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Dynamics of Adjustment in Agriculture

-Essays on Dairy Productivity, Dairy Quota System and Sustainable Corn Production-

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Tibor András Marton

aus

Budapest, Ungarn

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Referent: Prof. Dr. Thomas Heckelei

Korreferent: Prof. Dr. Jan Börner

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Kurzfassung

Die Arbeit umfasst eine Einführung und drei eigenständige Aufsätze zu Aspekten landwirtschaftlicher Anpassungsprozesse. Die Aufsätze beschäftigen sich insbesondere (1) mit der Produktivität der Milcherzeugung in Norwegen, bzw. wie sich diese zwischen verschiedenen Phasen des Quotensystems ändert; (2) mit räumlichen Übertragungseffekten der Entscheidung norwegischer Landwirte auf organische Produktionsverfahren umzustellen; und (3) mit der Vorhersage von Maiserträgen angesichts des Klimawandels. Alle drei Studien befassen sich mit der räumlich differenzierten, dynamischen Transformation des Agrarsektors angesichts sich ändernder politischer und biophysikalischer Treiber.

Die ersten zwei Aufsätze untersuchen die norwegische Milcherzeugung. Die Beziehung zwischen sich ändernder Milchquotenpolitik und der Produktivität von Milchviehbetrieben wird im ersten Manuskript analysiert. Der zweite strebt an das Verständnis der Umstellung auf organische Produktion zu erweitern, indem die Auswirkungen potenziell negativer Konversionsbeispiele in der Nachbarschaft einbezogen werden.

Der dritte Aufsatz öffnet ein Fenster in die Zukunft und beschreibt die Maisertragsentwicklung in Ungarn, indem sie gleichzeitig die Auswirkungen des Klimawandels und die Anpassung des Sektors anhand historischer Daten berücksichtigt.

Die in der Dissertation verwendeten Datensätze umfassen Zeitreihendaten über mehrere Jahrzehnte. Jedes Kapitel hat seine eigene Vorgehensweise mit unterschiedlichen Ansätzen zur Beantwortung der Forschungsfragen, ein gemeinsames Thema ist dennoch die Verwendung von Paneldatenmethoden, denn sie sind gut geeignet, die Dynamik der Anpassung zu untersuchen. Die verwendeten Datensätze sind sowohl ‚balanced‘ als auch ‚unbalanced‘ und werden entweder auf Ebene der individuellen Entscheidungseinheit- oder flächenbezogen erfasst.

Das erste Essay zeigt, dass mit sich ändernden Milchquotenregelungen Norwegens auch statistische Unterschiede in den Gruppenmittelwerten von Produktivitäts- und Effizienzmessungen verbunden sind und diskutiert die Beziehung zwischen dem Verhalten von Landwirten und den politischen Perioden. Im zweiten Essay demonstrieren wir, dass benachbarte Umstellungen von organischer zur konventionellen Produktion und der Ausstieg organischer Molkereien bemerkenswerte, negative räumliche Übertragungseffekte auf Entscheidungen zur Umstellung auf organische Erzeugung haben. Wir schaffen Bewusstsein für diese Phänomene, um in der Zukunft Politiken effizienter gestalten zu können. Die Forschung im dritten Aufsatz bestätigt, dass steigende Temperaturen und abnehmende Niederschläge die ungarische Maisertragsentwicklung negativ beeinflussen, dass diese aber durch technologischen Fortschritt und Verhaltensanpassung kompensiert werden können. Wir argumentieren, dass die negativen Auswirkungen des Klimawandels auf die Ertragsentwicklung überwunden werden können und dadurch eine nachhaltige und erfolgreiche Partnerschaft zwischen Land und Menschen geschaffen werden könnte.

Stichwörter: landwirtschaftliche Transformation, Paneldatenmethoden, dynamische Produktivitätsanalyse, Umstellung auf Bio-Landbau, Nachbarschaftseffekte, Ertragsprognose, Klimawandel

Abstract

The thesis comprises an introduction and three separate essays on aspects of agricultural adjustment processes. The essays specifically address (1) how the productivity of milk production in Norway changes between different periods of the quota system; (2) spatial spill-over effects on Norwegian farmers' decision to convert to organic production practices; and (3) the prediction of corn yields in the light of climate change. The three studies all address the spatially differentiated, dynamic transformation of the agricultural sector in light of changing policy and biophysical drivers.

The first two studies investigate Norwegian dairy production. The relationship between an evolving quota policy and productivity of dairy farms is analyzed in the first manuscript. The second aims at broadening the insights on conversion to organic production by introducing the effect of potentially negative conversion examples in the neighborhood.

The third study opens a window to the future and delineates the corn yield development in Hungary by simultaneously considering the impact of climate change and the adaptation of the sector using historic data.

The datasets used in the dissertation cover many years through a number of decades. Each chapter takes different approaches towards unfolding the research questions, but a common theme is to employ panel data methods as they are well suited to study the dynamics of adjustment. The employed datasets are balanced or unbalanced and recorded either at the individual unit or grid level.

In the first essay, we find statistical differences in the group means of productivity and efficiency measures under changing dairy quota regimes in Norway and highlight the relationship between farmers' behavior and policy periods. In the second essay, we demonstrate that neighboring reversion from organic to conventional production and exits of organic dairy exert notable negative spatial spill-overs on organic conversion decisions. We raise awareness of these phenomena for designing more

efficient policies in the future. The research reported on in the third essay confirms that rising temperature and decreasing precipitation will negatively affect Hungarian corn yield development but can be compensated by technological progress and behavioral adaptation. We argue that the negative prospects of climate change can be overcome to create a sustainable and prosperous partnership of land and people.

Keywords: agricultural transformation, panel data methods, dynamic productivity analysis, organic conversion, neighborhood effects, yield prediction, climate change

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Abbreviations

ANOVA	Analysis of Variance
CAP	Common Agricultural Policy
CDF	Cumulative Distribution Function
CPI	Consumer Price Index
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DOSoReMI	Digital, Optimized, Soil Related Maps and Information
DP	Direct Payments
daa	dekar, 10 th of a hectare
EEA	European Economic Area
E-OBS	Daily gridded observational dataset for precipitation, temperature, and sea level pressure in Europe
EU	European Union
FACE	Free Air CO ₂ Enrichment
FADN	Farm Accountancy Data Network
FE	Fixed Effect panel model
FORESEE	Open Database for Climate Change-Related Impact Studies in Central Europe
GCM	Global Climate Model
GDD	Growing Degree Day
HCSO	Hungarian Central Statistical Office
IPCC	Intergovernmental Panel on Climate Change
LT	Linear Trend
MC	Mundlak-Chamberlain device
MJ	Mega Joule
MTclim	Mountain Climate Simulator

NIBIO	The Norwegian Institute of Bioeconomy Research
NIBIO/BFJ	Price index for beef and other cattle by NIBIO
NILF	Norwegian Agricultural Economics Research Institute
NHD	Number of Heat Days
NOK	Norwegian currency, Norwegian Crown
NPK	Nitrogen, Phosphorus and Potassium fertilizers respectively
NUTS	Nomenclature of territorial units for statistics
OECD	Organisation for Economic Co-operation and Development
pH	potential of hydrogen
R&D	Research and Development
RAD	Total Short-Wave Radiation
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RE	Random Effect panel model
REWB	Random Effect Within Between model
RIAE	Research Institute of Agricultural Economics (Hungary)
SOM	Soil Organic Matter
SRES	Special Report on Emission Scenarios
UN	United Nations
VP	Vegetation Period
VRS	Variable Returns to Scale
WTO	World Trade Organization

Chapter 1

Research Context¹

1.1 Motivation and general research questions

Agricultural policy is set to achieve agricultural development through comprehensive programs. It aims to support farmers to increase yields, tackle climate change, maintain rural areas and keep the agricultural economy alive by advocating food production. In the European Union (EU) this goes back to 1962, when the Common Agricultural Policy (CAP) was launched. Over the last 60 years agricultural policy has gone through different adjustment processes, for instance, in developing production competition, enhancing positive spill-over effects and actively reducing the environmental impact of climate change on the evolution of future production yields in order to build a sustainable and prosperous partnership of land and people.

From a broader perspective the motivation of the dissertation is to evaluate and discuss some of the various adjustment processes of farming individuals under changing agricultural policy settings. In Chapter 2 the evolution of dynamic productivity growth of Norwegian dairy is in the focus; Chapter 3 investigates the spreading of organic dairy farms in Norway as well; and

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Chapter 1 Motivation and general research questions

Chapter 4 estimates the future perspective of Hungarian corn production by assessing the human impact towards increasing corn yield.

Beyond the general scientific interest in agricultural adjustment processes and whether policy designs truly facilitate the desired effects, each chapter addresses specific research questions. In case of Norwegian dairy, three time periods of differing dairy quota policies are defined (pre-quota, strict output quota, and transferable quota periods) and related to dynamic productivity growth. We differentiate the productivity and efficiency gaps between the distinctive periods. The originality of Chapter 2 extends to assessing single-output and multiple-output specifications to consider other outputs than milk and thus conceive the “true output set”.

Chapter 3 addresses production dynamics of Norwegian dairy from a different angle. The 21st century brought increasing demand for high quality and sustainably produced food. Therefore, policymakers promote the adoption of organic farming practices as one way to reduce the environmental impacts of farming in addition to addressing growing consumer concerns regarding food safety and health. We investigate the impact of neighborhood effects and individual farm characteristics on the decision process of organic dairy conversion. A large body of literature emerged considering the economic and social concept of neighborhood relations by appraising the effect of positive spatial spill-over with respect to technology, knowledge and farming practices. The existing theory on the neighborhood effect is incomplete, as up until now only the positive external spatial effects have been covered (e.g. Lewis et al., 2011). Chapter 3 argues that negative external effects can be similarly influential on farmers’ conversion decisions. Theoretically, neighboring farmers’ reversion from organic to conventional farming or exits of organic farms could both serve as a negative example that potentially reduces the likelihood of conversion. Dynamics of adjustment reacting to negative neighborhood effects can be expected in addition to positive effects. Those negative occurrences could provide knowledge about the disadvantages and challenges of organic production at the location or may point to a weak supply chain access in the local neighborhood. In the Norwegian dairy population, we observe a significant number of dairy farms that either terminate organic milk

Chapter 1 Motivation and general research questions

production or transfer back to conventional farming in spite of the enormous governmental subsidy. The research presented is the first to measure potentially negative effect of spatial spill-over and extends the literature by assessing the deterrence to organic conversion simultaneously to organic adjustment. The new theoretical perspective of negative examples and demonstrated empirical relevance may be important to policy makers that seek to promote the adoption of organic farming.

Chapter 4 deals with a major global challenge to agricultural production. The impact of climate change accelerates adjustment processes in agriculture and poses a range of challenges to sustain crop yield development in the future. The aim is to predict Hungarian corn yields for the period of 2020-2100. The analysis sets different temperature and precipitation scenarios against trending human impact and determines potential corn yield developments. Human impact is identified as the persisting overall efforts that made by farmers, policy makers, researchers and technology developers to increase yields. We argue that crop yield development is a complex process at different levels. In recent studies, particularly technology improvements are taken into account, and models typically account for new technology by including some exogenous rate of growth in yields (Hawkins et al. 2013; Moore and Lobell 2014; 2015; Hertel and Lobell 2014). To identify the effects of a specific technological innovation is extremely difficult due to time lags and data shortage, therefore we propose the use of a fixed time effect that we associate with “human impact”. The research question is whether the increasing human impact will offset the potential negative effects of climate change in the future?

In the remainder of this introductory chapter, the backbone of methodologies and data are outlined and the contribution of the thesis to the literature with respect to results, limitations and further research potentials is highlighted.

1.2 Methodologies and Data

1.2.1 Analyzing the Impact of Evolving Quota Policy on Dynamic Productivity Growth in Norway

The impact analysis of either imposing or abolishing output quota regimes on milk production has a tradition in agricultural economics (for instance, Guyomard et al. 1996; Boots et al. 1997; Lips and Rieder 2005; Witzke et al. 2009). General economic theory suggests that the imposition of quota generates economic inefficiency in the sector (Alston 1981; Hennessy et al. 2009). Oskam and Speijers (1992) claim that improved quota mobility by organizing quota trade or leasing system may speed up structural development. Still the impact analysis of evolving quota systems on productivity growth is incomplete due to the lack of long-term historic data.

Norway is a role model in recording agricultural accounts and thus it provides valuable sources for conducting economic analysis. The dataset used in the analysis is a relatively large, unbalanced panel of farm accountancy data, similar to the EU's Farm Accountancy Data Network (FADN), which covers 41 years between 1972-2012 with inputs and outputs of dairy farms. This period incorporates three time periods regarding output quota policy that we separately put to use.

We calculate the input oriented dynamic Luenberger productivity indicator and its components² by using a non-parametric approach (Data Envelopment Analysis, DEA). The decomposition of the productivity indicator permits to analyze whether there are significant differences in the development of productivity and its elements for the separated dairy samples. The original methodological framework (Chambers 2002) develops the representation of production technology in the context of the adjustment-cost theory employing the directional distance function approach and derives related static measures of production efficiency. Silva and Stefanou (2003) use non-parametric dynamic cost approach for production analysis and represent the adjustment-cost technology by a family of input requirement sets that

² The components are dynamic technical change, dynamic inefficiency change and dynamic scale inefficiency change.

provides dynamic difference measures of relative efficiency, as opposed to ratio measures (e.g. Nemoto and Goto 2003). Recently, Lansink et al. (2015) incorporate the properties of the dynamic production technology (Silva and Stefanou 2003) into the directional distance function scheme, which can exploit the Luenberger productivity growth measurement (Chambers et al. 1996) for sequential periods. The method of calculating the dynamic Luenberger productivity growth indicator and its components with DEA have been developed for multiple input and multiple output technology specification. Still, in empirical applications for instance on Spanish food industry (Kapelko et al. 2014, 2015) or on European dairy processing industry (Lansink et al. 2015) they use multiple-input and single-output specification. In case of dairy farms, beef is commonly produced jointly with milk. Consequently, a single-output technology specification may not be entirely appropriate, as construction of a single index of outputs can lead to aggregation problems (Kumbhakar et al. 2008). Therefore, we provide the computation of productivity developments for both, single-output (SO) and multiple-output (MO) specifications. We raise the importance of applying multi-output production technology for assessing productivity and efficiency measures in the dairy sector. On one hand, it describes the “true output set” of the technology; on the other hand, it is more informative as inference can be drawn on the output mix compared to the outcomes from the single-output specification.

1.2.2 The Case of Organic Dairy Conversion in Norway: Assessment of Multivariate Neighborhood Effects

The influence of local factors and farm interaction in the development of organic hubs are underpinned by the economic and social concept of the ‘neighborhood effect’ (Lewis et al. 2011; Gosme et al. 2012; Bjørkhaug and Blekesaune 2013; Wollni and Andersson 2014). The conceptual framework is based on the hypothesis that organic farming neighbors or spatially close farms can help reduce the uncertainty of organic conversion by lowering the fixed costs of learning about the organic system (Lewis et al. 2011), increasing the probability of conversion to organic farming. The applied empirical approach in Chapter 3 models Norwegian dairy farmers’ decision

to convert from conventional to organic production dairy at time t and jointly incorporates the effects of positive and negative neighborhood examples explicitly. The econometric model is a reduced form discrete choice panel data model with a binary probit link to explain the probability of organic dairy conversion conditional on farm characteristics and neighborhood affiliations. The probit model is subject to the binary decision of whether a conventional dairy farm converts to organic, where the decision is observed and monitored each year over a 14-year period. The employed panel dataset happens to be unbalanced (i.e., differing in the number of observations between groups) because of continuous entries and exits. Therefore, the estimation method must be adapted to an unbalanced panel setting. We follow the technical innovation of Papke and Wooldridge (2008) and use maximum likelihood estimation without the Gaussian quadrature as a pooled probit with bootstrapped standard errors by resampling the cross-sectional units. We use 500 bootstrap replications on the individuals to obtain the bootstrapped cluster-robust standard errors. This treatment of the standard error allows robust inference to any form of heteroscedasticity or temporal correlation across years for each farm (Cameron and Trivedi 2005; Cameron et al. 2008; Lewis et al. 2011).

The data used in the application is a unique georeferenced farm-level population set of Norwegian dairy holdings. The 14-year unbalanced panel construction (2002-2015) includes more than 179 thousand observations including the annual contributions of 55 thousand dairy farms. We record approximately 4 thousand organic dairy farms in the observation period. Based on the geographic information of each farmstead, we calculate the distances between the dairies in kilometers, labelling each dairy farms as either conventional, organic, reverting or exiting in each year, to allow the determination of the dynamic neighbourhood synthesis of individual farms. The actual numbers of multivariate neighbour vectors depend on the definition of the radius surrounding each individual farm. Defining this radius is relatively arbitrary and can hardly be based on precise information or theoretical knowledge. We intend to keep the focus on face-to-face information transfer, which assumes close proximity and personal discussions about the technology. In this manner, we derive the number of organic, reverting and exiting farms around each conventional dairy (i.e.,

potential organic convertor) within 3 and 5 km radii. In addition, farm characteristics such as herd size, cultivated area and farmers' age are also included in the analysis.

1.2.3 Human Impact Promotes Sustainable Corn Production in Hungary

Chapter 4 focuses on the future of Hungarian corn production in the light of climate change. The success of agricultural production depends on innovation and expanded use of factor endowments. Panel data regression methods are elaborated on historic observations (1970–2018) to use statistical knowledge for simulated future weather events (2020–2100) and to consider developing human impact for sustainable intensification. During data collection, there are repeated data measures over time (e.g., weather events) and other important variables (e.g., soil parameters) that are nested in individuals such as countries and grid cells, which include time-independent characteristics (Bell and Jones 2015; Bell et al. 2018; 2019). There are many different model specifications in terms of choosing the appropriate model framework, functional form, and including the most meaningful/influential covariates. Still, fixed-effect (FE) models are regularly employed to avoid the problem of individual heterogeneity bias and control out all between effects by including the higher-level entities as dummy variables (e.g. Roberts et al. 2013). However, the great advantage of FE models comes at a price of being unable to estimate the effects of higher-level processes and only dealing with occasion-level processes (Bell and Jones 2015). Therefore, FE models may not be practical in applications where time-invariant covariates (i.e., has only higher-level variance) are of particular interest, as they lose a large amount of information. Mundlak (1978a, b) worked out his solution to this issue by adding the higher-level mean of each time-varying covariate in the model (the so-called Mundlak device) to explicitly account for the between effect instead of controlling it out. The Mundlak device is treated the same way as other higher-level variables (i.e., time-invariant variable) and employs the covariates within a simple parsimonious RE framework. This yields to the same results as a FE model but supplemented with the between effects in addition to other time-invariant variables of interest (Bell et al. 2018).

The scope of the paper is to determine the effect of highly variable occasions, such as biophysical effects of heat units, wetness/humidity, and nested grid object information of soil organic matter, pH, and sand consistency on observed corn yields; we are interested in a grid-specific parameter on annual linear time trend t to identify annual shocks and long-time improvements. Instead of removing time trend from the model (i.e., detrending the raw data), and thus exclusively accounting for the climate-change-induced differences in yield (Roberts et al. 2013), we make a use of it by superposing on predicted corn yields.

We used the most general parametrization of the Mundlak model, which can model both within- and between-individual effects concurrently, and also explicitly models heterogeneity in the effect of predictor variables at the individual level (Bell et al. 2019). Our model specification closely follows the innovations published by Roberts et al. (2013) and Auffhammer et al. (2006), but applying the within-between random effects model. Three generic model specifications were performed subject to the involved variables. Each model has two sub-specifications (i.e., ‘Model A’ and ‘Model B’) conditional on assuming a coupled or decoupled growing season (i.e., distinguishing plant development phases to vegetative and reproductive growth periods). Specification “A” includes the variables in coupled form, corresponding to mainstream variable use; while specification “B” incorporates Growing Degree Days (GDD), radiation (RAD), and precipitation (P) in decoupled forms.

1.3 Contributions of the thesis

1.3.1 Analyzing the Impact of Evolving Quota Policy on Dynamic Productivity Growth in Norway

We show a direct relationship between evolving output quota regimes and the conformation of productivity and efficiency measures of dairy farms. Under strict output quota regulation, the productivity of the dairies are significantly lower than in the pre-quota period. Later, when the tradable quota regulation is in effect, the potentially increasing scale economies may

be one of the sources of productivity increase given the historically small average dairy farm size in Norway. The reallocation of quota to the most efficient producers allows farmers some degree of increase in output and thereby render a more efficient industry structure with the scale of operation closer to optimal size. Furthermore, we raise the importance of applying multi-output production technology for assessing productivity and efficiency measures in the dairy sector. On the one hand, it describes the “true output set” of the technology; on the other hand, it is more informative as inference can be made on the output mix if we compare the outcomes with the single-output specification. We find that the productivity decrease is smaller in the MO case than in the SO case under the strictly binding quota system. This suggests that farmers increase their outputs of (unconstrained) beef.

We find similar results for the pre-quota and transferable quota periods. The annual average productivity change is between 0.7-0.8% for SO and 0.3-0.4% for MO. The similar outcomes are explained by the counterbalance between the developments of investments and the progress of technical inefficiency. In case of strict quota period, we find investments stagnate, which leads to productivity decrease of 1.1% and 0.8% in SO and MO, respectively. The smaller productivity decrease in MO suggests that farmers increase their outputs of (unconstrained) beef. Furthermore, a decomposition of the dynamic technical inefficiency change (under constant returns to scale) to dynamic scale inefficiency and technical inefficiency changes (under variable returns to scale). In terms of scale efficiency, a statistically significant difference between the group means of quota periods and the pre-quota period is found. This suggests a quota-related effect that increasing scale efficiency accelerates structural change and facilitates the shift from small family-owned businesses to joint dairy farms.

Even though the analysis provides interesting differences between productivity developments under different dairy policy regimes, it does not establish any causal effect. For future research it would be valuable to target this direction and try to explain productivity changes by policy regimes while controlling for other drivers of productivity using an extended dataset.

1.3.2 The Case of Organic Dairy Conversion in Norway: Assessment of Multivariate Neighborhood Effects

The 21st century brought increasing demand for high quality and sustainably produced food. Therefore, policymakers promote the adoption of organic farming practices as one way to reduce the environmental impacts of farming in addition to addressing growing consumer concerns regarding food safety and health. Norwegian agricultural policy set ambitious goals for the stimulus of organic farming and offers a range of subsidies to support conversion. However, the goal of increasing organic production and consumption from 0.5% in 2005 to 15% by 2020 (Norwegian Ministry of Agriculture and Food, 2009) has never been reached. The reality in 2018 was only 2.2% share of organic in the entire food market (Landbruksdirektoratet, 2018). Therefore, instead of increasing subsidies one should increase the understanding of farmers' motives, reservations, and goals in terms of organic production to develop more informed policy approaches. We make an attempt to unfold in detail the spatio-temporal dynamics of shifts to organic technology in Norwegian dairy.

The essay identifies the factors of organic dairy technology adoption. We find that farmers' age, herd size and agricultural land used are less important elements of potential organic conversion than relations with neighboring dairy production. We demonstrate that spatial spillovers across economic agents influence the patterns of technology adoption. Although our model supports the findings of previous studies that the presence of organic dairies in close proximity positively affects organic dairy conversion, more remarkably, we find that neighboring organic reversions and exits introduce potential negative interaction effects. This result offers important implications for policymakers and extension services that intend to promote organic production.

As the literature only explored the positive interaction effects of conversion, we raise awareness about the existence of negative examples. We demonstrated that the negative effect of neighboring reversion is potentially stronger than the positive effect of neighboring conversion in absolute terms, policies should not only be focusing on new adaptors but also ensure that existing organic dairy farms remain active and successful. Correspondingly,

policies should increase efforts to improve extension and consultation, supporting farmers that are considering conversion to organic farming and helping them to explore whether converting could be successful in their specific situation. Based on this reasoning, our results support the decision by the Norwegian government to terminate organic conversion grants, which may ease conversion but are ill-suited for sustaining organic production in the long run.

Our result highlighted the critical influence that reversions have in terms of external effects on neighboring farms. Future research should focus on exploring the root causes underlying the decision to revert from organic to conventional farming. This should help policymakers to design new policies or adjust existing approaches to address the identified causes.

1.3.3 Human Impact Promotes Sustainable Corn Production in Hungary

The analysis on a gridded Hungarian database confirms that rising temperature and decreasing precipitation will negatively affect corn yields although developing human impact may dissolve the climate-induced challenges. We argue there is still room for sustainable intensification for corn production. The future is to carry out great investments in precision agriculture and large-scale irrigation infrastructure development by policy makers, farmers, and agricultural cooperatives.

Overall, our contribution of treating the increasing time trend in historic corn yields is substantially different than that in the mainstream literature, where the driving force behind increasing corn yield has been labelled as either “technology development,” “technological change,” or “improving adaptation capacity,” and modelled with, e.g., linear time trend, state-specific quadratic time trends, or year-fixed effects. We argue to compile all these different terminologies into one complex issue that we call human impact, which subsumes all unidentified effects that facilitate corn yield development. We find the contribution of human impact about 80 kg/ha/year to increase corn yield, of which we consider ca. 8 kg/ha/year for elevated CO₂.

Furthermore, this paper shows the importance of addressing time-invariant production factors, when historic yield evolution is modelled. The applied random-effects within-between ‘hybrid framework’ provides a wider range of variable use than the gold standard FE models. We confirm that soil parameters are crucial in future crop yield assessments and it certainly has prominence for modeling purposes.

Further research may consider a more detailed identification of the components of human impact and thus contribute to make more informed predictions under varying socio-economic scenarios.

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Chapter 2

Analyzing the Impact of Evolving Quota Policy on Dynamic Productivity Growth in Norway³

Abstract: In recent decades the Norwegian Dairy Industry has undergone substantial changes and experienced extensive restructuring; notably due to the evolving output quota system. The aim of the study is to analyze dynamic productivity growth rate of Norwegian dairy farms in the period of 1972-2012, and to decompose it into dynamic technical change, dynamic technical inefficiency change and dynamic scale inefficiency change under different quota designs. In this application, we use dynamic directional distance function approach for multi-input and, for comparison, single-output and multi-output technologies. Results indicate statistically significant differences in productivity and efficiency measures in the group means of changing policy periods which indicates differences in farmers' behavior.

Keywords: Dynamic Luenberger productivity growth indicator, Policy analysis, DEA, multi-input and multi-output technologies, Dairy industry

JEL classification codes: D21, D24, C61, O33

³ An earlier version of this chapter is published as Marton TA, Heckelei T, Hoveid Ø. 2015 Productivity and the Evolving Norwegian Dairy Quota System. 20th International Far Management Congress, Laval University, Québec City, Québec, Canada. p 185-192.

2.1 Introduction

In recent decades the Norwegian Dairy Industry has undergone substantial changes and experienced extensive restructuring similarly to most European countries. For Norway, dairy farming is the most significant and dominant agricultural industry that accounts for 30% of total farm revenue (Budsjettnemnda 2013). Likewise to the EU, balancing national milk supply and demand was an emerging issue in the late 70s. Throughout the past four decades several regulatory actions took place to adjust total milk production to domestic demand. Production quotas were imposed to curb overproduction, support farmers' income and stabilize milk price. Similar developments in the EU, the quota regimes in Norway were adjusted during implementation to render quota mobility more flexible over time. Reoccurring questions associated with different implementations of measures restricting individuals and sectoral output quantities have their effects on productivity and efficiency. The overall effect is theoretically not clear. A more rigid output regime may render input allocations and use easier to plan and control, but economies of scale may be more difficult to realize.

A number of studies addresses productivity and efficiency questions related to policy reforms in the European dairy sector (Colman 2000; Colman et al. 2002; Kumbhakar et al. 2008). Decisions made by farmers related to capital investment, herd expansion or reduction and such that are commonly constrained by quota limits may directly affect the overall productivity and efficiency of the milk sector. In accordance with the general theory, quota regulations that prevent output expansion of farms and reallocation of production rights between farms can cause lower growth in output and productivity (Boots et al. 1997; Kumbhakar et al. 2008). Production quotas hinder adjustment processes in an industry and thus retain inefficient production structures (Colman 2000). However, Kersting et al. (2016) analyze how tradable/non-tradable output quota influence the structural change of farm entry and exit within a dynamic stochastic equilibrium framework. They consider that a release of production capacity by exiting farms affect the investment options for entrants under tradable quota regime

and find that this system does not necessarily reduce average productivity of farms in the EU.

This paper aims to assess dynamic productivity developments in the Norwegian dairy sector during the pre-quota period and output quota regimes differentiated by mobility policies to clarify the potential differences in productivity and efficiency under the separated quota periods. We hypothesize that the potential industrial improvements in productivity and efficiency may be driven by various adjustment processes (e.g. investments, input management) which conceptually requires dynamic consideration in the methodology. The dataset used in the analysis is a relatively large unbalanced panel of farm accountancy data – comparable to the EU Farm Accountancy Data Network (FADN) – with inputs and outputs of dairy farms for a relatively long period of time 1972-2012. Kumbhakar et al. (2008) use the same data for shorter period (1976-2005) to explain farm-level output growth rate of Norwegian dairy, and to decompose it into output, input, socioeconomic and technical change components by applying a parametric specification of an input distance function. In contrast, we calculate the input oriented dynamic Luenberger productivity indicator and its components, which include dynamic technical change, dynamic inefficiency change and dynamic scale inefficiency change by using a non-parametric approach (Data Envelopment Analysis, DEA). The decomposition of the productivity indicator permits to analyze whether there are significant differences in the development of productivity and its elements for the farm sample under different quota periods. We statistically analyze the differences between the indicator distributions and test the hypothesized dissimilarities between the distinctive quota phases.

The method for calculating the dynamic Luenberger productivity growth indicator has been developed in Silva and Stefanou (2003), Lansink et al. (2015) and Kapelko et al. (2015a). The dynamic framework of productivity growth is based on a production technology, where the source of the intertemporal link of production decisions is adjustment cost connected with changes in the level of quasi-fixed factors (Kapelko et al. 2015b). The dynamic Luenberger indicator is based on dynamic directional distance functions developed for multiple-input and multiple-output technology set.

However, in all applied studies in the literature, only a single-output is used. Therefore, our contribution, apart from the comprehensive analysis of productivity development under various regulatory schemes, is that we compare the calculated productivity developments under both, single-output (SO) and multiple-output (MO) specifications.

In the following, we first discuss the background of changes in production regulation in the Norwegian dairy industry and develop the theory of productivity response to different quota regimes, followed by the model used for calculating the dynamic productivity growth indicator and its components. Then, we describe the dataset, present and discuss the empirical results and the performed statistical tests. In the last section we summarize our findings.

2.2 Background and theory

Norway is not a member state of the European Union (EU) and therefore Common Agricultural Policy (CAP) is not applied. However, the regulation of Norwegian and EU dairy systems is very similar for decades, partly because both are subject to the influence of the European Economic Area (EEA) and the World Trade Organization (WTO). In general, since the early 1960s the mostly family-operated European dairy farms have merged, transformed and increased their size dramatically as a result of modernization and structural realization. In Norway, while farms are larger now than in the past, this increase in size has been more moderate (Flaten 2002; Bjorkhaug and Blekesaune 2008; Sipiläinen et al. 2014). Almås and Brobakk (2012) refer to the Norwegian Agricultural Censuses which reveal that average size has increased from 4 cows in 1959, to 9.6 cows in 1979 and to 19.2 cows in 2009 and point out that Norway still has one of the smallest average farm sizes in a global context.

The Norwegian dairy regime went through several deregulations and re-regulations over the last decades (Almås and Brobakk 2012). The undergoing transformation is forced by both internal (effective farmers' organizations and co-operatives) and external pressures (liberalization

tendencies abroad, revival of neo-productivism and industrialization). The overall policy objective for producers is twofold: farmers are supposed to draw less from the state budgets (direct subsidies) and gain a larger proportion of their income directly from the markets. On the consumer side, prices for dairy products are expected to decrease through lowering production and transaction costs in the value chain (Jervell and Borgen 2000). The first attempt to curb overproduction is made between 1977 and 1983 by issuing pecuniary incentives to farmers who voluntarily stabilize or reduce milk output relative to a base year. Over these years, aggregate production has increased by 10% which was combined with contracting demand and led to 300 million liter milk surplus in 1982. Soon, it became evident that stronger production regulation is necessary if general milk price support shall be sustained. The so-called two-tier price system was imposed in 1983 (undertaken in the EU a year later in 1984). High price support is only paid for production within individual quota quantities such that above-quota production becomes unprofitable. Hence farmers generally adjust their output to the individually allocated quota levels with the implementation of this regulation. The initial quota allocations were based on the average output of previous years (1980-1982) reduced by the same percentage for all producers. In this paper we label this intervention system as “strict” or “restrictive” quota regime because of its rigid regulatory feature. As an effect of the quota the increase of milk supply got restraint, prices for dairy products stabilized, but the dairy supply cannot adjust to changes in demand and redistribution between farms only occurred by administrative procedures (Jervell and Borgen 2000).

Following lobby activities of the Norwegian Farmers Union and Dairy Cooperatives, the strict quota regime is reformed by relaxing the rigorous redistribution rules in 1997. The restrictive quota design is most crucial for farmers’ opportunity of generating income only from his/her farm because of the constraining output. Therefore, the government arranged the quota buy and sell scheme (also called transferable quota or quota-trading regime) which sought to achieve greater allocative efficiency and create a more desirable quota distribution in the industry, as well as overcome the previous issues of inflexibility and unfair characteristics of the strict quota system. The conflicting interest between the Farmers’ representatives and the

Ministry is addressed by the increased mobility of quotas which follows certain rules. To avoid regional quota accumulation, the country was divided into six milk-trade regions. Quota transfer was restricted to occur within the regions only. This arrangement allows output expansion for individual farms in case other farmers sell quota. As quota rights become a tradable production factor, farmers' incentives to either continue or exit milk production changes. Farmers intending to innovate and enlarge capacities to increase productivity and incomes from dairy production have to purchase quota rights. Those, who decide to downscale or exit dairy farming receive revenue from selling their production rights. Almås and Brobakk (2012) affirm that after 2000, farms enlargement in herd-size has accelerated and joint dairy farming increased in popularity. Increasing farm scale is one of the main strategies whereby family businesses try to reduce unit production cost and thus to become or remain competitive (Hemme et al. 2004). In a booming oil economy, the off-farm income of farmers' increases, hence they spend more on modernization (Almås and Brobakk 2012). These investments address farms productive capacity by increasing their stock of capital, replacing existing capital or implementing technological innovations (Doms and Dunne 1998; Kapelko et al. 2015b).

Figure 2.1 graphically illustrates the percentage change in annual average gross investments on dairy farms, national milk output, and other output for the period of 1972-2012. Compared to the base year, 1972, milk output reaches its peak in 1982 and later, as an effect of the strict regulation, it stagnates and slightly declines. From 1997, when the transferable quota system comes into effect, milk output starts increasing dynamically. In 2012, average milk output is about 140% higher of its 1972 level. Other output closely follows the milk quantities but the gap widens in the last years when investment picks up strongly. Investments grow substantially in the pre-quota (1972-1982) and the second half of the transferable quota periods (1997-2012), while being at rather low levels in the strict quota period (1983-1996).

Chapter 2 Background and theory

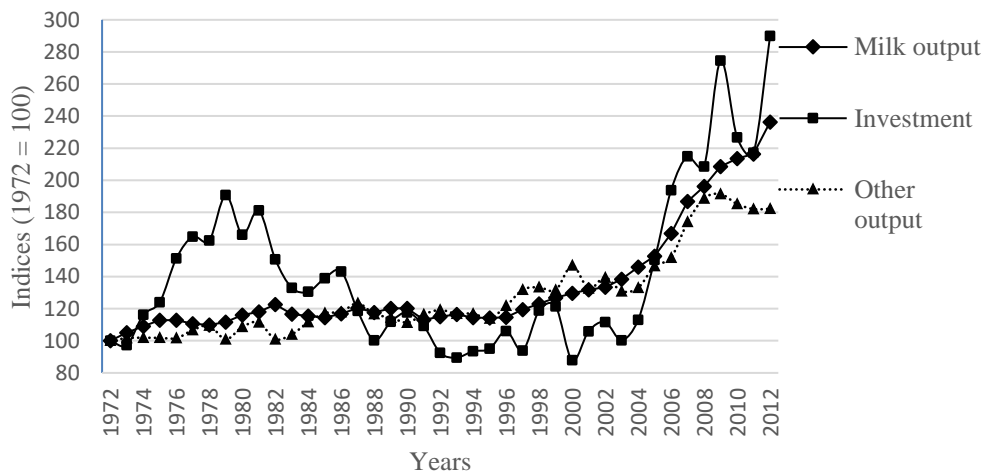


Figure 2.1 Developments in dairy outputs (milk and other) and investment growth 1972-2012

Source: The charts are derived from the FADN-type database

General economic theory suggests that the imposition of quota generates economic inefficiency in the sector, though the more freely traded the quota are, the smaller the inefficiency (Alston 1981; Oskam and Speijers 1992, Hennessy et al. 2009). Colman (2000) puts forward the theory by discussing the inefficiencies of milk quota regimes in the UK in a static manner. As a result of the regulation, “inefficiencies can arise (1) from constraints imposed on operation of the market, and (2) from the inability of milk producers to use the market to its full potential” (Colman 2000, p. 1). He argues that the economic inefficiency difference between tradable and strict regulations results from high-cost producers not being able to lease or sell quota to more efficient ones. Given the historically small average dairy farm size in Norway, the potentially increasing scale economy may be one of the sources of productivity growth when tradable regulation is in effect. The reallocation of quota to the most efficient producers allows farmers some degree of increase in output and thereby makes possible a more efficient industry structure with the scale of operation closer to optimal size (Huettel and Jongeneel 2011). We do not know how big the productivity and efficiency gap between the distinctive periods of pre-quota, strict quota and transferable quota regimes is. By calculating dynamic productivity indicator

that we link to economic efficiency given that farmers are price-takers, we hypothesize the productivity developments are the highest under the pre-quota period, modest in the transferable quota period and the smallest, when restrictive quota regulation is in effect.

To shed more light on the relationship between quota regimes, investments, productivity development and competitiveness of Norwegian dairy farms, we analyze the dynamics of the empirical phenomena described above. Porter and Van der Linde (1995) emphasize that competitive advantage of a producing unit “does not rest on static efficiency nor on optimizing fixed constraints, but on the capacity for innovation and improvement that shift the constraints” (p. 98), therefore assessment of industrial development should be put in dynamic context. Kapelko et al. (2015a) investigate the impact of new policy on the Spanish food processing industry expose that “the shortcoming of the static approach is that it does not account for the disequilibrium of capital factors and may not appropriately reflect productivity growth and its components when substantial investments are undertaken” (p. 2). For this reason, understanding the adjustment process (i.e. effect of change in capital as quasi-fixed input) is important because it largely determines the efficiency and competitiveness of a sector (Jorgenson and Timmer 2011).

2.3 Methods

2.3.1 Dynamic Luenberger indicator of productivity growth and its decomposition

The analytical foundations of the production theory have been widely explored in a static context (e.g. Debreu 1959; Shephard 1970; McFadden 1978). The static models are based on the assumption that firms are able to adjust their production technology instantaneously to any change in the quasi-fixed determinants and therefore there is no intertemporal linkage between production decisions. Early attempts were made by Lucas (1967) and Treadway (1970) to relax these restrictive assumptions and to associate the optimal rate of change in factor use with the theory of adjustment-cost.

They use systems of investment demand equations for explaining quasi-fixed factor employment and thus model the interaction between changing factor quantities (including investment) and output quantities in an intertemporal framework. The framework implies changes in firms' productivity and efficiency. Chambers (2002) develops the representation of production technology in the context of the adjustment-cost theory employing the directional distance function approach and derives related static measures of production efficiency. Silva and Stefanou (2003) use nonparametric dynamic cost approach for production analysis and represent the adjustment-cost technology by a family of input requirement sets that provides dynamic difference measures of relative efficiency, as opposed to ratio measures (e.g. Nemoto and Goto 2003). Recently, Lansink et al. (2015) incorporate the properties of the dynamic production technology (Silva and Stefanou 2003) into the directional distance function framework which can exploit the Luenberger productivity growth measurement (Chambers et al. 1996) for sequential periods.

The method of calculating the dynamic Luenberger productivity growth indicator and its components have been developed by Lansink et al. (2015) and Kapelko et al. (2014, 2015a). Even though they evolve the DEA model for multiple input and multiple output technology specification, in their empirical applications on Spanish food industry or European dairy processing industry they use multiple-input and single-output specification. However, dairy farms produce other outputs besides milk. Usually meat is produced jointly with milk and the farmer may produce several other outputs. Consequently, a single-output technology specification is not appropriate, as construction of a single index of outputs can lead to aggregation problems (Kumbhakar et al. 2008). Therefore, for multi-output farms, techniques that examine all the outputs simultaneously have to be used. One of the great advantages of the distance function formulation (Shephard, 1953, 1970) is that it overcomes the single-output technology restriction by allowing for multi-output and multi-input technologies (Kumbhakar et al. 2008).

In this paper we calculate dynamic input-oriented directional distance functions in a consistent, dynamic theoretical framework. We follow

Lansink et al. (2015) and Kapelko et al. (2015a) in the computation of the Luenberger indicator of dynamic productivity growth and its decompositions to identify the hypothesized productivity differences under the differentiated quota periods. The input orientation is in accordance with the nature of the quota regime where milk production is at the quota level for each dairy farm.

We pursue the characterization of the input requirement set by Silva and Stefanou (2003):

$$V_t(y_t; k_t) = \{(x_t, I_t) \text{ can produce } y_t, \text{ given } k_t\},$$

where y_t denotes the maximum amount of output of a firm can produce at time t by using the vectors of freely disposable variable inputs x_t and gross investments in quasi-fixed inputs I_t with given initial capital stock vector k_t . The input requirement set is assumed to have the following properties: closed, nonempty, strictly convex, lower bounded, positive monotonic in x_t and k_t , and negative monotonic in I_t ⁴.

The input-oriented dynamic directional distance function (Lansink et al. 2015 and Kapelko et al. 2015a) is an extension of the input-oriented static directional distance function (Chambers et al., 1996). In the static approach, only the set of variable inputs (x) is downscaled with the directional vector (g_x) ⁵, while in the dynamic approach, an additional entry is introduced for the quasi-fixed input term (associated with the expanding gross investment) is defined as follows:

⁴ For details and explanation on the properties, see Silva and Stefanou (2003), Silva and Lansink (2013) and Lansink et al. (2015).

⁵ $\bar{D}_i(y, x; g) = \sup\{\beta \in \mathfrak{R} : x - \beta g \in L(y)\}$

$$\bar{D}_t^l(y_t, k_t, x_t, I_t; g_x g_I) = \max \{ \beta \in \mathfrak{R}: (x_t - \beta g_x, I_t + \beta g_I) \in V_t(y_t; k_t) \}, \quad (1)$$

$$g_x \in \mathfrak{R}_{++}^N, g_I \in \mathfrak{R}_{++}^F, (g_x, g_I) \neq (0^N, 0^F),$$

if $(x_t - \beta g_x, I_t + \beta g_I) \in V_t(y_t; k_t)$ for some distance β , and $\bar{D}_t^l(y_t, k_t, x_t, I_t; g_x g_I) = -\infty$, otherwise. The distance function is the maximal translation of the input requirement set, $V_t(y_t; k_t)$, along the directional vectors g_x and g_I that permits keeping x_t and I_t feasible. This function represents the adjustment-cost production technology by assuming $\bar{D}_t^l(y_t, k_t, x_t, I_t; g_x g_I) \geq 0$ that fully characterizes the input requirement set (Silva et al. 2015) and measures the dynamic inefficiencies of firms by solving the maximization problem for β .

The dynamic Luenberger productivity indicator originates from the generalization of Luenberger's (1992, 1995) shortage function. Chambers (2002) defines the difference-based productivity indicator by taking the average of the "1 and 0 time technology Luenberger input indicator" represented by the value of the directional distance function. He assumes quadratic functional form for the distance function period. Silva and Stefanou (2003, 2007) initiate the more flexible nonparametric dynamic dual cost approach to estimate a DEA model.

In general, the distance functions can admit constant returns to scale (CRS) and variable returns to scale (VRS) assumptions on the technology. The DEA problem for calculating the dynamic distance function for time t under CRS assuming multiple input and quasi-fixed input (N, F) and multiple output (M) quantities is defined as follows⁶:

$$\bar{D}_t^l(y, k, x, I; g_x g_I | CRS) = \max_{\beta, \gamma} \beta \quad (2)$$

$$s. t. \quad y_m \leq \sum_{j=1}^J \gamma^j y_m^j, \quad m = 1, \dots, M;$$

$$\sum_{j=1}^J \gamma^j x_n^j \leq x_n - \beta g_{x_n}, \quad n = 1, \dots, N;$$

⁶ All variables are time specific, but the time subscripts are deleted to avoid notational clutter.

$$I_f + \beta g_{I_f} - \delta_f^j k_f \leq \sum_{j=1}^J \gamma^j (I_f^j - \delta_f^j k_f^j), \quad f = 1, \dots, F;$$

$$\gamma^j \geq 0, \quad j = 1, \dots, J;$$

where γ is the $(J \times 1)$ intensity vector of firm weights, and δ represents depreciation of capital that is firm-specific (J is the total number of firms in the sample).

We follow Lansink et al. (2015), who extend the Luenberger indicator of productivity growth (L) defined by Chambers et al. (1996) to the dynamic setting by using the dynamic directional distance functions (also called mixed period directional distance functions) in the DEA estimation. The indicator defines the productivity change between two successive time periods by taking the arithmetic average of productivity differences measured by the technology at time $t+1$ and t :

$$L = \frac{1}{2} \left\{ \begin{aligned} & [\overline{D}_{t+1}^i(y_t, k_t, x_t, I_t; g_x g_I) - \overline{D}_{t+1}^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I)] \\ & + [\overline{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I) - \overline{D}_t^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I)] \end{aligned} \right\}. \quad (3)$$

The calculation of the other three dynamic directional distance functions is formulated analogous to equation 1 and solved by the DEA model presented in equation (2). The mixed-period functions measure the distances of input and investment quantities at time t and $t+1$ relative to technology isoquants at time $t+1$ and t . The dynamic Luenberger indicator takes on positive or negative values indicating productivity growth or decline between time periods t and $t+1$.

The dynamic Luenberger can be intuitively decomposed into the contributions of technical change (ΔT) and technical inefficiency change (ΔTEI).

$$\Delta L = \Delta T + \Delta TEI. \quad (4)$$

Since the technology is represented by a family of input correspondences in the adjustment-cost framework, the dynamic technical change can be

described by the average distance (i.e. shift) between two technologies at time t and $t+1$ ⁷:

$$\Delta T = \frac{1}{2} \left\{ \begin{aligned} & [\overline{D}_{t+1}^i(y_t, k_t, x_t, I_t; g_x g_I) - \overline{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I)] \\ & + [\overline{D}_{t+1}^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I) - \overline{D}_t^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I)] \end{aligned} \right\} \quad (5)$$

Similarly to the dynamic Luenberger indicator, the input oriented dynamic technical change index takes on positive or negative value:

- $\Delta T \geq 0$: implies reduction of variable inputs and expansion of investments;
- $\Delta T \leq 0$: implies expansion of variable inputs and reduction of investments;

by producing the same relative output levels in time t and $t+1$.

The dynamic technical inefficiency change is the difference between the value of the dynamic directional distance function at time t and $t+1$ which is identical to either subtracting the mixed-period functions from ΔT or computing the difference between the Luenberger indicator and the dynamic technical change:

$$\Delta TEI = \overline{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I) - \overline{D}_{t+1}^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I). \quad (6)$$

The ΔTEI measures difference between the distance of a firm to the technology frontier at time t and the distance at time $t+1$. It also takes positive or negative value:

- $\Delta TEI \geq 0$: implies a firm more efficient at time $t+1$ than at t ;
- $\Delta TEI \leq 0$: implies a firm less efficient at time $t+1$ than at t .

Kapelko et al. (2014) develop the full decomposition of the dynamic cost inefficiency and dynamic productivity by employing a variable returns to scale (VRS) formulation in the nonparametric DEA model. The VRS directional distance function, $\overline{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I | VRS)$, is obtained by adding the constraint $\sum_{j=1}^J y^j = 1$ to equation (2). The difference between

⁷ For graphical illustration, see Lansink, Stefanou and Serra (2015).

$\bar{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I | VRS)$ and $\bar{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I | CRS)$ is the measure of dynamic scale inefficiency (ΔSEI), which indicates the inefficiencies in the scale of the firms relative to CRS technology. Hence permitting the VRS technology in the distance functions, the dynamic technical inefficiency change (ΔTEI) can be decomposed into dynamic technical inefficiency change under VRS (ΔPEI) and dynamic scale inefficiency change (ΔSEI). Hereby the dynamic Luenberger indicator is built on three components:

$$L = \Delta T + \Delta PEI + \Delta SEI, \quad (7)$$

where

$$\Delta PEI = \bar{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I | VRS) - \bar{D}_{t+1}^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I | VRS) \quad (8)$$

and

$$\begin{aligned} \Delta SEI = & \bar{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I | CRS) - \bar{D}_t^i(y_t, k_t, x_t, I_t; g_x g_I | VRS) \\ & - [\bar{D}_{t+1}^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I | CRS) - \\ & \bar{D}_{t+1}^i(y_{t+1}, k_{t+1}, x_{t+1}, I_{t+1}; g_x g_I | VRS)]. \end{aligned} \quad (9)$$

The interpretation of ΔPEI is similar to ΔTEI by assuming VRS instead of CRS technology. The scale efficiency change (ΔSEI) measures the difference between the position of the firm with regard to CRS and VRS technology between two periods of time. It indicates to what extent will any modification in size render the unit less or more efficient.

2.3.2 Analyzing indicator distributions

After calculating the productivity indicator and its components, we analyze differences of dynamic indicator distributions across farms between pre-quota, strict quota and transferable quota periods. Apart from presenting a graphical kernel representation, we perform analysis of variance (ANOVA) to test differences between group means. As a post hoc test we use the Tukey's honestly significant difference test (HSD) to determine which specific groups are different from each other (Tukey 1949).

2.4 Data and variables

The data source is the Norwegian Farm Accountancy survey, collected by the Norwegian Agricultural Economics Research Institute (NILF). The dataset includes production and economic data at farm level. The data extracted from the database is restricted to specialized dairy producers (more than 60% of the whole farm income is from milk production) of all size categories. Since we use DEA⁸ in the estimation, we identify observations outside the range of four times the standard deviation (+/-) from the mean and remove them together with incomplete observations (Atsbeha 2015). The participation in the survey is voluntary for farmers and there is no limit in the number of years a farm may be involved in the survey. About 10% of the survey farms are replaced each year. The final data set is an unbalanced panel with 16,761 observations for the period 1972-2012. Due to the dynamic setting, this data is balanced (rolling windows) for sequential years (t and $t+1$). As a result of balancing a number of observations are lost. Appendix 2.1 shows the number of remaining observations corresponding to the successive periods.

The primary output is milk, measured in total milk sales (1000 liters), secondary output is an aggregate of beef and other marginal products deflated by the NIBIO/BFJ price index of slaughtered cattle in 2012 price levels. The input set comprises variable input quantities as well as fixed and quasi-fixed input quantities. Variable input quantities are measured by purchased feed costs deflated by the NIBIO/BFJ price index of feed in 2012 price levels; fertilizer cost deflated by using NIBIO/BFJ price index of fertilizer in 2012 price levels; and other variable costs, such as veterinary expenses and contract work, deflated by the consumer price index (CPI) in 2012 price levels. As these are measured in monetary units we construct an aggregate input variable as a simple sum. Some fixed inputs are observed in quantities: labor is composed of family and hired labor work measured in 1000 hours; total land area of the farm or the joint farm (for both owned and rented land) is measured in hectares (ha). Other fixed assets are described by the value of capital which is identified as the end value of previous year (i.e.

⁸ DEA is mighty sensitive to outliers and missing observations.

machinery, houses), deflated by the industrial price index in 2012 price levels. Quasi-fixed costs are associated with the value of gross investment which is, by definition, the change in capital between sequential periods plus the deflated value of depreciation in year $t+1$ (calculated by NILF for the dairy sector for every year). The gross investment is deflated by the CPI in 2012 price levels. All monetary units are measured in 1000 Norwegian Crowns (NOK). Table 2.1 provides the descriptive statistics.

Table 2.1 Descriptive statistics of input-output data

<i>Pre-quota period (1972-1982)</i>					
	Units	Mean	St. dev.	Min	Max
Outputs					
<i>Milk</i>	1000 liter	74.57	37.20	3.07	222.07
<i>Secondary Output</i>	1000 NOK	220.05	164.17	19.81	1579.12
Beef	1000 NOK	112.94	63.80	7.17	546.89
Other output	1000 NOK	107.11	135.20	0.00	1143.46
Inputs					
<i>Variable Inputs</i>	1000 NOK	416.63	211.08	22.51	2009.50
Feed	1000 NOK	116.17	66.80	3.26	469.73
Fertilizer	1000 NOK	45.53	28.12	0.00	220.60
Other variable cost	1000 NOK	254.93	142.89	18.58	1482.96
<i>Fixed inputs</i>					
<i>Labor</i>	1000 hrs	3.81	1.05	1.06	9.73
Family labor	1000 hrs	2.96	0.76	0.20	6.45
Hired labor	1000 hrs	0.85	0.90	0.00	9.15
<i>Land</i>	hectares	14.65	7.26	3.60	47.60
<i>Capital</i>	1000 NOK	711.62	504.63	0.00	4049.37
Quasi-fixed inputs					
<i>Investments</i>	1000 NOK	150.85	203.28	-317.62	2505.28

Chapter 2 Data and variables

Strict quota period (1983-1996)

	Units	Mean	St. dev.	Min	Max
Outputs					
<i>Milk</i>	1000 liter	78.70	31.54	2.69	273.93
<i>Secondary Output</i>	1000 NOK	239.16	162.24	21.28	1519.48
Beef	1000 NOK	151.28	81.41	8.39	656.25
Other output	1000 NOK	87.88	123.36	0.05	1000.52
Inputs					
<i>Variable inputs</i>	1000 NOK	482.71	193.46	47.31	1683.43
Feed	1000 NOK	125.49	63.50	7.36	649.37
Fertilizer	1000 NOK	42.23	22.67	0.06	178.77
Other variable cost	1000 NOK	314.99	134.10	34.34	1028.34
<i>Fixed inputs</i>					
<i>Labor</i>	1000 hrs	3.61	0.90	0.67	8.30
Family labor	1000 hrs	2.79	0.72	0.30	7.00
Hired labor	1000 hrs	0.82	0.63	0.00	4.84
<i>Land</i>	hectares	16.06	6.82	2.80	50.70
<i>Capital</i>	1000 NOK	1118.92	608.24	-10.35	5525.73
<i>Quasi-fixed inputs</i>					
<i>Investments</i>	1000 NOK	117.37	159.33	-269.40	2102.75

Transferable quota period (1997-2012)

	Units	Mean	St. dev.	Min	Max
Outputs					
<i>Milk</i>	1000 liter	105.94	55.03	11.18	483.67
<i>Secondary Output</i>	1000 NOK	317.02	226.86	18.17	2255.35
Beef	1000 NOK	240.51	171.89	14.96	2146.12
Other output	1000 NOK	76.51	108.99	0.00	1204.32
Inputs					
<i>Variable inputs</i>	1000 NOK	712.32	372.15	128.34	4192.62
Feed	1000 NOK	190.29	108.92	8.55	1274.93
Fertilizer	1000 NOK	49.44	30.10	0.00	252.41
Other variable cost	1000 NOK	472.59	262.44	62.50	2893.16
<i>Fixed inputs</i>					
<i>Labor</i>	1000 hrs	3.52	0.91	0.91	7.96

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Family labor	1000 hrs	2.75	0.77	0.00	7.40
Hired labor	1000 hrs	0.77	0.57	0.00	5.17
<i>Land</i>	hectares	26.38	13.43	4.00	104.30
<i>Capital</i>	1000 NOK	1322.53	1000.04	-56.65	11537.26
<i>Quasi-fixed inputs</i>					
<i>Investments</i>	1000 NOK	156.04	388.11	-619.75	8618.19

Source: Norwegian FADN-type database

We calculate the dynamic productivity growth indicator and its components for both technology specifications: multi-input and single-output (SO) and multi-input and multi-output (MO). The multiple input set consists of one aggregate vector of variable costs (including feed, fertilizer, and other variable costs) (1); three fixed inputs including aggregated labor (hired and family) (2), land (3) and capital (4); and one quasi-fixed input of gross investments (5). In case of single-output we consider milk output, in the multi-output specification we employ an additional aggregate vector of total sales of beef plus sales of other outputs.

The descriptive statistics of the variables give an overview of the data that may clarify the production differences about the quota periods. Strict quotas in effect bring solid increase in the average output (78.7 thousand liter) compared to the pre-quota period (74.6 thousand liter), while it strongly increases under the transferable regime (105.9 thousand liter). Similar course is true for the mean variable costs and land use. However, average labor hours (both family and hired) decrease over time which may be a sign of modernization and technological improvement (Flatén 2002). As Figure 2.1 suggests, investment levels are the highest under the transferable quota period, however at period averages it is only slightly higher than the pre-quota levels. The lower level of investment under the restrictive period is in line with the theory of quota, that the dynamics of investments lose momentum under fully binding governmental policy, hence the forces of a competitive market or rivalry for the production rights are eliminated, therefore farm development and renewal is not the primal intention of the farmer.

2.5 Results and discussion

The relatively complex multi-input set and the novel multi-output specification for calculating the dynamic Luenberger index is quite challenging for computing the input-oriented dynamic directional distance functions. The production technology, described by input and output bundles is unitless, meaning that vectors with different measurements can be used. We use five inputs with three different units (hours, hectares and monetary unit in NOK) and in the multi-output case, we use two outputs with two units (liters and monetary unit in NOK). Briec and Kerstens (2009) analyze the precise conditions under which infeasibilities may or may not occur. The argumentation is based on the characteristics of the output set, in particular, focusing on the at least two-dimensional output case. They prove that for any non-zero direction there exists an input output vector such that the direction g is infeasible and argue that more infeasible observations are found under multi-output case than in single-output specification. Furthermore, infeasible directions occur when the output direction vector is null, which is our case since we calculate input-oriented directional distance functions with respect to outputs bound by the quota policies. In this case, at least one input dimension is essential for shaping the technology (here the best practice curve is calculated with DEA). Briec and Kerstens (2009) suggest reporting infeasibilities, so do Kapelko et al. (2015b, 2016) in their empirical applications. Kapelko et al. (2015c) address the investment spikes in different food processing industries (meat and oils- and fats industries) and record dissimilar number of infeasibilities (approximately 2% and 10% of the industry observations, respectively); although in both cases they distinguish one output and three inputs. The most common method for the treatment of infeasibilities in the context of dynamic distance functions based Luenberger indicator is to eliminate these observations from the computation averages. We report the number of feasible results besides the size of the data in details with the calculated shares of infeasibilities for all consecutive years (Appendix 2.1). As expected, we encounter lower shares of infeasible results in the SO case, than in the MO specification. All period shares of infeasible results at average are approximately 11% and 18% for SO and MO cases, respectively.

Table 2.2 presents the arithmetic averages of the dynamic Luenberger productivity indicator (ΔL) and its components of dynamic technical change (ΔT), dynamic technical inefficiency change (ΔTEI) assuming CRS, dynamic technical inefficiency change (ΔPEI) assuming VRS, and dynamic scale inefficiency change (ΔSEI) for the pairs of consecutive years, for the quota specific and overall sample periods for both output specifications. In the interpretation of the results, we focus on the implications of evolving quota policies on productivity and efficiency and on the economic meaning of the differences between the SO and MO cases. In general, with respect to the quota regimes the computed efficiency measures are consistent with our hypotheses on the effects of production quotas under different mobility policies.

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Table 2.2 Dynamic Luenberger Productivity change and its components for successive years and period averages

Years	ΔL (SO)	ΔL (MO)	ΔT (SO)	ΔT (MO)	ΔPEI (SO)	ΔPEI (MO)	ΔSEI (SO)	ΔSEI (MO)	ΔTEI (SO)	ΔTEI (MO)
1972/1973	0.017	0.004	-0.004	-0.016	-0.005	-0.001	0.026	0.021	0.021	0.020
1973/1974	0.016	0.005	0.009	-0.034	0.004	0.020	0.004	0.019	0.008	0.039
1974/1975	0.023	0.031	0.021	0.065	0.000	-0.023	0.002	-0.011	0.002	-0.034
1975/1976	0.008	0.012	0.001	-0.019	0.012	0.021	-0.004	0.010	0.007	0.030
1976/1977	-0.008	-0.002	-0.013	0.003	0.014	0.011	-0.010	-0.016	0.004	-0.005
1977/1978	-0.010	-0.007	0.020	0.007	-0.024	-0.021	-0.006	0.007	-0.030	-0.014
1978/1979	-0.018	-0.038	-0.027	-0.049	0.022	0.020	-0.013	-0.009	0.009	0.011
1979/1980	0.014	0.023	-0.005	0.031	0.017	-0.003	0.002	-0.005	0.019	-0.008
1980/1981	0.012	0.011	0.040	0.013	-0.025	-0.005	-0.002	0.003	-0.027	-0.002
1981/1982	0.013	0.001	0.008	0.013	0.005	-0.005	0.001	-0.008	0.005	-0.012
1982/1983	-0.014	-0.004	-0.033	-0.028	-0.004	0.010	0.022	0.014	0.019	0.024
1983/1984	-0.007	0.007	-0.002	0.022	0.006	-0.016	-0.010	0.001	-0.005	-0.015
1984/1985	-0.022	-0.018	-0.017	-0.009	-0.013	-0.011	0.008	0.001	-0.005	-0.009
1985/1986	-0.005	-0.006	-0.018	-0.038	0.002	0.006	0.011	0.026	0.013	0.032
1986/1987	0.003	0.002	-0.009	0.005	0.002	-0.007	0.009	0.004	0.012	-0.003
1987/1988	-0.021	-0.023	-0.023	-0.037	0.023	0.030	-0.021	-0.017	0.002	0.013
1988/1989	0.015	0.014	0.052	0.046	-0.026	-0.028	-0.012	-0.004	-0.037	-0.032
1989/1990	-0.010	-0.019	-0.069	-0.063	0.036	0.032	0.023	0.013	0.059	0.045
1990/1991	-0.041	-0.031	-0.033	-0.011	-0.024	-0.025	0.016	0.006	-0.008	-0.019
1991/1992	-0.021	-0.016	0.000	-0.015	0.006	0.014	-0.028	-0.015	-0.021	-0.001
1992/1993	0.000	-0.003	-0.010	-0.017	-0.022	-0.006	0.032	0.020	0.010	0.014
1993/1994	-0.013	-0.012	-0.013	0.001	0.002	0.003	-0.003	-0.015	0.000	-0.013
1994/1995	-0.006	-0.005	-0.006	-0.026	-0.010	0.006	0.011	0.014	0.001	0.021
1995/1996	-0.005	0.002	0.037	0.022	-0.009	0.002	-0.033	-0.022	-0.042	-0.020
1996/1997	0.002	0.014	0.034	0.020	-0.013	-0.017	-0.018	0.011	-0.031	-0.006
1997/1998	0.006	-0.004	-0.032	0.005	-0.002	-0.009	0.041	0.000	0.039	-0.009
1998/1999	0.015	0.011	0.035	-0.003	-0.007	0.007	-0.013	0.006	-0.020	0.014
1999/2000	-0.008	0.012	-0.017	0.014	0.016	-0.004	-0.007	0.003	0.009	-0.001
2000/2001	0.002	-0.014	-0.011	-0.023	0.002	0.002	0.011	0.008	0.013	0.009
2001/2002	0.047	0.035	0.074	0.057	-0.015	-0.004	-0.012	-0.018	-0.027	-0.022
2002/2003	0.014	-0.010	-0.011	-0.009	0.023	0.003	0.002	-0.004	0.025	-0.002
2003/2004	0.005	-0.008	0.035	-0.005	-0.026	-0.022	-0.004	0.019	-0.031	-0.003
2004/2005	0.009	0.013	-0.022	0.032	0.022	-0.006	0.009	-0.014	0.031	-0.020
2005/2006	0.016	-0.006	0.014	0.002	-0.007	-0.017	0.009	0.009	0.002	-0.008
2006/2007	0.032	0.028	0.049	0.062	-0.021	-0.027	0.004	-0.007	-0.017	-0.034
2007/2008	-0.005	0.001	0.000	-0.010	-0.008	0.006	0.003	0.005	-0.005	0.011
2008/2009	0.018	0.013	0.054	0.020	-0.006	-0.001	-0.030	-0.006	-0.036	-0.007
2009/2010	-0.004	-0.028	-0.063	-0.074	0.020	0.010	0.038	0.036	0.058	0.046
2010/2011	-0.021	-0.019	0.101	0.022	-0.072	-0.027	-0.049	-0.014	-0.122	-0.041
2011/2012	0.021	0.001	-0.078	-0.036	0.050	0.008	0.049	0.029	0.099	0.037
2012/2013	-0.006	0.005	-0.007	-0.008	-0.011	0.008	0.012	0.005	0.000	0.013
Pre-quota (1972/1982)	0.007	0.004	0.005	0.002	0.002	0.001	0.000	0.001	0.002	0.002
Strict quota (1983/1996)	-0.011	-0.008	-0.010	-0.011	-0.002	0.001	0.002	0.002	0.000	0.003
Transferable (1997/2012)	0.008	0.003	0.009	0.004	-0.003	-0.005	0.003	0.004	-0.001	-0.001
Full sample (1972/2012)	0.002	-0.001	0.002	-0.002	-0.002	-0.002	0.002	0.003	0.000	0.001

Source: own calculation

Under no-quota and tradable quota systems productivity is modestly increasing in the SO case by 0.7% and 0.8%, respectively, and by 0.4% and 0.3% in the MO specification. Under the strict system we compute an annual average productivity decrease of -1.1% (SO) and -0.8% (MO). The dynamic technical change is generally the largest component of the productivity change. This is consistent with the hypothesis that the quota policy primarily affects farmers' investments into new technologies. A relatively small fraction of productivity change can be attributed to the dynamic technical inefficiency change under CRS. This suggests that Norwegian dairy farms are rather homogenous in terms of technical endowments. If we have a closer look at the dynamic scale efficiency change and dynamic technical inefficiency change under VRS, the developments in scale efficiency change is noteworthy. The scale efficiency continuously increases over the full sample on average by 0.2% and 0.3% for SO and MO, respectively, indicating developments of farm sizes. Furthermore, we note that under the quota periods, the increasing scale efficiency is in counteraction to the loss sustained by the dynamic technical inefficiency change under VRS (PEI) which we can see from the very small (mostly zero) TEI results. These aggregated average outcomes are in line with our hypotheses of the quota effects, however for identifying causal effects, one would have to control for other factors.

We illustrate the developments of dynamic productivity indicator in Appendix 2.2 for the pairs of consecutive years to ease the understanding of the differences between the conformation of SO and MO. The productivity indicator is higher in SO than MO for the pre-quota and transferable quota periods. The profit maximizing dairy farms in one way or the other (under market conditions or by purchasing quota) can increase their output levels and keep focus on the production of milk. However, in the strict quota policy period the common way to increase or keep up productivity is shifting the output mix in favor of larger meat output share for the average farm. Therefore, the increase in unconstrained beef production results smaller productivity decrease in the strict period when we consider the change in the output mix by implementing multi-output specification. Kumbhakar et al. (2008) argue similarly and find this process when calculating output growth rates for the period of 1977-2005. Our results confirm the shift in the output

mix for the restrictive regime and the relations between SO and MO productivity measures for the other two periods suggest that farmers rather opt for increasing milk output than beef.

For validating these inferences, we test whether the differences in productivity measures are statistically significantly different between quota periods. We have more than two groups, so instead of a simple t-test we perform one-way ANOVA test and the related post hoc pairwise comparisons of the group means with Tukey's HSD test on dynamic productivity indicator and its components for SO and MO. Appendix 2.3 and 2.4 summarizes the test results. We report the F-statistics (i.e. variation among sample means over the variation within group means) and its significances for the ANOVA and also the differences, the lower and upper bounds at 95% confidence intervals and the P-values for the Tukey test. For the dynamic Luenberger productivity indicator the null hypothesis of the ANOVA-test (group means are equal) is strongly rejected in favor of the alternative that the periods are significantly different, suggesting that the specific quota phases have different impacts on the development of productivity. However, the post hoc tests under both SO and MO, show that difference between the pre-quota and transferable quota systems is not statistically significant. This supports the theory that in case of no strict constraint on output(s), producers show similar productivity behavior. As noted earlier, technical change contributes strongly to the productivity change and consequently we expect similar test results for this component. Both the ANOVA and Tukey-test are significant for all multiple comparisons. This should not be very surprising because it indicates that farmers' decisions purely made on the technology is driven by maximizing utilities under the evolving policy environment. This is reflected in the change of the output mix in the second period when farmers adjust their technology to the new binding regime and later to the increased mobility of production rights. The smaller fraction of productivity change, the differences in dynamic technical inefficiency change under CRS is insignificant for SO but significant for MO. In the MO case, the Tukey test shows only one significant difference between the transferable and strict quota periods validating that farmers' technical inefficiencies increased on average. Testing the group means of the elements of technical inefficiency

change (CRS) is more appealing because it gives evidence to the secondary effect of quota regime implementation in general, with no regard to quota mobility. The significance tests on the dynamic scale efficiency show that its development is positive under the quota system and significantly different from the pre-quota period. This reveals that quota regime assists the progress of structural change to achieve greater cost advantage that arises with increased outputs or shift in the output mix. This conclusion holds for SO and MO as well.

In Appendix 2.5 we draw Kernel density functions for the productivity and efficiency measures for SO and MO to graphically illustrate the differences between the quota periods for the whole distribution of productivity measures.

2.6 Summary and conclusions

To assess productivity differences in the Norwegian dairy sector across time periods with distinct policy regimes, we compute input-oriented dynamic directional distance functions in a consistent dynamic theoretical framework to construct the dynamic Luenberger productivity indicator and its components. The dynamic setting is based on the adjustment-cost model that accounts for the changes in the quasi-fixed inputs and thus incorporates the impact of current production decisions on future production. The observed substantial variation in investments over the considered time period 1972-2013 and the observed relation between investments and output growth render the dynamic approach relevant. An additional empirical contribution of this paper compared to the literature is the calculation of Luenberger productivity and efficiency measures for a multi-output specification in addition to the single-output one.

This study demonstrates a direct link between changing governmental policies and developments of productivity and efficiency. The production environment has significantly different impact on producers' productivity behavior under the distinctive quota periods. We take advantage of the nature of dynamic difference measures of relative efficiency. The

decomposition of dynamic Luenberger productivity indicator to dynamic technical change and dynamic technical efficiency change gives evidence for assessing the structure of productivity change. We conclude that average productivity of Norwegian dairy farmers increases similarly in the pre-quota and transferable quota periods, i.e. when output quantity is not strictly bound. The annual average productivity change is between 0.7-0.8% or 0.3-0.4% with respect to single-output or multi-output calculations for the pre-quota (i.e. pure market conditions) and the transferable quota periods (i.e. increased mobility of quota rights) as well. We explain the similar outcomes by the counterbalance between the developments of investments and technical inefficiency. In the strict quota period, investments stagnate which leads to productivity decrease of 1.1% or 0.8% in SO or MO case, respectively.

We continue by decomposing the dynamic technical inefficiency change (CRS) to dynamic scale inefficiency and technical inefficiency changes (VRS). We find statistically significant difference in scale efficiency between the group means of quota periods and the pre-quota period. It suggests a “secondary” quota effect that under regulated market conditions, scale efficiency increases and thus accelerates the ongoing structural change, the shift from small family-owned businesses to joint dairy farms. We also find that this gain is neutralized by the decrease in technical inefficiency change (VRS).

Finally, we raise the importance of applying multi-output production technology for assessing productivity and efficiency measures in the dairy sector. On one hand, it describes the “true output set” of the technology; on the other hand it is more informative hence inference can be made on the output mix if we compare the outcomes with the single-output specification. We find that the productivity decrease is smaller in the MO case than in the SO case under the strictly binding quota system. This suggests that farmers increase their outputs of (unconstrained) beef.

Even though the analysis provides interesting differences between productivity developments under different dairy policy regimes, it does not establish any causal effect. For future research it would be valuable to target

this direction and try to explain productivity changes by policy regimes while controlling for other drivers of productivity using an extended dataset.

2.7 References

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Appendix 2.5 Number of observations for pairs of consecutive years and occurrence of infeasible results

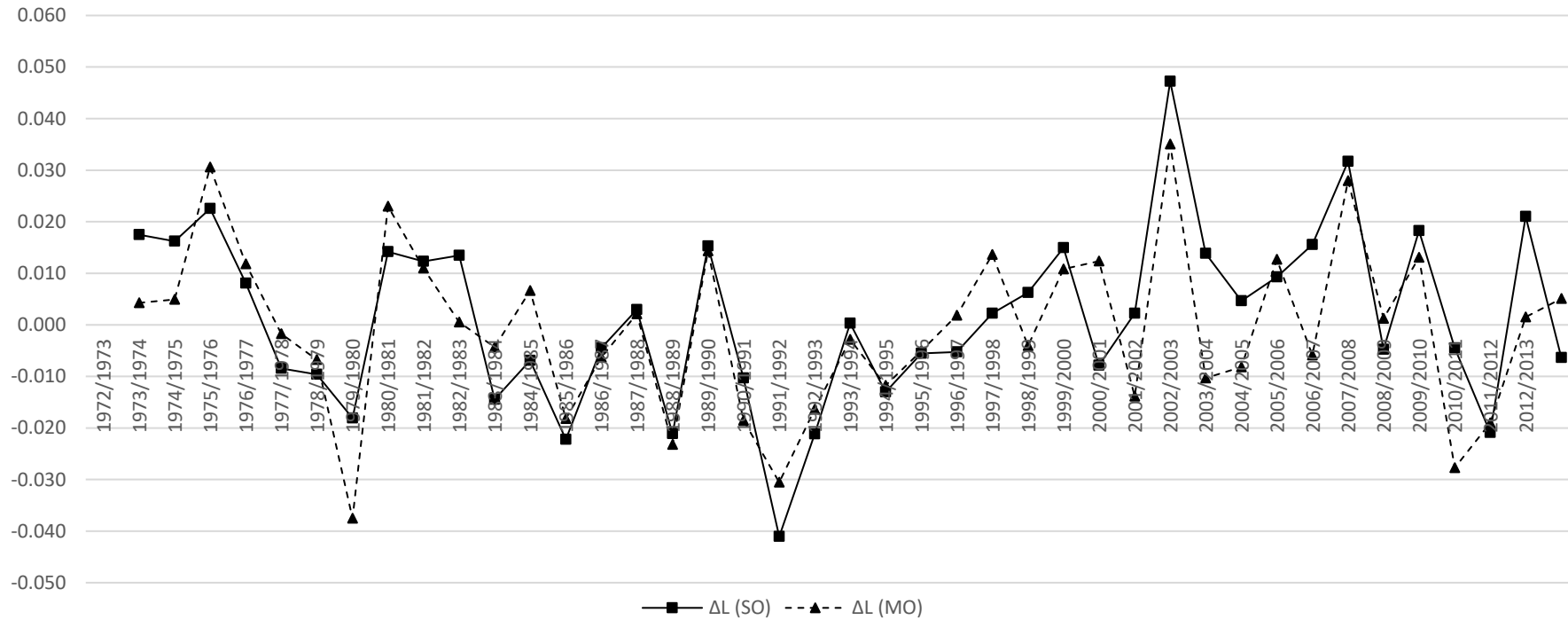
Years	Number of dairy farms	Number of feasible results, SO	Infeasibility (in %), SO	Number of feasible results, MO	Infeasibility (in %), MO
1972/1973	349	315	9.74	277	20.63
1973/1974	346	313	9.54	275	20.52
1974/1975	356	305	14.33	263	26.12
1975/1976	400	342	14.50	312	22.00
1976/1977	461	386	16.27	355	22.99
1977/1978	511	456	10.76	414	18.98
1978/1979	536	452	15.67	446	16.79
1979/1980	533	451	15.38	419	21.39
1980/1981	527	468	11.20	441	16.32
1981/1982	534	475	11.05	445	16.67
1982/1983	474	449	5.27	425	10.34
1983/1984	493	474	3.85	438	11.16
1984/1985	505	453	10.30	423	16.24
1985/1986	487	447	8.21	413	15.20
1986/1987	483	435	9.94	406	15.94
1987/1988	514	425	17.32	385	25.10
1988/1989	519	454	12.52	425	18.11
1989/1990	504	455	9.72	434	13.89
1990/1991	501	447	10.78	417	16.77
1991/1992	483	390	19.25	406	15.94
1992/1993	461	427	7.38	405	12.15
1993/1994	465	419	9.89	401	13.76
1994/1995	453	407	10.15	389	14.13
1995/1996	435	388	10.80	355	18.39
1996/1997	412	379	8.01	339	17.72
1997/1998	399	366	8.27	328	17.79
1998/1999	360	330	8.33	299	16.94
1999/2000	344	300	12.79	269	21.80
2000/2001	328	288	12.20	263	19.82
2001/2002	335	310	7.46	274	18.21

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2002/2003	325	285	12.31	256	21.23
2003/2004	308	264	14.29	239	22.40
2004/2005	305	270	11.48	246	19.34
2005/2006	289	262	9.34	239	17.30
2006/2007	279	254	8.96	234	16.13
2007/2008	278	255	8.27	235	15.47
2008/2009	278	251	9.71	235	15.47
2009/2010	285	236	17.19	208	27.02
2010/2011	288	257	10.76	234	18.75
2011/2012	309	284	8.09	260	15.86
2012/2013	309	275	11.00	245	20.71
<hr/>					
Pre-Quota	4553				
Stirct-Quota	6777	Max	19.25		27.02
Transferable- Quota	5019	Min	3.85		10.34
<hr/>					
Full Sample	16761	Mean	11.03		18.09
<hr/>					

Source: own calculation, FADN-type database

Appendix 2.6 Evolution of productivity over the period of 1972-2012 with respect to single-output and multi-output specification



Source: own calculation

Appendix 2.10 Single Output summary table of the ANOVA and Tukey HSD test results

		F-value	Difference	Lower	Upper	P-value
ΔL	ANOVA	63,69				0,0000
	Strict-Pre		-0,0161	-0,0205	-0,0116	0,0000
	Transferable-Pre		0,0028	-0,0018	0,0075	0,3220
	Transferable-Strict		0,0189	0,0147	0,0231	0,0000
ΔT	ANOVA	282,06				0,0000
	Strict-Pre		-0,0158	-0,0180	-0,0137	0,0000
	Transferable-Pre		0,0038	0,0016	0,0061	0,0002
	Transferable-Strict		0,0197	0,0176	0,0217	0,0000
ΔPEI	ANOVA	3,64				0,0263
	Strict-Pre		-0,0040	-0,0082	0,0003	0,0706
	Transferable-Pre		-0,0047	-0,0091	-0,0004	0,0303
	Transferable-Strict		-0,0007	-0,0047	0,0033	0,8996
ΔSEI	ANOVA	7,47				0,0005
	Strict-Pre		0,0038	0,0012	0,0063	0,0014
	Transferable-Pre		0,0038	0,0011	0,0064	0,0022
	Transferable-Strict		0,0000	-0,0024	0,0024	0,9999
ΔTEI	ANOVA	0,12				0,8858
	Strict-Pre		-0,0002	-0,0051	0,0046	0,9942
	Transferable-Pre		-0,0010	-0,0060	0,0040	0,8924
	Transferable-Strict		-0,0008	-0,0053	0,0038	0,9203

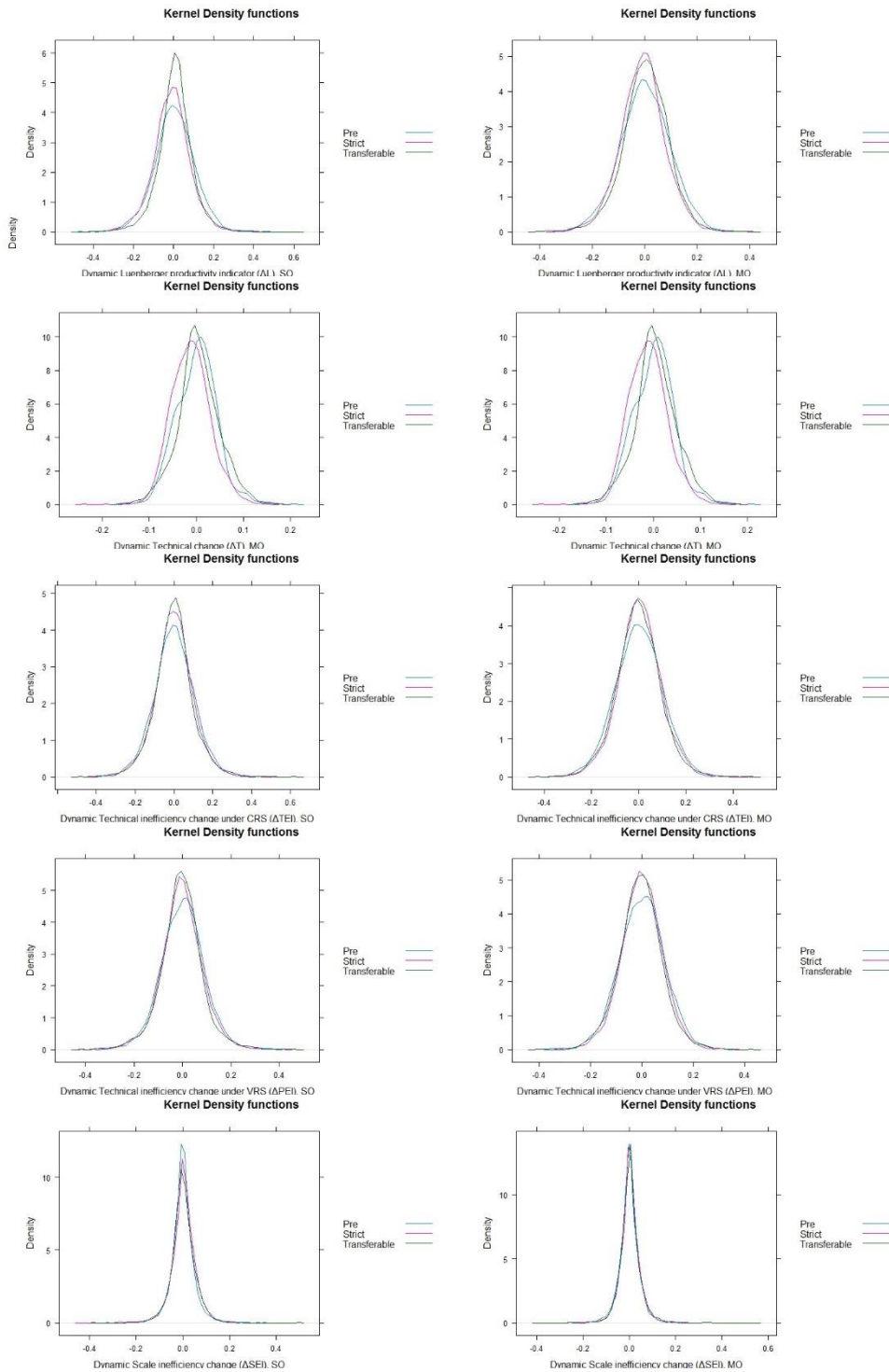
Source: own calculation

Appendix 2.11 Multiple Output summary table of the ANOVA and Tukey HSD test result

		F-value	Difference	Lower	Upper	P-value
ΔL	ANOVA	22,85				0,0000
	Strict-Pre		-0,0101	-0,0146	-0,0057	0,0000
	Transferable-Pre		0,0008	-0,0038	0,0055	0,9115
	Transferable-Strict		0,0110	0,0067	0,0152	0,0000
ΔT	ANOVA	195,33				0,0000
	Strict-Pre		-0,0129	-0,0150	-0,0107	0,0000
	Transferable-Pre		0,0034	0,0011	0,0056	0,0013
	Transferable-Strict		0,0163	0,0142	0,0183	0,0000
ΔPEI	ANOVA	7,63				0,0005
	Strict-Pre		-0,0007	-0,0049	0,0035	0,9205
	Transferable-Pre		-0,0064	-0,0108	-0,0020	0,0018
	Transferable-Strict		-0,0057	-0,0097	-0,0017	0,0024
ΔSEI	ANOVA	9,44				0,0000
	Strict-Pre		0,0034	0,0013	0,0056	0,0006
	Transferable-Pre		0,0039	0,0016	0,0061	0,0002
	Transferable-Strict		0,0004	-0,0016	0,0025	0,8837
ΔTEI	ANOVA	3,84				0,0214
	Strict-Pre		0,0027	-0,0020	0,0075	0,3644
	Transferable-Pre		-0,0026	-0,0075	0,0024	0,4438
	Transferable-Strict		-0,0053	-0,0098	-0,0008	0,0156

Source: own calculation

Appendix 2.12 Kernel density plots of L, T, TEI, PEI and SEI for SO and MO



Source: own calculation

Chapter 3

The Case of Organic Dairy Conversion in Norway: Assessment of Multivariate Neighborhood Effects⁹

Abstract: This study examines the impact of neighbourhood effects and individual farm characteristics on the decision process of organic dairy conversion in Norway, using a unique, spatially explicit farm-level panel set comprising information at the population level from 2003 to 2015. Our results reveal a positive spatial spillover of neighbouring conversion, confirming previous findings. Additionally, we demonstrate that neighbouring organic dairy reversion (i.e. switching back to conventional dairy farming) and organic dairy exits (ceasing to farm altogether) exert notable negative spatial spillovers on organic conversion decisions which have not yet been shown in the literature. If organic dairy production is an important policy goal, such negative spatial spillover requires consideration within policy design and extension.

Keywords: organic dairy conversion, multivariate neighborhood effect, spatial endogeneity, correlated random effect model, Mundlak-Chamberlain device

JEL classification codes: Q15, Q18, Q24

⁹ This chapter is published as Marton TA, Storm H. 2021 The Case of Organic Dairy Conversion in Norway: Assessment of Multivariate Neighbourhood Dffects. Q Open 1.1 (2021): qoab009.

DOI: 10.1093/qopen/qoab009

3.1 Introduction

In several countries, policymakers are taking action to promote the adoption of organic farming practices as one way to reduce the environmental impacts of farming in addition to addressing growing consumer concerns regarding food safety and health. The example considered in this study is Norway, where policymakers set ambitious goals for the promotion of organic farming, offering a range of subsidies to support conversion. Although the area of organic land and organic farm management has increased in Norway since the beginning of the millennium (Flaten and Lien, 2006; Røsnes, 2010; Norwegian Ministry of Agriculture and Food, 2010), the goal of the government to increase organic production and consumption from 0.5% in 2005 to 15% by 2020 (Norwegian Ministry of Agriculture and Food, 2009) has fallen far short of this goal. In 2018, only 2.2% of the entire food market was organic, and only 4.4% of the total agricultural area was directly under organic cultivation (Landbruksdirektoratet, 2018). Achieving these ambitious goals requires a more effective policy design to promote the adoption of organic farming practices. We should enhance our understanding of farmers' motives, reservations, and goals in terms of organic production to develop more informed policy approaches.

Existing research studies describe organic conversions from different perspectives, encapsulating it as a problem of optimal timing with an uncertain investment that incurs sunk costs (Musshoff and Hirschauer, 2008), analysing the role of moral and social considerations (Mzoughi, 2011). Further studies assume that potential adopters make a discrete choice based on the possibility of maximisation of expected utility subject to prices, profits and inputs, devoting elevated importance to economic and financial concerns (Koesling et al., 2008; Lewis et al., 2011). Some studies categorise farms according to their characteristics (e.g. farmers' attitudes, age, herd and land sizes, natural resource assets or risk deliberation) (Läppe and van Rensburg, 2011; Läppe and Kelley, 2013), explaining the choice of conversion through individual farm characteristics. Despite the broad range of concepts and approaches in the literature, there is a common understanding regarding the importance of physical localisation and

neighbourhood settings as influential to the emergence of organic hubs (i.e. a high density of organic farms in a small region).

Compelling attempts have been made to identify the influence of location factors in the development of organic hubs that are underpinned by the economic and social concept of the ‘neighbourhood effect’ (Lewis et al., 2011; Gosme et al., 2012; Bjørkhaug and Blekesaune, 2013; Wollni and Andersson, 2014). The conceptual framework is based on the hypothesis that organic farming neighbours or closely spatially related farms can help reduce the uncertainty of organic conversion by lowering the fixed costs of learning about the organic system (Lewis et al., 2011), increasing the probability of conversion to organic farming. Knowledge transfer regarding organic technology development and joint input purchase may further reduce barriers to conversion. Hence, co-operation in general leads to a smoother gateway to the supply chain.

One limitation of existing theory and empirical studies on the neighbourhood effect is that only positive external spatial effects have been covered (e.g. Lewis et al., 2011). In this study, we argue that negative external effects can be similarly influential on farmers’ conversion decisions. Neighbouring farmers’ reversion from organic to conventional farming¹⁰ or neighbouring organic farmers’ exiting farming altogether could serve as a negative example that potentially reduces the likelihood of conversion. Here similar mechanisms of the neighbourhood effect can be expected to act correspondingly to positive external effect. Those negative occurrences could provide knowledge about the disadvantages and challenges of organic production or lead to a weakening of supply chain access in the local neighbourhood.

To our knowledge, this potential deterrence to organic conversion has not yet been studied. For policymakers and extension services that seek to promote the adoption of organic farming, the role of negative examples must be understood to design the right policy strategies and set achievable goals. With the establishment of only positive externality policies, extension

¹⁰ Reversion: An organic producer at time t transforms to conventional technology at $t+1$. This is a technical designation of continuing as a conventional farm.

services solely focus on promoting conversion by as many farms as possible, irrespective of how many revert at a later stage. However, the existence of potentially negative externalities warrants a more selective approach to the promotion of organic conversion by only farms that have a low likelihood of reversion. Additionally, this approach would justify additional effort and support concentrating on keeping farms within organic production, rather than only focusing on the promotion of adoption as the primary goal.

Although the question of the role of negative examples is relevant more broadly, we restrict our study to Norway and specifically to dairy production as one of the most prominent agricultural activities in Norway. In this case, we can use a unique yearly panel dataset covering the period from 2002 to 2015. The data set covers (almost)¹¹ all farms in Norway, furnishing information about farmers' conversion decisions as well as the geographic location of each farm. Using an econometric panel model, we aim to explain the binary decision of whether a conventional dairy farm converts to organic farming during the observation period from 2002 to 2015. To account for neighbour interaction, we leverage the geographic information in the data to derive assorted variables describing conversion, reversion and exit of neighbouring farmers.

The remainder of the paper is structured into five sections: Section 2 introduces the natural and economic environment for dairy production in Norway; Section 3 details the adopted and extended theory; and Section 4 presents the data, the applied method, and the potential endogeneity issues. Finally, Section 5 discusses the results, and Section 6 concludes and highlights the policy-relevant findings.

¹¹ Excluding only very small farms that do not qualify for any farm subsidies.

3.2 Norwegian Case

Norwegian agriculture is characterised by unfavourable natural conditions¹² but enjoys great social and governmental appreciation and support. In 2010, the utilised agricultural area (UAA) was approximately 3.1% of the territory of the country (Eurostat, 2019), measuring about 1 million hectares; one of the smallest ratios within the European Economic Area. Weather conditions, coupled with the peculiar morphology of the territory, limit agricultural production. In 2010, the most common holdings specialise in sheep, goats and other grazing livestock (27%) and dairy (18%), and the rest are specialist cereals, oilseed and protein crops, general field cropping, specialist cattle-rearing and fattening of the total population of farms (Eurostat, 2012). In terms of economic size units, or the sum of the standard outputs (SO) per hectare of crop and per head of livestock, dairy is the most prominent subsector, accounting for 30% of the SO of all Norwegian farms in 2010 (Eurostat, 2012).

Agricultural policy endeavours to promote a diversified agricultural sector delivering a ‘multifunctional agriculture’ (Potter and Tilzey, 2007; Bjørkhaug and Richards, 2008; Forbord et al., 2014). Another goal is to maintain family farming identities (Forbord et al., 2014) and ensure that the current UAA is sustained. To achieve these objectives, government support for agriculture is significantly higher in Norway than in the EU (OECD, 2017).

Policies targeting organic agriculture came into effect in 2002 and have been renewed several times with an increase in payment rates¹³ and organic conversion grants to encourage farmers to convert to organic production. In 2005, the long-term strategic plan adopted by the government sought to increase organic production and consumption from 0.5% to 15% of overall

¹² Norway is one of the northernmost countries of the globe (58–71° latitude) covering oceanic and continental type of climates. The grazing season varies from three to nearly 6 months. In the southern regions, the grazing season runs from May to October, whereas further north, it is shorter, from mid-June to mid-September.

¹³ Revised in 2007, 2010, 2012, 2013 and 2015.

production and consumption by 2015. That ambition was somewhat reduced in 2009, projecting this desired level by 2020 (Norwegian Ministry of Agriculture and Food, 2009). Organic farming incurs more costs than conventional farming attributable to increased labour intensity, the prohibition of mineral fertiliser and non-organic plant protection and the use of specific technological settings (Flaten et al., 2005). To compensate for these additional costs, organic farms receive significantly higher financial support than conventional producers.

Norwegian agricultural policy divides the country into seven agricultural subsidy zones because of the major differences in longitudinal production conditions. For the organic livestock subsidy, including dairy cows, suckling cows and other cattle, the organic bonus rates vary between regions, with the northern zones receiving more financial support than the southern zones until 2015. For instance, the organic premium for dairy cows in 2003 was 880 NOK¹⁴ in the north and 630 NOK in the south on top of the average 2500 NOK per animal for conventional dairy cows.¹⁵ The geographic differences in such organic bonuses adjusted from almost 30% in 2003 to no difference in 2015. The same trend can be observed for the subsidy adjustments of suckling cows and other cattle. Moreover, organic dairy farmers receive not only livestock-based subsidies but also regional payments. Payments are provided to arable land, including cultivated pastures, corn, potatoes, green manure production and other ecological driven land use, the rates of which are not differentiated by region.

Flaten et al. (2006) explored the conversion motives of individual Norwegian dairy farmers and joint dairy farmers¹⁶ by the year of

¹⁴ NOK: Currency of Norway. 1 USD \approx 9 NOK.

¹⁵ The exact rate of conventional dairy subsidy may differ according to herd size.

¹⁶ Joint dairy farmers merge their dairy cow herds and share the workload, and the joint dairy production activity is regarded as a single farm with respect to payment eligibility and rules.

conversion,¹⁷ finding evidence that improved food quality and potential professional challenges of organic adoption are the most frequently cited reasons for all groups (early, mid, and late converters). Furthermore, the motivational force of income stability was cited as the least decisive motive. In Norway, since the 1990s, off-farm income generation has rapidly increased (Fleming and Lien, 2009), and dairy farming is generally a secondary engagement for most Norwegian dairy farmers. This explains the numerous cases of ‘hobby’ farms featuring rather small herds. These findings indicate that any analysis from a strictly economic perspective—e.g. coupling potential positive net value to organic conversion—should be expected to have only limited explanatory power in Norway. This dichotomy coincides with Lund and Algers’ (2003) description of Norwegian organic farmers’ motivations consistently being viewed as idealistic and reaching beyond financial concerns.

According to the Norwegian Agriculture Agency (Landbruksdirektoratet, 2018), in 2018, 2.2% of the entire food market was organic, and only 4.4% of the total agricultural area was registered organic. In the same year, the share of organic milk was up to 3.4% of total milk production, whereas Norwegian organic meat production was almost 1%. The government’s ambition of increasing organic production up to 15% by 2020 has remained unsuccessful, despite a massive increase in organic livestock and subsidy payments. In June 2018, Norway announced a new national strategy to promote organic farming until 2030. Support for organic farming has remained constant since 2014, but the organic conversion grants were phased out beginning in 2010 and eliminated altogether in 2016. The government’s justification for terminating organic conversion grants was to advance the simplification of the support scheme for organic farmers (Pekala, 2019).

¹⁷ Flaten et al. (2006) elaborated a questionnaire survey among Norwegian dairy farmers and outlined ten motives for organic conversion: food quality; professional challenges; soil fertility and pollution problems; ideology and philosophy; health risks (pesticides, etc); animal welfare; profitability; organic farming payments; natural conditions (soil, climate, etc) and income stability.

In our observation period (2002–2015), the number of all dairy farms decreased by almost 60%, but the number of operating organic dairy farms increased by 45% (Table 3.1). The general annual statistics demonstrate that the Norwegian dairy sector declined, losing almost 60% of its milk producers between 2003 and 2015. This decrease was a result of the reversion of previous organic dairy farms to conventional dairy farms, which is beyond the scope of this paper. Our focus remains on the aspects of neighbouring conformity in operating organic dairy farms (ΣODF in Table 3.1), which increases in the first 3 years, then stagnates until 2011 and later significantly decreases. The first organic policy boost in 2002 results in 172 newly registered organic dairy farms by 2003. This development appears to be the largest over the examined years. During the stagnation, organic entries and organic reversions remain at about the same pace. However, from 2012, the number of farms converting from conventional farming to organic (ΣEDF) is only a single digit, whereas the sum of organic reversals ($\Sigma RDF + \Sigma ExDF$, in Table 3.1) is approximately 20 farms annually. Considering the subsequent organic policy developments, in 2010, 2012 and 2013, the number of newly established organic dairy farms is even lower at the post-policy period than prior. Therefore, the first organic governmental intervention seems to have been successful, whereas additional increases to the organic payment rates do not appear to motivate organic conversion.

Table 3.1 Annual conformation of the Norwegian Dairy Industry

Years	Number of dairy farms (ΣDF)	Number of operating organic dairy farms (ΣODF)	Number of organic entries (ΣEDF)	Number of organic reversions (ΣRDF)	Number of organic exits ($\Sigma ExDF$)
2002	18782	185	-	3	3
2003	17521	179	172	24	20
2004	16673	307	37	17	22
2005	15948	305	28	13	23
2006	14556	297	24	15	23
2007	13545	283	30	10	16
2008	12725	287	39	9	10

2009	11751	307	35	6	15
2010	11022	321	34	13	13
2011	10424	329	19	10	24
2012	9761	314	7	5	12
2013	9250	304	8	12	10
2014	8817	290	2	10	15
2015	8310	267	7	-	-

Source: own calculation based on Norwegian Agricultural Authority, 2016

3.3 Theory

One theoretical explanation of emerging business trends is often tied to the patterns of the physical localisation of decision-makers; therefore, analysing the influence of regional proximity within the course of micro-behavioural decision factors and the possible inferences between spatially corresponding units is one of the core interests of agriculture and resource economics literature (Bockstael 1996; Weiss 1996; Nelson and Hallerstein 1997; Brock and Durlauf 2001, 2007; Anselin 2001, 2002). Explicitly including the neighbourhood effect in quantifying the social determinants of conversion decisions incorporates the concepts of social learning (Conley and Udry 2010), spatial spillover and landscape development (Irwin and Bockstael 2002). Consequently, spatial processes can be assumed to have a strong influence on farmers' organic conversion decision. We adopt the theoretical concept of developing neighbourhood relations, relying on the assumption that formerly converted neighbours may be instrumental in swaying the decision of potential converters by reducing the fixed cost of learning and risk, contributing to advanced supply level and in enhancing the competitiveness of the sector. Technology adoption literature explores the causes and effects of wide technological distribution in terms of economic and physical environments, individual characteristics, production uncertainty and spatial spillover (e.g. Lindner 1980; Feder and O'Mara 1982; Tsur et al. 1990; Adesina and Baidu-Forson 1995; Purvis et al. 1995; Koundouri et al. 2006; Oliveira and Martins 2011). For example, major road networks or locally favourable production conditions may both contribute to

spatially clustered behaviour. Economic units may be spatially dependent, as locational attributes influence each other and thus tend to share similar attributes (Goodchild 1992; Moffitt 2001). Lewis et al. (2011) examine spatial spillovers of organic dairy farming in southwestern Wisconsin and determine that the presence of neighbouring organic dairy farms is a statistically and economically significant explanatory measure in the decision to convert. They identify a nonlinear relationship in organic conversion between the number of initial organic farms and the expected number of new conversions that drive the clustered technology diffusion process.

Our key hypothesis in this context is that such diffusion processes are influential in two directions. In previous literature, it is primarily considered that new conversions lead to positive externalities (Lamine and Bellon, 2009; Geniaux et al., 2011; Bouttes et al., 2019). In this study, we hypothesise that reversions (or exits of organic farms) can exert similar negative externalities; an aspect that has not yet been considered in the literature to our knowledge. As shown in Table 3.1, those reversions and exits imply comparatively large relevance in the Norwegian case, yielding a noteworthy study case. The theoretical motivation of including proxies for bad examples assumes that people may learn from others' mistakes. We hypothesise that such negative examples serve to increase information uncertainty regarding the hurdles and difficulties of organic production, weakening local clusters in terms of the connections to upstream and downstream industries and the possibilities for local knowledge exchange. Overall negative examples are assumed to mirror the positive effects associated with a successful conversion to organic farming.

In our empirical approach, we endeavour to model farmers' decision quandary on whether to convert a conventional dairy farm to organic dairy at time t . We jointly incorporate the effects of positive and negative neighbourhood examples explicitly. For this, we derive the following determinants for each farm at time t :

- i. the number of neighbouring organic farms (which serve as a proxy of good examples);

- ii. the number of neighbouring reverting farms at $t-1$ (which represent bad examples from the organic viewpoint);
- iii. the number of neighbouring organic dairy exits at $t-1$ (which represent bad examples and assimilate a meaning of redundant milk production).

The actual numbers of multivariate neighbour vectors depend on the definition of the radius surrounding each individual farm. Defining this radius is relatively arbitrary and can hardly be based on precise information or theoretical knowledge. We intend to keep the focus on face-to-face information transfer, which assumes close proximity and personal discussions about the technology. For this reason, we calculate two small radii within 3 and 5 km. There are collateral arguments for determining two seemingly similar ranges: (i) the coefficients under different radius settings are comparable; (ii) and opens an opportunity for a potential robustness check on the model outcomes.

The applied econometric model is a reduced form discrete choice panel data model with binary probit link to explain the probability of organic dairy conversion. The 13-year dataset creates unbalanced panels of repeated observations of farm-level decisions.

3.4 Data, Method and Endogeneity issues

3.4.1 Data

As noted, our analysis is based on a Norwegian dataset that is unique for two reasons: first, direct payments (DP) are available for virtually any type of crop and animal; second, the Information Act requires full transparency of all beneficiaries of government spending. Hence, the amount of agricultural land used, herd size and farmers' age are made publicly available for each farm that receives DP. Additionally, geographic information, which is administered by the Norwegian Agriculture Authority, is available for research purposes. The data used in this application is therefore a unique georeferenced farm-level population set of Norwegian dairy holdings that

received DP. The 14-year unbalanced panel construction includes more than 179 thousand observations including the annual contributions of 55 thousand dairy farms. We record approximately 4 thousand organic dairy farms in the observed period.

On the basis of the geographic information of each farmstead, we calculate the kilometer distances between the dairies, labelling each dairy farms as either conventional, organic, reverting or exiting in each year, to allow the determination of the dynamic neighbourhood synthesis of individual farms. In this manner, we derive the number of organic, reverting and exiting farms around each conventional dairy (i.e. potential organic convertor) within 3 and 5 km radii.¹⁸ Organic certification is awarded by a Norwegian certifying agency after fulfilling 3-year certification standards for land and 1-year certification standards for a dairy herd. In the estimation, we consider the year that the conversion decision is made and not the certification date. Reversion from organic to conventional is easily identified in the dataset as farms that no longer receive the additional payments for organic production. Table 3.2 presents the summary statistics of the neighbour variables within 3 and 5 km radii.

Additionally, farm characteristics such as herd size, cultivated area and farmers' age are also available. Table 3.3 presents the summary statistics of those variables for organic dairy farms. The mean of organic herd size and land is continuously increasing. Both measures nearly doubled over the examination period. However, the slowly increasing but later constant number of organic cows illustrates the lack of organic breakthrough in the Norwegian dairy industry

¹⁸ Commonly, the measure of the radius is arbitrarily determined in the scientific literature. Our motivation in establishing a rather small radius is to reflect the real surrounding neighbours, which may in fact play a significant role in the information flow (Storm et al. 2015).

Table 3.2 Summary statistics of Independent Variables

Years	Number of organic neighbours within 3 km radius				Number of organic neighbours within 5 km radius				Number of reversions within 3 km radius				Number of reversions within 5 km radius				Number of organic exits within 3 km radius				Number of organic exits within 5 km radius			
	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max
2003	0	0.086	0.33	5	0	0.169	0.50	5	0	0.001	0.02	1	0	0.002	0.04	1	0	0.001	0.03	1	0	0.002	0.04	1
2004	0	0.177	0.47	5	0	0.334	0.71	7	0	0.023	0.15	1	0	0.036	0.18	2	0	0.006	0.08	1	0	0.013	0.11	1
2005	0	0.194	0.51	5	0	0.356	0.73	6	0	0.006	0.07	1	0	0.010	0.09	1	0	0.009	0.09	1	0	0.021	0.14	1
2006	0	0.170	0.47	4	0	0.332	0.72	6	0	0.009	0.09	1	0	0.015	0.12	1	0	0.011	0.13	3	0	0.020	0.17	3
2007	0	0.163	0.46	4	0	0.318	0.71	6	0	0.011	0.10	1	0	0.019	0.13	1	0	0.010	0.14	5	0	0.022	0.23	5
2008	0	0.169	0.48	5	0	0.328	0.72	6	0	0.005	0.07	1	0	0.013	0.11	1	0	0.008	0.09	1	0	0.018	0.13	2
2009	0	0.189	0.52	5	0	0.365	0.79	7	0	0.004	0.06	1	0	0.007	0.08	1	0	0.005	0.06	1	0	0.010	0.10	1
2010	0	0.203	0.55	6	0	0.393	0.83	7	0	0.003	0.05	1	0	0.004	0.06	1	0	0.009	0.11	4	0	0.016	0.16	4
2011	0	0.202	0.56	6	0	0.385	0.84	8	0	0.012	0.10	1	0	0.023	0.14	1	0	0.005	0.07	1	0	0.010	0.10	1
2012	0	0.187	0.52	4	0	0.354	0.77	8	0	0.006	0.07	1	0	0.015	0.12	1	0	0.013	0.12	2	0	0.030	0.18	2
2013	0	0.178	0.49	4	0	0.338	0.73	7	0	0.002	0.04	1	0	0.004	0.06	1	0	0.015	0.12	1	0	0.030	0.17	1
2014	0	0.175	0.48	4	0	0.341	0.73	7	0	0.008	0.09	2	0	0.012	0.11	2	0	0.005	0.06	1	0	0.008	0.08	1
2015	0	0.159	0.45	4	0	0.306	0.68	6	0	0.009	0.09	1	0	0.021	0.14	1	0	0.008	0.09	2	0	0.015	0.14	2

Source: Norwegian Dairy Population Data 2003-2015 (NIBIO).

Table 3.3 Summary statistics of Individual Characteristics of organic dairy farms

Years	Farmer's Age				Number of Organic Cows				Number of Utilized Organic Land in daa			
	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max
2003	16	47.34	10.40	86	0.5	15.33	7.36	143	0	19.89	74.35	2017
2004	17	47.71	10.25	89	0.5	15.72	7.60	140	0	21.08	80.04	1988
2005	18	47.98	10.21	90	0.5	15.83	7.66	145	0	21.47	81.38	2058
2006	19	48.25	10.12	90	0.5	16.44	8.26	152	0	21.12	80.99	2065
2007	20	48.44	10.05	87	0.3	17.00	8.73	141	0	21.27	84.03	2010
2008	19	48.91	10.01	88	0.5	17.70	9.60	136	0	21.20	85.13	1749
2009	19	49.29	10.04	88	0.5	18.12	9.88	121	0	22.49	89.79	2193
2010	20	49.59	10.06	89	0.5	18.95	10.42	113	0	23.19	92.18	2319
2011	19	49.83	10.10	87	0.5	19.61	10.98	117	0	23.48	99.35	2550
2012	19	49.94	10.17	89	0.5	20.59	11.82	121	0	23.69	102.29	2501
2013	19	50.21	10.26	90	0.5	21.52	12.44	132	0	22.46	103.04	2340
2014	19	50.08	10.33	91	0.5	21.94	12.77	128	0	22.89	105.43	2544
2015	20	50.18	10.33	92	0.5	23.39	13.87	124	0	23.64	107.61	2850

Source: Norwegian Dairy Population Data 2003-2015 (NIBIO).

3.4.2 Method

Organic dairy conversion is assumed to be conditional on farm characteristics and on quantified neighbourhood relations. We encode the latter as categorical variables with five levels (0, 1, 2, 3, 4 or more than 4 neighbours) for the number of neighbouring organic farms and neighbouring organic exits and three levels (0, 1, 2 or more than 2) for the number of neighbouring organic reversion. The groups are determined according to the actual number of differentiated neighbours.¹⁹ With the grouped parameter setting, we may correlate the regressors independently and thus hypothesise that

1. as the number of organic neighbours increases, the probability of organic conversion increases;
2. as the number of organic reversions and exiting organic farms increases, the probability of organic conversion decreases.

The response variable is $y_{nt} = 0$ in case a conventional farm n remains conventional in t and $y_{nt} = 1$ in case farm n converts from conventional to organic in time t . We use a probit panel model to estimate the probability of conversion conditional on farm characteristics and neighbourhood affiliations as follows:

$$Pr(y_{nt} = 1 | x_n, ORE_{nt}, z_t, z_r, z_{t \times r}, c_n) = \Phi(x_n' \beta + ORE_{nt}' \delta + z_t' \alpha + z_r' \varphi + z_{t \times r}' \gamma + c_n),$$

$$t = 1, \dots, T; r = 1, \dots, 7 \quad (3)$$

¹⁹ The number of individuals surrounded by more than four neighbours is insufficiently small (i.e. lack of frequency); therefore, we assign a joint group for limited individuals collectively. The same applies to creating three categorical levels for reversions instead of five.

where the conditional expectation x_n is a set of vectors of individual characteristics (herd and land sizes and farmers' age²⁰); ORE_{nt} ²¹ is the set of factor variables of organic neighbours, organic reversions and organic exits surrounding farm n at time t . z_t is a vector of period t -specific dummy variables, which is assumed to absorb all period-specific shocks, e.g. policy change at the major organic milk processor company that are the same for all farms; z_r is a vector of region r -specific dummy variables that capture time-invariant regional differences in the conditions for organic production. The regional dummies are identical to the agricultural subsidy zones. Moreover, the interaction terms between regional dummies and year-specific dummy variables are included to control for time-varying effects that are the same for all farms in one region. Finally, c_n denotes the unobserved effect, which is restricted in the applied correlated random effect framework and appears additively inside the standard normal cdf (Papke and Wooldridge, 2008). The inclusion of regional and time fixed effect as well as interaction effects is intended to control for potential endogeneity. The specific identification approach is discussed in the next section.

The applied econometric model is subject to the binary decision of whether a conventional dairy farm converts to organic, where the decision is observed and monitored each year over a 14-year period. The established panel dataset happens to be unbalanced (i.e. differing in the number of observations between groups) because of continuous entries and exits. Therefore, the estimation method has to be shaped for unbalanced panel setting. We follow the technical innovation of Papke and Wooldridge (2008) and use maximum likelihood estimation without the Gaussian quadrature as a pooled probit with bootstrapped standard errors by resampling the cross-sectional units. We use 500 bootstrap replications on the individuals to obtain the bootstrapped cluster-robust standard errors. This treatment of the

²⁰ Farmers' age is considered as a proxy of experience and potential risk-taking capacity. Age can be an important source of farm characteristics, as we hypothesise that the willingness to convert to organic farming is higher for younger farmers who are expected to be more open to adopting new technologies (Flaten et al., 2006).

²¹ ORE is our abbreviation for Organic, Reverting and Exiting organic neighbours.

standard error allows robust inference to any form of heteroscedasticity or temporal correlation across years for each farm (Cameron and Trivedi, 2005; Cameron et al., 2008; Lewis et al., 2011). The theoretical and methodological obstacle of accurately including the effect of social interactions is discussed in detail in the following.

3.4.3 The Endogeneity Issue

We endeavour to identify the effects of neighbouring behaviour on the decision of organic conversion, differentiating between positive and negative examples in the neighbourhood. Identification of these effects is challenging because of spatially confounding variables and potential unobservable factors that may cause endogeneity issues (Lewis et al., 2011; Hsieh and Lee, 2016).

The conditions for organic production might differ across space through spatial differences in organic pay price and isomorphic biophysical aptitudes of micro-regions (e.g. valleys or highlands). To control such effects, we include regional fixed effects z_r . Conditions for conversion might also vary across time (equally for all farms); for example, due to a change in the subsidy scheme or a change in market prices or regulations. We control for those effects by including time fixed effects, z_t . There might also be changes that vary across time and regions. Those effects are controlled for by adding interaction terms between the regional and yearly fixed effects. Although those sets of fixed effects should capture a substantial part of the unobserved confounders, there might still be unobserved effects that vary across space at a smaller spatial scale than those variation captured by the regional fixed effects. To control for those effects, we follow Lewis et al. (2011) considering a Mundlak-Chamberlain (MC) device in a correlated random effects estimation strategy (Mundlak, 1978; Chamberlain, 1982; Papke and Wooldridge, 2008). In this setting, we decompose the unobserved individual characteristics c_n into a mean zero normally distributed random variable and the average of the time-varying explanatory variables:

$$c_n = \psi_n + \frac{1}{T_n} \sum_{t=0}^{T_n} ORE'_{nt} \xi = \psi_n + \overline{ORE_n} \xi, \psi_n \sim Normal(0, \sigma) \quad (4)$$

Here, \overline{ORE}_n is commonly referred to as an MC device defined as the average of all time-varying explanatory variables. In our specific case, it is the average of all spatial neighbourhood variables capturing average neighbouring farm convergence, reversion and exits of organic farmers. In principle, the MC device is identical to the usual fixed effect estimate in linear cases, but the algebraic equivalence does not hold in nonlinear cases (Papke and Wooldridge 2008). With this approach, we control for the time-invariant unobserved spatial effects on a smaller spatial scale as captured by the regional fixed effects. For example, we can capture the fact that farms in a certain location are more likely to convert to organic. A specific example is the connection to major road networks as a crucial aspect in optimising the collection routes of dairies. The main dairy cooperative in Norway that collects organic milk, TINE, employs business agents to urge those farms that are favourably located to the circuit of the collection trucks to convert. Those types of effects are covered with the MC device as long as they are not time-varying. In fact, in terms of the specific example, TINE decided to cease personal marketing in 2011 since the market for organic dairy was saturated; instead, the focus turns toward preserving and strengthening those who had already converted (Skjelvik et al., 2017). This could potentially lead to confounders that are both spatial and time-varying and hence not fully covered by the MC device or the fixed effects potentially leading to some bias and overestimation of the spatial interaction effects that cannot be controlled by the identification strategy. However, we consider those specific types of confounders, which are both time and spatial varying, as a rather specific case and an acceptable limitation of the identification approach.

3.5 Results

Table 3.4 presents the parameter estimates for the predictor variables. The set of indicator variables, the annual and zonal dummies, are obtained in Appendix 3.1. The probit model outputs, for both 3 and 5 km radii, show the coefficients, their standard errors and the z-scores, as well as the associated p-values.

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Generally, for both radius settings, the results of the factor variables for describing neighbourhood effects and the period-specific variables support the hypothesised tendencies in the decision-making process of organic conversion. Specifically, we find an increasing probability of organic conversion with a higher number of organic neighbours. As the reference level is 0, which implies no organic neighbour, the first contrast predictor vector Organic Neighbour 1 increases the z-score by 0.275 at 3 km and 0.249 at 5 km radius. Organic Neighbours 2, 3 and 4 demonstrate increased positive effects on conversion, confirming the hypothesis that more neighbours increase the likelihood of organic conversion.

Table 3.4 Econometric Parameter Estimates for 3 and 5 km radii

<i>Variables</i>	3 kilometer radius				5 kilometer radius			
	Estimate	Std. Error	z-score	Pr(> z)	Estimate	Std. Error	z-score	Pr(> z)
Constant	-1.7357	0.13	-13.79	0.0000	-1.7053	0.11	-15.37	0.0000
Organic Neighbour 1	0.2755	0.08	3.62	0.0003	0.2496	0.06	3.91	0.0001
Organic Neighbour 2	0.5565	0.15	3.72	0.0002	0.4865	0.10	4.78	0.0000
Organic Neighbour 3	0.9786	0.25	3.92	0.0001	0.5455	0.20	2.77	0.0056
Organic Neighbour \geq 4	1.0413	1.46	0.71	0.4762	1.2459	0.21	5.87	0.0000
Avg. Organic Farms	-0.2236	0.07	-3.02	0.0025	-0.1763	0.05	-3.22	0.0013
Reverted Neighbour 1	-1.6709	1.40	-1.20	0.2312	-1.2817	1.13	-1.13	0.2568
Reverted Neighbour 2	-2.8675	1.01	-2.85	0.0044	-4.2790	0.35	-12.30	0.0000
Avg. Reverted Farms	4.6968	0.36	13.21	0.0000	3.6867	0.29	12.83	0.0000
Exited Neighbour 1	0.2936	0.23	1.29	0.1966	0.2858	0.13	2.20	0.0277
Exited Neighbour 2	-3.8392	0.23	-16.78	0.0000	-3.6282	0.20	-18.51	0.0000
Exited Neighbour 3	-3.5506	0.31	-11.34	0.0000	-3.2626	0.20	-16.22	0.0000
Exited Neighbour \geq 4	-3.8187	0.79	-4.83	0.0000	-3.2525	0.35	-9.27	0.0000
Avg. Exited Farms	0.3375	0.72	0.47	0.6399	-0.7291	0.58	-1.27	0.2048
Age	-0.0067	0.00	-4.13	0.0000	-0.0069	0.00	-4.45	0.0000
Herd size	0.0030	0.00	1.56	0.1181	0.0025	0.00	1.34	0.1811
Land size	0.0004	0.00	3.33	0.0009	0.0004	0.00	2.95	0.0032

Note: The standard errors are bootstrapped with 500 replications and clustered by farm. Source: own calculation.

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In case of considering the 3 km radius, the parameter vector of 4 or more organic neighbours is insignificant because the occurrence of 4 or more than 4 organic neighbours is very small. However, when we increase the observation window from a 3 to 5 km radius, the effect becomes statistically significant.

Furthermore, vectors indicating the number of reverted neighbours show a negative impact on organic conversion, supporting our hypothesis of negative externalities of reversion. In both models, having only one reverting neighbour (*Reverted Neighbour 1*) has a negative but insignificant effect. When the number of reverted neighbours increases to two, the parameter estimates become statistically significant and show large negative effects on conversion. Interestingly, in absolute terms, the negative effects of reverting neighbours are substantially larger than the positive effects of converting neighbours, indicating that negative examples have a more important effect on conversion compared with the positive effects.

The number of exited organic neighbours shows slightly surprising results. One exited organic farm in the neighbourhood—compared with the zero reference level—shows a positive but insignificant effect on organic conversion. However, in case of more than one organic exit, the parameter estimates become large negative significant numbers in congruence with our hypothesis. Yet (and this is only speculation), we explain the positive effect of one organic exit in the neighbourhood with the likely transmission of organic dairy cows and technology to a conventional dairy farmer in a close surrounding. Furthermore, there may be numerous reasons why organic farmers may decide to shut down their business. Individual reasons may vary between moving, merging, family issues, age, etc, but none of these relates to any system error in the organic dairy industry. However, in case of more than one organic exit at a time, we are entitled to surmise the presence of some unobserved negative external effect that directly makes them exit simultaneously.

Furthermore, as of the farm-specific attributes, our assumption that youth-induced risk-taking ability and potentially higher level of interest in environmental farming promote organic conversion—proxied by farmer's age—seems to be accurate because of the significant and negative

coefficients in both models. It indicates that younger farmers are indeed more likely to convert to organic. We find the coefficients of herd and land sizes very small and consider them marginal in the decision process of organic conversion.

The period-specific dummy predictors show a negative tendency. This confirms that the 2005 and 2009 organic farm policy goal is still far from reach, and the Norwegian organic dairy industry is slowly declining. After 2010, this decrease accelerates in both models, which corresponds to the significant decrease in the summary statistics of organic dairy entries in Table 3.1. The negative and significant parameter coefficients verify that more organic dairy farms exit organic production than conventional farms decide to convert to organic.

The identical model setting for 3 and 5 km radii allows us to analyse the likely differences between the outcome probabilities when the circumstances of farmers' neighbourhoods change. The model outcomes show analogous results, which confirms the robust specification of the functional form regarding close proximities.

3.6 Conclusion

This article explores the factors of organic dairy technology adoption in Norway during the years 2003–2015. We find that farmers' age, herd size and agricultural land used are less important elements of potential organic conversion than the neighbouring dairy relations. We demonstrate that spatial spillovers across economic agents are influential in the patterns of technology adoption. Although our model supports the findings of previous studies that the presence of organic dairies in close proximity positively affects organic dairy conversion, more remarkably, we find that neighbouring organic reversions and exits introduce potential negative interaction effects that had not been considered in previous literature.

The results offer important implications for policymakers and extension services that intend to promote organic production. Earlier literature only explored the positive interaction effects of conversion. Based on such results,

optimal policy design should promote as much conversion as possible, with each conversion creating positive spillovers. Our results concerning the existence of the negative effects of reversion, however, warrants a more nuanced and strategic policy approach. Given that we demonstrated that the negative effect of neighbouring reversion is potentially stronger than the positive effect of neighbouring conversion in absolute terms, policies should not only be focusing on new adaptors but also ensure that existing organic dairy farms remain active and successful. Correspondingly, policies should increase efforts to improve extension and consultation, supporting farmers that are considering conversion to organic farming and helping them to explore whether converting could be successful in their specific situation. Based on this reasoning, our results support the decision by the Norwegian government to terminate organic conversion grants, which may ease conversion but are ill-suited for sustaining organic production in the long run.

Our result highlighted the critical influence that reversions have in terms of external effects on neighbouring farms. Future research should focus on exploring the root causes underlying the decision to revert from organic to conventional farming. This should help policymakers to design new policies or adjust existing approaches to address the identified causes.

3.7 References

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Appendix 3.1 Parameter estimates of annual and zonal dummies for 3 and 5 km radii

<i>Variables</i>	3 kilometer radius				5 kilometer radius			
	Estimate	Std. Error	z-score	Pr(> z)	Estimate	Std. Error	z-score	Pr(> z)
Year 2004	-0.6538	0.17	-3.90	0.0001	-0.682	0.16	-4.25	0.0000
Year 2005	-1.1064	0.82	-1.34	0.1789	-1.086	0.78	-1.39	0.1644
Year 2006	-0.7655	0.36	-2.12	0.0337	-0.769	0.45	-1.72	0.0859
Year 2007	-0.7145	0.33	-2.20	0.0281	-0.721	0.26	-2.76	0.0057
Year 2008	-0.5891	0.17	-3.42	0.0006	-0.611	0.18	-3.49	0.0005
Year 2009	-0.7158	0.49	-1.46	0.1437	-0.711	0.43	-1.67	0.0957
Year 2010	-0.3124	0.15	-2.15	0.0319	-0.331	0.15	-2.25	0.0247
Year 2011	-0.6984	0.52	-1.34	0.1819	-0.689	0.63	-1.09	0.2768
Year 2012	-0.9177	1.27	-0.72	0.4689	-0.946	1.28	-0.74	0.4594
Year 2013	-1.2887	1.79	-0.72	0.4707	-1.264	1.75	-0.72	0.4691
Year 2014	-1.1003	1.90	-0.58	0.5627	-1.116	1.83	-0.61	0.5416
Year 2015	-1.1150	2.09	-0.53	0.5934	-1.114	1.90	-0.59	0.5580
Zone 2	-0.9497	0.17	-5.44	0.0000	-0.840	0.15	-5.51	0.0000
Zone 3	-0.3996	0.10	-3.95	0.0001	-0.438	0.10	-4.30	0.0000
Zone 4	-0.3963	0.10	-4.00	0.0001	-0.398	0.10	-3.87	0.0001
Zone 5	-0.5576	0.10	-5.41	0.0000	-0.569	0.10	-5.55	0.0000
Zone 6	-0.4851	0.16	-3.07	0.0022	-0.495	0.15	-3.35	0.0008
Zone 7	-0.7199	1.22	-0.59	0.5553	-0.730	1.16	-0.63	0.5279
Intersection Y2004; Z2	0.2863	1.16	0.25	0.8046	0.180	1.10	0.16	0.8697
Intersection Y2005; Z2	-0.3683	1.85	-0.20	0.8422	-0.190	1.78	-0.11	0.9148
Intersection Y2006; Z2	-2.7823	0.39	-7.12	0.0000	-2.727	0.47	-5.78	0.0000
Intersection Y2007; Z2	0.2987	1.52	0.20	0.8444	0.149	1.59	0.09	0.9251
Intersection Y2008; Z2	0.1833	1.54	0.12	0.9051	0.028	1.51	0.02	0.9851
Intersection Y2009; Z2	0.3319	1.65	0.20	0.8409	0.166	1.67	0.10	0.9207
Intersection Y2010; Z2	-3.2392	0.22	-14.98	0.0000	-3.173	0.20	-15.66	0.0000
Intersection Y2011; Z2	0.3655	1.68	0.22	0.8281	0.229	1.66	0.14	0.8904
Intersection Y2012; Z2	0.4985	2.00	0.25	0.8032	0.394	2.02	0.19	0.8455
Intersection Y2013; Z2	0.8807	2.33	0.38	0.7059	0.717	2.38	0.30	0.7637
Intersection Y2014; Z2	-2.3560	1.91	-1.24	0.2165	-2.340	1.84	-1.27	0.2027
Intersection Y2015; Z2	-2.5847	2.09	-1.24	0.2166	-2.349	1.90	-1.24	0.2158
Intersection Y2004; Z3	0.3207	0.22	1.49	0.1372	0.350	0.21	1.64	0.1001

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Intersection Y2005; Z3	0.3270	1.05	0.31	0.7546	0.308	0.94	0.33	0.7429
Intersection Y2006; Z3	-0.0433	0.77	-0.06	0.9550	-0.068	0.67	-0.10	0.9192
Intersection Y2007; Z3	0.1374	0.53	0.26	0.7953	0.146	0.39	0.37	0.7111
Intersection Y2008; Z3	0.2793	0.22	1.28	0.2005	0.286	0.22	1.29	0.1978
Intersection Y2009; Z3	0.1248	0.67	0.19	0.8518	0.072	0.56	0.13	0.8970
Intersection Y2010; Z3	-0.2902	0.33	-0.87	0.3837	-0.301	0.42	-0.71	0.4753
Intersection Y2011; Z3	-0.1906	1.35	-0.14	0.8879	-0.229	1.26	-0.18	0.8555
Intersection Y2012; Z3	-3.2733	1.28	-2.55	0.0106	-3.155	1.28	-2.46	0.0137
Intersection Y2013; Z3	0.5307	2.00	0.27	0.7902	0.499	1.88	0.27	0.7908
Intersection Y2014; Z3	-3.0684	1.90	-1.62	0.1059	-2.988	1.82	-1.64	0.1013
Intersection Y2015; Z3	-3.6497	2.11	-1.73	0.0840	-3.088	1.90	-1.62	0.1042
Intersection Y2004; Z4	0.1240	0.21	0.58	0.5641	0.157	0.23	0.69	0.4896
Intersection Y2005; Z4	0.6318	0.83	0.76	0.4474	0.592	0.79	0.75	0.4552
Intersection Y2006; Z4	0.2102	0.39	0.54	0.5919	0.182	0.48	0.38	0.7064
Intersection Y2007; Z4	0.3905	0.34	1.15	0.2517	0.367	0.30	1.24	0.2142
Intersection Y2008; Z4	0.2005	0.22	0.92	0.3579	0.218	0.22	0.99	0.3203
Intersection Y2009; Z4	0.6635	0.51	1.31	0.1894	0.624	0.44	1.42	0.1557
Intersection Y2010; Z4	0.0111	0.19	0.06	0.9544	-0.011	0.19	-0.06	0.9525
Intersection Y2011; Z4	0.3617	0.54	0.67	0.5029	0.305	0.66	0.46	0.6456
Intersection Y2012; Z4	0.2347	1.51	0.16	0.8768	0.212	1.48	0.14	0.8856
Intersection Y2013; Z4	0.5154	2.16	0.24	0.8116	0.438	2.13	0.21	0.8371
Intersection Y2014; Z4	-3.0448	1.90	-1.60	0.1090	-2.923	1.82	-1.60	0.1092
Intersection Y2015; Z4	0.2728	2.77	0.10	0.9214	0.315	2.54	0.12	0.9014
Intersection Y2004; Z5	-0.0105	0.51	-0.02	0.9835	0.031	0.48	0.07	0.9480
Intersection Y2005; Z5	0.6297	0.84	0.75	0.4550	0.618	0.81	0.76	0.4446
Intersection Y2006; Z5	0.2070	0.55	0.37	0.7081	0.187	0.50	0.38	0.7059
Intersection Y2007; Z5	0.0729	0.83	0.09	0.9298	0.069	0.66	0.10	0.9172
Intersection Y2008; Z5	0.1937	0.27	0.73	0.4671	0.213	0.27	0.80	0.4242
Intersection Y2009; Z5	-0.1955	1.50	-0.13	0.8963	-0.213	1.54	-0.14	0.8899
Intersection Y2010; Z5	-0.2815	0.75	-0.37	0.7091	-0.277	0.71	-0.39	0.6966
Intersection Y2011; Z5	-0.2054	1.56	-0.13	0.8952	-0.218	1.57	-0.14	0.8899
Intersection Y2012; Z5	-2.8803	1.26	-2.28	0.0227	-2.668	1.28	-2.08	0.0372

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Intersection Y2013; Z5	0.4331	2.37	0.18	0.8549	0.410	2.34	0.17	0.8612
Intersection Y2014; Z5	0.2862	2.31	0.12	0.9014	0.284	2.39	0.12	0.9055
Intersection Y2015; Z5	0.6304	2.25	0.28	0.7798	0.631	2.06	0.31	0.7592
Intersection Y2004; Z6	0.1148	1.18	0.10	0.9222	0.147	1.17	0.13	0.8999
Intersection Y2005; Z6	0.3760	1.83	0.21	0.8376	0.364	1.73	0.21	0.8334
Intersection Y2006; Z6	0.2739	1.23	0.22	0.8235	0.278	1.20	0.23	0.8169
Intersection Y2007; Z6	-0.0045	1.65	0.00	0.9978	0.003	1.66	0.00	0.9984
Intersection Y2008; Z6	0.2240	1.28	0.18	0.8607	0.237	1.24	0.19	0.8481
Intersection Y2009; Z6	0.1171	1.70	0.07	0.9449	0.102	1.63	0.06	0.9498
Intersection Y2010; Z6	-0.1259	1.62	-0.08	0.9381	-0.085	1.45	-0.06	0.9536
Intersection Y2011; Z6	0.3649	1.26	0.29	0.7719	0.345	1.37	0.25	0.8011
Intersection Y2012; Z6	-2.9063	1.26	-2.30	0.0213	-2.720	1.28	-2.12	0.0342
Intersection Y2013; Z6	-2.5830	1.79	-1.44	0.1491	-2.419	1.75	-1.38	0.1667
Intersection Y2014; Z6	-2.8144	1.90	-1.48	0.1384	-2.583	1.82	-1.42	0.1569
Intersection Y2015; Z6	0.6249	2.70	0.23	0.8171	0.626	2.57	0.24	0.8076
Intersection Y2004; Z7	0.4348	2.10	0.21	0.8361	0.466	2.03	0.23	0.8184
Intersection Y2005; Z7	0.6428	2.18	0.30	0.7677	0.695	2.14	0.32	0.7458
Intersection Y2006; Z7	0.5102	2.10	0.24	0.8082	0.533	2.06	0.26	0.7963
Intersection Y2007; Z7	0.6356	1.63	0.39	0.6958	0.676	1.77	0.38	0.7029
Intersection Y2008; Z7	-2.9708	1.23	-2.42	0.0157	-2.770	1.17	-2.37	0.0176
Intersection Y2009; Z7	-2.8280	1.32	-2.14	0.0321	-2.664	1.26	-2.11	0.0351
Intersection Y2010; Z7	0.2189	2.12	0.10	0.9177	0.240	1.99	0.12	0.9042
Intersection Y2011; Z7	-2.8463	1.29	-2.20	0.0276	-2.686	1.30	-2.06	0.0395
Intersection Y2012; Z7	0.8250	2.50	0.33	0.7410	0.863	2.38	0.36	0.7164
Intersection Y2013; Z7	-2.2470	2.16	-1.04	0.2983	-2.105	2.03	-1.04	0.2995
Intersection Y2014; Z7	-2.4421	2.26	-1.08	0.2803	-2.258	2.16	-1.04	0.2969
Intersection Y2015; Z7	-2.4361	2.41	-1.01	0.3124	-2.267	2.23	-1.02	0.3091

Source: own calculation.

Chapter 4

Human Impact Promotes Sustainable Corn Production in Hungary²²

Abstract: The aim is to predict Hungarian corn yields for the period of 2020–2100. The purpose of the study was to mutually consider the environmental impact of climate change and the potential human impact indicators towards sustaining corn yield development in the future. Panel data regression methods were elaborated on historic observations (1970–2018) to impose statistical inferences with simulated weather events (2020–2100) and to consider developing human impact for sustainable intensification. The within-between random effect model was performed with three generic specifications to address time constant indicators as well. Our analysis on a gridded Hungarian database confirms that rising temperature and decreasing precipitation will negatively affect corn yields unless human impact dissolves the climate-induced challenges. We addressed the effect of elevated carbon dioxide (CO₂) as an important factor of diverse human impact. By superposing the human impact on the projected future yields, we confirm that the negative prospects of climate change can be defeated.

Keywords: climatic variability, food security, sustainable intensification; trending adaptive capacity; panel data econometrics; technology development

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4.1 Introduction

Empirical studies put various climate, biophysical, and economic models in practice for assessing the impact of climate change on crop yields. The results and inferences vary due to model singularities, differences in input data, and the heterogeneity of global food production areas (Rosenzweig 1994; Kaufmann et al. 1997; Nelson et al 2014; Müller and Robertson 2014; Wiebe et al. 2015). Applications on a global scale have the potential to predict average global yields (under reported uncertainty) for the most important commodities with rather simple measures of highly aggregated growing season temperature and precipitation (Lobell and Field 2007; Lobell and Burke 2010; Schlenker et al. 2005). Nevertheless, there are many locally changing factors that likely affect corn yields—including political stability, land use, soil organic matter content, as well as the implementation of technological and agronomic developments—which researchers are unable to properly quantify and are thus cumbersome for modeling purposes. Drawing global supply and demand trends and understanding future challenges of food security are vitally important, but shaping targeted agricultural policy making requires more detailed information about the internal functioning of agents and about the dynamics of adjustments. Therefore, we argue to conceive studies with smaller spatial coverage, where essential local drivers may be considered and agronomic weather measures are executed at the potentially smallest (but realistic) gridded resolution to capture the most spatial heterogeneity and greatest data variability to decrease uncertainties.

4.1.1 On Hungarian Corn Production

Corn production is one of the most valuable sectors of Hungarian agriculture. Hungary has the fourth-largest production area of corn in the European Union (EU), which takes up about 1–1.3 million hectares depending on the state of crop rotation (Eurostat). Due to climatic, industrial, and demographic reasons, there is an increasing demand for corn in Europe (Bouma et al. 1998; Gnansounou 2010; Hernandez-Ramirez et al. 2011).

Among the European Member States, Hungary serves the second-largest corn export (after France), with the mean capacity of 3.7 million tons a year (based on the average production of 2007–2015, UN Comtrade). Studies show that Hungary’s climate is on the verge of humid oceanic, dry continental, and Mediterranean climate regions that is responsible for the highly variable weather (Biacs et al. 2003). The climate within the Carpathian Basin has become warmer and drier in the agriculturally most important period of the year: from May to September (Máté et al. 2008; Bartholy et al. 2011). Extreme weather events cause unequal rainfall distribution on Hungarian land and negatively influence soil fertility through natural water supply. Different soils react differently to the stress effects evolved as a result of lacking precipitation, so their drought sensitivity will not be the same (Kocsis et al. 2020). There is a marked tendency that drought and heat stress have become more common, which had a strong negative impact on corn yields in several years (Kocsis et al. 2018; Pinke et al. 2020).

Figure 4.1 shows the courses of Hungarian and European corn yields over the baseline period of 1970–2018. The volatility of Hungarian corn yield is higher than the European, although in this long time series, corn yields have nearly doubled for both graphs.

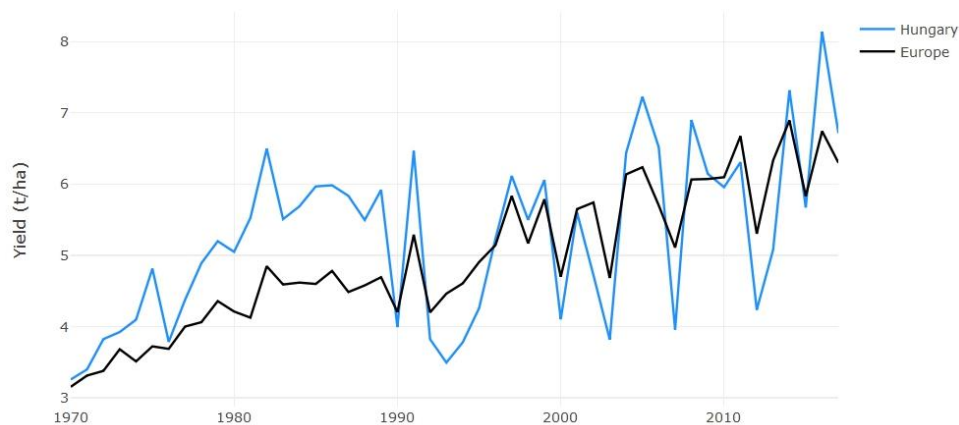


Figure 4.1 Development of corn yields in Hungary and Europe (1970–2018)

Source: Eurostat

By explaining the relation of Hungarian and European corn yield charts, we underline the historic moment in 1990, when the Soviet Union collapsed and

the satellite states like Hungary could start the process of democratic transformation. Under the Communist Regime, Hungarian farmers were forced to work in production cooperatives on confiscated land and destroyed the historically developed agricultural society of gentries. In lack of environmental considerations and climate protections, an unreasonably large amount of imported nonorganic fertilizer was used for mass cultivation. Large portions of the produced agricultural commodities were transported and absorbed by the Comecon markets. The planned socialist economy took a positive effect on Hungarian corn yields (i.e., it largely exceeded the European average yield), but it exploited farmland and caused serious environmental problems. The political transformation brought the termination of fertilization subsidies, the era of legal redresses, and compensations, which resulted in an enormous setback in agricultural yields compared to the rest of Europe in the beginning of the 1990s. Later, by the second half of the decade, the recouped agricultural society rehabilitated and reorganized agricultural production conditions and started to compete on new European markets. However, nothing illustrates better the current imperfections of Hungarian agricultural convergence, when the emergent occasions of adverse weather conditions affect less negatively the aggregated European corn yields, than the Hungarian corn production (see Figure 4.1., years of 2000, 2003, 2007, 2012). This implies that Hungary is more vulnerable to negative environmental impacts. Therefore, the financial stability is at stake of the export-driven corn production system in the light of climate change. In this manner, we reveal the fundamental challenge of future farming as to whether the development of adaptive capacity in Hungary will exceed the European improvement.

4.1.2 Motivation and Contribution

The aim of the study was to model the environmental and social impact indicators and explain the observed year-specific yield fluctuations. We analyzed the highly variable weather and other important production factors on historic corn yields (1970–2018) and used the responses to predict future yields for the period of 2020–2100. We intended to present the impact of climate change by employing various climate projections, but more

importantly, we desired to reveal that persisting human impact may increase adaptive capacity and efficiently tackle the potential negative impact of climate change. We applied the within-between random effect model on our balanced panel dataset to account for other substantial factors such as agronomic improvements and individual characteristics beyond weather variabilities.

First, we compiled a new data set that integrates the spatial distribution of yields, soil characteristics, and a number of climatic variables for the total coverage of Hungary at a 10 km × 10 km grid resolution. Second, we delineated a time trend that we associate with the cumulated human impact towards improving corn yields. Third, we estimated simultaneously three model specifications with respect to diversified variable settings and decomposed growing season periods (i.e., distinguishing vegetative and reproductive growth phases).

The rest of the paper is divided into four parts. In Section 2, we argue the binding assumptions of individual homogeneity, introduce the rest of the data and present the applied method. In Section 3, we interpret the results and discuss the most important implications; Section 4 summarizes the conclusions.

4.2 Materials and Methods

4.2.1 Biophysical and Social Environment

Earlier, Hungarian agricultural commodity yields were assessed by process-based crop models (Kovács et al. 1995; Fodor et al. 2014). These are designed to calculate crop yield (and other important parameters of the soil-plant system) as a function of weather and soil conditions, stipulate plant-specific characteristics, and take the basic crop management steps into account. Crop-model-based studies find corn yield critically sensitive to rising temperature on Hungarian rain-fed arable land (Fodor et al. 2014; Micskei et al. 2016). Despite their advantages (Lobell and Asseng 2017; Challinor et al. 2018; Raksapatcharawong et al. 2020; Tewes et al. 2020;

Cammarano et al. 2020), crop models are limited in their ability to express the continuous development in agrotechnology (e.g., use of slow-release fertilizer, progress in hybrid research, and evolving methods in application of pesticide: the increasing quality of agricultural operations in general) (Ewert et al. 2015) and agromanagement (e.g., organizing cooperatives for more efficient production, utilization of farm-to-fork strategies). We argue that the differences in model approaches are not superior to each other; on the contrary, they are rather complementary where the grounded research interest determines the applied modeling strategy. As our research objective is built on revealing the factors of corn yield development, we used a stochastic approach with panel data to make more sufficient projections with the inclusion of progressive human impact.

Generally, farmers' adaptive capacity to any change, especially to weather variabilities, is highly heterogeneous, due to the differences in factor endowments, production capacity, education, and experience, etc.; thus, it is a source of uncertainty and potential bias trap in stochastic modeling. Lately, global scale empirical models have been gaining ground in the scientific literature (Lobell and Gourdji 2012; Auffhammer et al. 2006; 2012), but they are restrained to simulate yield responses when cropping areas shift (Lobell and Field 2007; Auffhammer et al. 2006) or easily lead to heterogeneity bias as the within-country differences are overlooked. Therefore, we suppose that the conclusions of global studies on future yield trends may be partially misleading, but in lack of a better global tool, it remains considerable.

We address the binding issue of individual homogeneity with small-scale grid resolution and link to the explicit assumption that agricultural producers aim to achieve the potentially highest yields in every year under given circumstances, regardless of occurring individual differences in production endowments and in adaptive capacity. Instead of neglecting all agromanagement, infrastructural, and policy considerations per se—due to identification challenges—we propose to control these unobserved variabilities based on preceding adjustments. Still, the real farm-level differences are disregarded by using gridded data, but spatial proximity within the grid cells is assumed to imply some similarity in unobserved human factors (Anselin 2001).

The underlined simplification on farmers' behavior that they constantly maximize corn yields allows us to observe the aggregates of all unobserved effects in each year, which we perceive as the annual country aggregate of human impact towards increasing yields under variable weather and changing climate in the long run. In recent studies, technology improvements are taken for granted in the future, and models typically account for new technology by including some exogenous rate of growth in yields (Hawkins et al. 2013; Moore and Lobell 2014; 2015; Hertel and Lobell 2014). We argue that identifying the effect of a specific technological innovation is extremely difficult due to time lags and data shortage. We question the exclusive role of technology in the observed positive yield shifts. We believe that, in reality, achieving crop yield growth is a complex work at different levels. At the farm level, it is a process of making sequential decisions at every stage of the production under contrasting environmental settings (i.e., weather variability) that may simply include intensification (e.g., use of higher NPK doses), or finding more suitable hybrids. At the regulatory level, it is a process of providing a sustainable and resilient policy framework that supports healthy competitiveness, presents affordable financial assets for farmers, and administers the undergoing proprietary rights issues (e.g., tenancy in common affairs). The broad spectrum of human impact extends to agrotechnological development (crop breeding, technical advances, increasing factor endowments), policy environment (subsidy policy, political establishment), agricultural R&D and its translation into practice, knowledge spillovers, and capital accumulation. We acknowledge that the driving force of human impact is sourced from technological and agromanagement improvements for upward-trending yields, but we are aware of nontechnical aspects such as cooperation and knowledge transfer that substantially contribute to increase farm efficiency. In statistical crop models, when they refer to technology in the equation either by using state-specific quadratic time trends or year-fixed effects, they actually address the aggregate human impact (Lobell and Field 2007; Hertel and Lobell 2014; Schlenker et al. 2009; Roberts et al. 2013).

Furthermore, there is an increasing need to clarify the effect of elevated CO₂ on corn production, especially when long-term projections are considered. According to Leakey et al. (2009), CO₂ does not directly stimulate C4

photosynthesis, but can indirectly stimulate carbon assimilation in times and places of drought. Weigel and Manderscheid (2016) recorded practically zero yield increase in wet conditions but over 40% yield gain in dry conditions. We address elevated CO₂ and give 20% yield growth of maize as an upper estimate in case of a 200 ppm CO₂ increase (from 350 ppm to 550 ppm) based on long-term Free Air CO₂ Enrichment (FACE) experiments and crop model simulations (Castaño-Sanchez et al. 2020). Combining this figure with the ca. 80 ppm CO₂ level increase of the observation period (1970–2018), we forecast about 8 kg/ha/year corn yield increase due to elevated CO₂. We argue that this effect has been absorbed into the human impact trend in the past, but the decomposition of elevated CO₂ and the rest of human impact is feasible for the future.

4.2.2 Data

The accumulated dataset consists of 1104 (approx. 10 × 10 km) grid cells, which constitutes a balanced panel of 49 years over the period of 1970–2018. Average corn yields for each grid cell were obtained from the Research Institute of Agricultural Economics (RIAE) and from the Hungarian Central Statistical Office (HCSO). Yield averages for the period of 2011–2018 were collected from the Hungarian model farm network that includes about two thousand farms. RIAE has developed this form of data accumulation representatively by model farms covering arable land of Hungary. The spatial distribution of yields over the 1104 grid cells was determined by attributing the model farm yields to the spatial grid system, where the farm is located. The county (NUTS-3)-level HCSO yield data that is available for the period of 1970–2010 is correspondingly spatially disaggregated for the grid cells by using the spatial distribution patterns of the model farm network data. Thus, the continuous dataset incorporates the inconceivable effects of various political establishments, reflects the specific policy or management choices, as well as assimilates technological development which, in use, may more reliably predict future corn yield responses. We draw attention to the long time span of the baseline yield data, where advances in management practices, crop improvement, technical and nontechnical changes mutually affected agricultural productivity.

The observed meteorological and simulated future climate datasets were provided by the FORESEE database (Dobor et al. 2014). The FORESEE v3.1 (Kern et al. 2019) is derived from the E-OBS 17e dataset (Cornes et al. 2018) for the historical time period (1951–2018), and from the ENSEMBLES project (van der Linden and Mitchell 2009) for the future projections based on the IPCC SRES A1B emission scenario (Nakicenovic and Swart 2000). Though, the production of RCP (Representative Concentration Pathways)-based climate projections has been started, at present, FORESEE v3.1 is the only database meeting all the criteria required for this study: (1) observed data covers the study area with the required spatial resolution; (2) observed data covers the investigated time period; (3) climate projections (future data) have the same spatial resolution than that of the observed data and contain continuous daily data up to 2100; (4) climate projections are bias-corrected using the observed data of the database from a reference period that includes the investigated period; (5) the incorporated regional climate and global climate models (RCM-GCM) cover a sufficiently wide range, as for temperature and especially for precipitation, the RCM-GCM selection-related uncertainty is usually larger than the scenario-selection-related uncertainty (Hawkins and Sutton 2011). The FORESEE v3.1 database provides spatially interpolated meteorological fields for Central Europe for the period of 1951–2100. The bias-corrected, projected time series were derived by using 10 different RCMs embedded in three different GCMs (Dobor et al. 2015). The data at the original FORESEE resolution of $1/6^\circ \times 1/6^\circ$ was resampled to the finer resolution of $0.1^\circ \times 0.1^\circ$, in accordance with the gridded corn yield data of the 1104 cells. Kern et al. (2016) developed the applied methodology for the spatial transformation, with respect to elevation attributes.

In this paper, we selected six climate projections to present uncertainty for the period of 2020–2100 and assess the climatic response of Hungarian corn yield for different scenarios. As temperature and precipitation are the most influential indicators for corn development, we opted for showing the positive and negative extremes as well as the average projections for both impact indicators. By selecting the RCMs, we considered separately the mean temperature and the precipitation sums in the growing season for the period of 2071–2100. The FORESEE v3.1 is structured by daily

minimum/maximum temperatures and precipitation sums. We supplemented the basic dataset by deriving daylight average temperature and shortwave radiation flux (i.e., global radiation) on the same grid by using the widely validated MTCLim model (Thornton et al. 2000).

The gridded weather data products use spatial interpolation to incorporate the accessible time-variant weather station data into the panel structure of observations on a fixed spatial scale of 1104 grid cells. To account for the impact of temperature, we used the well-established nonlinear formulation of degree days, also known as Growing Degree Days (GDD) (Deschênes and Greenstone 2007; 2012; Baylis et al. 2011). GDD (Thermal Time) is a measure of heat accumulation calculated by taking the integral of warmth above a base temperature. As daily data is used in the study thermal, time is approximated with $\max(0.5 \times (T_{max} + T_{min}) - T_b, 0)$, where T_{max} and T_{min} are the daily maximum and minimum temperature and T_b is the base temperature which is set to 8 °C. GDD is the sum of daily values for the given period. For identifying heat stress, we aggregated the Number of Hot Days (NHD), when the daily maximum temperature exceeds 30 °C for the given period. In addition, for further specifications, we obtained the total short-wave Radiation (RAD), measured in MJ/m², considered wavelength between 0.2 µm and 3.0 µm from the sky falling onto a horizontal surface on the ground for the given period. Lastly, the simple measure of precipitation sum (P) was used for the given period measured in cm.

For the straightforward extension of the estimation methodology, we address the important subset of grid-cell-specific time-invariant measures of soil conditions. The soil data was retrieved from the 10 km resolution Digital, Optimized, Soil Related Maps and Information (DOSoReMI) database (Pásztor et al. 2018). DOSoReMI is an observation-based dataset where locally measured soil parameters—Soil Organic Matter content (SOM), sand fraction, and pH—are spatially interpolated with the help of geophysical, terrain, land cover, and remotely sensed data. The native resolution of DOSoReMI is 100 m, but versions with coarser resolution are available up to a 10 km resolution. SOM and sand fraction are measured in percentage points of the topsoil (0–30 cm).

We explored the various interactions of the specified variables, although theoretically some may have an inverted U-shape for corn yield. Therefore, in our model specification, we define the squared terms of GDD, RAD, and P to account for potential higher-order interactions as well. As a null hypothesis, we expected GDD, P, RAD, SOM, and pH to positively correlate with corn yield and, on the contrary, the NHD, sand fraction, GDD^2 , RAD^2 , and P^2 to negatively affect corn yields. The spatial distribution of yield and the most important weather measures are illustrated in Appendix 4.1. The vegetation period (VP) cell values are aggregated for the period of 2009–2018.

4.2.3 Methodology

Fixed-effects (FE) modeling is used more frequently in applied econometric analysis, reflecting its status as the “gold standard” (Schurer and Yong 2012). However, random-effects (RE) models have gained increasing prominence in various scientific fields (Molenberghs and Verbeke 2001; 2005; Beck and Katz 2007) due to their greater flexibility and generalizability. Both methods are applicable to address complex research questions, including nested neighborhood relations (Jones et al. 1992; Lewis et al. 2008; 2011) and temporal hierarchies (Beck and Katz 2007; Bell and Jones 2015).

Many research problems in agricultural economics, especially related to future production issues in light of climate change, describe the quantitative matter with hierarchical data structure. It is imposed during data collection as there are repeated measures over time at Level 1 (i.e., highly variable occasions, e.g., weather events) and nested in individuals at Level 2 (‘higher-level entities,’ e.g., countries, grid cells, etc.), which may include time-independent characteristics (Bell and Jones 2015; Bell et al. 2018; 2019). There are many different model specifications in terms of choosing the appropriate model framework, functional form, and including the most meaningful/influential covariates. Still, FE models are regularly employed to avoid the problem of individual heterogeneity bias and control out all between effects by including the higher-level entities as dummy variables (e.g. Roberts et al. 2013); however, the great advantage of FE models comes at a price of being unable to estimate the effects of higher-level processes

and only dealing with occasion-level processes (Bell and Jones 2015). Therefore, FE models may not be practical in applications where time-invariant covariates (i.e., has only higher-level variance) are of particular interest, as they lose a large amount of information.

Mundlak (1978a, b) worked out his solution to this issue by adding the higher-level mean of each time-varying covariate in the model (the so-called Mundlak device) to explicitly account for the between effect instead of controlling it out. The Mundlak device is treated in the same way as any higher-level variable (i.e., time-invariant variable) and performs the covariates within a simple parsimonious RE framework. This yields to the same results as a FE model, but supplemented with the between effects in addition to other time-invariant variables of interest (Bell et al. 2018).

We used the most general parametrization of the Mundlak model, which is able to model both within- and between-individual effects concurrently, and also explicitly models heterogeneity in the effect of predictor variables at the individual level (Bell et al. 2019):

$$y_{it} = \mu + \beta_{1W}(x_{it} - \bar{x}_i) + \beta_{2B}\bar{x}_i + \beta_3 z_i + v_{i0} + v_{i1}(x_{it} - \bar{x}_i) + \phi_i t + \varepsilon_{it0}$$

This model is also called the ‘within-between RE’ model, where y_{it} is the dependent variable, x_{it} is a set of time-varying independent variables, and z_i is a set of time-invariant independent variables. Each variable of x_{it} is divided into two parts, β_{1W} and β_{2B} , representing the average within and between effects, respectively. The β_3 parameter exclusively stands for the between effect of the specific z_i variable, as it has no within effect due to the lack of variation in time. The random setting of the model includes two terms: a random effect that is attached to the intercept (v_{i0}) and another random term attached to the within slope (v_{i1}). Each of these is assumed to be normally distributed. Finally, ϕ_i is a grid-specific parameter on annual linear time trend t to identify annual shocks and long-time improvements.

The scope of the paper is to determine the effect of highly variable occasions, such as biophysical effects of heat units, wetness/humidity, and nested grid object information of soil organic matter, pH, and sand consistency on observed corn yields. Our model specification closely follows the innovations published by Roberts et al. (2013) and Auffhammer et al. (2006),

but applying the within-between random effects model stated above. Three generic model specifications were performed subject to the involved variables. Each model has two sub-specifications (i.e., ‘Model A’ and ‘Model B’) conditional on assuming a coupled or decoupled growing season (i.e., distinguishing plant development phases to vegetative and reproductive growth periods). Specification “A” includes the variables in coupled form, corresponding to mainstream variable use; while specification “B” incorporates GDD, RAD, and P in decoupled forms. The included variable structures are listed in Table 4.1.

Table 4.1 Summary table of performed variable structures in each model

Variables	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B
GDD	+		+		+	
GDD ²	+		+		+	
GDD _{VEGETATIVE}		+		+		+
GDD ² _{VEGETATIVE}		+		+		+
GDD _{REPRODUCTIVE}		+		+		+
GDD ² _{REPRODUCTIVE}		+		+		+
RAD _{VEGETATIVE}	+	+				
RAD ² _{VEGETATIVE}	+	+				
RAD _{REPRODUCTIVE}	+	+				
RAD ² _{REPRODUCTIVE}	+	+				
P	+		+		+	
P ²	+		+		+	
P _{VEGETATIVE}		+		+		+
P ² _{VEGETATIVE}		+		+		+
P _{REPRODUCTIVE}		+		+		+
P ² _{REPRODUCTIVE}		+		+		+
NHD	+	+	+	+	+	+
SOM	+	+	+	+		
pH	+	+	+	+		

Sand + + + +

Furthermore, we made predictions for corn yield of each of the regression models replacing observed weather data with projected future weather. Instead of removing trending human impact from the model (i.e., detrending the raw data), and thus exclusively accounting for the climate-change-induced differences in yield (Roberts et al. 2013), we rather superposed the predicted human impact when making predictions for the future. Additionally, we relied on the works of Weigel and Manderscheid (2016) and Castano-Sanches (2020) with respect to the effect of elevated CO₂ on corn yield and disjointed this absorbed effect from the human impact. Methodologically, it means an artificial 8 kg/ha/year shift of the dependent variable. Though we know that the actual trend is highly dependent on the greenhouse gas concentration trajectory, this rate of elevated CO₂-induced yield rise is assumed to be continuous in future decades, regardless of other aspects of human impact. Hereby, we were able to make predictions for future corn yield conformation either by assuming persistent human impact with absorbed CO₂, or no human impact but elevated CO₂ effect. Later at yield predictions, we designated the results with and without persisting human impact.

The applied REWB models can be fit in modeling software packages such as R, Stata, or SPSS. They are considered random-effects models with the mean of x_{it} included as an additional explanatory variable (Howard, 2015). We used “plm,” ”lme4,” and “Metrics” packages in R for calculation (Croissant and Millo 2008; Bates et al. 2015; Hamner et al. 2018) and “plotly” for visualization (Sievert 2020).

4.3 Results

We parametrize six models, all of which are presented in Table 4.2. The ‘A’ and ‘B’ specifications indicate whether we consider the growing period in its overall length or differentiate the major plant growth phases.

In all model specifications, we found the 49-year linear time trend significant and positive on Hungarian corn yields. Yet, we mutually

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accounted for all types of human impacts, including elevated CO₂. With all models, we calculated between 77 and 81 kg/ha of average yield increase. The results of temperature indicators confirm our initial hypothesis that increasing GDD and RAD will contribute to corn yield growth, although under “B” specifications, we reveal some negative and significant estimates. This suggests that increasing temperature in the vegetative plant development phase may set back the potential yield. Correspondingly, the within effect of heat stress (NHD) caused decreasing yields in all cases. (The within and between effects have different substantive meanings as they capture within-group and between-group relationships, respectively. The level 1 within effect captures the difference on Y between units that are higher or lower than average on X relative to their group, whilst at level 2, the between effect captures the difference between groups that have a higher or lower X as a whole (Bell et al. 2018). Therefore, researchers interpret the within effect as the causal effect (Spanos 2006; Schurer and Yong 2012). The significant results of wetness indicator P show positive estimates. The squared-term confirms that precipitation-induced inland water could cause moderate reduction.

Table 4.2 Regression Results of REWB models from a Variety of Panel Specifications

Predictors	Model 1A			Model 1B			Model 2A			Model 2B			Model3A			Model3B		
	Estimates	SE	p	Estimates	SE	p	Estimates	SE	p	Estimates	SE	p	Estimates	SE	p	Estimates	SE	p
(Intercept)	303.348	218.238	0.165	200.941	207.542	0.333	0.756	5.060	0.881	-32.381	13.771	0.019	-0.537	5.362	0.920	-52.862	15.829	0.001
Time trend	0.081	0.001	<0.001	0.079	0.001	<0.001	0.078	0.001	<0.001	0.077	0.001	<0.001	0.078	0.001	<0.001	0.077	0.001	<0.001
GDD within	0.005	0.000	<0.001				0.006	0.000	<0.001				0.006	0.000	<0.001			
GDD between	0.009	0.008	0.231				-0.010	0.007	0.170				-0.015	0.008	0.063			
GDD ² within	0.000	0.000	<0.001				0.000	0.000	<0.001				0.000	0.000	<0.001			
GDD ² between	0.000	0.000	0.551				0.000	0.000	0.032				0.000	0.000	0.009			
RAD _{VEG} within	0.097	0.004	<0.001	0.068	0.004	<0.001												
RAD _{VEG} between	0.051	0.290	0.862	-0.947	0.322	0.003												
RAD ² _{VEG} within	0.000	0.000	<0.001	0.000	0.000	<0.001												
RAD ² _{VEG} between	0.000	0.000	0.935	0.000	0.000	0.004												
RAD _{REP} within	-0.003	0.004	0.490	-0.022	0.004	<0.001												
RAD _{REP} between	-0.485	0.179	0.007	0.417	0.210	0.047												
RAD ² _{REP} within	0.000	0.000	0.058	0.000	0.000	<0.001												
RAD ² _{REP} between	0.000	0.000	0.005	0.000	0.000	0.065												
P within	0.008	0.000	<0.001				0.009	0.000	<0.001				0.009	0.000	<0.001			
P between	-0.004	0.015	0.770				0.026	0.014	0.061				0.061	0.015	<0.001			
P ² within	0.000	0.000	<0.001				0.000	0.000	<0.001				0.000	0.000	<0.001			
P ² between	0.000	0.000	0.895				0.000	0.000	0.102				0.000	0.000	<0.001			
NHD within	-0.069	0.001	<0.001	-0.069	0.001	<0.001	-0.074	0.001	<0.001	-0.071	0.001	<0.001	-0.074	0.001	<0.001	-0.071	0.001	<0.001
NHD between	-0.099	0.020	<0.001	-0.027	0.020	0.181	-0.070	0.014	<0.001	0.027	0.017	0.112	-0.044	0.015	0.003	0.079	0.020	<0.001
SOM	0.245	0.073	0.001	0.291	0.068	<0.001	0.156	0.073	0.033	0.149	0.075	0.046						
pH	0.315	0.064	<0.001	0.251	0.060	<0.001	0.285	0.067	<0.001	0.220	0.067	0.001						
Sand	-0.015	0.002	<0.001	-0.014	0.002	<0.001	-0.016	0.002	<0.001	-0.016	0.002	<0.001						
GDD _{VEG} within				-0.007	0.001	<0.001				-0.004	0.001	<0.001				-0.004	0.001	<0.001
GDD _{VEG} between				-0.189	0.095	0.046				-0.223	0.104	0.031				-0.343	0.122	0.005
GDD ² _{VEG} within				0.000	0.000	<0.001				0.000	0.000	<0.001				0.000	0.000	<0.001
GDD ² _{VEG} between				0.000	0.000	0.106				0.000	0.000	0.064				0.000	0.000	0.013
GDD _{REP} within				0.016	0.001	<0.001				0.018	0.001	<0.001				0.018	0.001	<0.001
GDD _{REP} between				0.182	0.073	0.012				0.196	0.080	0.015				0.300	0.094	0.001
GDD ² _{REP} within				0.000	0.000	<0.001				0.000	0.000	<0.001				0.000	0.000	<0.001
GDD ² _{REP} between				0.000	0.000	0.030				0.000	0.000	0.030				0.000	0.000	0.004
P _{VEG} within				0.015	0.001	<0.001				0.018	0.000	<0.001				0.018	0.000	<0.001
P _{VEG} between				-0.182	0.030	<0.001				-0.132	0.033	<0.001				-0.191	0.038	<0.001
P ² _{VEG} within				0.000	0.000	<0.001				0.000	0.000	<0.001				0.000	0.000	<0.001
P ² _{VEG} between				0.001	0.000	<0.001				0.000	0.000	<0.001				0.001	0.000	<0.001
P _{REP} within				0.001	0.000	0.130				-0.002	0.000	<0.001				-0.002	0.000	<0.001
P _{REP} between				0.045	0.017	0.009				0.030	0.017	0.079				0.077	0.020	<0.001
P ² _{REP} within				0.000	0.000	0.091				0.000	0.000	<0.001				0.000	0.000	<0.001
P ² _{REP} between				0.000	0.000	0.043				0.000	0.000	0.173				0.000	0.000	<0.001
σ ²	1.08			1.05			1.13			1.06			1.13			1.06		
N	1104 _{ID}			1104 _{ID}			1104 _{ID}			1104 _{ID}			1104 _{ID}			1104 _{ID}		
Observations	54,096			54,096			54,096			54,096			54,096			54,096		
Marginal R ² /Cond R ²	0.370/0.711			0.396/0.710			0.356/0.673			0.369/0.701			0.303/0.667			0.309/0.709		
AIC/BIC	163,312/163,552			161,855/162,166			165,734/165,903			162,580/162,820			165,978/166,120			162,806/163,020		
RMSE	1.0229			1.0083			1.0465			1.0143			1.0461			1.0136		

Note: Significant estimates are shown in bold. Own calculation.

In addition, these results show empirical relevance for including time-invariant determinants in statistical approaches when modeling the relationship between environmental impact indicators and crop yields. Soil parameters have a powerful and robust association with yields. Despite the occurring difficulties in model identification, the results confirm our expectations and yield to large significant results. Furthermore, this point is underlined when we examine the predictive capacity of the REWB model. The marginal R^2 describes solely the proportion of variance explained by the fixed factors, while the conditional R^2 describes the proportion of variance explained by both the fixed and random factors. In the case of linear mixed-effect models, such as REWB, the random slopes will not be controlled out. The conditional R^2 are considerably greater in all cases than the marginal R^2 . We infer that using the REWB model is a better choice, because it has more explanatory power and provides opportunity to assess soil determinants. According to the estimated model performance indicators (RMSE, AIC, BIC), we find Model 1B to be the most accurate model specification.

The table of regression results is a very important summary of the model specification assortment, but Figure 4.2 provides the graphical illustration of the model charts compared to the observed yields.

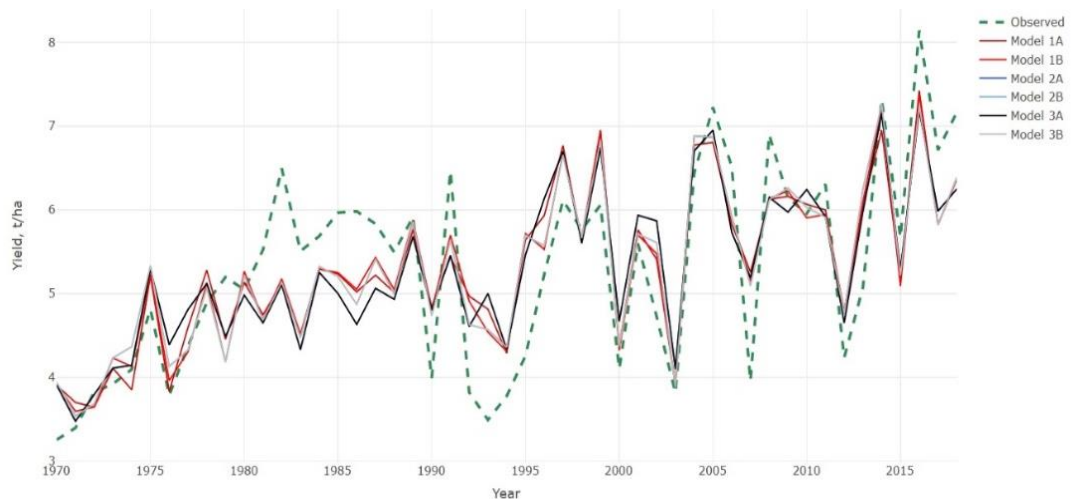


Figure 4.10 Observed and modelled corn yields in Hungary (1970–2018)

Source: own figure

In general, the predicted model specifications closely follow the observed annual aggregates. However, the deviations in the 1980s and in the mid-1990s can be attributed to the external influencing effects occurring over the transition period, for instance, political instability, transformation of farm structure, and other effects, all of which are implicitly addressed in the human impact and thus lower the year-to-year sensitivity of the models.

These models are used for estimating future corn yields as we make predictions with projected future weather. We either superpose the foreseen linear trend and account for persisting human impact in the future or disjoint the elevated CO₂ effect from the human impact. We find the contribution of human impact about 80 kg/ha/year to increase corn yield, of which we consider ca. 8 kg/ha/year for elevated CO₂ (see Section 2). We argue that elevated CO₂ level is independent from human impact (it rather may be seen as a humanity impact), and therefore, we cover for the elevated CO₂ in the future when no persisting human impact is assumed.

We show the results of both possible alternatives and assess future corn yields with and without persisting human impact. The sets of result figures are presented in the Appendix, together with an imposed linear trend on the annual aggregated yield outcomes (LT) (see Appendix 4.2–4.13). We find the most favorable climate projection of RCA-HadCM3Q0 (assumes the highest precipitation and the mildest GDD increase compared to other projections) only slightly decreasing in the future without continuous human impact. However, if we assume that human innovations will persist as much as in the past, we find the opposite directions of the trends. The preferential projection of RCA-HadCM3Q0 increases the most of all, by confirming that positive social and environmental effects reinforce each other. The charts exhibit that corn yields may reach the 12–16 t/ha level by the end of the century.

Here, we present the ensemble of the six climate projections collectively for all model specifications, together with the linear trend (LT) of the aggregated results (Figures 4.3 and 4.4), to filter out the feasible differences between the RCMs and afford to assess the attainable distinctions between the models. The pairwise coloring of the graphs is entitled to help easier perception of the respective charts. In general, models with specification

Chapter 4 Results

“A”, when the growing period is not divided into vegetative and reproductive growth phases, predict higher corn yields than models with specification ”B”. This suggests that, when more detailed model specification is applied, the predicted results show fairly identical and more robust results (see all “B” specifications). In other words, when we decrease the explanatory power of the set of independent variables, in Model 2A and Model 3A (compared also to Model 1A, not only to all “B” specifications), we find that the results of these two models go far beyond the rest.

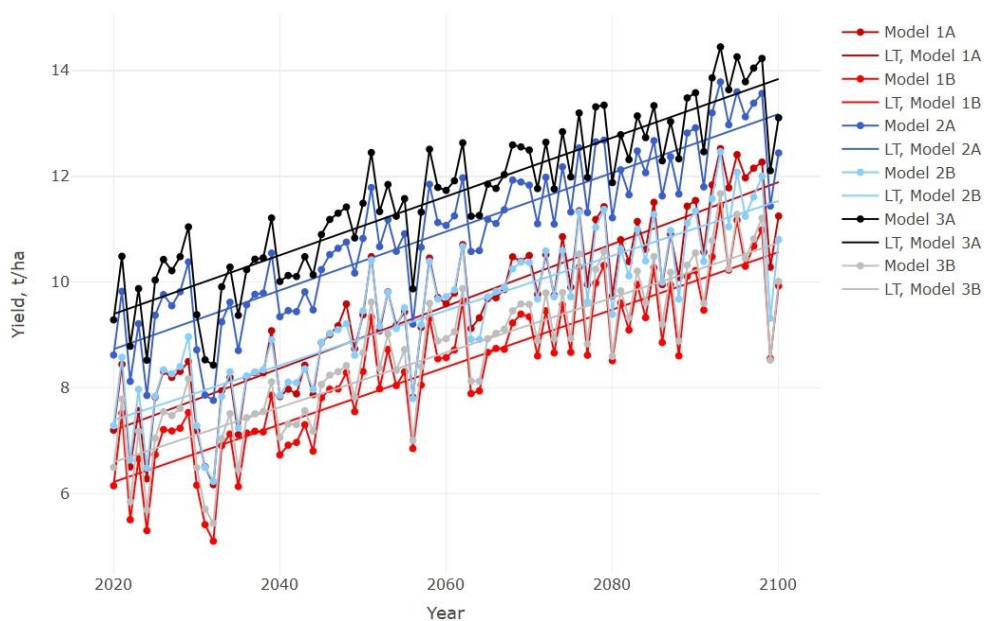


Figure 4.11 Ensemble of six RCM simulations for all model specifications with persisting human impact

Source: own figure

All models confirm that climate change in general will have a negative impact on Hungarian corn yields. The compiled model charts from all projection outcomes confirm the great importance of sustaining competitiveness and improving farm efficiency. The comparison of the ensembles reveals that corn cropping systems are in real danger due to climate change, but it is not impossible to sustain a vivid corn production for future generations.

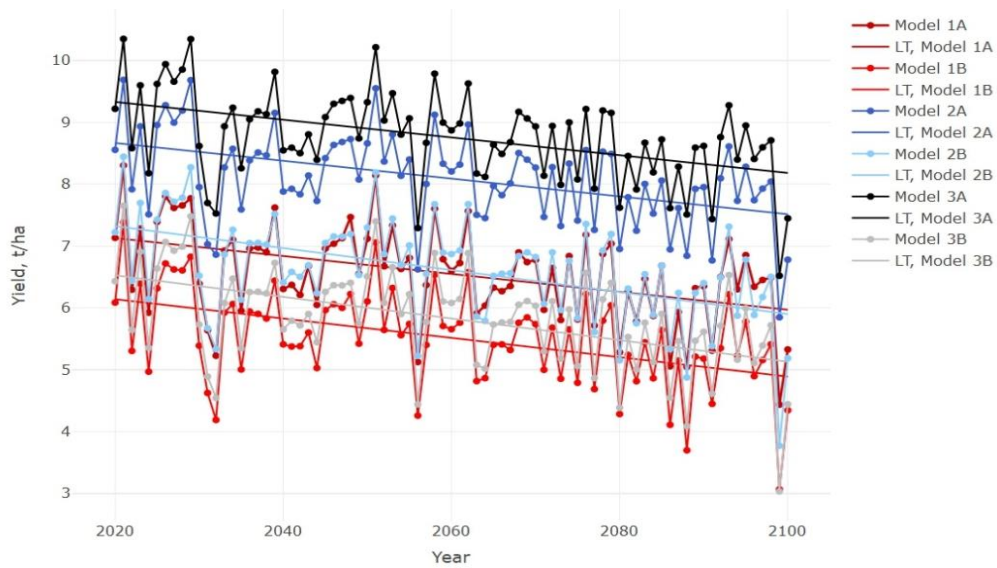


Figure 4.12 Ensemble of six RCM simulations for all model specifications without persisting human impact

Source: own figure

4.4 Conclusions

Overall, our approach of treating the increasing trend in historic corn yields is substantially different than that in the mainstream literature, where the driving force behind increasing corn yield has been labelled as either “technology development,” “technological change,” or “improving adaptation capacity,” and modelled with, e.g., linear time trend, state-specific quadratic time trends, or year-fixed effects. We argue to compile all these different terminologies into one complex issue that we may call human impact, which subsumes all unidentified effects that facilitate corn yield development. In our view, long-term climate-yield interactions can only be addressed when human impact is explicitly considered. In reality, not only weather-related factors determine corn production, but also farmers’ behavior, production conditions, political establishment, research and development, as well as technological capabilities, etc. The technical problem of identifying these effects separately lies in finding the proper proxies for these determinants, and therefore, researchers often overlook these issues and focus merely on quantifiable weather components;

methodologically, the increasing level of CO₂ in the anthropogenic impact, or at least an aftermath. For long-term prediction, we disjoined this secondary effect and superposed its positive impact on corn yield when only the effect of elevated CO₂ is considered.

Furthermore, the given heterogeneity between farms or production areas is also often disregarded. This paper shows the importance of addressing time-invariant production factors, when historic yield evolution is modelled. We confirm that soil parameters are crucial in future crop yield assessments, as it certainly has some implications for modeling. We applied the REWB hybrid framework that allows a wider range of variable use than the gold standard FE models. In principle, REWB allows for hierarchical data structure and approves time-invariant covariate use. We suppose that such indicators of soil characteristics and other individual characteristics will favor increasing prominence for modeling purposes.

Altogether, we elaborated six model specifications. Three “A” and three “B” settings indicate whether the growing period is considered in its overall length or differentiate the major plant growth phases, the vegetative and reproductive phases, respectively. We find the separation very meaningful and reveal the relative importance of more precipitation and radiation in the vegetative phase. The identified squared terms that are designed to account for the nonlinear relationship between weather variables and corn yield are zero in most cases. This implies that, for a study area like Hungary, where both soil and climate are rather favorable to corn production (relatively small area is affected by inland water, and the probability of the extremely long heat waves is low), the use of squared terms may be omitted. The rest of the results are found to be in line with the general theory of corn yield assessments.

Regarding human impact, with all models we calculated between 77 and 81 kg/ha of average annual increase in corn yields for the past that we superposed for future predictions. This indicates that activities of farmers and rather supportive establishment may lead to persistent development of Hungarian corn production. We show the potential best and worst possible outcomes for Hungarian corn production in the light of climate change until 2100 based on bias-corrected RCM simulations.

We find evidence that the Hungarian corn cropping system is vulnerable in the long run, but sustaining human impact certainly has the potential to reverse the projected decreasing trend. Still, there is room for sustainable intensification for corn production in Hungary, where “reversing the curve” means calling to organized actions of policy makers, farmers, and agricultural cooperatives to carry out great investments in precision farming, large-scale irrigation infrastructure development to provide more suitable farming conditions.

Further research may consider a more detailed identification of the components of human impact and thus contribute to make more comprehensive predictions.

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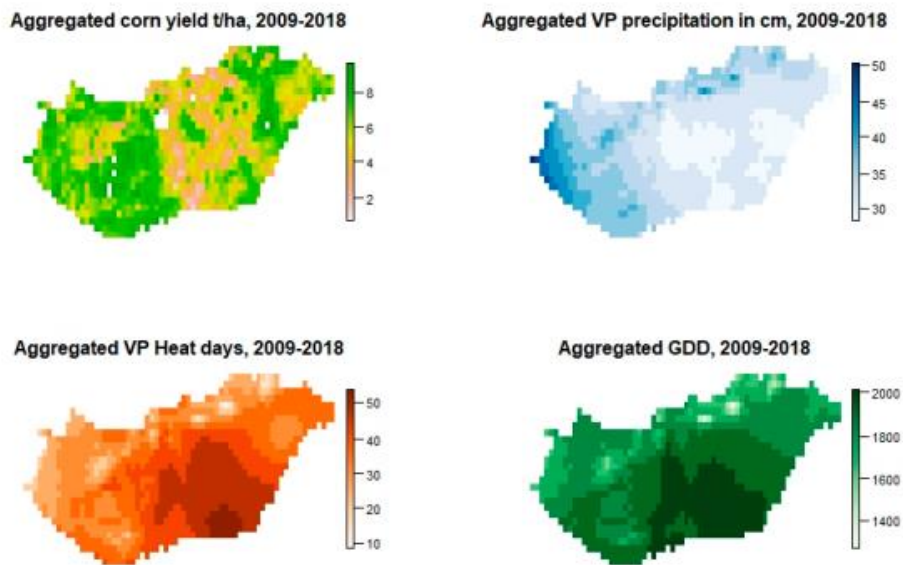
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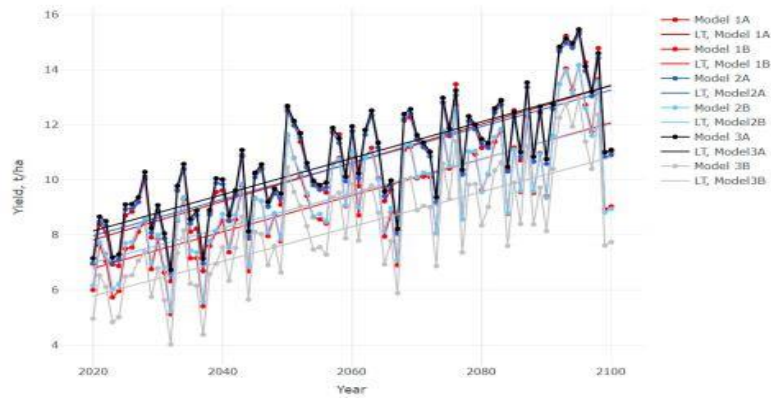
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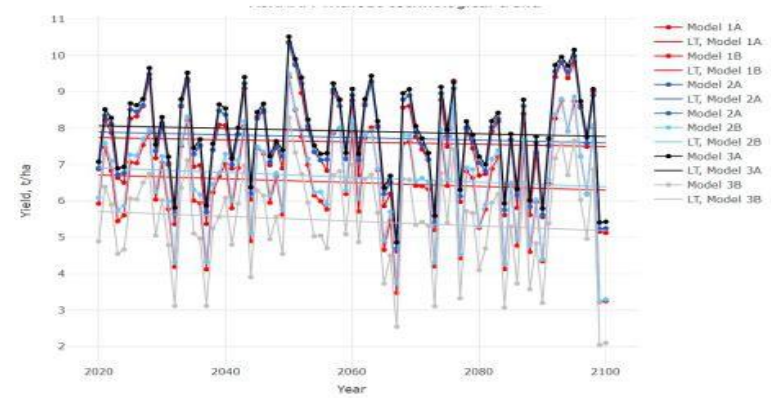
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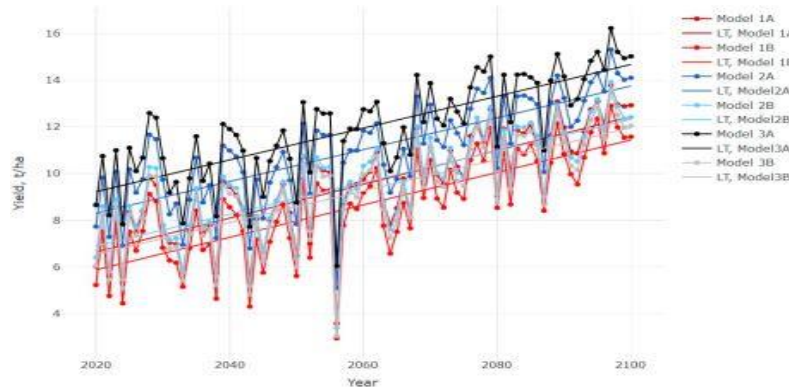
Appendix 4.1 Spatial distribution of yield, P, NHD, and GDD



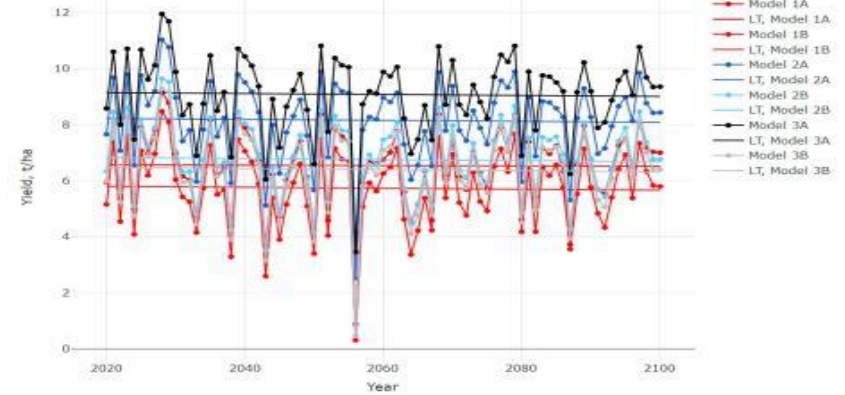
Appendix 4.2 HIRHAMS5.ECHAM with Human Impact



Appendix 4.3 HIRHAMS5.ECHAM without Human Impact

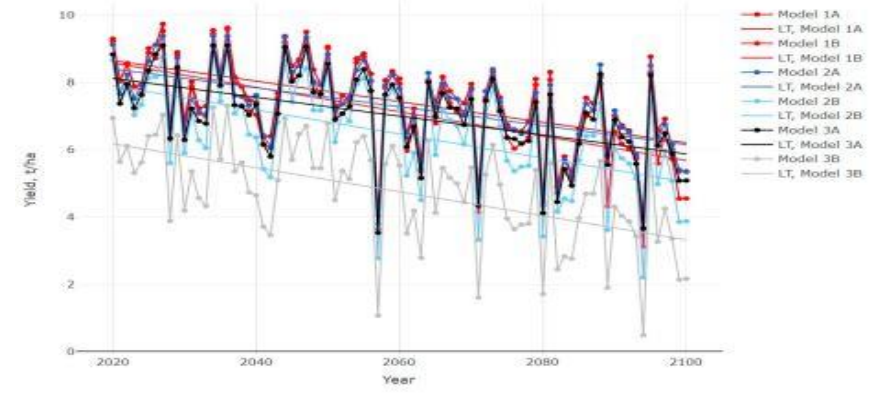
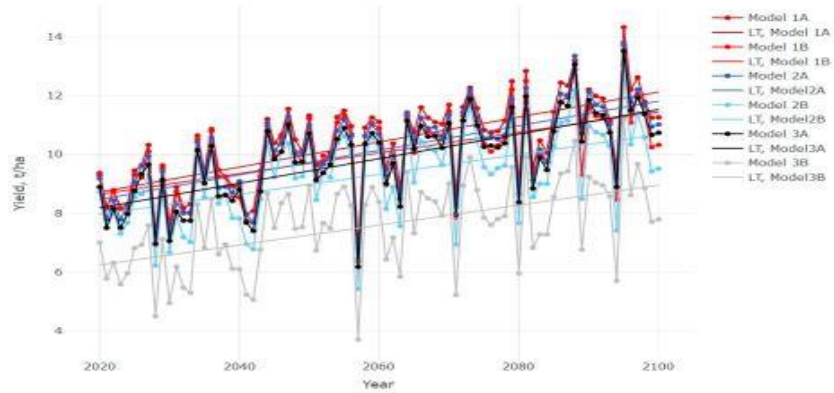


Appendix 4.4 RCA.HadCM3Q0 with Human Impact

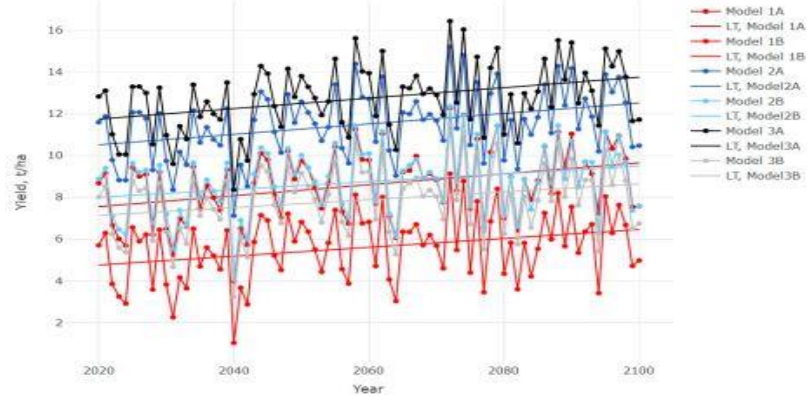


Appendix 4.5 RCA.HadCM3Q0 without Human Impact

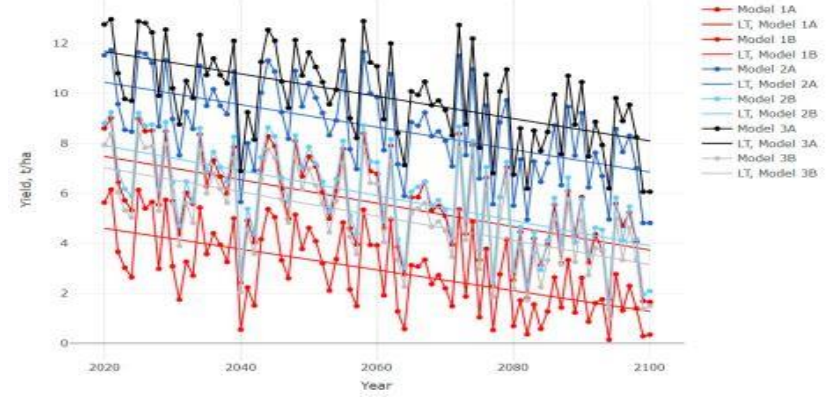
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Appendix 4.6 CLM.HadCM3Q0 with Human Impact



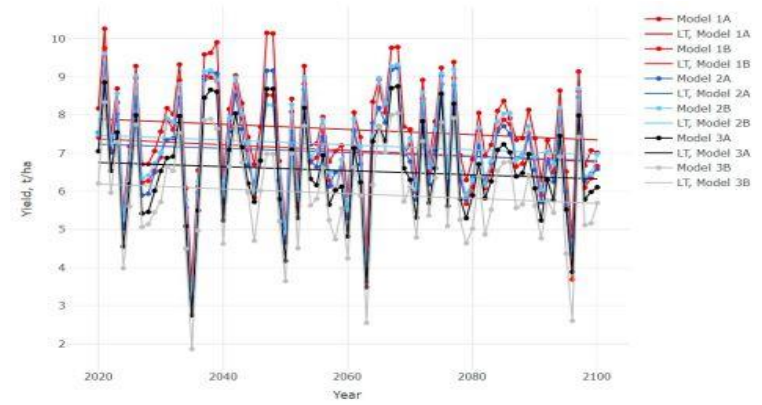
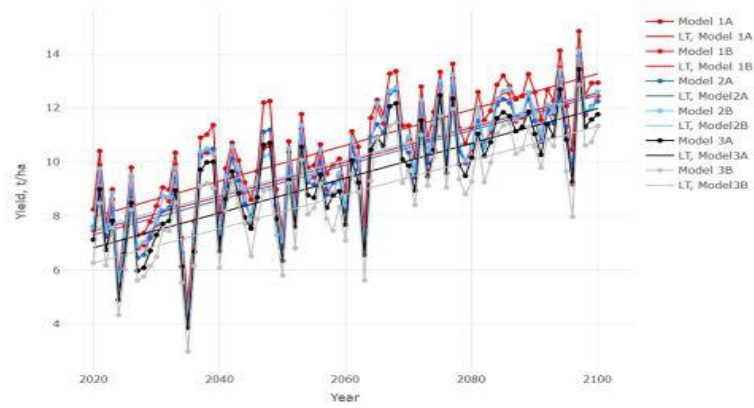
Appendix 4.7 CLM.HadCM3Q0 without Human Impact



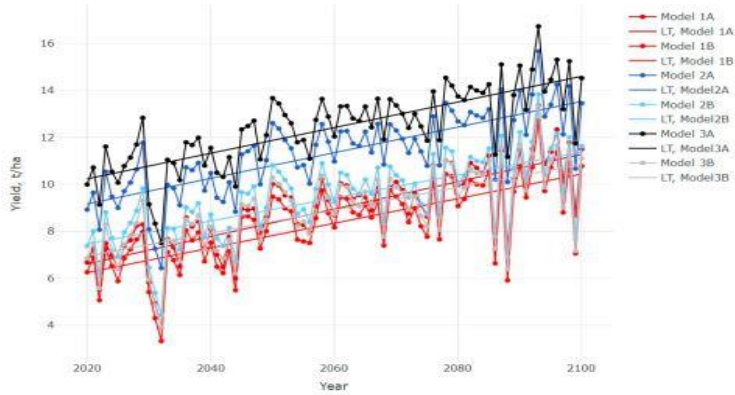
Appendix 4.8 HADRM3Q0.HadCM3Q0 with Human Impact

Appendix 4.9 HADRM3Q0.HadCM3Q0 without Human Impact

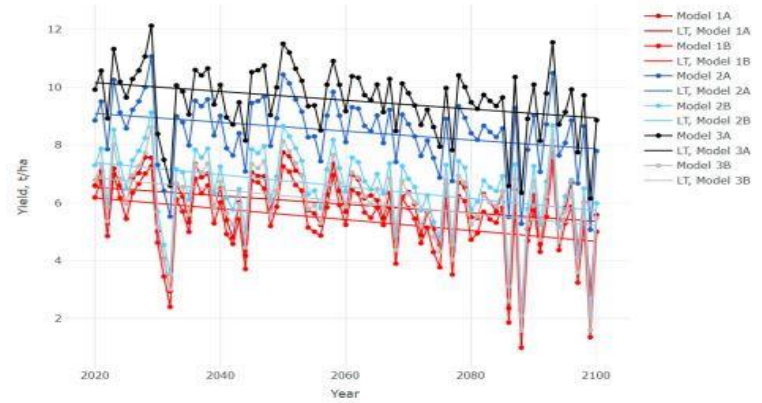
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Appendix 4.10 HIRHAMS.ARPEGE with Human Impact



Appendix 4.11 HIRHAMS.ARPEGE without Human Impact



Appendix 4.12 RCA.ECHAM5 with Human Impact

Appendix 4.13 RCA.ECHAM5 without Human Impact