptation–that is, profit maximization is assumed to take place through strategic reconciliation of past climate and past profitability. This presumption leads to the assumption that local climatic trends are "visible" to landlords and tenants, and thus climate enters into their utility functions, impacts their bids, and contributes to the determination of the equilibrium rental price schedule. In this regard, assumption 1 may arise due to a discrepancy between true climate and what enters the agent's (tenant or landlord) utility function as climate. Even if it is assumed that the values of $\mathbf{X}_1$ and $\mathbf{X}_1^*$ coincide, or that actual climate is correlated with what is perceived as climate, it would be too optimistic to assume that farmers are aware of the exact probability distribution of $\mathbf{X}_1^*$ (*e.g.*, Schneider *et al.*, 2000). Assumption 2, on the other hand, may hold in cases where the used value for climate contains a prediction error of spatial or aspatial nature irrespective of what enters into the utility functions. For example, the failure to interpolate climate correctly at a location may be due to the omission of relevant topographical attributes (*e.g.*, altitude).

Admittedly, neither is climate perfectly captured by those whose behavior is under examination nor is it perfectly predicted by the interpolator. This viewpoint leads to bias and inconsistency because both $Cov(\varepsilon, \mathbf{X}_1^*) \neq 0$ and $Cov(\varepsilon, \mathbf{X}_1) \neq 0$. An additional source of error in Eq. (5.3) may be attributed to the omission of variables that are correlated both with climate and the dependent variable of the Ricardian model (*e.g.*, CO_2 concentrations, altitude). This viewpoint may lead to simultaneous-equation bias between Eqs. (3) and (4).

In all, there are reasons to expect that $Cov(\varepsilon, \mathbf{u}^*) \neq 0$. Since in many cases climate data come to the agricultural economist as secondary data, coping with this nonzero covariance *post hoc* might be more cost-effective than opting for row climate data that would have to be processed anew. In this regard, a straightforward approach is to use information from other variables (instruments) that are relevant (*i.e.*, sufficiently correlated with the interpolated regressors) and valid (*i.e.*, uncorrelated with the disturbance of the Ricardian model). In the following, we resort to IV estimation and treat climatological normals as endogenous.

In addition to that, we account for spatial autocorrelation in the model specification, which had been expected at least as a side effect. Reasons such as the underlying mismatch between the actual scale and the analyzed scale (farms *vs.* districts), the spatial mismatch between the scales of collection of the farm and climate data (farms *vs.* stations), and the inclusion of interpolated and integrated predictors, are all likely to result in some form of positive spatial correlation (Anselin, 2001; 2002). As the necessary statistical justification favors spatial error correlation over spatial lag dependence in our case (see section 2.5), we take a spatial-autoregressive error modeling perspective in section 2.4.

2.3 Data and variables

The steady-state farm profitability indicator we use is the land rental price, which constitutes an observed market price and the only indicator of monetary nature directly available in the census database. Data on rents draw on all individual 284,530 transactions that occurred in 1999 (FDZ, 2011). Renting farmland is very common in Germany: in 1999, farms that rented land comprised 57.1% of all farms, and rented acreage comprised 56.5% of the total utilizable agricultural area (UAA). Each farm was assigned to the district of their registration by the statistical office. As per hectare rental rates are not reported in the census, we created a mean price (€/ha) at the farm level by dividing total cash rents by total rented acreage. Mean rental prices, then, were arithmetically averaged at the district level, thus constituting an economic indicator of average farm profitability and so, our dependent variable. Rent transactions in Germany are not regulated by policies, and landlords and tenants negotiate for rental prices.

Data on observed climatological normals come from the German Weather Service (DWD, 2007). In the absence of detailed (*e.g.*, seasonal, monthly) data for temperature, we rely on mean annual measurements (°C). On the other hand, we use mean total precipitation (mm) during March, April, May and June. The decision to formularize precipitation in this way was dictated by the fact that seasonal precipitation measures led to unacceptably high collinearity (even after mean-centering), as precipitation is very highly correlated across seasons (>0.90). In addition to that, those four months constitute the main growth phase of arable crops, and significantly determine product quality and yield in Germany from an agronomic viewpoint. Hence, our analysis draws on the most efficient parameterization of climate given the available data. Climatological normals refer to the internationally defined 1961–1990 reference period. The values of either attribute for each district are based on zonal statistics on 1 km raster cell averages that are the result of a local and deterministic interpolator (first-degree inverse-distance weighting with the five nearest monitoring stations) that outperformed competing ones in terms of cross-validation (Lippert *et al.*, 2009: 598). Only rasters with agriculturally managed areas are considered. Spatial interpolation and zonal averaging were carried out with the Esri ArcGIS Geostatistical Analyst and Spatial Analyst extensions.

Soil data originate from FZ Jülich (2009). We include a soil productivity index that was developed by soil scientists as a comparison basis for the fiscal evaluation of farms in the 1930s. The index is conveniently measured on a 0–100 scale (=100 for highest potential yield) and considers only the mixture of particles, genesis, and degradation of arable soils. By construction, the soil index is climate-invariant. The variable used, an arithmetic mean for areal soil quality, is the result of zonal averaging related to only agriculturally managed areas. Based on a Digital Elevation Model (Jarvis *et al.*, 2008), a variable depicting the average slope (%) of farmland was generated in a similar way to control for potential profit reduction due to the increased costs that steepness entails.

Rental price differentials in two locations with similar climate and topographical characteristics may be the result of farmland availability, among else. To control for potential competition for local agricultural parcels, a proxy variable that equals the number of total farms per district was created. This will be referred to as the "competition" variable. This variable serves also as a proxy for East Germany, where farms are historically substantially larger and, hence, fewer per district.

Proximity to densely populated areas may inflate land rental prices. In order to control for nonagricultural pressure of urban nature, we considere the ratio of total district population (Statistisches Bundesamt, 2012) to total UAA. This is a relative measure of the direct tradeoff between the urban and agriculture uses of land.

Due to data privacy issues, the analysis was carried out at the guest scientist workstation of FDZ/Stuttgart. Estimation and testing procedures were done by means of Stata/SE 12.

The usual "disclaimer" applies. First, any excluded institutional (*e.g.*, know-how), technological (*e.g.*, high yield varieties), policy-related (*e.g.*, prices, subsidies) or environmental (*e.g.,* extreme weather, climate variance, CO_2) factor that might be associated with changes in farm productivity is assumed to remain constant. This is a shortcoming of the cross-sectional setup, and could in parts be ameliorated by additional data or information in the time domain (*e.g.,* Masetti and Mendelsohn 2011). Second, irrigation issues (*e.g.*, Cline, 1996; Fischer and Hanemann, 1998; Darwin, 1999; Kurukulasuriya *et al.*, 2011) are not addressed because the 1999 census had not gathered any related data. In the descriptive model run, irrigation is of minimal importance for the predominantly rainfed German agriculture. Finally, the signs or magnitudes to be displayed are not intended to serve as crude substitutes for individual-level relationships. This follows from realizations in the hedonic literature that conclusions drawn from aggregate studies may be scale-dependent for environmental attributes. With more selective, detailed, and up-to-date farm and climate data, we hope to elaborate on these issues in the future.

2.4 Model specification

Our Ricardian model considers both endogeneity in the climatological normals, and spatial-autoregressive disturbances. In matrix notation, the model can be expressed as:

$$\mathbf{y} = \mathbf{Y}\gamma + \mathbf{X}\beta + \mathbf{u} \tag{6.1}$$

$$\mathbf{u} = \rho\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \tag{6.2}$$

where $\mathbf{y}$ is a 439×1 vector of observations on district-averaged rental prices, $\mathbf{Y}$ is a 439×3 matrix of 3 endogenous climate variables, γ is the corresponding 3×1 parameter vector, $\mathbf{X}$ is a 439×4 matrix of our exogenous soil, slope, "competition" and population RHS covariates, β is the corresponding 4×1 parameter vector, $\mathbf{W}$ is a nonstochastic, nonsingular, 439×439 spatial-weighting matrix, ρ is a spatial-autoregressive scalar parameter, $\mathbf{u}$ is a 439×1 vector of spatially correlated disturbances, and $\boldsymbol{\varepsilon}$ is a 439×1 vector of independently but heteroskedastically distributed errors.

Setting $\gamma = \rho = 0$ and treating climate variables as exogenous causes the model in Eq. (6) to reduce to a typical linear regression model. Setting $\gamma = 0$ and treating climate variables as exogenous yields the spatial-autoregressive error (SER) model. At the moment, consider a linear aspatial specification with endogenous climate regressors, which we are led to by setting $\rho = 0$.

Motivated by recent recommendations in Anselin and Lozano-Gracia (2008) for their interpolated measures of air quality, our set of instruments comprises second-degree polynomials in the coordinates (longitude, latitude) of district centroids, mean altitude and its square, and the pairwise products of the first-degree terms. Thus, we have nine instruments in total. The relevance of these instruments is not difficult to justify on theoretical grounds. Coordinates act for the overall spatial patterns of temperature and precipitation, and proxy climate as a *global* spatial trend (large-scale process). Hence, in any study area that is not unreasonably small, they are naturally correlated with the true values of climate. Altitude is included because it is correlated with climate but neglected in the inverse-distance interpolator. Correlation of the instruments with the overall disturbance is rather unlikely, as the latter embodies *local* (spatial) patterns of omitted variables. The extent to which this justification of validity loses its realism is, of course, an empirical matter that should be tested. It has to be made distinct that these instruments cannot be employed *post hoc* if they have been used *ad hoc* through regression-based interpolation (*e.g.*, Mendelsohn *et al.*, 1994; Kurukulasuriya and Ajwad, 2007, among others); this would lead to a situation where the endogenous climate variable is predicted perfectly by its instruments, and so, to biased OLS estimation. If our proposed instruments are explicitly used *ad hoc* (*i.e.*, during the interpolation), one ought to find alternative instruments.

In empirically proceeding, an important methodological aspect pertains to the instrumentation of the quadratic counterpart of a climate variable. The inclusion of such quadratic terms intends to serve as an approximation of the nonlinear effects typically suggested by agronomic experiments, and has become panacea in applications of the Ricardian approach. Intuition would suggest instrumentation of the linear term, taking the squares of the corresponding fitted values, and then using them as an exogenous variable. However, this operation is incorrect because the linear fitted value of the square does not equal the square of the linear fitted value (Wooldridge, 2002: chapter 9). As such, any quadratic counterpart should be treated as an additional endogenous variable.

Recall the model in Eq. (6) but with exogenous climate variables (*i.e.*, **X** being a 439×7 matrix). In general, this setup allows the disturbances to be dependent. Spatial correlation is captured by the endogenous vector **Wu**, which subsumes spatial structure into the error covariance matrix and so, is usually treated as nuisance. Apart from the use of interpolated measures that may also result in a systematic spatial pattern for the error structure, data aggregation or integration might also give rise to this specification (Anselin, 2002). In the presence of spatially correlated disturbances, OLS estimation produces biased *t*-statistics, and may thus lead to erroneous significance of some parameters.

In defining spatial connectivity, we rely on a queen-contiguity layout according to which a matrix element w_{ij} equals 1 if districts i and j are contiguous, and 0 if they are not. To ensure the nonsingularity of **W** only continental districts were kept, which led to the exclusion of the island of Rügen from the set. In sum, the average number of neighboring districts in 1999 was 5, ranging from a minimum of 1 to a maximum of 12 links. In specifying **W**, we consider two normalization schemes. The first is the typical normalization by row according to which each element of **W** is divided by the number of contiguous districts, thus facilitating the interpretation of ρ as error correlation in the spatial domain. An alternative standardization follows the spectral norm, which leads to the division of each matrix element by the largest of the moduli of **W**'s real characteristic roots (see Kelejian and Prucha, 2010).

For the estimation of the aspatial models we rely on standard OLS and two-stage least squares (2SLS). For the estimation of the spatial-IV models we apply a spatial 2SLS estimator that uses **X** and our proposed instruments as instruments for **Y**, and **X** and **WX** as instruments for **Wu** (for estimation details, see Arraiz *et al.*, 2010 and Drukker *et al.*, 2013).

2.5 Empirical results

Basic descriptive statistics for our variables are given in Table 2.1. Regressors are only weakly associated with each other, and pairwise correlations display no spurious magnitudes. Further diagnostics indicate no collinearity-induced estimation problems. Preliminary Box-Cox regressions supported the log-transformation of the dependent[7] as well as the "competition" variables, which were then used as such. Since nonlinearity could be established only for precipitation, a quadratic counterpart was retained only for this climatic attribute[8].

We now move to Table 2.2, which depicts results from three estimation methods: OLS (the usual version of the Ricardian model), IV (standard 2SLS with interpolated climate treated as endogenous), and SER-IV (spatial 2SLS with interpolated climate treated as endogenous, and spatially lagged disturbances). We begin the review of our results by focusing on the OLS coefficients.

The parameter estimates for both climatic attributes are highly statistically significant. Overall, higher annual temperature and spring precipitation levels are associated with higher land rental prices. For spring precipitation, there is also a cutoff point on rental prices that is reflected in the negative sign of the quadratic term. This means that, *ceteris paribus,* rental prices increase at a decreasing rate up to a cutoff point, which is found at the level of 487 mm (approx. twice the mean). The overall result is not bewildering for a generally temperate/mesothermal country.

The signs of both climate variables are in accordance with those in Lang (2007) for similar climatic attributes, but only partially with those in Lippert *et al.* (2009). More specifically, temperature was found to be beneficial in Lippert *et al.* (2009), but the effect of precipitation negative for the country as a whole and without a cutoff. In order to understand the reason for this contradictory result and satisfy our curiosity, we replicated and further tested model II in Lippert *et al.* (2009: 599). By means of a Ramsey RESET test based on variable augmentation[9], we found that the negative sign of spring precipitation is attributed to misspecified functional form or omitted-variable bias, in either case induced by the dummy

7 The untransformed dependent variable is strictly positive and highly skewed.

8 Nonlinearity in temperature could not be established with the analyzed data, as the quadratic counterpart was not significant. This might be attributed to the fact that mean annual temperature is a very general temperature index, or to the aggregate nature of our analysis.

9 This specification test regresses the dependent variable against its fitted values and the square of the fitted values. Significance of the latter leads to rejection of the null: the conditional mean is specified incorrectly, or there are omitted variables (Cameron and Trivedi, 2009: 96).

variable *East*; model II passes the test only in the complete absence of the dummy, and the effect of precipitation becomes then positive. Model I does not pass a RESET test either. Hence, based on this result, the corresponding estimates for climate are biased and inconsistent. Two likely reasons for this outcome are that the use of few explanatory variables had led to omitted variables, or that the linear functional form had not taken into account important nonlinearities.

Back to our results, the signs of the nonclimate predictors obey conventional wisdom. Average rental prices are higher in districts with more productive soils but lower when farmland is found in steeper slopes. The positive effect of the variable measuring the frequency of farms on rental prices could be thought of as the result of higher competition for agricultural land. The positive effect of the population variable supports the general perception that rental prices are higher in denser districts, possibly because of urban pressure.

The explained variation of the aggregate OLS model is fairly good ($R^2_{\text{var}} = 0.44$) for the aggregate cross-sectional setup with a limited number of covariates. In the Ricardian literature, higher R^2 values frequently have been the result of inclusion of highly collinear terms (*e.g.*, seasonal climatological normals in linear and quadratic form) that inflate *t*-statistics, or variables that are endogenous to (and thus significantly correlated with) climate but enter the model as exogenous. The OLS model passes functional form and heteroskedasticity tests, but additional diagnostics indicate endogeneity in the climate variables and spatial autocorrelation.

Invalid or weak instruments cause IV estimators to lose precision and potentially become worse than OLS. At first, we formally assessed the exogeneity of the climate variables by means of robustified exogeneity tests (Wooldridge, 1995). First, we focused on the single exogeneity of one climatological normal at a time. This led to testing either the single exogeneity of temperature or the joint exogeneity of the two precipitation variables. Then, the joint exogeneity of all three variables was assessed. As the results do not differ significantly for various combinations of the instruments, we proceeded with the set that maximized the χ^2_3 value of the joint exogeneity test: longitude, latitude, altitude, and their squares and pairwise products. The chosen set is overidentifying: regressing the IV residuals on all nine instruments gives Adj. $R^2 = 0.001$, with $F_{9,429} = 1.08$ and *p*-value 0.38, and all regressors (instruments) are far from being significant. No invalid-instruments problem is flagged.

Then, we assessed the quality of our instruments. Typical pairwise Pearson correlation coefficients between the instruments and the endogenous regressors are satisfactorily high, ranging from |0.19| to |0.65|, and are highly significant. In addition to that, values of the *F*-statistic for joint significance of the instruments in first-stage regressions exceed by far the rule-of-thumb value of 10 in all three cases, and Shea's partial R^2 values range from 0.20 to 0.34. There is no evidence of weak instruments (*e.g.*, Staiger and Stock, 1997).

Next, consider the effect on the OLS results of treating climatological normals as endogenous. The significance of the linear terms for the climate variables remains high in IV, and that of the quadratic term improves. Interestingly, changes in the magnitude of the climatic attributes are of the opposite direction. The effect of temperature remains positive but is reduced by 44%. On the other hand, the estimates of the linear and quadratic terms for precipitation are approximately four times higher than in OLS. This means that land rental prices are now four times higher in the beginning of the precipitation response function, and that the slope of the latter decreases four times faster. As a consequence, the cutoff point for precipitation is now found earlier, at the level of 383 mm. At this point, the OLS precipitation response function is still increasing. From a qualitative perspective, it is interesting to note the accordance of this finding with earlier results in Anselin and Lozano-Gracia (2008), whose OLS measures of two interpolated air quality variables were also found to be biased in opposite directions.

Nonclimate variables are similarly affected by the estimation method. A notable change is the change of significance between "competition" and slope, with that of the former attenuating and that of the latter strengthening in the IV model. Further, the effect of slope becomes stronger in magnitude. The soil and population variables remain highly significant with negligible changes in magnitude. In comparing the explanatory performance between the two models, IV (R^2_{var} = 0.54) serves as a considerable improvement over OLS. Robust standard errors in IV are higher by a factor of 1.5, on average.

We next assessed the presence of spatial correlation using the specialized testing procedures described in Anselin *et al.* (1996) and Anselin and Kelejian (1997). The corresponding Langrange multiplier (LM) and Anselin-Kelejian (A-K) test results show strong evidence of positive spatial autocorrelation irrespective of the normalization of the weights. As the robust LM tests favored spatial error over lag dependence, we proceeded with two SER-IV models differing only in the spatial-weighting matrix.

The general picture remains the same with the IV case. An exception is some loss of significance for precipitation in SER_S-IV but, other than that, the coefficients of the climate variables are again lower (temperature) and larger (precipitation) in magnitude than in OLS. Temperature estimates are 14%-16% lower, and precipitation estimates are about two times the OLS ones. Precipitation cutoffs are now found around the levels of 433 mm and 450 mm, between the OLS and IV cutoffs. The statistical significance of the "competition" variable seems to be washed away, but its effect remains still positive. The estimate for slope is closer to OLS than to IV. The soil and population variables remain stable across models.

Once again, variance ratios improve from OLS to SER-IV, though are a little lower than in IV. Robust standard errors in the SER specifications are higher by a factor of 1.4 on average than those in OLS. In either spatial model, the estimated spatial-autoregressive coefficient is positive, moderate, and highly statistically significant. Since spatial autocorrelation pertains even after accounting solely for potential errors in the interpolated variables, it may be attributed to the underlying mismatch between the actual spatial scales of the variables and the scales at which they have been analyzed herein.

2.6 Marginal impacts and simulation

The implicit price of a climatic attribute can be obtained as the derivative of the rental price equilibrium equation with respect to that attribute. These derivatives correspond to the typical marginal effects which, in our log-linear models, can be calculated at the sample means of rental price and precipitation.

In Table 2.3, we report the calculated marginal effects for temperature and precipitation for the four estimation methods. In addition to point estimates, we attach a confidence band which consists of ± two standard errors around each point estimate. For temperature, the OLS result suggests a point estimate of 95 €/°C compared to 53–82 €/°C as the range across the IV and SER-IV models. For precipitation, a striking relative difference can be seen, as the direction of change is opposite, and the OLS point estimate is underestimated by up to 56%. More specifically, the OLS result of 3.9 €/mm/month is contrasted with a range of 5.8–8.9 €/mm/month when accounting for errors in variables and spatial-autoregressive disturbances. Overall, ignoring endogeneity in the climate variables leads to unrealistic indications of precision for the marginal implicit prices for climate.

For our simulation exercise we used processed microclimate projections from the regional climate model REMO (MPI, 2006; see also Lippert *et al.*, 2009: 600). These changes are based on IPCC’s storylines for the period 2011–2040. Scenarios B1, A1B, and A2 prescribe annual temperature increases that range between 1.3 °C and 1.5 °C, and spring precipitation increases that range between 36 mm and 56 mm. In summarizing the average behavior of the whole sample toward future (nonmarginal) climate change, we calculated an average impact measure that equals the average difference between the base-fitted and scenario-predicted land rental prices (Table 2.4).

Based on our results, equilibrium rental prices at the end of the 2011–2040 period would be expected to rise irrespective of the storyline. Benefits from about 8% to 13% would be expected without substantial variation among models (Table 2.4, Figure 2.1). The OLS welfare estimates lie between the IV and the SER_R-IV estimates. The overall conclusion that climate change appears to be beneficial for the agriculture in Germany matches earlier conclusions.

2.7 Concluding remarks

An important aspect of assessing the effectiveness of environmental policies that address the impacts of climate change on agriculture is the quantification of the economic value of the accrued benefits or damages. In doing so, the established Ricardian approach assumes that, *ceteris paribus*, the climate-induced benefits or damages will be reflected into the value or price of agricultural land.

In this article, we contribute to the empirical literature on the Ricardian approach by considering a distinct methodological aspect that is of paramount relevance whenever one relies on interpolated ground station data. From an errors-in-variables perspective, we accounted for endogeneity in the interpolated climatological normals. In doing so, cost-effective instruments that capture the global scale of climate change were used *post hoc*. We further explicitly considered spatial autocorrelation, which had been expected as a side effect and even persisted after IV estimation.

Our results highlight the importance of departing from the OLS world to improve the explanatory power of a Ricardian model that is based on interpolated measures of climate. The effect of doing so via IV procedures, either in an aspatial or spatial framework, is both significant with respect to the coefficient estimates as well as for the calculation of their marginal implicit prices. Given that the use of aggregate data already leads to a partial dampening in measurement errors that come from disaggregate scales, the persistence of errors in variables at the district scale turns out to be a very special result that requires further attention.

In essence, OLS estimates for interpolated climate regressors are likely to be misleading with a bias of inconsistent direction. This matches earlier results in the econometrics literature. In our empirical example, the implicit price of temperature was overestimated, whereas that of precipitation was underestimated. In the latter case, the positive effect of precipitation is underestimated in areas of low precipitation levels, and results to a lagged overestimation of the cutoff point. Since errors in variables contaminate the estimates of all variables in the model, the degree of controversy in the final results is likely to increase in cases where more interpolated climate regressors are included (*e.g.*, for the typical seasonal parameterization of climate).

Based on our results, it might seem intuitive to conclude that the presence of errors in interpolated predictors does not seem to affect the simulative fidelity of a Ricardian model or, in other words, to suggest that OLS results may not be inappropriate at least as estimates of welfare impacts. However, one has to keep in mind that this may happen because some climatic attributes are upward, and others downward biased. In our case, under a simultaneous future increase for both climatic attributes, the overestimated effect of temperature took it up for the underestimated effect of precipitation. Consequently, although simulation-based welfare calculations might not differ substantially across models, the magnitude of change implied by OLS as well as the cutoff points of the climate response functions may be incorrect. In other words, one might end up with a virtually consistent welfare effect, but with biased and inconsistent parameter estimates, marginal impacts of unrealistic size, and misleading local welfare effects. Consequently, our empirical exercise uncovers a methodological aspect that can improve the calculation of welfare effects.

Certainly, evidence from additional studies and contexts is needed to establish the extent to which our results are generalizable. It is hoped that errors in variables in Ricardian models of climate change will merit further examination whenever interpolated measures of climate are involved. Theoretically, even if the availability of satellite data ameliorates the need to treat temperature as endogenous, errors in variables pertain at least to interpolated precipitation. In any case, if an RHS set comprises a number of climate variables that is greater than ours, the instruments used here can be manipulated (*e.g.*, higher-degree polynomials, more interaction terms). The IV procedure presented is generally extensible to the realm of structural (*e.g.*, Seo and Mendelsohn, 2008) or panel-data-based Ricardian models (*e.g.*, Masetti and Mendelsohn, 2011).

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Table 2.1 – Summary statistics

Variable	Mean	SD	Min	Max
Mean land rental price (€/ha), 1999	286.76	392.67	.[b]	.[b]
Mean annual temperature (°C), 1961–1990	8.42	0.90	5.17	10.64
Mean total spring precipitation (mm), 1961–1990[a]	269.83	68.37	175.95	617.83
Soil productivity (0–100)	46.13	12.27	23.31	77.77
Slope (%)	1.76	1.14	0.09	5.31
Abs. frequency of all farms, 1999	1134.69	1145.81	4.00	6219.00
Total population/UAA (thousands/ha), 1999	0.03	0.12	0.01	1.70

[a] Values correspond to the March-through-June growing season.
[b] Values are not displayed due to data privacy restrictions by FDZ.

Note: District averages (*N* = 439). See section 2.3 for details.

Source: Own calculations, based on DWD (2007), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and Statistisches Bundesamt (2012).

Table 2.2 – Endogeneity in the interpolated climatological normals: aspatial OLS, aspatial IV/2SLS, and heteroskedasticity-consistent spatial-IV Ricardian estimates

Variable	OLS		IV/2SLS		SER_R-IV		SER_S-IV	
Temperature	0.3309	***	0.1833	***	0.2783	***	0.2852	***
	(0.0345)		(0.0638)		(0.0702)		(0.0691)	
Precipitation	0.0075	***	0.0263	***	0.0143	***	0.0126	**
	(0.0022)		(0.0051)		(0.0041)		(0.0047)	
$(\text{Precipitation})^2$	-77×10^{-7}	*	-34.37×10^{-6}	***	-16.53×10^{-6}	**	-14×10^{-6}	*
	(3×10^{-6})		(7×10^{-6})		(6×10^{-6})		(7×10^{-6})	
Soil productivity	0.0183	***	0.0188	***	0.0157	***	0.0163	***
	(0.0022)		(0.0025)		(0.0028)		(0.0027)	
Slope	-0.0755	*	-0.1843	***	-0.0966	*	-0.1064	*
	(0.0294)		(0.0407)		(0.0426)		(0.0429)	
Ln(frequency of all farms)	0.0744	***	0.0340		0.0349		0.0508	*
	(0.0211)		(0.0244)		(0.0215)		(0.0241)	
Population/UAA ratio	1.7462	***	1.6903	***	1.6859	***	1.7812	***
	(0.2507)		(0.2741)		(0.2334)		(0.2332)	
Intercept	-0.1360		-1.4710	*	-0.6627		-0.4303	
	(0.4474)		(0.6421)		(0.8479)		(0.8403)	
Wu	-		-		0.4380	***	0.5622	***
					(0.0715)		(0.0894)	
Homoskedasticity/BP-PH	0.06	(0.81)	26.20	(0.00)	-		-	
Exogeneity/Wooldridge	-		37.23	(0.00)	-		-	
Overidentification (augm.)	-		met		-		-	
RLM_{err}/A-K, row	40.03	(0.00)	38.67	(0.00)	-		-	
RLM_{err}/A-K, spectral	48.44	(0.00)	42.84	(0.00)	-		-	
R^2_{var}	0.44		0.54		0.49		0.48	

Notes: The dependent variable is mean land rental price (€/ha, logarithmized) at the district level (N = 439). Variables are defined in Table 2.1 and described in section 2.3. In the IV and SER-IV models, the three climate variables are instrumented by polynomials in the coordinates and altitude (see section 2.4). All spatial-weighting matrices are based on first-order queen contiguity. Spatial weights are normalized by row in SER_R-IV, and by the largest matrix eigenvalue in SER_S-IV. Standard errors (default for OLS, robust for IV and SER-IV) in parentheses. For the tests, p-values in parentheses. *, ** and *** denote significance at the 0.05, 0.01 and 0.001 levels respectively.

Source: Own estimations, based on DWD (2007), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and Statistisches Bundesamt (2012).

Table 2.3 – Marginal implicit prices of climate (1961–1990)

Model	Annual temperature (€/°C)	Spring precipitation (€/mm/month)
OLS	95 (85 – 105)	3.9 (3.1 – 4.6)
IV	53 (34 – 71)	8.9 (7.5 – 10.3)
SER_R-IV	80 (60 – 100)	6.2 (4.8 – 7.5)
SER_S-IV	82 (62 – 102)	5.8 (4.3 – 7.3)

Notes: Marginal effects are evaluated at mean rental price (287 €/ha) and mean precipitation (270 mm). Confidence bands of ± two standard errors (default for OLS, robust for IV and SER-IV) around the point estimates in parentheses. All point estimates are significant at the 0.01 level. See section 2.6 for details.

Source: Own estimations, based on Table 2.2.

Table 2.4 – Simulated nonmarginal impacts per climate scenario

	Average rental price increase (in logs, %)		
Model	**B1**	**A1B**	**A2**
OLS	10.4	11.1	12.3
IV	8.1	8.7	9.7
SER_R-IV	10.7	11.5	12.7
SER_S-IV	9.7	10.6	11.9

Source: Own estimations, based on Table 2.2 and MPI (2006).

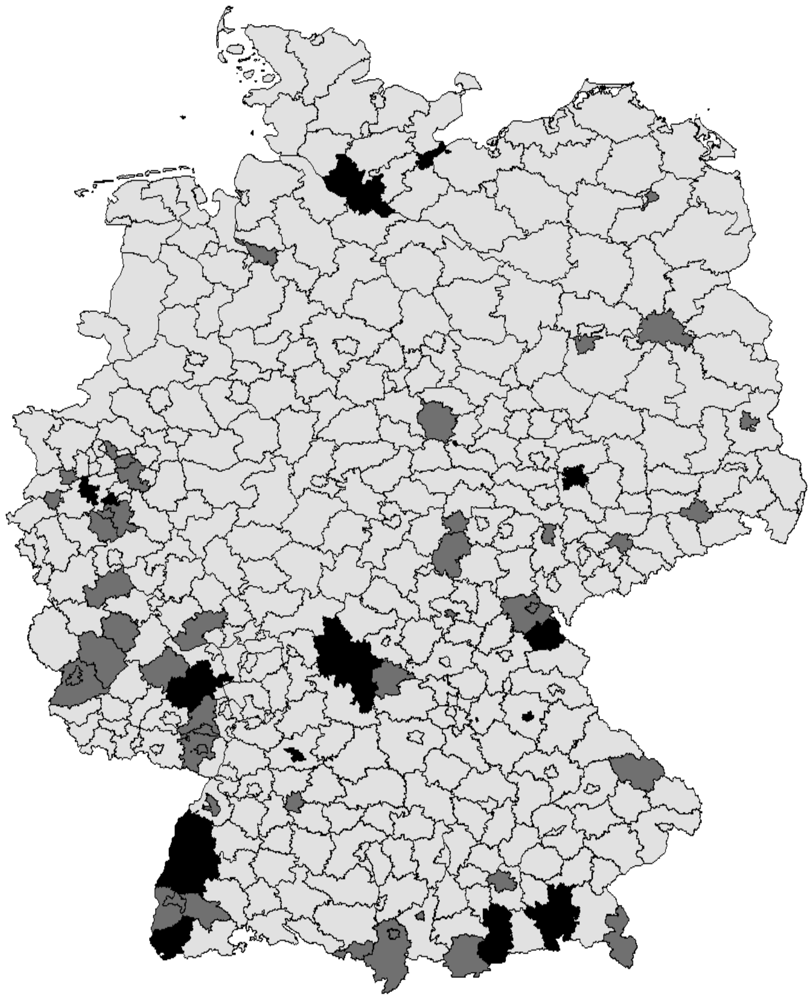

Figure 2.1 – Qualitative representation of simulated effects on mean land rental prices: B1, A1B, and A2 climate scenarios (2011–2040)

Notes: Irrespective of the scenario, all models presented in Table 2.2 predict benefits (*light grey*); all models predict damages (*dark grey*); models do not agree on the effect (*black*). District averages (N = 439).

Source: Own elaboration, based on Table 2.2 and MPI (2006).

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CHAPTER 3

Adaptation and climate change impacts: a structural Ricardian analysis of farm types in Germany[10]

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Abstract

This paper offers the first structural Ricardian analysis for a European country. Based on census data on over 270,000 farms, we explore the climate-dependent incidence of six farm types, and the climate-induced impacts on land rental prices in Germany. The models account for weighting, and interpolated climatological normals are estimated endogenously from an errors-in-variables perspective. Our results indicate that permanent-crop farms are more likely to dominate in higher annual temperatures, whereas forage and mixed farms in areas of higher annual precipitation levels. Land rental prices display concave response to precipitation, and appear to increase linearly with rising temperature. Moderate-warming simulation results for the near decades benefit any farm type in the penalization of forage farms. Rental prices would be expected to increase irrespective of the farm type.

Keywords

Adaptation; climate change; economic impacts; structural Ricardian analysis; Germany

JEL classifications

D21, O13, Q12, Q54, R32

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3.1 Introduction

A voluminous literature argues that the agricultural sector is adaptable to climate change in the sense that management, technological, and resource-use changes can be undertaken relatively expeditiously. Intrinsically driven by this commonplace assumption, a series of empirical studies by means of cross-sectional adaptation models have recently emerged. Published work has covered the climate-dependent choice between crops (Seo and Mendelsohn, 2008a; Wang *et al.*, 2010) and livestock (Seo and Mendelsohn, 2008b), the resilience of mixed farms (Seo, 2010), and the choice to irrigate (Kurukulasuriya *et al.*, 2011) under changing climate. A comprehensive literature review of the general toolkit of adaptation measures at the farm level can be found in Kurukulasuriya and Rosenthal (2003). Extensive reviews of analogous studies are given in Mendelsohn and Dinar (2009: chapters 9 and 10).

Cross-sectional adaptation models are the natural extension of the so-called Ricardian models (Mendelsohn *et al.*, 1994), which have been extensively applied over the last two decades. Traditional Ricardian models have explored the role of climatic attributes in the determination of farmland values and prices in countries all over the world (Mendelsohn and Dinar, 2009: chapters 7 and 8). Early impact studies focused on the identification of climate-induced farmland-value differentials by assuming, among else, implicit adaptation–that is, any climate-induced choice is reflected into the price of farmland. The recent spur in structural Ricardian models is deemed to be a conceptually attractive starting point to open the "black box" of adaptation: observed on-farm decisions are estimated in the first part, and economic impacts conditional on those decisions are estimated in the second part.

Empirical applications of the structural Ricardian approach are absent for Europe. Published work pertains solely to the traditional version of the approach, and is limited to farm-level analyses for England, Wales (Maddison, 2000) and the Italian Alps (De Salvo *et al.*, 2013), a province-level analysis for Spain (Garciaa and Viladrich-Grau, 2009), and two district-level studies for Germany (Lang, 2007; Lippert *et al.*, 2009). In the latter case, both studies have arrived at a common conclusion: changing climate will likely benefit the country's agriculture in the near future.

The scope of this article is twofold: to examine the climate-dependent probabilistic occurrence of farm types in Germany, and to quantify the underlying economic impacts. In the first part, we estimate a polycategorical selection model to investigate the extent to which the decision to opt for certain farm types is driven by climate (*adaptation model*). This part draws on the whole farm population. In the second part, a multitude of linear models are used to examine the influence of climate on the profitability of each farm type (*impacts module*). This part considers only the farms for which a profitability indicator is directly available in the census. The models take into account weighting considerations as well as potential measurement errors due to the use of interpolated climate predictors. Our empirical assessment draws on microdata from the 1999 agricultural census. Since the farm data are not geocoded, our assessment is pursued at the level of communities (*Gemeinden; n* = 9,684), which is the lowest spatial scale after complete disaggregation.

The work underlying this article adopts a number of innovations. From a general point of view, this is the first application of the structural Ricardian approach for a European country. Our study complements previous work by Lang (2007) and Lippert *et al.* (2009) that aimed to answer *what* the impacts of climate change have looked in the past or might look like in the future, by attempting to explicitly quantify *how* adaptation may occur in terms of the choice of the farm type. Second, from a data-utilization point of view, ours is the largest actual dataset to date for which a structural Ricardian analysis has been performed. Previous Ricardian models for Germany have been estimated at the fairly aggregate scale of districts (*N* < 440), and previous applications for other countries have drawn on smaller sample sizes and/or randomly selected farms. Third, from an agronomic viewpoint, our setup deviates from the general classification of farms into specialized crop, specialized livestock, and mixed. The calculation of a measure of relative economic size by the statistical office enables us to examine a wider spectrum of farm types that covers agricultural activities in greater detail. Finally, from a methodological viewpoint, we take an explicit errors-in-variables perspective and account for the stochasticity of the interpolated climate regressors. Recent empirical work highlights the possibility that the inclusion of spatially interpolated variables into hedonic models is likely to give rise to endogeneity problems (Anselin and Lozano-Gracia, 2008). In order to avoid biased estimation of the climate response functions and marginal impacts, we perform a *post hoc* IV-based trend surface analysis for the interpolated measures of climate.

The remainder of the article is sketched as follows. Data sources and variables are discussed in section 3.2. We introduce the modeling framework in section 3.3, and present our empirical results in section 3.4. Following the *modus operandi* of the approach, a simulation exercise is presented in section 3.5. Section 3.6 concludes.

(Continued on the next page)

3.2 Data and variables

The basic data used in this study come from two main sources: the 1999 agricultural census of Germany (FDZ, 2011) for individual farm characteristics, and the German Weather Service (DWD, 2007) for observed weather attributes. Agricultural information draws on over 400,000 interviewed (>2 ha) farms that managed over 15 million hectares at the time. Access to these data was obtained through a special contract with FDZ. Information on past weather is based on actual measurements by 663 and 4,710 ground monitoring stations for temperature and precipitation respectively. Weather data on the internationally defined 1961–1990 reference period were processed to generate historical climatological normals, which constitute a conceptually elegant and estimably simple RHS operationalization of climate in cross-sectional setting.

The apparent spatial mismatch between the scales of collection of the farm and the climate data necessitates the use of spatial interpolation for the latter. Since the 1999 census data are not geocoded at the farm level, prediction of climate was impracticable for individual farms. We proceeded with an aggregation at the community level ($N \approx 11{,}000$), which forms the lowest spatial scale for which identifiers exist for each farm in the census. With this operation, the unknown farm location posed no longer a problem for spatial interpolation, since all variables can be zonally aggregated. Furthermore, small-area aggregation has three particularly attractive consequences. First, the use of small-area aggregates increases the range of the response from (randomly selected) individuals to a group of farms (Richardson and Monfort, 2000: 206). Second, measurement or numerical errors in any RHS variable are partially dampened by small-area averaging. And third, the final dataset becomes substantially more manageable than its disaggregated counterpart. On the other hand, the apparent loss of some variability due to aggregation was unavoidable.

In the 1999 census, farms are categorized into various farming systems. Categorization has been performed by the statistical office, draws on the relative contribution of standardized gross margins of various farming activities (Statistische Ämter der Länder, 2009; HLBS, 1981: 59–63), and is as follows. Standardized gross margins per hectare and livestock unit based on bookkeeping data of selected farms are multiplied by each farm's activity-specific acreage and livestock numbers. The resulting products are then summed, thus forming a standardized gross margin per farm. Given these gross margins, farms are classified into 40 groups, which we further merged into the following mutually exclusive and exhaustive categories: cash crops (wheat, barley, potato, sugar beer), forage (grazing livestock), livestock fattening (pigs and poultry), permanent crops (fruit trees, vine, hop), horticulture (vegetables, floriculture, tree nursary), and mixed farming. Our classification rule is as follows: if at least 50% of the standardized gross margin of a farm comes from farming activities of a certain group, the farm belongs to that group. For example, if at least 50% of the standardized gross margin of a farm came from potato and cereal cultivation, it would be a cash-crop farm. Finally, in cases where no specific group of activities reaches a standardized gross margin share of at least 50%, the corresponding farms are classified as mixed.

In the adaptation model, the utilization of individual data of nominal nature at the community level impels the generation of a unique farm type. Dominance based on the absolute frequencies of all farm types was used as a measure of central tendency (*e.g.,* a community consisting of 10 cash-crop farms, 6 fattening farms, and 5 mixed holdings, would be a cash-crop community). Farm-specific acreage was used in a second round to handle frequency ties (8%). Information on acreage is factored into the derivation of standardized gross margins, and was also utilized directly in the form of an additional regressor.

The steady-state farm-profitability indicator used in the impacts module is the mean land rental price (€/ha) per farm, which we averaged at the community level. This is the only indicator of monetary nature that has been observed in the market, and that is directly available in the census. Therefore, the impacts module considers only the farms that rented part of their farmland. This poses no problems for a Ricardian analysis in Germany: renting farmland is rather the norm than the exception, and rental prices are not state-regulated.

As any environmental factor, temperature and precipitation exert a twofold impact on farm profits: they affect total revenues by altering yield levels, and total costs by altering the supply and/or productivity of inputs. Our parameterization of climate relies on mean annual temperature (°C) and mean total annual precipitation (mm) through the climate reference period. The values of either climatic attribute at each community are based on zonal statistics on 200 m raster cell averages that are the result of a local and deterministic interpolator (first-degree inverse-distance weighting with the five nearest stations) that outperformed other interpolators in terms of cross-validation (Lippert *et al.*, 2009: 598). Interpolation and zonal averaging were carried out with the Esri ArcGIS Geostatistical and Spatial Analyst extensions. Data limitations led us to the use of annual–instead of seasonal–measures of climate. Only precipitation is parameterized as second-degree polynomial[11].

[11] Inclusion of a quadratic counterpart for temperature was insignificant in any equation, and so the quadratic counterpart was removed to avoid efficiency loss in the corresponding parameter estimates. The annual index may smoothen seasonal variation and thus mask a nonlinear response.

To account for soil productivity, we include a climate-invariant index that was developed by soil scientists as a comparison basis for the fiscal evaluation of farms in the 1930s (FZ Jülich, 2009; Schachtschabel *et al.*, 1984: 415). The soil index is measured on a 0-100 scale (=100 for highest potential yield) and considers only the mixture of particles, genesis, and degradation of arable soils. A slope index (%), extracted from a raster-based Digital Elevation Model, is further used to control for land steepness (Jarvis *et al.*, 2008). Using the Esri ArcGIS Spatial Analyst extension and upon considering only agriculturally managed areas (BGR, 2007), the soil and slope indices were manufactured as zonal arithmetic averages.

Given the unavailability of population data at the community scale, we constructed a variable that measures the distance between any community and the nearest large city[12]. In doing so, polygon centroids were manufactured as reference points to calculate pairwise spherical distances with the haversine formula. This operation assumes a uniform distribution for all points (farms) within the polygons (communities), and that the joint location of the former can be approximated by the geometric center of the latter. Farms situated closer to (farther away from) urban areas are hypothesized to produce goods that are heavier (lighter) or more (less) expensive to transport[13]. Proximity to urban centers is expected to inflate rental prices due to nonagricultural pressure, and to increase farm profitability due to the possibility of easier product distribution.

Agricultural policies, such as payments in less-favored areas, directly influence regional land use in Germany. Based on the census data, we include a dummy variable for communities wherein the tendency to abandon agriculture is high due to low population density and/or harsh edaphoclimatic conditions. In the choice model, the variable takes on the value of 1 if the number of farms of the dominant farm type that receive less-favored-area (LFA) payments is greater than the number of farms of any other farm type that receive LFA payments in the respective community. In the linear regression models, the LFA variable takes on the value of 1 if at least 50% of the relevant farms are entitled to receive LFA payments. Though the statistical office could not provide us with detailed information on the generating process of the LFA attribute, point-biserial correlations between the LFA variable and the climate or soil variables depicted weak associations. Being in less-favored areas is expected to decrease the incidence of agriculture.

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[12] The 80 most populated cities (>100,000 residents) in 2000 were considered (Statistisches Bundesamt, 2013).

[13] This hypothesis originates from von Thünen's concept of homocentric rings. Note that von Thünen's example includes assumptions that are not made here (*e.g.*, uniform soil quality) but are directly testable.

The adaptation module includes two further control variables. The first is the (weighted) average size of the farms of the dominant type. The idea behind is that regionally different farm sizes in Germany (to a large extent exogenously determined by former inheritance traditions) also affect the farm-type choice. The size of forage or cash-crop farms, for instance, is typically larger than that of other farm types. The second variable is of socioeconomic nature and controls for additional income; it equals 1 if the number of farms of the dominant farm type that receive off-farm income is greater than the number of farms of any other farm type that receive off-farm income in the respective community. Existence of off-farm income by farm holders implies off-farm employment, which is expected to affect adaptation to climate change.

After removing forest holdings, farms with missing or misreported values, communities with mismatches in the regional identifiers or labels, and communities with less than 3 interviewed farms[14], the final sets were constructed. The set used for multinomial choice analysis consists of 9,684 communities that comprise 272,527 dominant farms (64% of all), and the set used for conditional regressions covers 275,723 farms that rented land (64.7% of all). Detailed descriptive statistics are shown in Tables 3.1 and 3.2.

3.3 Econometric framework

3.3.1 Models

In the first part, we use the multinomial logit model, which can be thought of as a simultaneous estimation of binary logits that yields a comparison of the effects of a given set of regressors on the choice of the farm type[15]. The model is tractable for many nominal outcomes, and can be derived and expressed as a probability, odds, or discrete choice model (Long, 1997: 152–156). The resulting formal statement is the same in either case:

$$\Pr(\mathbf{y} = m \mid \mathbf{X}) = \frac{\exp(\mathbf{X}\beta_{m|b})}{\sum_{j}^{J} \exp(\mathbf{X}\beta_{j|b})} \quad \text{for } m = j, \ldots, J \tag{7}$$

Let **y** be the random response variable "most frequent farm type at the community level" consisting of J = 6 nominal alternatives: cash crops, forage, fattening, permanent crops, horticulture, and mixed farming. The RHS set of Eq. (7) translates the probability of observing outcome m given the row vector **X** of actual values of the conditioning climate and

[14] This is due to data protection, by contract with the statistical office.

[15] The multinomial probit model, albeit more flexible, is not estimable for 6 outcomes.

other variables, the coefficient vector β_m, and a reference farm type *b* whose parameters are normalized to 0 to ensure unique model identification (here: the "forage" equation). The model setup guarantees that estimated probabilities will be nonnegative and sum to 1. Specification issues discussed in section 3.3.2 led us to a log-pseudolikelihood approach (StataCorp, 2009: 1095). Estimation proceeded with a modified version of the Newton-Raphson optimization method (StataCorp, 2009: 1013).

The model structure requires that probabilities be determined without reference to other outcomes that might be available. This is a shortcoming of the usual i.i.d. assumption. Recent evidence by Cheng and Long (2007) suggests that commonly used tests of the property of independence of irrelevant alternatives (IIA), namely a Hausman omnibus test and the Small-Hsiao approximate likelihood-ratio test, provide inconsistent results even in controlled settings. In light of this empirical finding, McFadden's (1973: 113) early recommendation to use this model only when the outcomes *"can plausibly be assumed to be distinct and weighted independently in the eyes of each decision maker"* does not lose its realism in our case: the alternatives are derived on the basis of relative economic size, and farm-type dominance is educed through absolute frequencies (see section 3.3.2).

In the second part, we estimate the usual Ricardian models conditional on the farm type. This setup reveals the total benefits or costs of climate on land rental prices under the presumption of efficient adaptation (see Mendelsohn *et al.*, 1996 for the microeconomic backdrop). Following standard hedonic theory, average rental prices of farms of the m^{th} farm type are taken to be a function of the same climatic and other characteristics (Eq. 8). This yields six conditional specifications, one for each farm type. Note that treating the agricultural market as distinct and exogenously estimable subsets remains a usual operational convention to keep the analysis tractable. A more causally sound path, on which we hope to elaborate in the future, would be the specification of a single conditional mean with endogenous farm-type selection.

The driving hypothesis is as follows: efficient adaptation (*i.e.*, profit maximization through strategic reconciliation of past climate and past profitability) leads to the assumption that local climatic trends are "visible" to landlords and tenants. Hence, climate enters into their utility functions, impacts their bids, and contributes to the determination of the equilibrium rental price schedule.

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3.3.2 Specification issues

Since the farms to be analyzed in an aggregate manner were not selected from the population with equal probability, randomness of the nominal dependent variable in the adaptation model becomes questionable, and weighting becomes an issue of concern. A further intricacy that also supports weighted estimation is that without any adjustment, communities would be treated as equal aggregate objects irrespective of their size. This assumption is not supported by the right-skewed and leptokurtic actual distribution of community sizes.

The general idea behind weighting is that communities with more (fewer) farms are manufactured to be given greater (lower) emphasis. To adjust for this peculiarity, we generated a weighting variable that equals the absolute number of farms that each community represents. For example, in the adaptation model, a weight of 20 (80) for a horticultural community means that the latter is representative of 20 (80) horticultural farms–those of the dominant farm type. What matters is the relative contribution of the weights. This implies that in a hypothetical sample of 1,000 horticultural farms that dominate in total, the above communities would be attached probability weights of 20/1,000=0.02 and 80/1,000=0.08 respectively, with the probability weights of all horticultural communities summing to 1. Letting similarly the probability weights of each farm type sum to 1 yields an indication of what the disaggregated population looks like, allows communities to behaviorally reflect their farms, and is a way to partially compensate for the loss of information due to aggregation.

In order to determine whether weighting makes any difference from an estimation point of view in our nonlinear model, we modified two tests that have been originally proposed within the framework of linear regression: DuMouchel and Duncan's (1983) variable-augmentation test, and Pfefferman's (1993) Hausman-type test of design ignorability. For the first test, probability weights were plugged into the model in the form of an additional predictor, and a Wald test of the joint significance of the resulting five parameter estimates was run, since the test result would otherwise vary with the omitted category. The rationale behind this test is based on the notion that the probability of an individual farm being represented by a community depends on the number of dominant farms. For the second test, both weighted and unweighted versions were first estimated, the pairwise differences between the estimates of temperature and precipitation between those versions were then bootstrapped (200 reps.), and finally two Wald tests of the joint significance of each set of pairs were run. Bootstrapping was introduced to avoid the assumption of full efficiency for one of the estimators under H_0 in the standard Hausman test (Cameron and Trivedi, 2005: 378). Robust standard error estimation is necessitated by the intrinsically heteroskedastic nature of the unweighted version, as well as by the use of weights in the weighted version. In the linear models, the weighting variable equals the number of farms that rent land, and DuMouchel and Duncan's test is directly applicable.

A final methodological note pertains to the two-stage estimation of the models. Errors in variables associated with the values of spatially interpolated environmental measures gain increasing attention in the hedonic literature (Anselin and Lozano-Gracia, 2008). Climatic attributes are likely to be correlated with the overall disturbance term of a Ricardian model. Such correlation may be the result of any discrepancy between true (unobserved) climate, perceived (unknown) climate, and used (interpolated) climate[16], or of simultaneous-equation bias arising from any omitted variable (*e.g.,* of topographical or geographical nature) that is correlated both with climate and farm profitability (*e.g.*, CO_2 concentrations). Either path would degrade the exogeneity of the interpolated variable(s) and lead to biased and inconsistent OLS parameter estimation (Greene, 2002: chapter 5). The extent of that bias need not necessarily be large, but can be accounted for through IV estimation.

We implement a *post hoc* trend surface analysis on the interpolated variables. We use first-degree polynomials in the coordinates of community centroids (longitude, and longitude*latitude) and the spatial lags of temperature and precipitation as instruments. The relevance of these instruments is not difficult to justify on theoretical grounds. Coordinates act for the overall spatial patterns of temperature and precipitation, and proxy climate as a *global* two-dimensional spatial trend, which is of course neglected by the inverse-distance interpolator. The underlying rationale for including spatial lags is that environmental phenomena such as climate are spatially autocorrelated and thus, the lags account indirectly for (systematic) *regional* patterns in climate. Clearly, all instruments are naturally correlated with the true values of climate. Invalidity (*i.e.*, correlation with the disturbance) is unlikely to be an issue because the errors in the conditional models embody *local* patterns of omitted variables (*e.g.,* common unobserved characteristics within a community), opposed to the large-scale process proxied by coordinates or the mesoscale patterns in proximal communities proxied by spatial lags. Both endogeneity of the climate variables and the realism of the aforedescribed causal mechanism are supported on statistical basis in our case: exogeneity of the climate variables is rejected, and the overidentifying restrictions are met for any conditional equation (see section 3.4).

[16] Note that this implies that climate might enter the farmer's utility function at another scale (*e.g.*, interval), or that the used value for climate may contain (systematic) prediction errors.

We can now express the conditional Ricardian specification for the m^{th} farm type in matrix notation as:

$$\mathbf{y}_m = \mathbf{Y}\gamma + \mathbf{X}\beta + \varepsilon_m \qquad (8)$$

where $\mathbf{y}$ is a $n_m\times1$ vector of observations on the community-mean rental price (logarithmized[17]), $\mathbf{Y}$ is a $n_m\times3$ matrix of 3 endogenous climate variables, γ is the corresponding 3×1 parameter vector, $\mathbf{X}$ is a $n_m\times4$ matrix of our exogenous covariates, β is the corresponding 4×1 parameter vector, and $\boldsymbol{\varepsilon}$ is a $n_m\times1$ vector of independently and heteroskedastically distributed innovations. We obtain consistent estimates of β and γ with the unweighted and weighted versions of the standard 2SLS estimator.

Due to data protection, the analysis was carried out in the framework of remote data access. Neither were we allowed to obtain any data by FDZ/Kiel in hand nor to develop maps that would help us visualize the results. Estimation and testing procedures were carried out using Stata/SE 10.

3.4 Empirical results

Regressors in all models are weakly associated with each other, and the highest correlation (=0.52) occurs between precipitation and slope in the conditional model for forage farms. Pairwise Pearson and point-biserial correlations display no spurious magnitudes. Calculated mean VIF values lower than 10 and condition indices lower than 20 do not indicate near-linear dependencies among the regressors in any particular model.

We begin the review of our results with the choice analysis. First, the differences between the unweighted and a probability-weighted version of the hexanomial choice model–both with robust standard errors–were assessed. A Wald test based on variable augmentation rejects the hypothesis that weighting has no overall effect (χ^2_5 = 70.90, p_{bonf} = 0.000). In addition to that, the robust Hausman test result hints at significant differences in the parameters estimates of temperature and precipitation resulting from weighted and unweighted estimation (χ^2_5 = 48.59, p_{bonf} = 0.000; χ^2_5 = 51.27, p_{bonf} = 0.000). Based on these results, we proceeded with the probability-weighted version. Note that assuming correct model specification, the coefficients from the unweighted model would merely ignore disproportionality.

[17] Log-linear functional forms were adopted since the dependent variable was strictly positive and highly skewed in all conditional equations.

Next, the effect of introducing instrumentation was assessed. Two choice models were estimated: one accounting only for weighting (robust standard errors) and another one accounting both for weighting and errors in the interpolated variables (bootstrapped standard errors). Though the models were similar in terms of parameter significance, we proceeded with the version that combines both features as it slightly outperformed in terms of overall predictive accuracy (count-R^2).

In assessing the overall performance of the two-stage probability-weighted hexanomial model, we calculated a count-R^2 measure: the farm type with the highest estimated probability at each community was taken to be the predicted outcome. Based on this rule, a percentage of communities wherein the dominant farm type is accurately predicted was obtained. The analogous value of 72% indicates a satisfactory predictive performance if one considers the multi-equation and cross-sectional nature of the model. By category, the model seems to do a satisfactory predictive job for the three most frequent outcomes: cash-crop (71%), forage-based (81%), and permanent-crop (71%) communities. Horticultural-crop communities are predicted moderately well (34%), whereas the remaining mixed- and fattening-farm communities have fewer accurate predictions (12% and 1% respectively). McFadden's (1979: 307) pseudo-R^2 (=0.34) suggests that the RHS set used offers an excellent fit in terms of proportional pseudolikelihood improvement over the only-intercept model.

We begin the review of our results by looking at the coefficients of the nonclimate variables in Table 3.3. More productive soils are associated with an increased likelihood of incidence of cash or permanent crops over forage farming. Soil needs to be productive to maximize growth, yield, and thus profit from cash crops. Fruit trees must be planted in good soils to guarantee good root environment which will lead to optimal tree growth and yield maximization. Less productive soils may lead farmers to mixed activities and livestock fattening.

With forage-based communities being the base, higher slopes are associated with the incidence of permanent-crop and mixed-farm communities. Steep slopes are well suited for fruit trees and shrubs as they allow the creation of tight networks of roots that bind soil particles together. Filling hillsides with trees and shrubs contributes in slowing the force of rushing water downhill. In Germany, since areas of steep inclination are often unsuitable for the cultivation of other crops, a high proportion of viticulture is also found on hillsides.

Being in less-favored areas reduces the likelihood of crop production in general. This relationship is reflected in the statistically significant negative signs of the coefficients associated with this variable. Livestock fattening and horticulture are the types least likely to find in less-favored areas.

The incidence of communities with horticulture, cash crops, or mixed farms decreases with increasing distance from urban centers. The tendency of horticultural-crop communities to be located closer to the markets might reflect the lower transportation costs that reduce the relative cost of production, or simply the fact that vegetables are more perishable than dairy or meat products. Forage farming is more likely farther away from urban centers.

On average, cash-crop farms tend to receive off-farm income more frequently. This may hint at part-time farming, possibly because crop production does not require that the farm operator be always present in the farm. The opposite holds for horticulture, livestock fattening, and mixed farming, which may generally be more labor-intensive.

The coefficients of average farm size obey conventional wisdom: the larger the average farm size, the more likely the incidence of communities with mainly land-extensive crops (*e.g.*, wheat, barley). On the contrary, the smaller the farm size, the more likely the incidence of communities with labor-intensive farm types such as horticulture.

We move now to the interpretation of variables that proxy climate. Compared to the case of forage farming, the likelihood of observing communities wherein any other farm type dominates increases with higher annual temperature. Especially during the growing season, fruit trees and vines need plenty of sunlight to enhance full ripening and balance acidity and sugar levels. Vegetables generally require much sunlight, though some, such as carrot, spinach and lettuce, require less than others. Spring barley needs higher average temperatures especially during flowering. Mixed farms are also more likely to dominate in warmer areas than forage farms.

Precipitation displays a statistically significant negative relationship for any group except for fattening farms (concave) and horticultural farms (not significant), relative to the base case. This might explain why the vast majority of German farms do not rely on irrigation. Compared to the base case, the likelihood of observing those farm types decreases with increasing precipitation, since forage farming is likely rendered more productive.

We continue with the review of results from the conditional regression models (Table 3.4). DuMouchel and Duncan's standard test for weighting suggests that models 3, 5 and 6 be weighted. This had been expected to some extent as the mean numbers of farms that rent land in these subgroups are lower than the corresponding standard deviations, and the respective distributions resemble platykurtosis.

Weak instruments cause IV estimators to lose precision and potentially become worse than OLS. In our case, typical pairwise Pearson correlation coefficients between the instruments and the endogenous regressors are statistically significant at the 0.01 level and not too low to flag weak-instrument problems (>0.17). Values of the *F*-statistic from the first-stage regressions exceed by far the value of 10 in all cases (Staiger and Stock, 1997). Joint exogeneity of the three climate variables is rejected by means of Wooldridge's (1995) robust score in all cases. Regressing the 2SLS residuals from any equation on all instruments gives a near-zero R^2 value and insignificant *p*-values for the instruments. Hence, the overidentifying restrictions are not rejected. We conclude that each conditional mean should be specified such that endogeneity in the interpolated climate variables be accounted for through IV estimation, and that the instruments are neither weak nor invalid.

The explained variation of the aggregate log-linear IV models ranges from 25% to 60% in logs, and from 5% to 75% in levels. One should note that structural covariates that are endogenous to climate (*e.g.,* livestock density) or simultaneously determined with rental prices (*e.g.,* share of rented land) have not been included as regressors to avoid other types of endogeneity. Thus, these equations should be viewed as reduced-form specifications.

Most variables are highly statistically significant. The exceptions are soil productivity for permanent crops, distance to the cities in the permanent- and cash-crop equations, and temperature for horticultural farms. The log-linear specification of the conditional means allows cross-comparisons in the form of semielasticities.

The higher the soil productivity, the higher the land rental price. Cash-crop (fattening) communities have the highest (lowest) significant semielasticity for this regressor. The negative sign of slope in generally implies a reduction of rental prices due to land steepness. The positive sign of slope in model 4 might seem striking at a first glance, but a reasonable explanation lies in the joint consideration of viticulture with fruit trees: vineyards, which are typically met on steeper areas and are characterized by higher rental prices than fruit farms on average, outweigh fruit farms in the group (75% *vs.* 25%). Groups employing livestock production have the highest negative semielasticities for slope. This may be explained by the fact that maize cultivation is important in animal husbandry on the one hand, but problematic on steep slopes on the other hand. Being in less-favored areas decreases rental prices irrespective of the farm type. Finally, rental prices of horticultural farms significantly decrease with increasing distance from urban centers. Livestock- or mixed-farm communities are located farther away from urban centers.

Higher temperature levels are associated with the incidence of higher land rental prices in all conditional models. Permanent-crop communities have the highest, and cash-crop communities have the lowest temperature semielasiticities. Given the positive first-degree and negative second-degree terms for precipitation, a concave response is found in all models. Cutoff points are all above the respective sample means, and range from 897 mm (cash crops) to 1162 mm (forage). The high cutoff point also for mixed farms (1103 mm) implies that the latter might be more resilient to precipitation changes in Central Europe. A schematization of point predictions at varying levels of either climate variable is shown in Figures 3.1 through 3.4.

We conclude our analysis with a brief discussion on two robustness checks. First, we re-run the analysis upon including a dummy variable *East* into each model specification. Whenever significant, the dummy variable was negative, and there was some quantitative change in the precipitation variables and their standard errors. However, we did not opt for this variable for two reasons. First, since the dummy is highly correlated with precipitation (= -0.61) it affects the precision of its estimates. And second, *East* is correlated with the disturbances in the conditional models. Given the large size of the area covered by the dummy, confounding with unobserved or omitted factors is not surprising. Finally, the analysis was re-run with clustered standard errors per federal state. This led to negligible quantitative change in the standard errors of the climate variables.

3.5 Simulation of future farm types and land rental prices

For our simulation exercise, we used spatially processed data on future climate projections from the regional climate model REMO (MPI, 2006; Lippert *et al.*, 2009). IPCC's A1B moderate-warming storyline for the period 2011–2040 was chosen since it lies between storylines B1 and A2 and does not differ significantly from them, possibly because our study area is relatively small[18]. At the community level, A1B is accompanied by an average annual temperature increase of 1.6 °C (+20% from the 1961–1990 period) and an average total annual precipitation increase of 161 mm (+21%). In summarizing the potential behavior of communities in the adaptation model, scenario-predicted probabilities were calculated. The resulting farm types are cross-tabulated against the base-fitted ones in the classification Table 3.5. In the impacts module, we summarize the average behavior of each group by calculating

[18] Between storylines B1 and A2, the difference in temperature increase amounts to 0.13 °C, and that in precipitation to about 50 mm.

an average impact measure: the average difference between the base-fitted and scenario-predicted rental prices (Table 3.6).

Based on our results, dominant farm types at the end of the 2011–2040 period would be expected to change in 3,586 (37%) communities. This can be calculated by summing the off-diagonal elements of Table 3.5. The number of communities wherein cash-crop, fattening, permanent-crop, horticultural, or mixed farms currently dominate would increase, whereas the number of forage-based communities would decrease. Similarly, equilibrium rental prices would be expected to rise compared to the 1999 levels. As Table 3.6 shows, permanent-crop farms, horticultural farms, and mixed farms would gain the most under this scenario. The overall conclusion that climate change appears to be beneficial for agriculture in Germany is in accordance with conclusions made in earlier analyses at the district scale (Lang, 2007; Lippert *et al.*, 2009).

In interpreting the results of Tables 3.5 and 3.6 three important remarks have to be made. First, these results should be interpreted as reflecting how instantaneous A1B-based changes in long-term annual temperature and precipitation averages would culminate in new steady-state equilibria of farm types or rental prices, distinctly and *ceteris paribus*. This results from the nonsimultaneous estimation of the two models, their comparative static nature, and the implicit assumption of space-time ergodicity (*i.e.*, that changes in one area over time are taken as equivalent to differences across many areas in a pure cross section). Second, Table 3.5 portrays changes in the dominant farm types at the community level. For instance, the result that permanent-crop communities would triple does not necessarily imply a shift (conversion) to permanent crops; it merely implies an increase in the profitability of permanent crops and so, an increase in the number of communities wherein permanent crops would dominate, *ceteris paribus*. Finally, the impact estimates might be somewhat overestimated in the sense that they provide an upper bound for the expected benefits. This is a shortcoming mainly of the driving pressumption of efficient adaptation, but also of the unavailability of a more selective (*e.g.*, seasonal) temperature indicator that might had portrayed a nonlinear (*e.g.*, concave) response.

3.6 Concluding remarks

In this article, we contribute to the empirical literature on the effects of climate change on agriculture by developing the first structural Ricardian model for a European country. Upon relying on census farm data and interpolated climate data, we developed a two-stage multinomial model for the climate-dependent incidence of six farm types, and a series of conditional models for the identification of rental price differentials due to climate differentials. We accounted for weighting due to farm disproportionality in the communities, as well as for potential errors in the interpolated measures of climate. We concluded with a moderate-warming simulation exercise based on regional climate projections for the upcoming decades.

Our results showed that climate is a significant determinant of the choice of the farm type, and of land rental prices in Germany. Overall, permanent-crop farms are more likely to dominate in higher temperatures, whereas forage or mixed farms in areas of higher precipitation levels. Irrespective of the farm type, rental prices appear to increase with rising temperature, and display hill-shaped response to precipitation. A moderate-warming simulation for the near decades highlights an increase in the number of communities wherein cash-crop, fattening, permanent-crop, horticultural, or mixed farms would dominate, and a decrease in the number of communities wherein forage farming would be dominant. This result is merely the net long-run outcome of numerous short-term adaptation rounds to climate-induced productivity changes, *ceteris paribus*. Moderate warming appears to increase rental prices irrespective of the farm type, *ceteris paribus*.

A few remarks ought to be made for the overall results of our study. First, any excluded institutional (*e.g.,* know-how), technological (*e.g.,* high yield varieties), policy-related (*e.g.,* prices) or environmental factor (*e.g.,* extreme weather events, CO_2) that might be associated with changes in farm profitability is assumed to remain constant. This is a shortcoming of the cross-sectional setup, and could be ameliorated by additional information from other model types and data in the time domain. Second, our study does not address irrigation issues because the 1999 census had not gathered any related data. Although irrigation has been of very little importance for the predominantly rainfed German agriculture, water availability might change in the future. Finally, the displayed signs and impacts are not intended to serve as crude substitutes for relationships at other scales of aggregation or for more selective parameterizations of climate; this follows from realizations in the literature that environmental effects may be scale-sensitive and measure-dependent.

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Table 3.1 – Summary statistics by farm type (adaptation model)

	Farm types					
Sample	**1**	**2**	**3**	**4**	**5**	**6**
Communities	3,904	4,876	109	356	118	321
Dominant farms	74,103	153,909	5,524	31,812	2,130	5,049
% in all farms	54.4	61.3	38.2	72.0	51.4	46.9
Community means						
Temperature	8.48	7.99	8.71	9.09	8.68	8.05
Precipitation	657.25	831.88	759.47	778.41	646.93	859.29
Soil productivity	48.10	42.49	40.19	52.90	44.47	34.60
Slope	1.37	1.84	0.84	2.89	1.18	2.86
Distance to city	19.07	22.55	19.97	13.53	14.16	21.50
Average farm size	76.28	34.97	38.18	7.84	6.22	19.82
LFA	0.33	0.66	0.42	0.31	0.33	0.72
Off-farm income	0.75	0.76	0.62	0.92	0.42	0.65

*Note*s: Farm-type groups: 1 – cash-crop communities, 2 – forage-farm communities, 3 – fattening-farm communities, 4 – permanent-crop communities, 5 – horticultural-crop communities, 6 – mixed-farm communities. See section 3.2 for details.

Source: Own calculations, based on BGR (2007), DWD (2007), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and Statistisches Bundesamt (2013).

Table 3.2 – Summary statistics by farm type (impacts module)

	Farm types					
Sample	**1**	**2**	**3**	**4**	**5**	**6**
Communities	8,497	8,858	3,246	1,170	2,053	4,954
Farms that rent land	78,610	135,813	17,835	16,162	5,019	22,284
Community means						
Rental price	162.10	139.25	211.24	422.60	855.59	166.25
Temperature	8.33	8.20	8.31	8.75	8.57	8.21
Precipitation	709.55	766.68	789.03	779.67	780.44	815.43
Soil productivity	46.03	44.10	46.74	50.79	47.39	44.87
Slope	1.52	1.73	1.64	2.36	1.71	2.02
Distance to city	20.04	21.08	18.98	15.83	16.32	19.66
LFA	0.46	0.56	0.51	0.38	0. 40	0.59

*Note*s: Farm-type groups: 1 – cash-crop communities, 2 – forage-farm communities, 3 – fattening-farm communities, 4 – permanent-crop communities, 5 – horticultural-crop communities, 6 – mixed-farm communities. See section 3.2 for details.

Source: Own calculations, based on BGR (2007), DWD (2007), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and Statistisches Bundesamt (2013).

Table 3.3 – Multinomial logit estimates for the most frequent farm type at the community level

	Farm types				
Variable	**1**	**3**	**4**	**5**	**6**
Temperature	0.7199 **	0.9627 **	1.8567 **	0.9377 **	0.2567 *
	(0.0433)	(0.1041)	(0.1167)	(0.2281)	(0.0849)
Precipitation	0.0027	0.0635 **	0.0095	-0.0039	-0.0116 **
	(0.0016)	(0.0067)	(0.0058)	(0.0091)	(0.0027)
(Precipitation)^2	-57×10^{-7} **	-33×10^{-6} **	-73×10^{-7} *	-19×10^{-8}	-62×10^{-7} **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Soil productivity	0.0221 **	-0.0172 *	0.0497 **	0.0155	-0.0415 **
	(0.0021)	(0.0077)	(0.0063)	(0.0099)	(0.0056)
Slope	0.3719 **	-0.1737	0.6088 **	-0.2826	0.1830 **
	(0.0316)	(0.0889)	(0.0779)	(0.1829)	(0.0446)
LFA	-0.6829 **	-1.0861 **	-0.8757 **	-1.0529 **	0.2188
	(0.0690)	(0.2791)	(0.1801)	(0.2834)	(0.1674)
Distance to city	-0.0051 *	0.0153	-0.0020	-0.0397 *	-0.0131 *
	(0.0020)	(0.0078)	(0.0067)	(0.0170)	(0.0047)
Off-farm income	0.6648 **	-0.7044 *	0.2492	-1.6543 **	-0.2280 **
	(0.0735)	(0.2557)	(0.2645)	(0.3481)	(0.1570)
Average size	0.0115 **	0.0066	-0.1920 **	-0.2444 *	-0.0295 *
	(0.0010)	(0.0049)	(0.0367)	(0.1144)	(0.0104)
Intercept	-7.0646 **	-38.830 **	-20.718 **	-2.4803	1.8000
	(0.8977)	(2.9889)	(3.2183)	(4.5337)	(1.4622)
Measures of fit					
Count-R^2	0.72				
McFadden-R^2	0.34				

Notes: Farm-type groups: 1 – cash-crop communities, 2 – forage-farm communities (base), 3 – fattening-farm communities, 4 – permanent-crop communities, 5 – horticultural-crop communities, 6 – mixed-farm communities. Variables are described in section 3.2. Instrumentation of the climate variables and probability-weighting take place in the first and second stages respectively (see section 3.3.2). Bootstrapped (50 reps.) standard errors in parentheses. * and ** denote significance at the 0.05 and 0.001 levels respectively.

Source: Own estimations, based on BGR (2007), DWD (2007), FDZ (2011), FZ Jülich (2009), and Statistisches Bundesamt (2013).

Table 3.4 – Conditional IV/2SLS Ricardian estimates for land rental prices

	Conditional models					
Variable	**1**	**2**	**3**	**4**	**5**	**6**
Temperature	0.0377**	0.0629**	0.1124**	0.2547**	0.0569	0.1741**
	(0.0102)	(0.0080)	(0.0140)	(0.0364)	(0.0510)	(0.0137)
Precipitation	0.0104**	0.0086**	0.0105**	0.0078**	0.0127**	0.0075**
	(0.0003)	(0.0002)	(0.0004)	(0.0008)	(0.0012)	(0.0003)
$(\text{Precipitation})^2$	-58×10^{-7}**	-38×10^{-7}**	-58×10^{-7}**	-44×10^{-7}**	-67×10^{-7}**	-34×10^{-7}**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Soil productivity	0.0132**	0.0083**	0.0040**	0.0026	0.0097**	0.0046**
	(0.0004)	(0.0004)	(0.0007)	(0.0018)	(0.0021)	(0.0010)
Slope	-0.1046**	-0.1370**	-0.1602**	0.0875**	-0.0652*	-0.1125**
	(0.0069)	(0.0053)	(0.0106)	(0.0187)	(0.0285)	(0.0137)
LFA	-0.2908**	-0.2408**	-0.1172**	-0.4116**	-0.3109**	-0.3426**
	(0.0125)	(0.0134)	(0.0241)	(0.0655)	(0.0655)	(0.0352)
Distance to city	-0.0005	0.0021**	0.0021*	-0.0018	-0.0105*	0.0071**
	(0.0004)	(0.0004)	(0.0007)	(0.0021)	(0.0035)	(0.0012)
Exogeneity						
Robust score, χ^2_3	503.63	392.82	42.43	56.39	31.37	120.35
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Measures of fit						
R^2_{var} (logs)	0.53	0.60	0.52	0.25	0.31	0.54
R^2_{var} (levels[a])	0.64	0.75	0.63	0.19	0.05	0.71

[a] Based on the unbiased log-retransformation $E(\mathbf{y}|\mathbf{X}) = \exp(\mathbf{X}'\beta)\exp(0.5\sigma^2)$, $\boldsymbol{\varepsilon} \sim N(0, \sigma^2)$.

Notes: The dependent variable is the mean land rental price (€/ha, logarithmized) of each group at the community level. Farm-type groups are as follows: 1 – cash-crop communities, 2 – forage-farm communities, 3 – fattening-farm communities, 4 – permanent-crop communities, 5 – horticultural-crop communities, 6 – mixed-farm communities. Variables are described in section 3.2. Instrumentation of the climate variables takes place in the first stage of all equations, and probability weights are used in the second stage of models 3, 5 and 6 (see section 3.3.2). All models include an intercept. Huber/White/sandwich standard errors in parentheses. * and ** denote significance at the 0.05 and 0.001 levels respectively.

Source: Own estimations, based on BGR (2007), DWD (2007), FDZ (2011), FZ Jülich (2009), and Statistisches Bundesamt (2013).

Table 3.5 – Base-fitted (1961–1990) *vs.* scenario-simulated (2011–2040, A1B/IPCC) most frequent farm types

		Scenario-simulated farm types						
		1	**2**	**3**	**4**	**5**	**6**	Sum
Base (model-fitted) farm types	**1**	2,858	395	259	257	8	19	3,796
	2	1,507	2,928	332	419	19	254	5,459
	3	0	0	1	0	0	0	1
	4	2	12	0	238	1	55	308
	5	0	1	1	19	40	3	64
	6	4	2	13	0	4	33	56
	Sum	4,371	3,338	606	933	72	364	9,684

Notes: Numbers are community frequencies (n = 9,684). Farm-type groups: 1 – cash-crop communities, 2 – forage-farm communities, 3 – fattening-farm communities, 4 – permanent-crop communities, 5 – horticultural-crop communities, 6 – mixed-farm communities. Reading the table by row tells what the base-fitted dominant farm type would turn to in the new equilibrium (see section 3.5). Numbers on the main diagonal are the unaffected cases.

Source: Own estimations, based on BGR (2007), DWD (2007), FDZ (2011), FZ Jülich (2009), MPI (2006), and Statistisches Bundesamt (2013).

Table 3.6 – Base-fitted (1961–1990) *vs.* scenario-simulated (2011–2040, A1B/IPCC) land rental prices

	Conditional models					
Rental price (€/ha)	**1**	**2**	**3**	**4**	**5**	**6**
(1) Observed, in levels (logs)	162 (4.92)	139 (4.75)	211 (5.23)	423 (5.62)	856 (6.01)	166 (4.92)
(2) Fitted, in levels[a] (logs)	167 (4.92)	148 (4.75)	255 (5.42)	445 (5.62)	934 (6.22)	196 (5.03)
(3) A1B-simulated, in levels[a]	194	207	300	556	1092	292
(4) Difference, (3) – (2)	+27	+59	+45	+111	+158	+96

[a] Based on the unbiased log-retransformation $E(\mathbf{y}|\mathbf{X}) = \exp(\mathbf{X}'\beta)\exp(0.5\sigma^2)$, $\varepsilon \sim N(0, \sigma^2)$, after log-linear model fitting/prediction.

Notes: Numers are means at the community level. Farm-type groups: 1 – cash-crop communities, 2 – forage-farm communities, 3 – fattening-farm communities, 4 – permanent-crop communities, 5 – horticultural-crop communities, 6 – mixed-farm communities. All estimates significant at the 0.05 level.

Source: Own estimations, based on BGR (2007), DWD (2007), FDZ (2011), FZ Jülich (2009), MPI (2006), and Statistisches Bundesamt (2013).

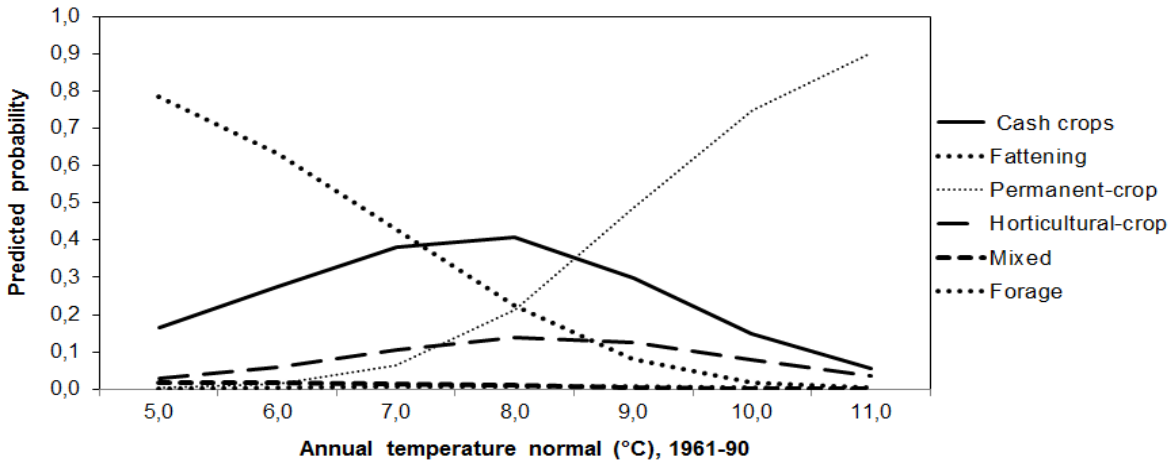

Figure 3.1 – Temperature response functions (adaptation model)

Source: Own elaboration, based on Table 3.3.

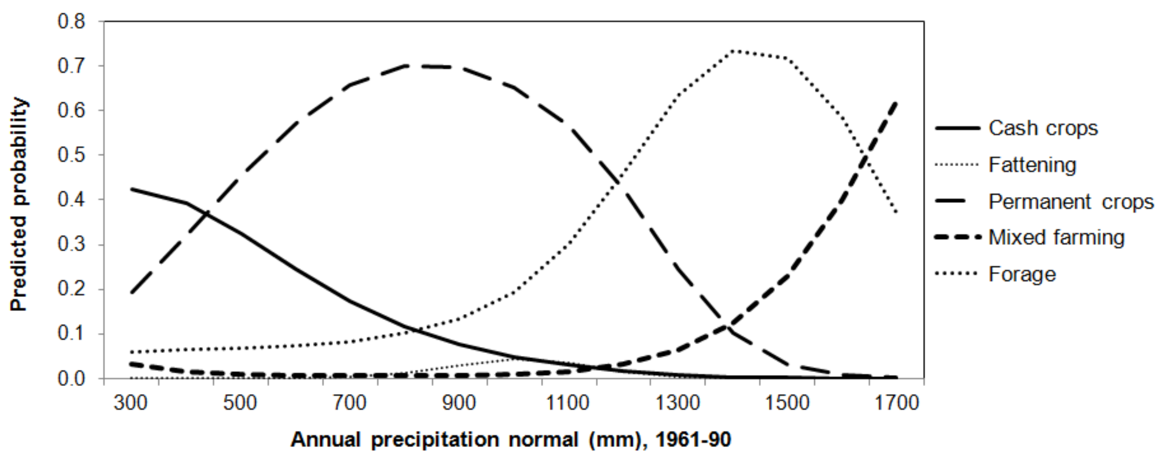

Figure 3.2 – Precipitation response functions (adaptation model)

Source: Own elaboration, based on Table 3.3.

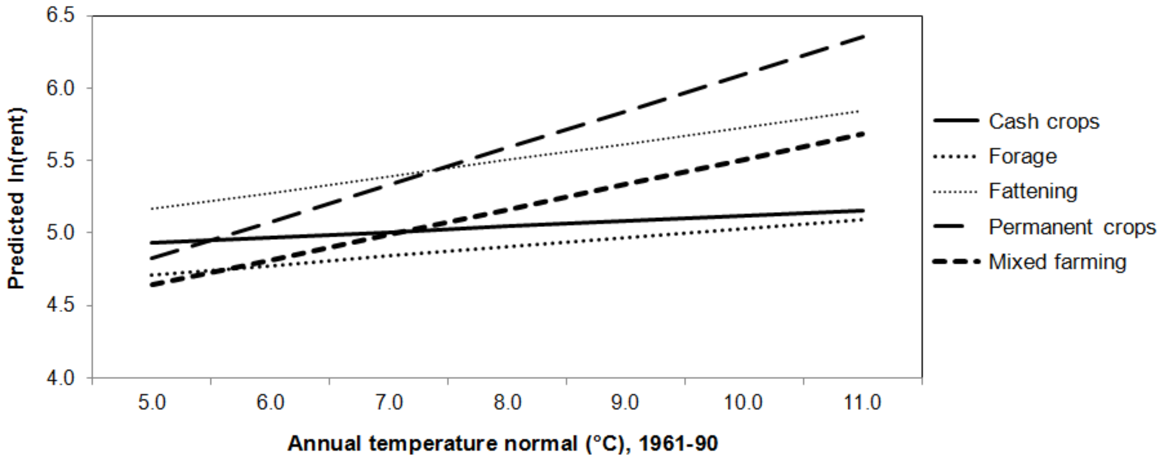

Figure 3.3 – Temperature response functions (impacts module)

Source: Own elaboration, based on Table 3.4.

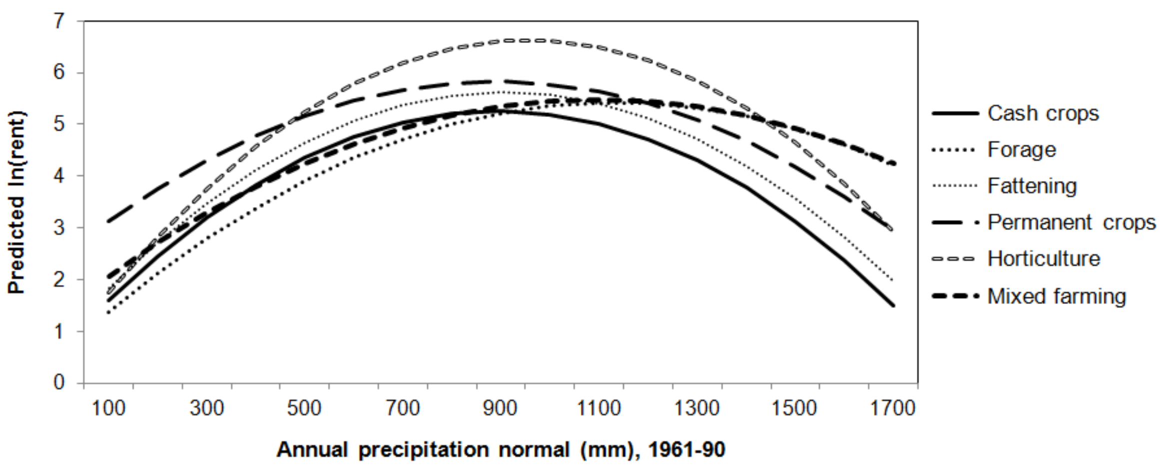

Figure 3.4 – Precipitation response functions (impacts module)

Source: Own elaboration, based on Table 3.4.

◊

CHAPTER 4

Endogenous farm-type selection, endogenous irrigation, and spatial effects in Ricardian models of climate change[19]

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Abstract

In the estimation of Ricardian models, the endogeneity of adaptation measures is typically ignored. In this article, we propose a new version of the Ricardian approach that explicitly treats the choice of the farm type and irrigated acreage as endogenous to climate. Based on the latest census data on over 270,000 farms in Germany, we estimate a cross-sectional spatial-IV model that decomposes the effects of climate on farm profitability into direct (unmediated) and indirect (mediated by the farm-type and irrigation variables). Our results showed that explicitly modeling the endogenous nature of adaptation improves substantially the explanatory fidelity of the Ricardian model, and that not doing so may bias the magnitude of the total effect of climate on farm profitability in either direction.

Keywords

Ricardian analysis; instrumental variables; spatial econometrics

JEL classifications

O13, Q12, Q51, Q54, R32

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4.1 Introduction

The valuation of economic benefits or damages from climate change is a well-honored topic in agricultural and environmental resource economics. In this context, the Ricardian approach (*e.g.*, Mendelsohn *et al.*, 1994) has generated a voluminous literature over the last two decades. In this article, we extend the conceptual and analytical framework of this approach by proposing a variant that can explicitly account for the endogeneity of any adaptation strategy that may be of interest.

The rationale behind the Ricardian approach is that, *ceteris paribus*, farms in various areas will have the effects of local climate reflected into their value. In essence, climate is assumed to lead to a redistribution of crops and livestock species in space, which implies a redistribution in the expected behavior of farms. Therefore, regressing a farm-profitability indicator against climatic and other (control) land and site attributes can serve the purpose of impact assessment. Empirical applications dealing with the approach are extensively reviewed in Mendelsohn and Dinar (2009).

Recent empirical work takes into account a number of contemporary aspects that were formerly critically received (*e.g.*, Cline, 1996; Quiggin and Horowitz, 1997; Darwin, 1999; Kaufmann, 1998; Schneider *et al.*, 2000). Published empirical advancements pertain to the control for spatial autocorrelation (Polsky, 2004; Schlenker *et al.*, 2006; Lippert *et al.*, 2009; Kumar, 2011), the development of a structural Ricardian framework for farm types (Seo and Mendelsohn, 2008a; Wang *et al.*, 2010) and irrigation (Kurukulasuriya *et al.*, 2011), and the utilization of panel data (Massetti and Mendelsohn, 2011). Empirical applications typically focus on one issue at a time. With the exception of panel-data estimation, the overall attractiveness of our study is in that it is the first to account for all the other aforementioned aspects simultaneously.

The purpose of this article is twofold. Our first motivation is to propose a new analytical strategy to explicitly account for the endogeneity of any adaptation measure to climate. In this study, we focus on two long-run measures: the occurrence of the farm type, and the potentially irrigated acreage. Our second motivation is to assess the extent to which endogenously modeling adaptation affects the partial effects of the climatic attributes. We pursue this assessment by means of an empirical investigation of farms in Germany, with microdata from the latest census (2010). Due to data privacy restrictions, the analysis was carried out for small-area aggregates at the administrative level of community associations (*Gemeindeverbände*; n = 3,515), henceforth communities for ease of notation.

The work underlying this article extends the scope of the Ricardian framework by adopting the following innovations. From a conceptual viewpoint, this is the first application of the approach that models the endogenous nature of adaptation explicitly. The effects of climate on the occurrence of the farm type and on the choice to irrigate have been considered previously only through conditional regressions (*e.g.*, Seo and Mendelsohn, 2008b; Kurukulasuriya *et al.*, 2011); neither have the corresponding endogeneities been treated from an IV perspective nor jointly into a single Ricardian model. We show how this can be performed using nonlinear projections of the endogenous variables as instruments. Second, from a data-processing point of view, we implemented a hybrid spatial interpolator that accounts both for systematic and probabilistic climate variation. This might not be a novelty in the field of geostatistics, but is in the framework of the Ricardian approach where climate variables are typically generated with less complex interpolators. Third, from a methodological viewpoint, we take an explicit spatial econometric perspective that allows us to obtain consistent parameter estimates irrespective of the source of spatial dependence and, based on a recent discussion, to elicit a multitude of partial effects with and without spatial correlation. Ultimately, the combination of endogeneities of spatial and aspatial nature requires the application of spatial 2SLS (S2SLS).

The remainder of the article is sketched as follows. We first present brief theoretical background in section 4.2. A description of the data is given in section 4.3. This is followed by a review of the econometric framework in section 4.4, and by the presentation of our empirical results in section 4.5. Section 4.6 concludes.

4.2 Theoretical background

4.2.1 Accounting for endogenous adaptation

The theoretical backdrop of the Ricardian approach draws upon the traditional hedonic literature. The equilibrium price (here: land rental price), P, of a hectare of land in the agricultural market can be expressed as a function of the land and site attributes, z:

$$P = f\,(z_c, z_{nc}) \tag{9}$$

It is convenient to distinguish between a vector of attributes whose levels can be controlled (z_c), and another vector of attributes whose levels cannot be controlled (z_{nc}) (Palmquist, 1989). In our empirical example, z_c covers the occurrence of the farm type (*e.g.*, arable crops *vs.* livestock *vs.* permanent crops), and the potentially irrigated acreage (*i.e.*, acreage covered by installed irrigator); climatic, topographical and geographical characteristics are subsumed into z_{nc}. The usual assumptions that approximate perfect competition are assumed to hold in order for endogenous selection of the levels of attributes in z_c to be triggered, thus leading to the farm structure that maximizes profits. Local climatic trends are assumed to be "visible" through the process of efficient adaptation–that is, through strategic reconciliation of past climate and past profitability. Hence, climate enters into the utility functions of landlords and tenants, impacts their bids, and contributes to the determination of the equilibrium rental price schedule.

The traditional version of the approach assumes implicit adaptation. In essence, regressing land prices or farm profits against climatic attributes enables the calculation of the total monetary effect of climate without formally modeling the "black box" of adaptation. This aspect might have been considered as cost-effective in early applications, but the increasing policy interest on adaptation renders it an issue that merits further exploration. For instance, a recent trend pertains to the distinction between climate-induced effects on farm-level choices and those effects on farm profitability. The analytical procedure typically followed is first to run a nonlinear choice model and then net-revenue regressions conditional on the choice.

In this article, we offer an alternative approach to examine the causal ordering of the climate variables more closely. We take an IV perspective that allows for the decomposition of the effects of climate on farm profitability into implicit and explicit. The term "implicit" refers to the effect of climate that is unmediated and not explicitly modeled. The term "explicit" refers to the effect of climate that involves mediation by other variables, which are explicitly modeled. Alternatively, one could think of these effects as *direct* and *indirect* partial effects: the implicit effect is a direct effect in the sense that one calculates the direct impact of climate on farm profitability; the explicit effect is an indirect effect in the sense that one calculates the indirect impact of climate on farm profitability through variables that reflect some kind of adaptation. We propose a way to separate these effects, and pursue an empirical example with farm types and irrigation treated as mediating variables (*i.e.*, the ones that are affected *by* climate, and affect farm profitability *along* with climate). The distinction between direct and indirect effects will be made evident in section 4.5.2. We formularize this concept into a single Ricardian model that treats a farm-profitability indicator, farm types, and potential irrigation as endogenous to climate.

4.2.2 Spatial effects and the Ricardian approach

Recent econometric work highlights the potential bias and efficiency loss that may arise when spatial autocorrelation is ignored in the estimation of property-value models (*e.g.,* LeSage and Pace, 2009). As the main motivations for incorporating spatial effects have not been fully acknowledged in the framework of the Ricardian approach, we briefly discuss the main ones below.

A first motivation (M1) relies on purely econometric arguments to minimize omitted-variable bias by including otherwise omitted information through spatial lags (LeSage and Pace, 2009: chapter 3). The latter may also protect against unobservable factors (*e.g.,* water accessibility for irrigation) that may be correlated with the decisions of multiple farmers.

A second motivation (M2) is to control for spatial dependence that may appear as a side effect due to aggregation. Areal aggregates are not land markets but are typically used as proxies to explore the role of climate in the determination of land prices. However, cross-sectional data for aggregate objects are more likely to be correlated with each other for, by construction, they contain less information than their disaggregated counterparts, which may be truly independent (Anselin and Bera, 1998: 239). Therefore, aggregation (or averaging) may cause homogeneity to otherwise more heterogeneous land prices or farm profits and thus, may lead to spatial dependence that should be accounted for. Similarly, the inclusion of interpolated regressors that are the result of scale mismatches (*e.g.,* farm *vs.* meteorological station) may also lead to spatial autocorrelation (Anselin, 2001).

Recent literature highlights interactions among landlords (M3) as a factor that may give rise to spatial relationships. Patton and McErlean (2003), for instance, argue that landlords may base their starting price on estimates by land price assessors, and that these estimates are presumably based on transactions in the vicinity. This realization may be the result of insufficient information about land characteristics (Maddison, 2004), and highlights a need to depart from the standard aspatial framework.

The existence of commonalities in land-use behavior (M4) is another relevant factor. Proximal farms often communicate with each other in terms of production patterns, input choice and use (Kumar, 2011), or technology adoption. It is worthwhile to note that incorporation of such commonalities into the traditional Ricardian model is precluded by the conceptual framework of the approach itself: since structural attributes (*e.g.,* share of grassland, share of irrigated land) are assumed to be endogenous to climate, any variable reflecting farm structure should be instrumented to avoid simultaneous-equation bias.

A last motivation relates to observed farmland investments that create external benefits for adjacent parcels (*e.g.*, drainage, access to road maintenance, hedge cutting, building structures, machinery pooling) (M5). However, the extent to which this happens systematically enough to lead to an overall clustering of land prices or farm profits would require a farm level analysis with spatially lagged explanatory variables.

To conclude, the incorporation of spatial econometric structure (where warranted by the data) into a Ricardian model offers at least three advantages. First, it allows us to obtain consistent and unbiased parameter estimates in the presence of spatial autocorrelation and irrespective of the origin of the latter. Second, a single parameter is used to parsimoniously reflect an average level of autocorrelation over multitudinous relationships (LeSage and Pace, 2009: 10). Finally, it is possible to exploit the spatial-autoregressive structure to elicit welfare estimates that incorporate or neglect potential spatial effects.

4.3 Data and variables

Farm data utilized in this study come from the 2010 agricultural census (FDZ, 2011). Agricultural information draws on all 273,178 interviewed farms (>5 ha, with nonmissing information) that managed over 11 million hectares at the time. Data protection issues by the statistical office led us into grouping individual farms into 3,515 communities.

The steady-state farm profitability indicator used is the mean land rental price (€/ha) per farm, which we arithmetically averaged at the community level. This is the only indicator of monetary nature that has been observed in the market, and that is directly available in the census. Rent transactions in Germany are not regulated by policies, and rental prices are the result of negotiations between landlords and tenants.

Renting agricultural land is very common in Germany. In 2010, 197,150 (72%) farms rented part of their land. These transactions are made up of 48,222 (71%) transactions of crop farms, 3,171 (43%) transactions of horticultural farms, 12,113 (53%) transactions of permanent-crop farms, 90,024 (75%) transactions of forage farms, 21,156 (76%) transactions of livestock farms, and 22,464 (83%) transactions of mixed crop-livestock farms. The preceding parentheses show that farms that rent land are overrepresented in each subgroup except in the case of horticulture. The mean rental price of 259€ per hectare hides considerable variability across groups: on average, rental prices are lower for forage farms (181€) and higher for permanent-crop (631€) and horticultural farms (1507€).

The census covers additional information (*e.g.*, farm type, acreage covered by installed irrigators, subsidies) that was utilized in the analysis. Definitions and basic descriptive statistics for the full set of variables are given in Table 4.1.

Climate data utilized in this study come from a large sample of ground monitoring stations (DWD, 2013). Weather data series for the 1980–2009 period were transformed to historical climate averages, which constitute a conceptually elegant and estimably simple RHS operationalization of climate in cross-sectional setting. Many procedures are available to allocate climate measures to the communities. In this application, we considered a hybrid spatial interpolator that decomposes the climate data into two processes: a large-scale process that generates a systematic three-dimensional trend component through hypersurfaces, and a small-scale process that generates a locally fluctuated component. Theoretical, operational, and schematic details are given in Appendix A. Ultimately, we parameterize climatological normals as mean seasonal temperature (°C) and mean total seasonal precipitation (mm). The four seasons were merged into two–that is, spring and summer, autumn and winter–since they are very strongly pairwisely correlated and their impacts would be difficult to otherwise isolate. Climate variables are used as mean-centered second-degree polynomials in the Ricardian model, thus operationalizing Quiggin and Horowitz's (2003) concept of the "climatic optimum".

In addition to climate variables reflecting the first moment (see Schneider *et al.*, 2000), we include historical standard deviations for the critical period for crop growth. Opposed to year-to-year variance (see Mendelsohn *et al.*, 2007), standard deviation is directly comparable to the historical mean. Furthermore, we included an indicator variable for extreme climate in spring and summer, which takes on the value of 1 for too high temperatures (higher than the 90th percentile) or too low precipitation (lower than the 10th percentile). Though we experimented with additional extreme climate indicators (*i.e.*, very high/low temperature, very high/low precipitation), the aforementioned indicator is the only one that does not lead to the loss of observations in the irrigation model (section 4.4) due to separation.

We include a climate-invariant soil index to control for soil productivity (FZ Jülich 2009). The index is measured on a 0-100 scale (=100 for highest potential yield), and considers only the structure of soil particles, and the genesis and degradation of arable soils. A slope index (%) and information on altitude (m) were extracted from a raster-based Digital Elevation Model (Jarvis *et al.*, 2008) using the Esri ArcGIS 10 Spatial Analyst extension. Based on zonal statistics, topographical variables were manufactured as polygonal averages (Appendix B, Figure B1).

In addition, we control for the distance between any community and the nearest large city, as well as for the distance to the nearest port (City Mayors, 2013; World Port Source, 2013). Polygon centroids were manufactured as reference points to calculate pairwise distances through geodesic calculi (Figure B2). Farms situated closer to (farther away from) urban areas often produce goods that are heavier (lighter) or more (less) expensive to transport. Proximity to urban centers may inflate the value of land due to nonagricultural pressure, and proximity to cities or ports may increase farm profits–and thus, rental prices–due to the possibility of easier product distribution.

4.4 Econometric framework

We carry out a forward specification analysis. We first obtain the OLS estimates for the usual version of the Ricardian model. Then, we introduce the farm-type and irrigation variables, whose exogeneity is rejected. Finally, we control for the presence of spatial autocorrelation in the IV model.

The literature on spatial econometrics differentiates between three parameterizations of dependence: spatial-autoregressive (SAR), spatial-X (SLX), and spatial-autoregressive error (SER). The SAR specification introduces a spatially lagged dependent variable, the SLX specification incorporates spatially lagged independent variables, and the SER specification models spatial correlation through the disturbances. These parameterizations can be combined in numerous ways (see Elhorst, 2010).

In this application, we estimate a log-linear[20] Ricardian model for land rental prices with a first-order spatial lag in the dependent variable, and additional endogenous regressors, henceforth SAR-IV. The model can be expressed in matrix notation as:

$$\mathbf{y} = \mathbf{Y}\pi + \mathbf{X}\beta + \lambda\mathbf{W}\mathbf{y} + \mathbf{u} \tag{10}$$

or in its reduced form as:

$$\mathbf{y} = (\mathbf{I}\text{-}\lambda\mathbf{W})^{-1}\,(\mathbf{Y}\pi + \mathbf{X}\beta + \mathbf{u}) \tag{11}$$

where $\mathbf{y}$ is an 3,515×1 vector of observations on the dependent variable, $\mathbf{Y}$ is an 3,515×5 matrix of observations on the RHS endogenous variables (*Crop*, *Livestock*, *PermCrop*, *HortCrop*, *Irrig*), π is the corresponding 5×1 parameter vector, $\mathbf{X}$ is a 3,515×22 matrix of

[20] The untransformed dependent variable was strictly positive and highly skewed.

RHS exogenous variables, β is the corresponding 22×1 vector of regression coefficients, **W** is an exogenous, nonsingular, 3,515×3,515 spatial-weighting matrix with zero diagonal elements, **Wy** is a 3,515×1 endogenous vector, λ is the corresponding scalar parameter, **u** is a 3,515×1 vector of independent and homoskedastic disturbances, and **I** is a 3,515×3,515 unit matrix. Setting $\lambda = 0$ causes the model in Eq. (10) to reduce to a typical IV model.

In Eq. (10), spatial effects are captured by the endogenous spatial lag, **Wy**, which consists of a weighted average of the values of **y** in proximal locations. Thus, **Wy** formalizes the determination of a potential mean land rental price at *i* based on mean rental prices in proximal communities. In the literature, the most common conceptualization of **Wy** pertains to the empirical counterpart of the equilibrium solution of potential spillovers (*e.g.,* M3, M4), in which case λ is interpreted as an indication of the strength of those spillovers (see Brueckner, 1998). In addition to that, the vector **Wy** accounts for simultaneity in the rent transactions that is induced by the cross-sectional framework. Finally, similar to the notion that farms that rent land proxy the profitability of all farms, the neighborhood relations in **W** should be viewed as proxies for the actual neighbors. We are comfortable with this assumption since the spatial scale of the analysis is essentially close to the decision making process.

Spatial-weighting matrices (**W**) are a standard tool in spatial econometrics to incorporate the spatial structure of observations. In this application, we use a matrix specification that combines actual cardinal distance, an ordinal layout, and information on the overall contiguity pattern. First, we translated Tobler's (1970: 236) first law of geography[21] into a real-valued mathematical distance decay, $w_{ij} = f\,(d_{ij})$, where f is an inverse-spherical-distance function for community centroids. This geostatistics-based starting point captures spatial effects between communities due to proximity, and copes with the existence of unconnected observations (3%). Second, we supplemented the distance decay with a nearest-neighbor (*nn*) scheme. Ordering by neighbors avoids the induction of heteroskedasticity due to irregular polygon sizes, and bypasses an uneven contiguity-based weighting that could result in a less precise λ. And third, while the number of nearest neighbors is typically chosen arbitrarily, we deduced it from the observed connectivity pattern: we set it equal to 6, which is the median number of queen-contiguity links. Mean distances range from 5 km (1st neighbor) to 11 km (6th neighbor). Finally, the weights were normalized by row, thus treating absolute

[21] *"Everything is related to everything else, but near things are more related than distant things"*.

distances as relative and facilitating the interpretation of λ as "correlation" in the spatial domain.

For the aspatial models, we employ the standard OLS and 2SLS estimators. For the estimation of the SAR-IV model, we apply an extension of the 2SLS estimator that deals with the endogeneity of $\mathbf{Wy}$ (see Drukker *et al.*, 2013, and the sources cited therein). The instruments of the respective matrix $\mathbf{Q}$, $\mathbf{Q} = (\mathbf{X}, \mathbf{WX}, \mathbf{W}^2\mathbf{X}, \mathbf{H})$ are discussed below.

For the spatial lag in the dependent variable, we use $\mathbf{WX}$ and $\mathbf{W}^2\mathbf{X}$ as instruments (see Kelejian and Prucha, 1998). This frequent way to approximate the mean of $\mathbf{Wy}$ results from manipulating Eq. (11)[22]. As instruments for farm-type selection, we use the predicted probabilities from a tractable, reduced-form, multinomial logit model for the "dominant" farm type at the community level. The formal statement of the model is:

$$\Pr(\mathbf{y} = m \,|\, \mathbf{X}) = \frac{\exp(\mathbf{X}\beta_{m|b})}{\sum_{j}^{J} \exp(\mathbf{X}\beta_{j|b})} \qquad \text{for } m = j, \ldots, J \tag{12}$$

Let $\mathbf{y}$ be the random response variable "most frequent farm type at the community level" consisting of $J = 5$ nominal alternatives: crops, livestock production, forage farming, permanent crops, and horticulture[23]. The RHS set of Eq. (12) translates the probability of observing outcome m given the row vector $\mathbf{X}$ of actual values of the conditioning climate and other variables, the coefficient vector β_m, and a reference equation b (here: forage) whose parameters are normalized to 0 to ensure unique model identification. The model setup guarantees that predicted probabilities will be nonnegative and sum to 1.

Using those fitted probabilities as instruments for the endogenous farm-type variables in the land-rental-price model has four appealing features. First, it avoids the search for natural instruments and so, for additional data. Second, since the fitted probabilities are nonlinear functions of $\mathbf{X}$ and not perfectly correlated with $\mathbf{X}$, they can safely serve as instruments (Wooldridge, 2002: chapter 18). Third, this approach is fully robust to any misspecification in the multinomial model (*e.g.*, due to potential violation of the IIA property or due to the omission of spatial effects) because the fitted probabilities are merely used as instruments, not as regressors (Wooldridge, 2002: chapter 18). And fourth, this approach can

[22] The truncated power expansion of $(\mathbf{I}-\lambda\mathbf{W})^{-1}$, $(\mathbf{I}-\lambda\mathbf{W})^{-1} = \mathbf{I} + \lambda\mathbf{W} + \lambda^2\mathbf{W}^2 + \ldots$, expresses the rental price at i as a function of i's own characteristics ($\mathbf{X}$), the characteristics of neighboring communities ($\mathbf{WX}$) and those of their neighbors ($\mathbf{W}^2\mathbf{X}$), subject to a distance decay operator (LeSage and Pace, 2009: 14).

[23] Since mixed crop-livestock farms are sparsely distributed and rarely dominate, they were randomly allocated to the crops and livestock groups.

also be applied in a straightforward manner if farm-level data are analyzed, in which case binary indicators can be used for the endogenous farm types.

We move now to the irrigation model. Kurukulasuriya *et al.* (2011) use water flows and topographical variables as instruments to account for the endogeneity of irrigation to climate through conditional regressions. In the absence of natural instruments as those, we construct an instrument similar to our preceding approach: the predicted probability from a reduced-form binary probit model whose dependent variable takes on the value of 1 if an irrigator is installed in at least 50% of all farms in the respective community. The model we fit is:

$$\Pr(irrigation = 1) = \Phi(\mathbf{X}\beta) \tag{13}$$

where Φ is the standard cumulative normal distribution.

In this setup, the five nonlinear projections from Eqs. (12) and (13) serve as instruments for the five endogenous farm-type and irrigation variables of Eq. (10). Since these instruments are aspatial, we constructed extra instruments by taking the spatial lags of the predicted probabilities. From a conceptual viewpoint, taking the spatial lags of the predicted probabilities from Eq. (12) is based mainly on motivation M4 (section 4.2.2). The rationale behind the spatial lag of the predicted probability from Eq. (13) is the so-called "resource flow" approach: a farmer's decision of whether to install an irrigator depends on the characteristics of that farm and on the existence of irrigators in the vicinity, which all depend on overall water availability. Since the matrix **H** now contains ten instruments, overidentification in the IV model becomes testable. Finally, note that whereas the model in Eq. (10) considers only the 197,150 farms that rent land, the nonlinear models in Eqs. (12) and (13) are estimated for all 273,178 farms.

Due to data protection, the analysis was carried out in the framework of remote data access. Neither were we allowed to obtain any data by FDZ in hand nor to develop maps that would help us visualize the results. Estimation procedures were carried out using Stata/SE 13.

4.5 Empirical results

4.5.1 Regression output

We begin the review of our results with a brief look on the overall performance of the reduced-form models that were used to generate instruments (Appendix C, Tables C1 and C2). The farm-type model shows a satisfactory predictive performance both as a whole (count-R^2 = 77%) and by category: permanent crops (96%), forage (82%), horticulture (78%), crops (74%), and livestock (37%). The overall fit of the irrigation model is lower, as zeroes are predicted accurately by 99% and ones by 35%. Given the aggregate nature of the probit and the occurrence of zero inflation, this had been somewhat expected[24]. Finally, values of the McFadden-R^2 (0.48 and 0.52) suggest that the RHS set used offers substantial improvement over the only-intercept specifications.

We now move to Table 4.2, which depicts the results from three estimation methods: OLS (the usual version of the Ricardian model), IV (standard 2SLS with farm types and irrigation treated as endogenous), and SAR-IV (S2SLS with a spatially lagged dependent variable, and with farm types and irrigation treated as endogenous). Regression diagnostics are presented separately in Table 4.3.

First, consider the OLS results for the topographical and geographical predictors. Overall, the coefficients of the land characteristics are highly significant, and their signs obey conventional wisdom. Average rental prices are higher in districts with more productive soils, and increase when communities contain urban centers or ports. Nature- and water-protection payments are associated with an increase, whereas other agri-environmental payments with a decrease in rental prices. The latter relationship likely indicates less-favored areas. Full-time farming appears to be associated with an increase in rental prices. The negative sign of the indicator variable for East Germany is well known, and is attributed to historical social, political, and structural conditions (Möller *et al.*, 2010), as well as to the absence of nonagricultural pressure.

We now move to the climate coefficients. The parameter estimates of the temperature normals are highly statistically significant. Higher temperatures in the warmer seasons are associated with a total decrease in rental prices, *ceteris paribus*. This negative effect can be interpreted with the help of the results from the multinomial model (Table C1). Warming in the growing season decreases the occurrence of crop and livestock farms and increases the occurrence of permanent-crop farms, relative to forage farms. Since in the current structure of the sector crop and livestock farms outweigh permanent-crop farms (46% *vs.* 6%), the benefits from a temperature increase are lower for permanent-crop farms than the damages for crop and livestock farms. On the other hand, higher temperatures in the colder seasons are associated with a total increase in rental prices, *ceteris paribus*. The usual argument for this finding is that higher temperatures in autumn imply fewer problems during the harvesting

[24] Only a handful of farms rely on irrigation. The dependent variable in the probit model takes on the value of 1 in 126 communities (3.5% of all).

period. Furthermore, higher temperatures in the winter decrease the occurrence of livestock deaths as well as the need to feed livestock more. Overall, the annual effect on rental prices appears to be positive and thus, in qualitative accordance with the corresponding estimate in a previous study (Lippert *et al.*, 2009). Finally, note that opposed to applications for larger countries (*e.g.*, Brazil, Mexico, South Africa), nonlinearity in temperature is not empirically found in our case, possibly due to lower temperature variation. For example, the seasonal standard deviation in Germany (1 °C) is substantially lower than that in Mexico (4 °C; Mendelsohn *et al.*, 2009).

Precipitation normals display concavity in the warmer seasons, and convexity in the colder ones. In spring and summer, rental prices increase at a decreasing rate up to a cutoff point (362 mm). The positive response may attributed to the fact that forage farms, which constitute the most frequent farm type (45%), are presumably more productive than crop or permanent-crop farms under increasing precipitation (see Table C1). A similar concave relationship was also found in a previous study (Lang, 2007). In autumn and winter, rental prices decrease with increasing precipitation up to a cutoff point (219 mm). The negative sign of the linear term may be explained by difficulties associated with harvest. Two possible reasons for the positive sign of the quadratic term pertain to the fact that high soil moisture prior to the growing season reduces both the impact of field operations (*e.g.*, planting) on unwanted soil compaction and the need to irrigate in the beginning of the growing season (b_{Prec_aw} = -0.04 in Table C2). Note that benefits in the warmer seasons appear to outweigh damages in the colder seasons, *ceteris paribus*. Finally, higher precipitation variability in the growing season is associated with a decrease in rental prices.

The explained variation of the aggregate OLS model is moderate (R^2_{var} = 0.42). The OLS model passes a heteroskedasticity test, but additional diagnostics indicate endogeneity in the variables reflecting farm structure, and spatial autocorrelation.

In formally assessing the endogeneity of the farm-type and irrigation variables, we performed a series of joint exogeneity tests using the instruments described in section 4.4. Exogeneity of the farm-type and irrigation variables is very strongly rejected (Table 4.3). Furthermore, regressing the IV residuals against the instruments gives R^2 = 0.0001, with $F_{10,3504}$ = 0.25 and *p*-value 0.96, while all regressors (instruments) are far from being significant. Therefore, no invalid-instruments problem is flagged.

Weak instruments may cause IV estimators to lose precision. Hence, we then assessed the quality of our instruments. Typical pairwise Pearson correlation coefficients between the instrumental and instrumented variables range from |0.37| to |0.74| and are highly significant.

In addition to that, values of the $F_{10,3482}$-statistic for joint significance of the instruments in the first-stage regressions range between 56 and 393, thus exceeding the rule-of-thumb value of 10 in any case (see Staiger and Stock, 1997). There is no indication of weak instruments.

The IV specification accounts indirectly and partially for spatial correlation through the lagged instruments. We next assessed the presence of overall spatial correlation using a *post hoc* Wald test on the spatial-autoregressive parameters of two models: SAR-IV and SER-IV. Wald tests are asymptotically equivalent to the standard LM tests for spatial correlation under homoskedasticity, but bear the advantage of greater computational convenience in Stata. The corresponding test results showed strong evidence of positive spatial autocorrelation in either case, with the value of the χ^2_1 test maximized in the SAR case. Therefore, we proceeded with the SAR-IV specification.

Next, consider the effect on the OLS results of accounting for endogeneity in the farm-type and irrigation variables, as well as for spatial autocorrelation. The overall fit is now very satisfactory (=0.86 in IV; =0.79 in SAR-IV). The significance of the estimated coefficients of the topographical and geographical predictors remains fairly stable across estimators, with a few exceptions: the gain in significance for the negative effect of *Slop*, the reduction of significance for *Soil*, and the loss of significance for *Ln(Alt)* and *Subs2*.

The variables reflecting farm structure represent a change in the conditional mean relative to forage farms, which had been excluded from the model specification to avoid perfect multicollinearity. As expected, the significance of the respective coefficients is high in either model. Average land rental prices increase with increasing percentage of crop, livestock, horticultural, or permanent-crop farms. The IV estimates are consistently greater in absolute value. This difference may be attributed to the existence of **Wy**, which factors into the SAR-IV equation sources of potential spatial effects (M2, M3) in addition to M4.

Communities with larger potentially irrigated acreage are characterized by lower land rental prices. The effect of *Irrig* is negative in either case, albeit significant at the 0.05 level only in the IV specification. As Table C2 also suggests, the effect of climate on irrigation is not statistically negligible: warm winters increase the acreage potentially covered by an irrigator ($b_{Temp\_aw\_sq}$ = 0.33), whereas rainy winters decrease it (b_{Prec_aw} = -0.04). A possible explanation for the negative sign of *Irrig* on land rental prices is that the water available for irrigation is not enough to compensate for the actual temperature increase in the growing season ($b_{Temp\_ss} < 0$). Hence, irrigation appears to help farmers only to reduce further yield loss. Another reason could be that precipitation has increased such that farm types that formerly needed to irrigate now need not do so. If one takes into account that that future projections for Germany prescribe increases both in precipitation and temperature (see Lippert *et al.*, 2009), either reason seems plausible. Practically, the need to irrigate will be higher if the land is generally not productive (b_{Soil} = -0.02 in Table C2).

The significance of the coefficients of the climate variables remains high throughout and thus seems to not be affected by the estimation method. An exception is the linear term for precipitation in the colder seasons in SAR-IV, which is no longer significant. However, the absolute values of the climate variables vary considerably across estimators. Compared to OLS, temperature estimates are lower (larger) in IV (SAR-IV) for the warmer seasons, and lower for the colder seasons. The cutoff points for precipitation are found later for the warmer seasons (446 mm in IV, 500 mm in SAR-IV) and earlier for the colder seasons (136 mm in IV, 137 mm in SAR-IV). These quantitative changes are attributed to the fact that the direct and indirect climate effects are confounded in the OLS coefficient estimates (see section 4.5.2).

The estimated spatial-autoregressive coefficient is positive, moderate, and significant, thus indicating moderate spatial dependence in rental prices. This dependence may be attributed to the multitude of reasons given in section 4.2.2. It might also be the result of obvious crossovers between the communities (*i.e.*, landlords owing parcels in more than one community, tenants renting parcels in more than one community) or partially due to spatial correlation in the climate variables (*e.g.*, spatially correlated elements from the semivariograms may carry over into the Ricardian model). In the absence of a behavioral model of interactions–which is beyond the scope of this study–it would be difficult to identify an exact process that leads to spatial dependence. Fortunately, this aspect can be made distinct in the calculation of partial effects.

We conclude this section with a brief discussion of two robustness checks on the models of Table 4.2. The first was a re-run of the IV and SAR-IV specifications with heteroskedasticity-consistent standard errors, which did not lead to any important change in the significance of the climate or the endogenous variables[25]. Second, we assessed what is perhaps the most cited disadvantage of the Ricardian approach (Auffhammer and Schlenker, 2013): the possibility of omitted-variable bias, which stems from nonorthogonality between the climate variables and the disturbances. There appears to be no evidence for this pitfall in our case: regressing the residuals from the IV and SAR-IV models against the climate variables produces an *F*-statistic equal to zero and insignificant estimates.

[25] For a heteroskedasticity-robust version of the SAR-IV model, see Arraiz *et al.* (2010) and the sources cited therein.

4.5.2 Partial effects

In the absence of detailed projections that would serve the purpose of a simulation exercise, we perform a detailed examination of the partial effects of the climate variables. Drawing on standard utility maximization theory, the WTP can be seen as the extra amount land users "must" pay to move to (or to avoid) a bundle with another level of a climatic attribute, *ceteris paribus*.

Following Baron and Kenny's (1986) approach, we distinguish between direct and indirect marginal effects. The direct effect shows the change of the conditionally expected rental price due to a marginal change in the climatic attribute of interest, and can thus be obtained as the derivative of the rental price equilibrium equation (Table 4.2) with respect to that attribute. The indirect effect shows the change of the conditional mean if the endogenous farm-type and irrigation variables were to change simultaneously by the amount prescribed by a marginal change in the climatic attribute. Therefore, the indirect effect can be calculated by summing the individual indirect effects accruing from the first-stage regressions (Table C3), which equal the derivatives of the first-stage equations with respect to the climatic attribute of interest[26]. The total effect is the sum of the direct and all the indirect effects. All point estimations were performed at means.

In the OLS model and for the quadratic formulation of climate, the marginal effect equals $(\beta_1+2\mathbf{X}\beta_2)\mathbf{y}$. In the IV model, this corresponds to the direct effect. In the spatial model, an IV-like derivation of the direct effect corresponds to the *no*-multiplier effect, which neglects the simultaneity-in-observations induced by the SAR structure. Upon enriching the information set by a global spatial multiplier that shows the movement to the next rental price equilibrium, it can be shown that the *with*-multiplier effect is equal to $(1-\lambda)^{-1}(\beta_1+2\mathbf{X}\beta_2)\mathbf{y}$, where $(1-\lambda)^{-1}$ represents the convergence of $(\mathbf{I}-\lambda\mathbf{W})^{-1}$ given that $|\lambda|<1$ (see Annex). The need to separate the effect of the spatial multiplier is extensively discussed in Small and Steimetz (2012).

In Table 4.4 we report the calculated marginal effects of the continuous climate variables for the various estimation methods. For temperature in the warmer seasons, the OLS result suggests a point estimate of 33€ to avoid a marginal temperature increase, compared to 23€–44€ as the range across IV and SAR-IV. The IV and SAR-IV total effects are made up of negative direct effects (30€–54€) that are partially compensated by positive indirect effects (5€–12€). The latter effects result from substitutions among farm types and changes in the

[26] The partial effect of the instruments with respect to climate can be safely ignored in the calculation of the indirect effects. This accrues from the overidentification test result (Table 4.3).

potentially irrigated acreage. For the total effect of temperature in the colder seasons, the OLS result suggests a point estimate of 82€ to meet a marginal temperature increase, which is contrasted to 16€–28€ as the range across IV and SAR-IV. The reason for this quantitative difference is the large size of the negative indirect effects (20€–36€), which are neglected in the OLS model. For precipitation normals, the OLS total effects (21€ and 5€) are relatively close to the IV (28€ and 4€) and *with*-multiplier (26€ and 4€) estimates, as the indirect effects are relatively low. Finally, there is some indication that the use of year-to-year variability measures merits further investigation. In our particular example, the negative effect of increasing precipitation variability appears to outweigh the positive effect of the respective historical mean across all non-OLS specifications.

Although it is sometimes suggested that OLS coefficients reflect the total effect of climate, not only our findings do not generally support this, but it is also interesting to note the inconsistency in the direction of the difference across cases. The main conclusion is therefore that the magnitude of the OLS estimates may be severely misleading, in the sense that the total effect of climate may either be over- or underestimated.

In interpreting the results of Tables 4.2, 4.4, and C3, three important remarks have to be made. First, the attractive feature of the dichotomization of the total effect is that it flexibly allows for an economic assessment of adaptation. It becomes possible to infer whether the adaptation measures of interest would likely be, on average, economically worthwhile (indirect effect > 0) or not (indirect effect < 0) under marginal changes in climate. This appealing distinction cannot be made in the usual version of the Ricardian approach, wherein the direct (unmediated) and indirect (mediated) climate effects are confounded. Second, interpretation of the indirect effects is done relative to the omitted case (here: forage farms). For example, increasing temperatures in the growing season trigger an increase in the average acreage of permanent crops and a decrease in the acreage of arable crops *relative* to the acreage of forage crops. In other words, a positive (negative) indirect effect implies damages (benefits) for forage farms. Finally, it is important to note that only two adaptation strategies were modeled herein. Additional adaptation measures with presumably positive indirect effects (*e.g.*, altering the timing of field operations, introducing new crop varieties) remain subsumed into the OLS total effects and the IV and SAR-IV direct effects.

(Continued on the next page)

4.6 Concluding remarks

An important aspect of assessing the effectiveness of environmental policies that address the impacts of climate change on agriculture is the quantification of the economic value of the accrued impacts. In doing so, the established Ricardian approach assumes that, *ceteris paribus*, the value or price of agricultural land reflects climate-induced benefits or damages.

In this article, we contribute to the empirical literature on the Ricardian approach by considering the incorporation of otherwise omitted adaptation measures into a single Ricardian model. From an IV perspective, we focused on the endogeneity of the choice of the farm type and irrigated acreage to climate. In doing so, we used nonlinear projections of the endogenous variables as well as the spatial lags of those projections as instruments. We further explicitly controlled for spatial autocorrelation, which was warranted by the data.

Our results highlight the importance of departing from the OLS world to improve the conceptual fidelity and explanatory power of a Ricardian model that includes variables that are endogenous to climate. The effect of doing so through IV estimation, either in an aspatial or spatial framework, is significant with respect to the coefficient estimates of both the climate variables and those variables that are endogenous to climate. In essence, the OLS welfare estimates are likely to be misleading with a bias of inconsistent direction. This is attributed to the fact that the usual version of the approach neglects the endogenous nature of adaptation, and thus confounds the direct and indirect effects. Certainly, evidence from further studies and contexts is necessary to establish the extent to which this finding is generalizable. Our approach is extensible to the case of farm-level data, which conveniently allow for the economic effect of more detailed adaptation tactics (*e.g.*, new crop varieties, alternative fallow and tillage practices) to be explored. Furthermore, short-term adaptation strategies (*e.g.*, timing of operations) can also be modeled with a panel-based Ricardian model for farm profits.

How comparable is our proposed estimation strategy to the conditional-regressions approach previously used in the literature? Three main advantages can be distinguished. First, it is more cost-effective in terms of number of estimated models. While the conditional-regressions setup would lead us estimate 10 land-rental-price regressions–that is, 5 models for rainfed irrigation and 5 models for irrigated farms, all conditional on the farm type–we have modeled multitudinous relationships into a single specification. The second advantage from explicitly treating adaptation as endogenous through IV estimation is that the direct and indirect effects of climate can be distinguished and compared; in the usual version of the

Ricardian model they are confounded, thus not allowing assertions on whether the given adaptation measures are actually worthwhile. Finally, our approach is more realistic in the context of simulation exercises where climate projections enter as input, simply because farm profits change along with the theoretically optimal use of land. If conditional regressions are used for simulation, the assumption that the choice of the farm type and irrigation are not simultaneously affected by climate change is, needlessly, too restrictive.

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Table 4.1 – Variable definition and descriptive statistics

Variable	Description	Mean	SD
Rent	Mean land rental price (€/ha)	258.76	293.99
Temp_ss	Temperature normal (°C), spring and summer, 1980–2009	12.79	0.98
Temp_aw	Temperature normal (°C), autumn and winter, 1980–2009	4.91	1.13
Prec_ss	Precipitation normal (mm), spring and summer, 1980–2009	191.00	65.27
Prec_aw	Precipitation normal (mm), autumn and winter, 1980–2009	404.03	84.64
Temp_sd	Spring-to-spring standard deviation (°C), 1980–2009	3.95	0.23
Prec_sd	Spring-to-spring standard deviation (mm), 1980–2009	27.27	6.63
ExtrClim	=1 for extreme climate (drought) in spring and summer, 1980–2009	0.19	0.39
Crop	Rented acreage of crop farms (wheat, barley, potato, sugar beet) in total rented acreage of all farms (%)	33.72	29.13
Livestock	Rented acreage of livestock farms (pigs, poultry) in total rented acreage of all farms (%)	16.33	17.29
PermCrop	Rented acreage of permanent-crop farms (fruit trees, vine, hop) in total rented acreage of all farms (%)	2.03	9.40
HortCrop	Rented acreage of horticultural farms (vegetables, floriculture) in total rented acreage of all farms (%)	0.69	4.11
Forage	Rented acreage of forage farms (grazing livestock) in total rented acreage of all farms (%). Base (omitted) category.	47.22	33.16
Irrig	Ratio of mean potentially irrigated acreage in total rented acreage	0.14	0.51
Soil	Soil productivity (0-100)	47.02	14.83
Slop	Land steepness (%)	2.66	2.52
Ln(Alt)	Logarithm of altitude (m)	5.34	1.31
City	=1 if a large city exists in the community[a]	0.07	0.25
DiCity	Haversine distance (km) to the closest large city[a]	19.81	12.77
Port	=1 if an inland, dry, or cargo port exists in the community[b]	0.02	0.14
DiPort	Haversine distance (km) to the closest port[b]	45.01	28.07
East	=1 if East Germany	0.03	0.16
Subs1	Farms receiving nature (Natura 2000) and water protection (WFD) payments (%)	5.69	14.88
Subs2	Farms receiving other agri-environmental payments (%)	54.23	26.16
Full	Farms where on-farm income exceeds off-farm income (%)	29.77	13.99

[a] The 250 most populated cities (>42,000 residents) were considered.
[b] 83 inland, dry, and cargo ports were considered.

Notes: Community arithmetic averages (n = 3,515, with 197,150 farms that rent land therein), with the exception of the percentage, distance, and dummy variables. Categorization of farms into types (*Crop*, *Livestock*, *PermCrop*, *HortCrop*, *Forage*) is done by the statistical office, and is based on the concept of standard output that is used in FSS and FADN. Variables are described in detail in section 4.3.

Source: Own calculations, based on City Mayors (2013), DWD (2013), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and World Port Source (2013).

Table 4.2 – Endogeneity of farm types and irrigation to climate: OLS, IV, and spatial-IV Ricardian estimates

Variable	**OLS**		**IV**		**SAR-IV**	
Temp_ss	-0.12619	**	-0.18943	**	-0.11687	**
Temp_ss_squared	-0.04538	**	-0.06054	**	-0.03795	**
Temp_aw	0.31772	**	0.22555	**	0.13920	**
Temp_aw_squared	0.07921	**	0.08264	**	0.04364	**
Prec_ss	0.01381	**	0.01985	**	0.01037	**
Prec_ss_ squared	-19.1×10^{-6}	**	-22.26×10^{-6}	**	-10.36×10^{-6}	**
Prec_aw	-0.00346	**	-0.00165	**	-0.00082	
Prec_aw_ squared	7.91×10^{-6}	**	6.058×10^{-6}	**	2.993×10^{-6}	**
Temp_sd	-0.10429		-0.05087		0.11309	
Prec_sd	-0.08191	**	-0.13485	**	-0.07141	**
ExtrClim	0.04666		-0.00831		-0.02495	
Soil	0.00713	**	0.00142		0.00133	*
Slop	-0.01068		-0.02500	**	-0.01484	**
Ln(Alt)	0.09754	**	0.03641		0.02373	
DiCity	0.00039		-0.00109		-0.00030	
City	0.13057	**	0.16756	**	0.16141	**
DiPort	0.00073		0.00126	**	0.00109	**
Port	0.19780	**	0.18277	**	0.18419	**
East	-0.65466	**	-0.60432	**	-0.39961	**
Subs1	0.00223	**	0.00174	**	0.00108	*
Subs2	-0.00350	**	-0.00014		-0.00068	
Full	0.00608	**	0.00417	**	0.00308	**
Crop	-		0.00981	**	0.00535	**
Livestock	-		0.03443	**	0.02348	**
PermCrop	-		0.03811	**	0.02431	**
HortCrop	-		0.01749	**	0.01033	**
Irrig	-		-0.13406	*	-0.02317	
Wy	-		-		0.43960	**
R^2_{var}	0.42		0.86		0.79	

Notes: The dependent variable is the mean land rental price (€/ha, logarithmized) at the community level (n = 3,515). Variables are defined in Table 4.1 and described in section 4.3. In the IV and SAR-IV models, farm-type and irrigation variables are instrumented by their nonlinear projections and the spatial lags of those projections (see section 4.4). Forage is the omitted farm type. All spatial-weighting matrices are based on inverse-haversine-distance (6-*nn*), and are normalized by row. * and ** denote significance at the 0.05 and 0.01 levels respectively (homoskedastic standard errors).

Source: Own estimations, based on City Mayors (2013), DWD (2013), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and World Port Source (2013).

Table 4.3 – Model diagnostics for Table 4.2

Test	OLS	IV	SAR-IV
Homoskedasticity			
Breusch-Pagan score, $F_{1,3513}$	1.62 (0.20)	-	-
Joint exogeneity			
Durbin score, χ^2_5	-	344.32 (0.00)	-
Wu-Hausman score, $F_{5,3482}$	-	75.63 (0.00)	-
Robust score, χ^2_5	-	146.86 (0.00)	
Overidentification			
$F_{10,3504}$	-	0.25 (0.96)	-
R^2_{cor}	-	0.000	-
Spatial effects			
Wald test for $\lambda = 0$, χ^2_1	-	-	122.21 (0.00)

Note: *P*-values in parentheses.

Table 4.4 – Direct, indirect, and total marginal WTP for climate (1980–2009)

Variable/WTP (€/ha)	OLS	IV	SAR-IV	
			With-multiplier	*No*-multiplier
Temp_ss (°C)				
Direct	-	-49.02	-53.96	-30.24
Indirect	-	5.29	12.30	6.89
Total	-32.65	-43.72	-41.66	-23.35
Temp_aw (°C)				
Direct	-	58.36	64.27	36.02
Indirect	-	-34.00	-35.84	-20.08
Total	82.21	24.36	28.44	15.94
Prec_ss (mm/mo)				
Direct	-	30.82	28.73	16.10
Indirect	-	-3.08	-2.96	-1.66
Total	21.45	27.74	25.77	14.44
Prec_aw (mm/mo)				
Direct	-	-2.56	-2.28	-1.28
Indirect	-	-1.25	-1.58	-0.89
Total	-5.38	-3.81	-3.87	-2.17
Temp_sd (°C)				
Direct	-	*ns*	*ns*	*ns*
Indirect	-	*ns*	*ns*	*ns*
Total	*ns*	*ns*	*ns*	*ns*
Prec_sd (mm)				
Direct	-	-34.89	-32.97	-18.48
Indirect	-	-2.66	-2.59	-1.45
Total	-21.19	-37.55	-35.56	-19.93

Notes: The direct effect is obtained as the derivative of Eq. (10) (Table 4.2) with respect to the climatic attribute of interest. The indirect effect is the sum of the products of the derivatives of the first-stage regression equations with respect to the climatic attribute of interest, the parameter estimates of the corresponding endogenous variables from Table 4.2, and the rental price. In the *with*-multiplier case, the effects are also multiplied by the spatial multiplier, $(1-\lambda)^{-1}$. The marginal effects of precipitation show the increase in the rental price due to an increase of 6 mm in the respective half-year period (*i.e.*, 1 mm/month each month). All point estimations were performed at means. Direct effects are significant at least at the 0.05 level. For the calculation of the indirect effects, only the significant ($p < 0.05$) counterparts from the first-stage regressions were considered. See section 4.5.2 for details.

Source: Own estimations, based on Table 4.2 and on the first-stage regressions.

APPENDIX A (to chapter 4)

Interpolation details

Tables A1, A2

Figures A1, A2, A3

Climate data come from measurements by 238 stations for temperature and 1,558 stations for precipitation (DWD, 2013) (Figure A1). The maximum elevation of stations is 1,500 m. The data were transformed to historical climate averages (1980–2009) per season.

First, we modeled climate as a large-scale process through trend surface analysis, which explores the distribution of climate through hypersurfaces (*e.g.*, Unwin, 1978). This approach is useful in our case because the trends have underlying physical explanations. For example, northern (coastal) Germany has a maritime-influenced climate which is characterized by warm summers and mild winters. Farther inland, climate is marked by greater seasonal temperature variations (*e.g.*, warmer summers and colder winters). The Alpine regions in the south have mountain climate with lower temperature and higher precipitation levels.

We approximated seasonal climate surfaces by polynomials of longitude, latitude, and altitude, which were fitted by OLS. The results are shown in the upper panel of Tables A1 and A2. Log-linear functional forms were used for precipitation, and retransformation bias was accounted for through the corresponding root-mean-square error estimates (see Aitchinson and Brown, 1957). Unwin (1978: 14) recommended the usual R^2_{cor} measure between the observed (at stations) values and the fitted values to describe the relative strength of the trends. The corresponding values in our equations range from 0.89 to 0.94 for mean seasonal temperature, and from 0.58 to 0.84 for mean total seasonal precipitation. Overall, the created surfaces have very marked quadratic trends for seasonal temperature, and marked cubic trends for seasonal precipitation. The estimated equations were used to interpolate climate at community centroids and at mean polygon altitudes. Communities are relatively small spatial objects, and the approximation of the joint location of farms by the polygon centroid is operationally convenient.

In the second step, we improved the precision of the estimates from the trend equations. The residuals obtained from the fitted trend models were interpolated through kriging. Kriging generates optimal weights based on a semivariogram model of spatial autocorrelation (*e.g.*, Oliver, 2010: 319f.). The characteristics of the various semivariograms are shown in the lower panel of Tables A1 and A2. The final prediction at any location equals the corresponding trend surface prediction plus the kriged residual.

Trend surface interpolation was carried using Stata/SE 11. Residual kriging and the corresponding polygonal averaging were carried out using the Esri ArcGIS 10 Geostatistical and Spatial Analyst extensions. Seasonal interpolated surfaces are shown in Figures A2 and A3.

Table A1 – Spatial interpolation of mean seasonal temperature (1980–2009): trend hypersurfaces (OLS) and semivariogram models

	Spring		Summer		Autumn		Winter	
Part I: Trend surfaces								
Longitude	-0.0278	*	-1.032	**	-0.618	***	-0.797	***
$(\text{Longitude})^2$	-		-		0.0245	***	0.0246	***
Latitude	3.305	***	-0.896	***	-3.561	***	-2.166	*
$(\text{Latitude})^2$	-0.0387	***	-		0.0322	***	0.020	*
Altitude	-0.0067	***	-0.0066	**	-0.0051	***	-0.0048	***
Longitude*Latitude	-		0.0222	***	-		-	
Intercept	-57.24	***	63.44	***	111.90	***	66.03	**
R^2_{cor}	0.94		0.93		0.89		0.90	
n (stations)	236		232		238		235	
Part II: Semivariograms								
Number of lags	8		8		8		8	
Lag size (km)	25.78		26.26		25.58		25.90	
Nugget	0.10290		0.12380		0.11272		0.13448	
Range	2.0624		2.1008		2.0464		2.0720	
Minor range	1.05178		0.70248		1.13689		1.49539	
Direction	128.496		141.855		125.332		136.406	
Partial sill	0.02726		0.02375		0.05812		0.07052	

Notes: In Part I, the dependent variable is the respective historical mean (°C). *, ** and *** denote significance at the 0.05, 0.01, and 0.001 levels respectively. In Part II, all semivariogram models are spherical and anisotropic.

Source: Own estimations, based on BKG (2010) and DWD (2013).

Table A2 – Spatial interpolation of mean total seasonal precipitation (1980–2009): trend hypersurfaces (OLS) and semivariogram models

	Spring		Summer		Autumn		Winter	
Part I: Trend surfaces								
Longitude	1.058	***	1.019	***	1.909	***	1.844	***
$(\text{Longitude})^2$	-0.0653	***	0.00794	***	-0.0916	***	-0.110	***
$(\text{Longitude})^3$	0.0023	***	-		0.0032	***	0.00396	***
Latitude	-53.24	***	-71.06	***	-2.351	***	-0.839	***
$(\text{Latitude})^2$	1.030	***	1.364	***	0.0257	***	0.0108	***
$(\text{Latitude})^3$	-0.00663	***	-0.00869	***	-		-	
Altitude	0.00078	***	0.000606	***	0.000894	***	0. 00117	***
Longitude*Latitude	-0.00999	***	-0.0234	***	-0.0227	***	-0.0187	***
Intercept	917	***	1233.3	***	55.19	***	16.62	***
R^2_{cor} (in logs)	0.79		0.84		0.73		0.58	
n (stations)	1,548		1,546		1,558		1,553	
Part II: Semivariograms								
Number of lags	8		8		8		8	
Lag size (km)	10.03		10.03		10.03		10.03	
Nugget	0.00219		0.00079		0.00155		0.00639	
Range	0.8024		0.8024		0.8024		0.8024	
Minor range	0.70403		0.69792		0.61773		0.62313	
Direction	99.843		75.585		112.148		111.093	
Partial sill	0.01391		0.00962		0.02067		0.03681	

Notes: In Part I, the dependent variable is the respective historical mean (mm, logarithmized). The dependent variable is unbiasedly retransformed as $E(\mathbf{y}|\mathbf{X}) = \exp(\mathbf{X}'\beta)\exp(0.5\sigma^2)$, $\boldsymbol{\varepsilon} \sim N(0, \sigma^2)$, after interpolation. *** denotes significance at the 0.001 level. In Part II, all semivariogram models are spherical and anisotropic.

Source: Own estimations, based on BKG (2010) and DWD (2013).

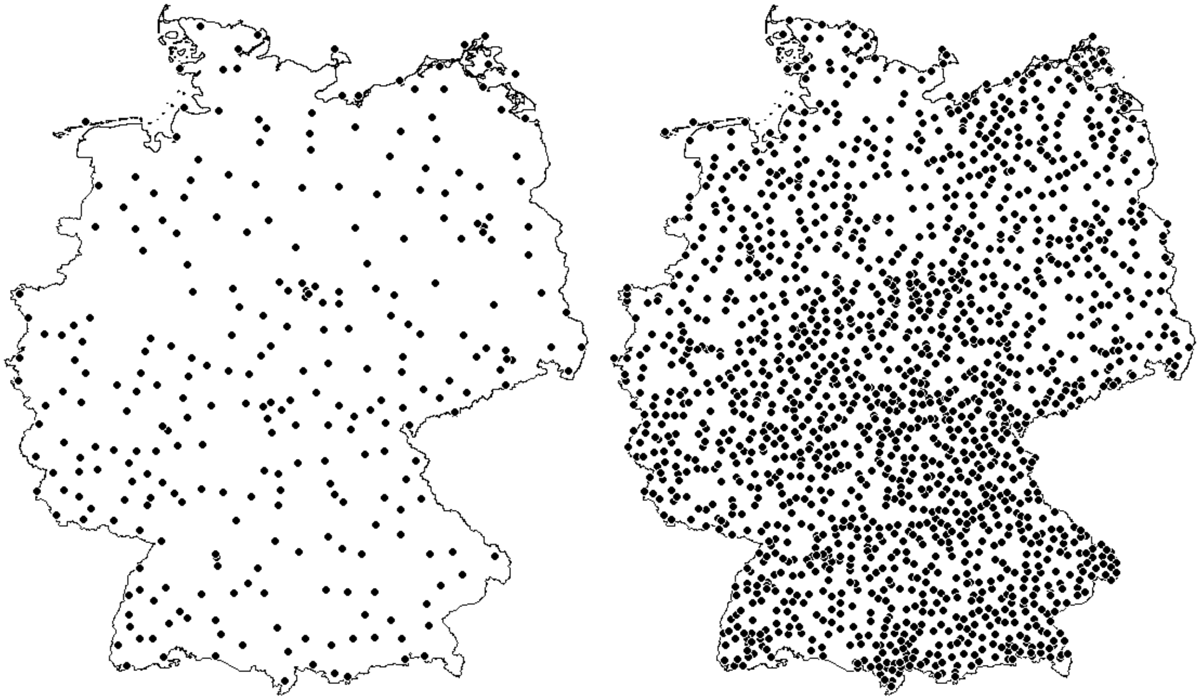

Figure A1 – Spatial distribution of weather monitoring stations (1980–2009)

Note: Left panel is for temperature (n = 238), and right panel for precipitation (n = 1,558).

Source: Own elaboration, based on BKG (2010) and DWD (2013).

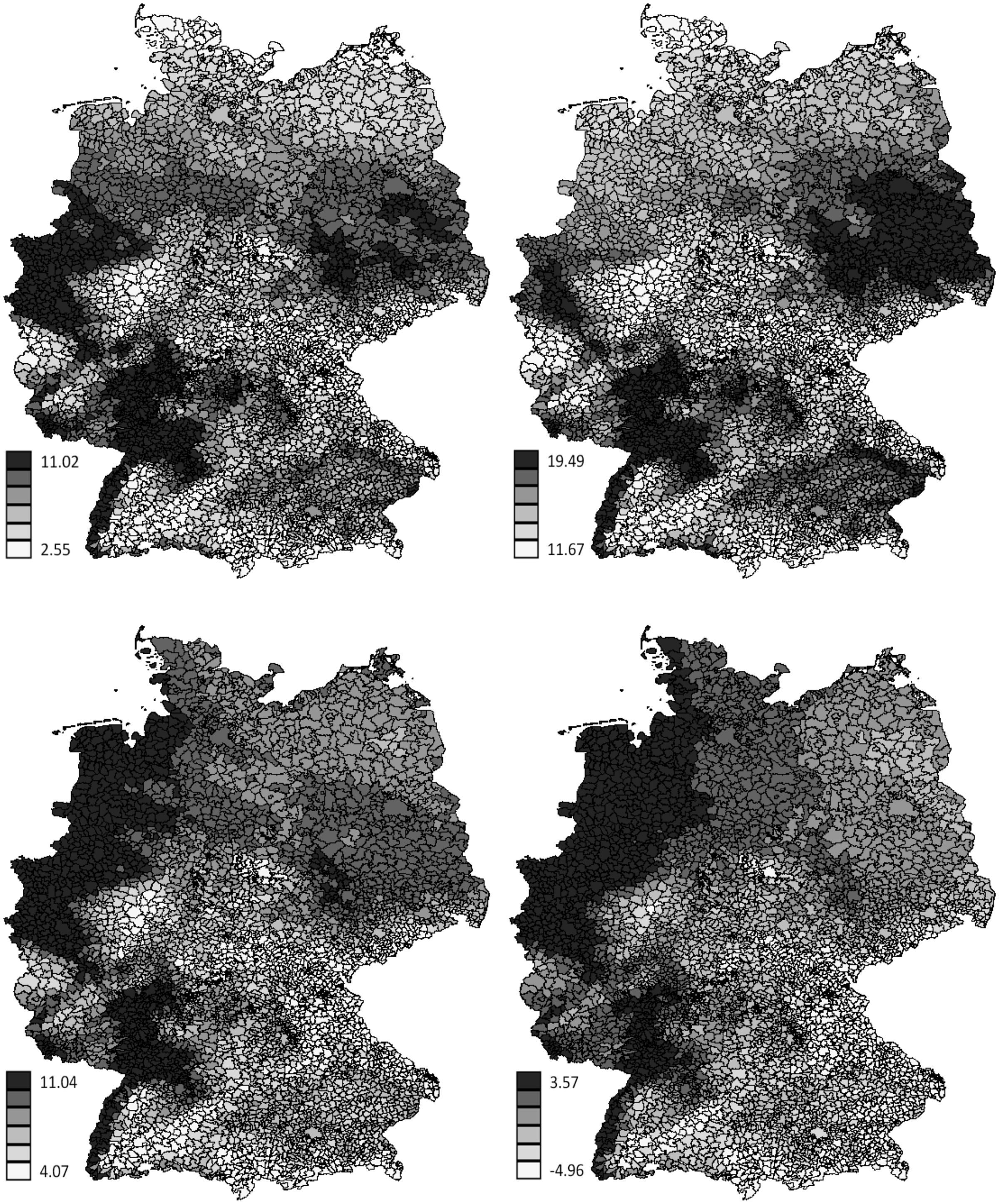

Figure A2 – Interpolated surfaces of mean seasonal temperature (°C, 1980–2009)

Notes: Upper-left panel is for spring; upper-right for summer; lower-left for autumn; and lower-right for winter. Zonally rearranged at the level of community associations (*Gemeindeverbände; N* = 4,810).

Source: Own elaboration, based on BKG (2010) and DWD (2013).

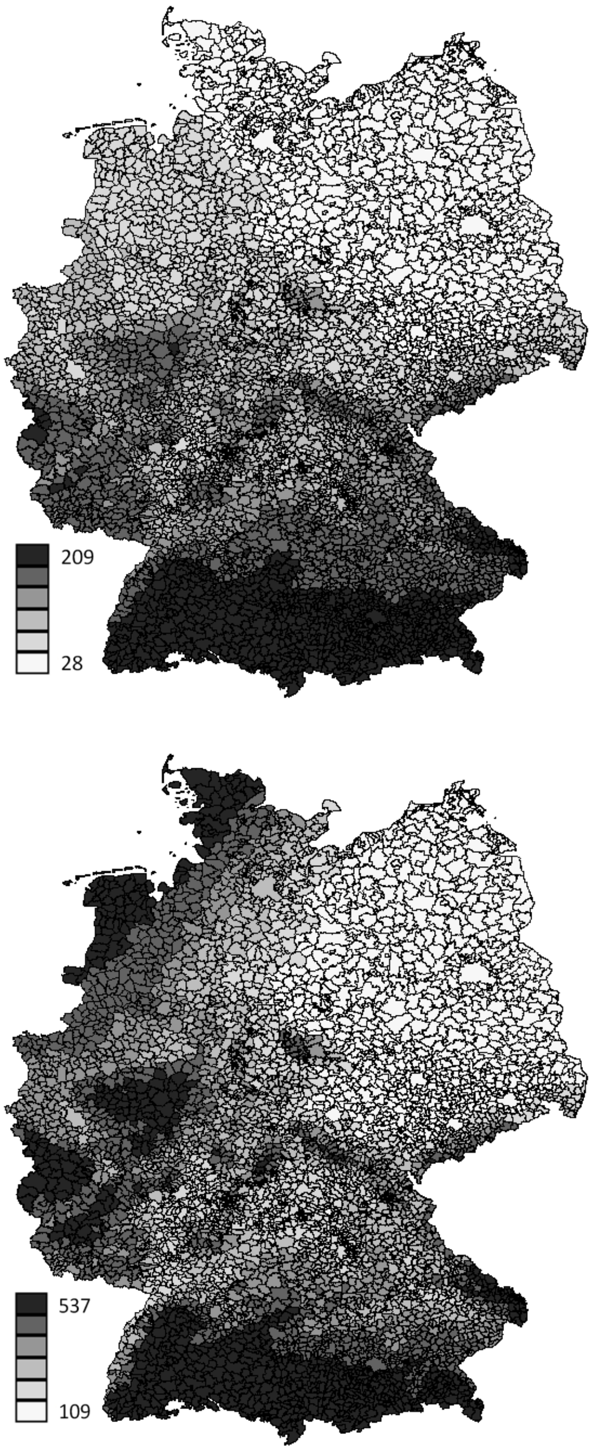

Figure A3 – Interpolated surfaces of mean total seasonal precipitation (mm, 1980–2009)

Notes: Upper-left panel is for spring; upper-right for summer; lower-left for autumn; and lower-right for winter. Zonally rearranged at the level of community associations (*Gemeindeverbände; N* = 4,810).

Source: Own elaboration, based on BKG (2010) and DWD (2013).

APPENDIX B (to chapter 4)

Figures B1, B2

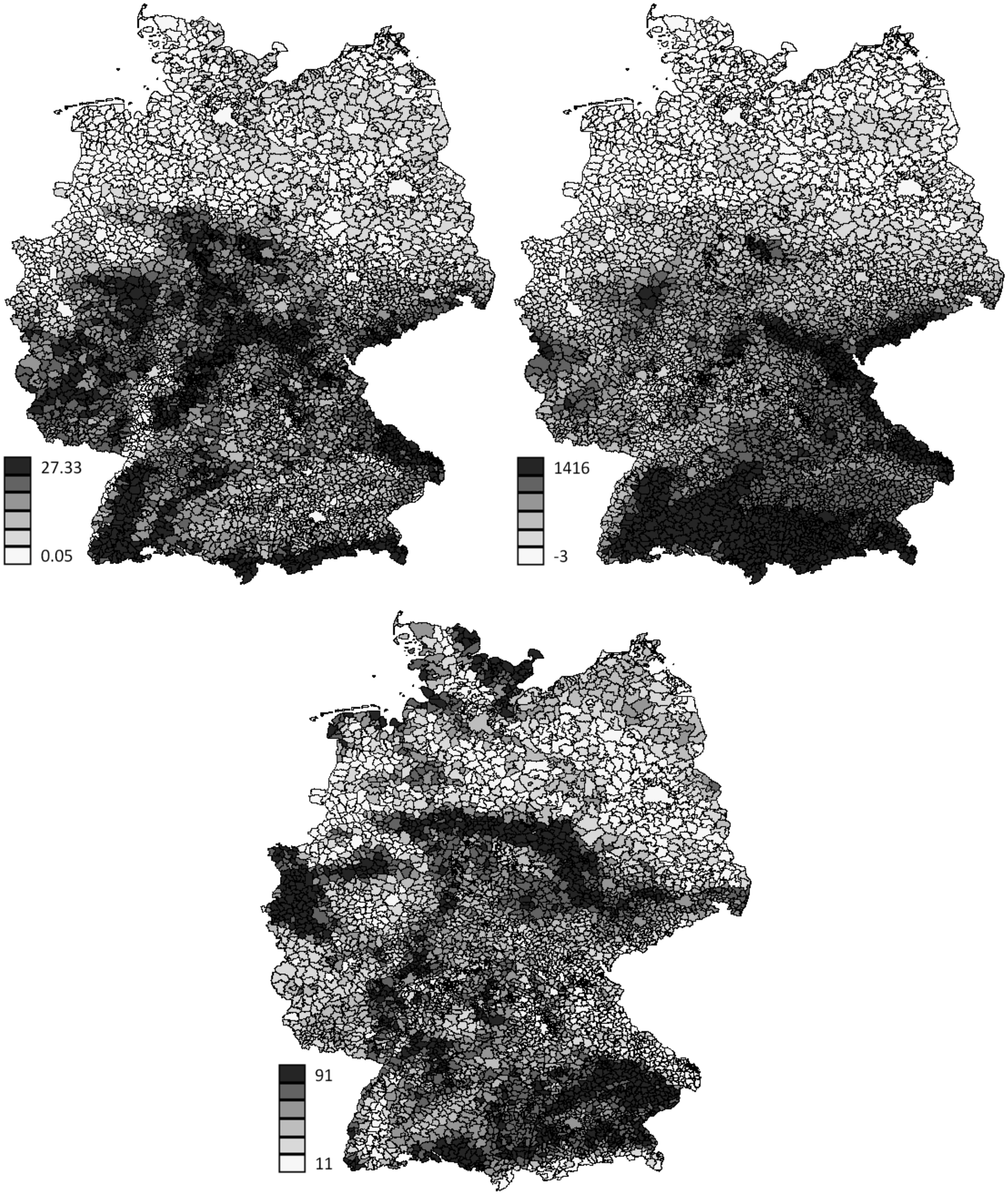

Figure B1 – Spatial distribution of topographical and edaphic factors

Notes: Upper-left panel is for slope (%); upper-right for altitude (m); and lower for soil productivity (0–100). Zonally rearranged at the level of community associations (N = 4,810).

Source: Own elaboration, based on BKG (2010), FZ Jülich (2009), and Jarvis *et al*. (2008).

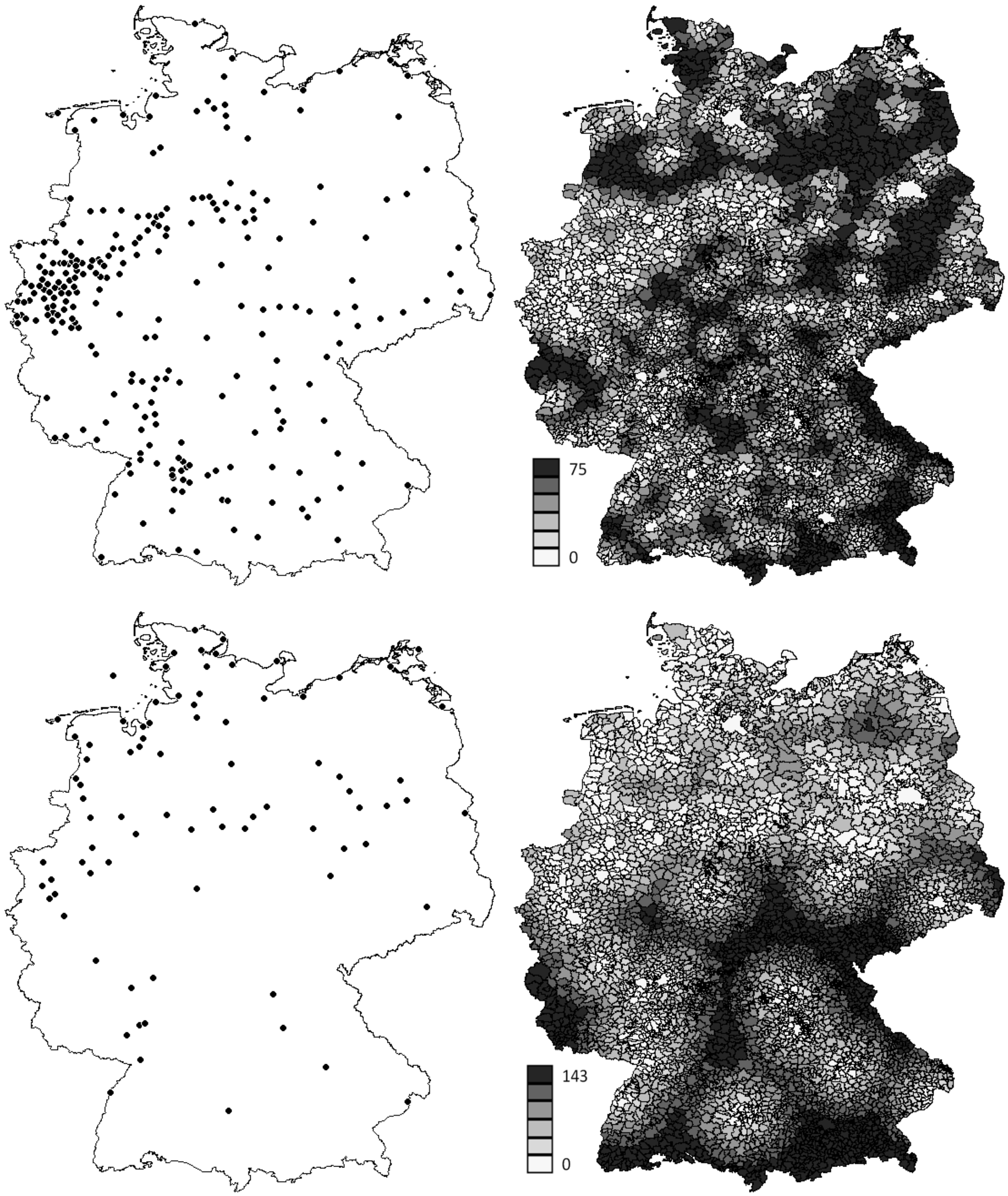

Figure B2 – Large cities and ports (left), and polygon distances to the nearest large city or port (right)

Notes: Upper panels are for large cities (>42,000 residents; n = 250), and lower panels for inland, dry, and cargo ports (n = 83). Distances are measured in kilometers. Zonally rearranged at the level of community associations (N = 4,810).

Source: Own elaboration, based on BKG (2010), City Mayors (2013), and World Port Source (2013).

APPENDIX C (to chapter 4)

Tables C1, C2, C3

Table C1 – Multinomial logit estimates for the most frequent farm type at the community level

	Farm types							
Variable	**Crop**		**Livestock**		**PermCrop**		**HortCrop**	
Temp_ss	-0.8406	**	*ns*		4.3115	*	*ns*	
Temp_ss_squared	*ns*		-1.4955	**	*ns*		*ns*	
Temp_aw	1.6817	**	2.8919	**	*ns*		*ns*	
Temp_aw_squared	-0.1976	**	*ns*		*ns*		*ns*	
Prec_ss	-0.0280	**	*ns*		-0.2200	**	*ns*	
Prec_ss_ squared	-0.0001	*	*ns*		*ns*		*ns*	
Prec_aw	-0.0257	**	0.0340	**	*ns*		*ns*	
Prec_aw_ squared	0.0001	**	-0.0002	**	*ns*		*ns*	
Temp_sd	*ns*		10.7128	**	*ns*		*ns*	
Prec_sd	0.2921	**	*ns*		2.0697	**	*ns*	
ExtrClim	*ns*		*ns*		*ns*		*ns*	
Soil	0.0487	**	*ns*		0.0806	**	0.0750	*
Slop	-0.3995	**	-1.2332	**	*ns*		-1.4129	*
Ln(Alt)	1.2226	**	1.7326	**	-1.6123	*	*ns*	
City	*ns*		*ns*		*ns*		*ns*	
DiCity	*ns*		0.0381	**	*ns*		*ns*	
Port	1.2630	**	*ns*		*ns*		*ns*	
DiPort	*ns*		-0.0223	**	*ns*		*ns*	
Subs1	*ns*		*ns*		*ns*		*ns*	
Subs2	-0.0066	*	0.0179	**	-0.0368	*	-0.0846	**
Full	*ns*		*ns*		0.1275	**	0.1489	**
AvSiz	0.0116	**	0.0134	**	-0.4057	**	-0.3682	**
East	-3.7939	**	*ns*		*ns*		*ns*	
Intercept	-20.3527	*	-47.4710	**	-34.2767		-122.9933	
Measures of fit								
Count-R^2	74%		37%		96%		78%	
McFadden-R^2	0.48							

Notes: The base is forage farming (82% correctly predicted). In the calculation of the count-R^2 measure, the farm type with the highest estimated probability was taken to be the predicted outcome for each community. * and ** denote significance at the 0.05 and 0.01 levels respectively. See section 4.4 for details.

Source: Own estimations, based on City Mayors (2013), DWD (2013), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and World Port Source (2013).

Table C2 – Binary probit estimates for irrigator installation

Variable	Estimate	
Temp_ss	*ns*	
Temp_ss_squared	*ns*	
Temp_aw	*ns*	
Temp_aw_squared	0.3271	*
Prec_ss	*ns*	
Prec_ss_ squared	*ns*	
Prec_aw	-0.0359	**
Prec_aw_ squared	*ns*	
Temp_sd	*ns*	
Prec_sd	*ns*	
ExtrClim	*ns*	
Soil	-0.0201	**
Slop	-0.5904	**
Ln(Alt)	0.4853	**
City	*ns*	
DiCity	-0.0154	*
Port	*ns*	
DiPort	*ns*	
Subs1	*ns*	
Subs2	-0.0075	*
Full	0.0243	**
AvSiz	*ns*	
East	-1.6233	*
Measures of fit		
Correct predictions (zeroes)	99%	
Correct predictions (ones)	34%	
McFadden-R^2	0.52	

Notes: The dependent variable takes on the value of 1 if irrigators are installed in at least 50% of all farms in a community. * and ** denote significance at the 0.05 and 0.01 levels respectively. See section 4.4 for details.

Source: Own estimations, based on City Mayors (2013), DWD (2013), FDZ (2011), FZ Jülich (2009), Jarvis *et al.* (2008), and World Port Source (2013).

Table C3 – Decomposed indirect marginal WTP (€/ha) for climate (1980–2009)

Variable	IV	SAR-IV	
		With-multiplier	*No*-multiplier
Temp_ss (°C)			
Crop	-14.12	-13.74	-7.70
HortCrop	10^{-6}	10^{-6}	7×10^{-7}
PermCrop	0.04	0.04	0.02
Livestock	13.56	24.20	13.56
Irrig	5.81	1.79	1.00
Total	5.29	12.30	6.89
Temp_aw (°C)			
Crop	*ns*	*ns*	*ns*
HortCrop	-5×10^{-7}	-6×10^{-7}	-3×10^{-7}
PermCrop	*ns*	*ns*	*ns*
Livestock	-34.00	-35.84	-20.08
Irrig	-5×10^{-7}	-2×10^{-7}	-10^{-7}
Total	-34.00	-35.84	-20.08
Prec_ss (mm/mo)			
Crop	2.61	2.54	1.42
HortCrop	*ns*	*ns*	*ns*
PermCrop	-2.34	-2.66	-1.49
Livestock	-2.41	-2.54	-1.42
Irrig	-0.94	-0.29	-0.16
Total	-3.08	-2.96	-1.66
Prec_aw (mm/mo)			
Crop	*ns*	*ns*	*ns*
HortCrop	*ns*	*ns*	*ns*
PermCrop	*ns*	*ns*	*ns*
Livestock	-1.61	-1.69	-0.95
Irrig	0.36	0.11	0.06
Total	-1.25	-1.58	-0.89
Prec_sd (mm)			
Crop	-2.66	-2.59	-1.45
HortCrop	*ns*	*ns*	*ns*
PermCrop	*ns*	*ns*	*ns*
Livestock	*ns*	*ns*	*ns*
Irrig	*ns*	*ns*	*ns*
Total	-2.66	-2.59	-1.45

Notes: Each indirect effect is the derivative of the corresponding first-stage regression equation with respect to the climatic attribute of interest, multiplied by the parameter estimate of the analogous endogenous variable from Table 4.2, and by the rental price. The individual indirect effects in the *with*-multiplier case are also multiplied by the spatial multiplier, $(1-\lambda)^{-1}$. The marginal effects of precipitation show the increase in the rental price due to an increase of 6 mm in the respective half-year period (i.e., 1 mm/month each month). All point estimations were performed at means. The total indirect effect is the sum of the individual indirect effects. Forage is the base case. Only the significant ($p < 0.05$) counterparts from the first-stage regressions were considered. See section 4.5.2 for details.

Source: Own estimations at means, based on the first-stage regressions from Table 4.2.

ANNEX (to chapter 4)

Derivation of the *with*-multiplier partial effect

in the SAR model

Assume a log-linear SAR model with quadratic specification for climate, $\mathbf{X}_1$:

$$\ln\mathbf{y} = \lambda\mathbf{W}(\ln\mathbf{y}) + \beta_1\mathbf{X}_1 + \beta_2\mathbf{X}_1^2 + \ldots + \mathbf{u}$$

where $\mathbf{W}$ is an exogenous, nonsingular, $N\times N$ spatial-weighting matrix, and λ is the corresponding spatial-autoregressive scalar parameter. Upon solving for simultaneity, the conditional mean can be expressed in its reduced form as:

$$\ln\mathbf{y} = (\mathbf{I}-\lambda\mathbf{W})^{-1}(\beta_1\mathbf{X}_1 + \beta_2\mathbf{X}_1^2 + \ldots)$$

where $\mathbf{I}$ is an $N\times N$ unit matrix. A uniform change in $\mathbf{X}_1$ across all observations leads to a partial effect in $\mathbf{y}$ that can be expressed as:

$$\begin{aligned}
\vartheta(\ln\mathbf{y})/\vartheta\mathbf{X}_1 &= (\mathbf{I}-\lambda\mathbf{W})^{-1}(\beta_1 + 2\beta_2\mathbf{X}_1) \\
[\vartheta(\ln\mathbf{y})/\vartheta\mathbf{X}_1]\,\mathbf{y} &= (\mathbf{I}-\lambda\mathbf{W})^{-1}(\beta_1 + 2\beta_2\mathbf{X}_1)\,\mathbf{y} \\
\vartheta\mathbf{y}/\vartheta\mathbf{X}_1 &= lim_{N\to\infty}(1 + \lambda^1 + \lambda^2 + \ldots + \lambda^N)(\beta_1 + 2\beta_2\mathbf{X}_1)\,\mathbf{y} \\
\vartheta\mathbf{y}/\vartheta\mathbf{X}_1 &= lim_{N\to\infty}(1-\lambda^{N+1}/1-\lambda)(\beta_1 + 2\beta_2\mathbf{X}_1)\,\mathbf{y} \\
\vartheta\mathbf{y}/\vartheta\mathbf{X}_1 &= (1-\lambda)^{-1}(\beta_1 + 2\beta_2\mathbf{X}_1)\,\mathbf{y}
\end{aligned}$$

where $(1-\lambda)^{-1}$ represents the sum-to-infinity geometric series in the matrix inverse, given that $|\lambda|<1$. As N gets larger, the term λ^{N+1} will approach zero in the limit. See also Kim *et al.* (2003: 35).

◊

CHAPTER 5

Conclusions and outlook

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This dissertation has extended the conceptual and analytical framework of the Ricardian approach. We have identified certain limitations, theoretically described and analytically illustrated specific methods to deal with those limitations, and provided empirical illustrations for the case of German agriculture. In particular, our studies have sought to deal with potential errors in the interpolated climate variables (chapters 2 and 3), the development of a structural Ricardian model based on aggregate data (chapter 3), the treatment of endogeneity of specific long-run adaptation measures to climate (chapter 4), and the consideration of spatial autocorrelation in addition to the above issues (chapters 2 and 4). The Ricardian literature is either limited or nonexistent on these subjects. We ought to know whether explicitly accounting for these issues improves the explanatory power of the Ricardian model, and whether not doing so has implications for the climate parameter estimates.

In the final chapter, we staple together the empirical applications presented in chapters 2, 3, and 4. First, we discuss the limitations in our applications (section 5.1). Then, we provide an overview of our main contributions and a synthesis of our main empirical findings (section 5.2). The dissertation concludes with the propagation of possible future research avenues (section 5.3) and an epilogue (section 5.4).

5.1 Limitations of the presented studies

The work presented herein has offered new perspectives on the Ricardian approach. However, the studies carried out are subject to certain limitations.

First, a number of caveats of the Ricardian approach (see section 1.3.5) were not taken into account. Of those caveats, perhaps the most important one is the omission of relevant factors that affect farm choices and profits, either directly (*e.g.*, input and output prices) or indirectly (*e.g.*, CO_2 concentrations). In this context, the good news is that the direction of the bias that omitted factors may induce in the climate parameter estimates can be inferred (see Wooldridge, 2002: chapter 3). For example, the bias in β_{temp} would be positive if the omitted factor in question had a positive (negative) effect on the dependent variable and were positively (negatively) correlated with temperature. Similarly, the bias would be negative if the omitted factor had a negative (positive) effect on the dependent variable and were positively (negatively) correlated with temperature. The bad news is that since the effect of any omitted factor is not estimated, neither can one be certain about the sign of the effect of the omitted factor in question on farm profits nor about the correlation between that factor and the climate variable of interest.

Second, our analyses were not performed at the farm level for two reasons. The first reason is that since farms in the 1999 census are not geocoded, their absolute location is unknown, and thus interpolation of the measures of climate was impracticable at the farm level. In addition to that, though farms in the 2010 census are geocoded, the coordinates (of the farmers' offices) are available for use only from within FDZ/Kiel. For these reasons, the analyses presented drew on (small-area) aggregates. Although the apparent loss of some precision due to aggregation was unavoidable, the aggregates in chapters 3 and 4 are as close as possible to the disaggregated population.

Third, due to the lack of irrigation data in the 1999 census, the influence of irrigation on land rental prices and farm-type choices was not taken into account in chapters 2 and 3. From a practical point of view, the omission of irrigation is not likely to be an important issue in our case, as agriculture in Germany has been predominantly rainfed. In particular, given that irrigated farms comprise a small fraction of the farm population, equilibrium rental prices would not be substantially affected even if rental prices of the few irrigated farms were to be affected by changes in water supply. However, water availability may become an issue in the future. Since information on irrigation exists only in the 2010 census, the analysis presented in chapter 4 took the effects of irrigation into account.

Fourth, it is often argued that the inclusion of future climate projections should be standard practice in impact assessment. In this regard, the absence of directly utilizable climate projections for Germany posed an impediment. Though chapters 2 and 3 drew on climate data that had been utilized in a previous study (Lippert *et al.*, 2009), detailed seasonal data that were required for a simulation exercise in chapter 4 could not be obtained in reasonable time frame.

A final note pertains to the framework of remote data access, which allowed us to analyze individual farm data without obtaining them in hand (see section 1.5). As a direct consequence of this, a number of operational issues were encountered. The main issues included the refusal by FDZ to provide us with user-generated data (*e.g.*, fitted values from regression models) and user-generated maps with aggregated information that would help us visualize the results, changes in software versions in FDZ during the project, and compatibility errors with respect to add-in routines. The latter point is the reason that an explicit spatial econometric perspective was not taken in chapter 3.

Despite the aforementioned limitations, the extensions and empirical applications presented herein comprise a set of concrete contributions to the scientific community. These contributions are presented below.

5.2 Contributions

In this section, we decompose the contributions of our studies into conceptual, methodological, empirical, and data-related. For ease of future applications, a discussion of applicability issues is also provided.

5.2.1 Conceptual

A first conceptual contribution is the explicit treatment of endogeneity in the variables that reflect long-term adaptation, which was dealt with in chapter 4. We proposed a new spatial-IV version of the Ricardian approach where the occurrence of the farm type and potentially irrigated acreage are simultaneously determined *by* climate and determine farm profitability *along* with climate. Accounting for the endogeneity of those measures with respect to climate improves substantially the conceptual and explanatory fidelity of the Ricardian model. Furthermore, the following points are allowed for: (*i*) simultaneous changes in land-use behavior; (*ii*) a distinction between direct (unmediated) and indirect (mediated) climate impacts on farm profitability; and (*iii*) inference on whether changes in farm types and in the potentially irrigated acreage would likely be economically worthwhile. Albeit appealing, either one distinction cannot be made with previous versions of the approach. Neglecting endogeneity in variables that reflect adaptation may result in bias of inconsistent direction and unknown magnitude in the climate parameter estimates.

A second conceptual contribution is the explicit recognition of the potential stochasticity in the interpolated measures of climate. In order for the derivative of the regression equation with respect to a climatic characteristic to be interpreted as a marginal implicit price, the climatic characteristic of interest must be measured as accurately as possible, and in a way that is captured by farmers (Freeman, 2003; Palmquist, 2005). Both these points are of paramount relevance because the behavior of farmers is exactly what is attempted to be disclosed. A number of arguments laid down in chapter 2 imply that those two assumptions may not perfectly hold in practice; discrepancies of unknown patterns between interpolated, "true", and perceived climate may lead to a correlation of the disturbance term of the Ricardian model with the interpolated climate variables. This aspect has been neglected in previous applications, wherein interpolated climate has been treated as "true" climate without errors. In chapters 2 and 3, we have illustrated how this perspective can be taken into account in the traditional and structural versions of the Ricardian approach, by coupling an *ad hoc* interpolator (small-scale climate) with an IV-based *post hoc* "correction" (large-scale climate). Neglecting the potential endogeneity in the interpolated variables may severely bias the partial effects of the latter in inconsistent direction.

A third conceptual contribution pertains to the issue of spatial autocorrelation. This statistical phenomenon might have been dealt with in previous studies in agricultural economics, but the processes likely to give rise to spatial autocorrelation had remained largely unacknowledged (see section 4.2.2). In this context, we have acknowledged a multitude of reasons that may lead to spatial lag dependence (chapter 4) or spatial error correlation (chapter 2) in the Ricardian model. Even though it is difficult to identify the exact process that leads to similarities in space, which is typically the case in the aggregate cross-sectional framework, those reasons should not be overlooked in the interpretation of results from spatial-autoregressive models.

Published studies on the structural Ricardian framework rely on samples of individual farms and on the main farm types (crop, livestock, mixed). Given the availability of detailed farm data on the whole farm population, a final conceptual contribution is the first estimation of a structural Ricardian model with aggregated data, wherein actual farm types were replaced by the probability-weighted most frequent farm type (chapter 3). In addition to that, we have offered a more detailed decomposition of farm types (*i.e.*, arable crops, permanent crops, horticulture, livestock fattening, forage, and mixed).

5.2.2 Methodological

The IV method provides a general solution to the issue of endogenous explanatory variables–that is, when at least one regressor is correlated with the disturbances–which leads to biased and inconsistent OLS estimates. Although IV estimation is popular in empirical economics, applications in the context of the Ricardian approach are nonexistent. There are at least two cases that call for IV estimation in the Ricardian approach: (*i*) the inclusion of variables that reflect farm structure, and (*ii*) the potential existence of errors in interpolated climate data. In these contexts, we have offered two IV-based solutions that can be applied at any level of aggregation: (*i*) the explicit consideration of the endogenous nature of adaptation measures, such as the choice of the farm type and the choice of irrigation (chapter 4), and (*ii*) a *post hoc* trend surface analysis for the interpolated measures of climate (chapters 2 and 3).

IV estimation requires that the instruments be relevant (*i.e.*, sufficiently correlated with the endogenous regressors) and valid (*i.e.*, uncorrelated with the disturbances). These criteria are often conflicting and so, it is practically difficult to find legitimate instrumental variables. In order to ease further use by future users, our second methodological contribution pertains to sets of instruments that are cost-effective; there is no need to obtain additional data than those that are either way necessary to perform the analysis. For example, the nonlinear projections of the variables that reflect adaptation are constructed by the user, and polygonal information on administrative boundaries, from which one can calculate the centroid coordinates, are accessible online. In addition, we have provided theoretical considerations (for any case) and statistical support (for the given cases) for both the relevance and invalidity of the instruments.

Our third methodological contribution is the consideration of an explicit spatial econometric perspective in addition to the standard IV framework. To our knowledge, chapters 2 and 4 are the first studies in agricultural economics that account for spatial autocorrelation (*i.e.*, endogeneity of spatial nature) in addition to standard endogeneity (of aspatial nature) in the RHS variables.

Our final methodological contribution is the computation of various types of marginal climate impacts. In particular, the IV perspective allows for a distinction between direct (unmediated) and indirect (mediated by other variables) climate impacts on farm profitability. Where warranted by the data, the SAR perspective allows for a distinction between *with*- and *no*-multiplier effects; the former takes into account potential spatial dependence in the dependent variable irrespective of the origin of that dependence, whereas the latter filters out that dependence. The *no*-multiplier effect from a SAR (or SAR-IV) model is not analytically comparable to the standard marginal effect from an OLS model, since OLS estimates would be biased and inconsistent in the presence of spatial dependence.

5.2.3 Empirical

We now move to the empirical contributions of the dissertation. We first succinctly synthesize the main empirical findings of our studies, and then outline the contexts in which those findings may be deemed useful.

The positive impact of historical annual temperature on average land rental prices is consistent thoughout chapters 2, 3, and 4, and in qualitative accordance with the corresponding estimate in a previous study (Lippert *et al.*, 2009). This positive effect holds either if one looks at all farms jointly (chapter 2), at the individual farm types (chapter 3), or at all farms under endogenous farm-type substitutions (chapter 4). Permanent-crop farms appear to value temperature the most (chapters 3 and 4). The positive effect of annual temperature is made up of benefits in the colder seasons that outweigh damages in the warmer seasons (chapter 4). The latter damages are even lower if farm-type substitutions are explicitly modeled endogenously to climate.

Rental prices display a concave (convex) response to precipitation for the warmer (colder) seasons (chapters 2 and 4). The concave relationship for the warmer seasons is in qualitative accordance with the relationship found in a previous study (Lang, 2009). Concavity appears to pertain also to the annual effect (chapter 3). Forage farms appear to be more resilient to high precipitation levels than the rest farm types. This holds either if one looks at the individual farm types and precipitation cutoff points (chapter 3) or at all farms under endogenous farm-type substitutions (chapter 4). There is an indication that mixed farms are also resilient to precipitation (chapter 4).

Our simulation exercises highlight an increase in average rental prices (*i*) irrespective of the climate scenario at the scale of districts (chapter 2), (*ii*) under a moderate-warming (A1B) scenario irrespective of the scale (chapters 2 and 3), and (*iii*) irrespective of the farm type (chapter 3). In addition to that, scenario A1B indicates that the most frequent farm type would change in one out of three communities, in which case forage farms would be penalized (chapter 3).

Overall, the benefits from changing climate seem to outweigh the damages for the sector as a whole. However, we surmise that this is a net effect that pertains to the scales analyzed, the given parameterizations of climate, and under the assumptions of the Ricardian approach that were not relaxed or accounted for (see section 1.3.5). These points being acknowledged, ways in which our studies and findings may be deemed useful can be described.

The studies presented herein can serve as a general cross-validation tool for impact assessments that follow other methods. As the strength of each impact assessment approach is usually the weakness of another approach, the optimal strategy to understand climate impacts is to employ at least two approaches that rely on different assumptions (Mendelsohn, 2007). Therefore, our models may constitute a useful way to cross-validate the direction of yield estimates from production functions or the economic impacts from farm management models in Germany. For example, if a prominent agroeconomic model (which shows the lower bound of adaptation) and a well-specified Ricardian model (which shows the upper bound of adaptation) yielded positive impacts, the true effect would likely be positive. A similar comparison was recently done within a World Bank project in China (World Bank, 2008). However, we surmise that plugging individual-farm data into aggregate models for the purpose of farm-level prediction is generally not recommended. Since any aggregate scale cannot perfectly coincide with the actual scale at which changes are observed and recorded (*i.e.*, farm level), neither can our estimates be precisely transposed to the case of individual farms nor can they serve as crude substitutes for farm-level relationships. The latter situation is usually referred to as ecological fallacy (*e.g.*, Anselin and Tan Cho, 2002), and generally implies that environmental processes are likely to be scale-dependent (Atkinson and Tate, 2000). Ecological fallacy is an important aspect to consider while interpreting an aggregate Ricardian model in particular, as climatic variations tend to be observed at scales lower and ranges larger than those at which we are likely to analyze them.

The empirical studies presented herein can serve as impact assessments on their own merits. The Ricardian models presented are the result of careful specification, estimation, and testing, and comprise a multitude of consistent impact estimates at three spatial scales. For practical applications, obtaining a picture of vulnerability of the sector in terms of direction of impacts and of potential adaptation strategies–which had not been explored in previous Ricardian studies for Germany–is always worthwhile.

Finally, our studies may help in planned adaptation. Our results hold under a host of assumptions, but the Ricardian approach has the advantage of turning structurally complex and dynamic phenomena into simpler and static upon comparing climatic changes to traded goods in a stylized manner. Admittedly, this is a way to make the impacts of climate change visible in policy decisions. The results presented in chapters 3 and 4 can be deemed useful to policymakers *not* as a predictive tool of autonomous adaptation, but as an informative tool to designing policies for proactive adaptation.

5.2.4 Data-related

In chapter 4, we have processed detailed and up-to-date climate data that can be utilized beyond this dissertation. For example, the trend hypersurfaces (Appendix A, Tables A1 and A2) can be used to predict temperature and precipitation at any point across the country. In addition to that, the models presented in chapter 4 can be used to predict the most frequent farm type and average land rental prices in any community association across the country.

5.2.5 Applicability

In chapter 2, an IV approach to dealing with errors in the interpolated climate variables was outlined. The implications of that approach in relation to the Ricardian model were empirically illustrated in the traditional version of the model in chapter 2, and in the structural version in chapter 3. The errors-in-variables approach is suitable in cases where the interpolated data are received for use and the row climate data are unavailable, or the interpolated data are to be more efficiently exploited without obtaining (and re-processing) the row climate data. In addition to that, it should be clear that the instruments to be used *post hoc* (during the estimation of the Ricardian model) should not have been used as surrogate variables *ad hoc* (during interpolation). If many climate variables are to be modeled endogenously, interaction terms and higher-degree polynomials can be additionally employed.

In chapter 3, spatial lags of the interpolated variables were used as additional instruments in the errors-in-variables approach. The use of those spatial lags might not seem to bring any additional advantage to the use of coordinates, and might seem intriguing; if one assumes that the climate variable contains an error, that error may also carry over–albeit reduced–into the spatial lag. The spatial lags of the interpolated variables serve a twofold purpose: they (*i*) capture climate at the meso-scale (regional), and (*ii*) account for spatial autocorrelation in climate (*i.e.*, climate is not a discontinuous phenomenon that is bounded by administrative boundaries). For the given case, spatial lags are statistically well-behaved instruments (see section 3.4).

A final note on the errors-in-variables approach pertains to the application of that extension to the structural version of the Ricardian approach. In the absence of readily available routines that estimate an IV multinomial model, the first- and second-stage regressions have to be performed by the user. In such cases, the most straightforward way to derive estimates of standard errors is bootstrapping.

In chapter 4, a spatial-IV approach to dealing with the endogeneity of adaptation measures was developed and empirically illustrated. The approach fully exploits the cross-sectional framework, and is applicable without the need to obtain additional data than those typically needed. Additional variables may also be used for the instrumentation of the endogenous regressors. However, since the nonlinear projections of the endogenous variables have a host of attractive features (see section 4.4), the use of instruments other than those projections is not necessary.

5.3 Future research

The perspectives and methods in this dissertation have been developed and applied with a diversity of issues from various scientific disciplines and sub-disciplines in mind. However, the exploration of the potential of the Ricardian approach has just started.

In chapter 4, the roles of farm-type selection and of the potentially irrigated acreage in modeling adaptation endogenously have been explored. These adaptation strategies are long-term decisions and have merited frequent empirical investigation through conditional regressions (*e.g.,* Mendelsoh and Dinar, 2009: chapter 9). The advantage of our approach is that it is easily extensible to a panel-based Ricardian model of intertemporal profits (*e.g.*, Deschênes and Greenstone, 2007) that would conveniently allow for the exploration of economic impacts from short-term adaptation. Overcited short-term adaptation strategies that lay at our avail pertain to altering the timing of field operations (*e.g.*, sowing, planting, harvesting), the introduction of new crop varieties, the implementation of alternative fallow and tillage practices, livestock diversification, altering the timing and duration of grazing, and the implemention of feed conservation techniques (Smit and Skinner, 2002; Kurukulasuriya and Rosenthal, 2003). All these cases can be modeled endogenously to climate either as continuous or binary indicators for adaptation. The use of nonlinear projections of the endogenous regressors as valid instruments still holds (see Wooldridge, 2002: chapter 18). Data on short-run adaptation measures, however, are likely available only through field surveys.

Future studies should exploit advances from the field of spatial econometrics, which has moved from the margins to the mainstream during the last decade. From a theoretical point of view, spatial models at the disaggregate level are an attractive tool that can be used to identify the role of interactions among farmers in coping with climate change. For example, what is the extent to which farmers may coordinate in terms of input, crop, and livestock choices as a result of changing climate? Or what is the extent of competition for water available for irrigation under changing climate? From an analytical viewpoint, spatial-autoregressive structure can now be imposed in a number of ways that deviate from the standard SAR and SER models (see Elhorst, 2010), large weights matrices no longer pose a computational impediment (see Drukker, 2013), model comparison is less computationally demanding (see LeSage and Pace, 2009: chapter 6), and various alternatives and shortcuts exist to come up with marginal impacts in addition to the *with*- and *no*-multiplier effects (see LeSage and Pace, 2009: chapter 2). Finally, the lack of appropriate analytical software is no longer invoked as a major impediment for a spatial econometric perspective (Anselin, 2010). Examples of tremendous success in mainstream statistical packages are the Spatial Econometrics Toolbox in MATLAB (LeSage and Pace, and colleagues) the 'spdep' package in R (Bivand and colleagues), and the recent 'sppack' in Stata (Drukker and colleagues).

5.4 Epilogue

The literature on the Ricardian approach dates back to the 1990s, but prevailing issues surrounding this approach have recently started to take steps change. This is the avenue that was also followed in this dissertation, which took up the challenge of improving the conceptual and methodological reliability of the approach.

Users of the Ricardian approach now have access to an array of methods that can be used to tackle persistent problems in a stylized manner, and to improve the conceptual fidelity and explanatory performance of the Ricardian model. Methodological extensions should generally balance analytical complexity with structural comprehensiveness and theoretical understanding. Coming hand-in-hand with that recognition, it is hoped that this dissertation will guide users of the approach in producing innovative empirical results upon maximizing the potential of cross-sectional data. Besides, as 1991 Nobel-winning economist Ronald Coase said, *"if you torture the data long enough, nature will confess."*

5.5 References

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Summary

The so-called Ricardian approach is an econometrics-based climate change impact assessment frequently used by agricultural and environmental economists. The intuition behind this approach is that, in the long run, the optimal behavior of farms is climate-dependent. In essence, the approach explores the role of climate in determining farm profitability and potential adaptation, by regressing economic or behavioral measures of agricultural outcomes against climatic and various other land and site attributes. The overall output of the approach enables (*i*) the identification of profitability differentials due to climate differentials, (*ii*) marginal implicit pricing of climate, and (*iii*) a probabilistic exploration of long-run adaptation strategies.

This cumulative dissertation took up the challenge of improving specific conceptual and methodological aspects of the Ricardian approach in order to render it a more realistic impact assessment tool. In particular, we aimed at a more efficient treatment of the variables that proxy climate, and at the imposition of structure on equations that can reflect adaptation. Three empirical studies were pursued for over 270,000 German farms at three spatial scales: districts (N = 439), community associations (n = 3,515), and communities (n = 9,684). For this reason, secondary data of various formats (*e.g.*, farm census records, measurements by weather stations, digital images) on a host of characteristics (*e.g.*, farm-specific, climatic, topographical, geographical) were extensively processed (*e.g.*, integrated, geocoded, spatially interpolated, zonally rearranged) and spatially matched. We took a multi-model and multi-stage approach from an instrumental-variables (IV) perspective, which we coupled with advances from the subfield of spatial econometrics.

Interpolated measures of climate (*e.g.*, temperatute and precipitation) are typically treated as "true" climate without errors in the Ricardian approach. However, discrepancies of unknown patterns between interpolated, actual, and perceived climate may lead to a correlation of the disturbance term of the Ricardian model with the interpolated measures of climate. From an errors-in-variables perspective, we performed a *post hoc* IV-based trend surface analysis where interpolated temperature and precipitation are (re-)estimated endogenously. Our results suggest that neglecting the potential endogeneity in the interpolated variables may severely bias the partial effects of the latter in inconsistent direction. The proposed methodology can be applied to any regession model with interpolated regressors.

The effect of climate on the choice of the farm type and the choice of irrigation had been considered previously only through conditional regressions; neither had the corresponding endogeneities been treated from an IV perspective nor jointly into a single Ricardian model. We proposed a new spatial-IV version of the Ricardian approach where farm-type occurrence and the choice of irrigation are simultaneously determined *by* climate, and determine farm profitability *along* with climate. We used nonlinear projections and the spatial lags of those projections as instruments for the endogenous farm-type and irrigation variables. Accounting for the endogeneity of those measures with respect to climate improves substantially the conceptual and explanatory fidelity of the Ricardian model. Furthermore, the following points become possible: (*i*) substitutions among farm types; (*ii*) a distinction between direct (unmediated) and indirect (mediated) climate impacts on farm profitability; and (*iii*) inference on whether changes in farm types and in the potentially irrigated acreage would likely be economically worthwhile. Neglecting endogeneity in variables that reflect adaptation may result in bias of inconsistent direction and unknown magnitude in the climate parameter estimates. Our proposed strategy opens up directions for promising future research, as principally any short- or long-term adaptation strategy can now be explicitly modeled.

From an empirical viewpoint, our results showed that historical climate change has generally been beneficial to the sector as a whole. The impact of historical mean annual temperature (precipitation) on average land rental prices is positive (concave). Indicatively, permanent-crop and vegetable farms value temperature more than the rest farm types, whereas forage farms, and to a certain extent mixed farms, stand out for their resilience to precipitation. Climate change in the near decades is likely to be beneficial, but the magnitude of benefits depends on the farm type one looks at.

By reducing complex and dynamic phenomena to comprehensive dimensions, and by overlapping spatial variation in historical climate with spatial variation in the behavior of farms, we provided a picture of vulnerability of the sector as a whole. In this context, not only serve the empirical studies presented herein as impact assessments on their own merits; they may also serve as a general cross-validation tool for other impact assessment approaches *(e.g.*, farm management models).

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Zusammenfassung

Die Ricardische Analyse, basierend auf dem ökonometrischen Ansatz, ist eine häufig verwendete Methode von Agrar- und Umweltökonomen, um die ökonomischen Auswirkungen von Klimaveränderungen abzuschätzen. Die intuitive Idee dahinter ist, dass langfristig gesehen, das optimale Verhalten von landwirtschaftlichen Betrieben klimaabhängig ist. Man kann die Rolle des Klimas in Bezug auf die Profitabilität von Betrieben und deren Anpassungspotential erfassen, indem eine Regressionsanalyse durchführt wird, wobei ökonomische und verhaltenstechnische Variablen landwirtschaftlicher Einkommen, klimatischen und anderen lokationsspezifischen Variablen gegenüberstellt werden. Zusammenfassend kann man festhalten, dass der Ansatz Folgendes ermöglicht: (*i*) eine Identifikation klimainduzierter Veränderungen in der Profitabilität, (*ii*) marginal implizite Preisfestsetzung des Klimas und (*iii*) eine wahrscheinlichkeitsbasierte Untersuchung von langfristigen Anpassungsstrategien.

Diese kumulative Dissertation hat sich der Herausforderung gestellt, spezifische konzeptionelle und methodische Aspekte der Ricardischen Analyse zu verbessern, mit dem Ziel einer realitätsgetreueren Analyse. Im Speziellen war die Zielsetzung, eine effizientere Handhabung der Proxi-Variablen für Klima zu erreichen und der Schaffung einer Struktur für Gleichungen, die die Anpassungsmaßnahmen beschreiben. Es wurden drei empirische Studien durchgeführt für über 270,000 deutsche landwirtschaftliche Betriebe auf drei Verwaltungsebenen: Kreisebene (N = 439), Gemeindeverbändeebene (n = 3,515) und Gemeindeebene (n = 9,684). Aus diesem Grund wurden verschiedene Sekundärdaten (z.B., landwirtschaftliche Zensusdaten, Wetterstationsaufzeichnungen, Rasteraufnahmen in Bezug auf Bodenqualität) räumlich kompatibel gemacht (z.B., integriert, geocodiert, räumlich interpoliert, zonenmäßig umgeordnet) und räumlich zusammengeführt. Wir verwendeten einen Multi-Model- und Multi-Stufen-Ansatz basierend auf Instrumentalvariablen (IV), die mit weiterentwickelten analytischen Ansätzen aus dem Feld der räumlichen Ökonometrie zusammenführt wurden.

Interpoliertes Klima (Temperatur oder Niederschlag) wird üblicherweise als „wirkliches“ Klima in der Ricardischen Analyse verwendet. Jedoch können Abweichungen unbekannter Form zwischen interpoliertem, tatsächlichem und wahrgenommenem Klima dazu führen, dass eine Korrelation des Residuals des Ricardischen Modells mit den interpolierten Klimaaufzeichnungen entsteht. Betrachtet man unsere Herangehensweise aus

der Sicht der Messfehler in den unabhängigen Variablen, so haben wir eine Post-hoc IV-basierte Oberflächentrendanalyse durchgeführt, wobei interpolierte Temperatur und Niederschläge endogen korrigiert werden. Unsere Ergebnisse lassen den Rückschluss zu, dass bei einer Vernachlässigung der potentiellen Endogenität in den interpolierten Variablen, ein großer Bias in den partiellen Effekten entstehen kann. Dieser Bias kann sowohl positiv als auch negativ gerichtet sein. Die vorgestellte Vorgehensweise kann auf jegliche Regressionsmodelle mit interpolierten Regressoren angewendet werden.

Der Einfluss des Klimas auf Betriebstyp und Ausmaß der Bewässerung wurden bisher lediglich mit Hilfe der konditionalen Regressionsanalyse betrachtet. Ebenso wenig wurden entsprechende Endogenitäten aus einer IV-Perspektive verbunden mit einem Ricardischen Model verwendet. Wir präsentieren hiermit eine neue räumliche IV-Version der Ricardischen Analyse, bei der die Profitabilität des Betriebes das Resultat *von* Betriebstyp- und Bewässerungsentscheidung sowie Klima ist und gleichzeitig die Entscheidung für einen Betriebstyp und Ausmaß der Bewässerung *durch* das Klima beeinflusst werden.

Wir verwenden nicht lineare Projektionen und Spatial Lags dieser Projektionen als Instrumente für die endogenen Betriebstyp- und Bewässerungsvariablen. Berücksichtigt man die Endogenität dieser Variablen in Bezug auf das Klima, so verbessern sich konzeptionelle Genauigkeit sowie der Erklärungsgehalt des Ricardischen Models. Darüber hinaus wird Folgendes ermöglicht: (*i*) Wechsel des Betriebstyps; (*ii*) eine Unterscheidung zwischen direkten (unmittelbaren) und indirekten (mittelbaren) Klimaeinflüssen auf die Betriebsprofitabilität; (*iii*) Rückschlüsse darauf, ob Veränderungen im Betriebstyp und Bewässerungspotential ökonomisch sinnvoll wären. Vernachlässigt man die Endogenität in den Variablen, die für die Anpassung stehen, so mag dies zu verzerrten Schätzungen der Klimavariablen führen. Der Bias ist von unbekannter Größenordnung und kann von widersprüchlicher Richtung sein. Unser Ansatz weist eine vielversprechende Richtung für zukünftige Forschungsansätze auf, da hiermit grundsätzlich jegliche kurz- oder langfristige Anpassungsstrategie explizit modelliert werden kann.

Von einem empirischen Gesichtspunkt aus zeigen unsere Ergebnisse, dass der Klimawandel historisch gesehen vorteilhaft für den gesamten Sektor war. Der Effekt auf die Landpachtpreise durch Einflüsse der historischen mittleren Jahresdurchschnittstemperatur (Jahresmittel der Niederschläge) ist positiv (konkav). Es gibt Anzeichen, dass Dauerkulturbetriebe und Gemüsebaubetriebe mehr von einer Erhöhung der Temperatur begünstigt sein könnten als andere Betriebstypen, wohingegen Grünlandbetriebe und bis zu einem gewissen Maße Gemischtbetriebe hervorstechen durch ihre Anpassungsfähigkeit an erhöhte Niederschlagsaufkommen. In naher Zukunft werden die Auswirkungen des Klimawandels auf die landwirtschaftlichen Betriebe wahrscheinlich positiv bleiben, jedoch die Richtung des Effekts ist abhängig vom Betriebstyp.

Durch eine Reduktion von komplexen dynamischen Phänomenen hinzu erfassbaren Dimensionen und durch Überlappung räumlicher Variation im historischen Klima mit räumlicher Variation des Verhaltens von Betrieben, konnten wir die Vulnerabilität des Sektors als Ganzes für Klima zeigen. In diesem Kontext dienen die empirischen Studien der Folgenabschätzung an sich; sie können jedoch auch als generelles Instrument zur Kreuzvalidierung für andere Ansätze zur Folgenabschätzung fungieren (z.B., Betriebsmanagement Modelle).

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Author's declaration

I hereby declare that this doctoral dissertation is a result of my own work, and that no other than the indicated aids have been used for its completion. All quotations and statements that have been used are indicated. Furthermore, I assure that the work has not been used, neither completely nor in parts, for achieving any other academic degree.

Thomas Chatzopoulos
Stuttgart-Hohenheim, February 2015

Curriculum vitae

Personal information

Full name:	Thomas Chatzopoulos	Address:	G. Gennimata 56, 56121, Thessaloniki, Greece
Birthdate:	31.01.1986	*e*-mail:	t_chatzopoulos@uni-hohenheim.de tchatzop@hotmail.com
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University degrees

PhD degree *04.2011 – 03.2014*	Agricultural Economics / University of Hohenheim, Stuttgart Thesis: Microeconometric analysis of the impacts of climate change on German agriculture: applications and extensions of the Ricardian approach. *Magna Cum Laude*.
MSc degree *10.2008 – 01.2011*	Agricultural Economics / University of Hohenheim, Stuttgart Thesis: Investigating noncompliance of organic operators with the organic standards: a count-data regression analysis for Germany. Thesis grade: A
BSc degree *10.2003 – 06.2008*	Agricultural Sciences / Aristotle University of Thessaloniki, Thessaloniki Thesis: Perspectives for agro-economic development of the Chios Mastiha: a sampling survey (in Greek). Thesis grade: 10/10

Work experience

Scientific staff *01.2011 – 03.2014*	Institute of Farm Management (410A), University of Hohenheim Tasks: scientific research, lectures (postgraduate level)
Academic assistant *10.2010 – 01.2011*	Institute of Farm Management (410A), University of Hohenheim Tasks: tutorials and workshops (postgraduate level)
Intern *07.2007 – 08.2007*	The Greek Biotope/Wetland Center (EKBY), Thessaloniki Tasks: data processing for agri-environmental projects

Lectures & tutorials

Lectures 32 hrs	*Mathematical programming for agricultural economists*, WS 2010-11, 2011-12. Part of the module 'Advanced Policy Analysis Modeling' (Prof. Dr. H. Grethe). *Certification in organics: definitions, concepts and experiences*, SS 2012. Part of the module 'Problems and Perspectives of Organic Farming' (Dr. S. Zikeli).
Tutorials 10 hrs	*Economic concepts for noneconomists*, WS 2010-11. Part of the module 'Socioeconomics of Organic Farming' (Prof. Dr. S. Dabbert).

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Curriculum vitae (cont'd)

Computer skills

Econometrics/Statistics:	Stata/Mata, R
Geospatial analysis:	Stata/Mata, Esri's ArcGIS, GeoDa, R
Mathematical programming:	GAMS
Other:	MS Office, Photoshop

Language skills

Greek (native), English (fluent), Italian (good), Spanish (basics), German (basics)

Further training

16.5 – 10.6.2011	Spatial Econometrics Advanced Institute, Sapienza Università, Rome, Italy
103 hrs	Spatial econometrics - theory & applications.

Miscellaneous

2008 Awarded paper (6th place) in the 14th National Student Contest: *Economy and the Environment in Greek reality*. Economia Business Tank, Oikonomiki, Athens.

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