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Empirical analysis of farm structural change at EU-level

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Kurzfassung

Die drastischen Veränderungen der landwirtschaftlichen Betriebsstruktur in Europa haben zu einer Vielzahl wissenschaftlicher Studien in diesem Bereich geführt. Die neuesten dieser Studien konzentrieren sich dabei zunehmend auf regionale Unterschiede des Strukturwandels und die räumliche Interaktion der Betriebe. Die vorliegende Dissertation analysiert den EU15-Agrarstrukturwandel auf regionaler Ebene. Agrarstrukturwandel ist hier definiert als die Veränderung der Anzahl der landwirtschaftlichen Betriebe in verschiedenen Betriebsklassen über die Zeit. Die agrarökonomische Literatur wird mit dem Ziel der Identifikation eines methodischen Ansatzes besprochen, der es erlaubt den agrarstrukturellen Wandel in einem derart großen Umfang und gebunden an eine multidimensionale Betriebstypologie zu erklären und zu modellieren.

Als geeignetster methodischer Ansatz stellt sich eine Markowketten-Analyse heraus. In den beiden empirischen Teilen der Arbeit werden Markowketten-Übergangswahrscheinlichkeiten geschätzt, die jeweils die Wahrscheinlichkeit eines Betriebes repräsentieren, von einem Betriebstypen zum nächsten in einer bestimmten Zeitperiode zu wechseln. Die Übergangswahrscheinlichkeiten werden mit Hilfe eines Generalised Cross-Entropy-Schätzers bestimmt, welcher - erstmalig in der Literatur - die Kombination zweier verschiedener Datenarten in einer Schätzung erlaubt. Verglichen mit vorhergegangenen Studien führt die Kombination der Datenarten zu einer deutlichen Vergrößerung der empirischen Basis für die Schätzung der Übergangswahrscheinlichkeiten. Die Markowkette konstituiert sich aus aggregierten Daten, die die Verteilung der Betriebe auf die Betriebstypen in der Population wiedergeben. Spezifische Wechsel von Testbetrieben zwischen den Betriebstypen, sogenannte Mikrodaten, werden als a priori-Information in den Schätzansatz eingebunden. Für jede von etwa 100 EU15-Regionen werden Übergangswahrscheinlichkeiten basierend auf FADN (Farm Accountancy Data Network) Daten von 1990/1995 bis 2005 geschätzt.

Die Arbeit unterteilt theoretisch relevante Determinanten des Strukturwandels in die Konzepte *technischer Fortschritt/economies of scale*, *Theorie des landwirtschaftlichen Haushalts*, *Pfadabhängigkeit*, *Immobilität des Bodens*, *Politik* und *Marktbedingungen*. Funktionen der (teilweise zeitvariierenden) Übergangswahrscheinlichkeiten werden erklärenden Variablen aus diesen Konzepten in Querschnittsanalysen gegenübergestellt. In zwei empirischen Anwendungen wird der Agrarstrukturwandel einmal allgemein über alle Betriebsspezialisierungen hinweg und einmal mit Fokus auf Milchviehbetriebe analysiert. Beide Anwendungen offenbaren große regionale Unterschiede des agrarstrukturellen Wandels. Während der erwartete Einfluss der Determinanten aus dem Konzept *technischer Fortschritt/economies of scale* größtenteils bestätigt wird, weicht der Effekt der Einflussgrößen aus den anderen Konzepten auf die Übergangswahrscheinlichkeiten zum Teil von den Hypothesen ab. Insgesamt ist die Identifikation der zugrundeliegenden Prozesse über Regionen hinweg nur bedingt möglich. Die Dissertation bestätigt somit die weithin propagierte Komplexität des agrarstrukturellen Wandels.

Schlagwörter: Agrarstrukturwandel, Markowketten-Analyse, FADN Daten, Querschnittsanalyse, Regionen, EU15.

Abstract

The drastic changes of the European farm structure have led to plenty of research on farm structural change with recent studies focusing more and more on regional differences and spatial interaction of farmers. The thesis adds to this literature by providing a large-scale analysis of farm structural change across EU15 regions. For this purpose, farm structural change is defined as the change of the number of farms in different farm types over time. The agricultural economics literature is reviewed in order to find a methodological approach suitable to model and to analyse farm structural change at such a large regional scale and adhering to a multi-dimensional farm typology.

A Markov chain estimation framework is identified to be the best suitable approach for the task at hand. In both empirical parts of the thesis, Markov chain transition probabilities are estimated representing the likelihood of a farm to change from one farm type to another in a given period of time. For the estimation of the transition probabilities, a generalised cross-entropy estimator is applied. The estimator allows, for the first time, the combination of two different data types in one estimation step, thereby significantly improving the empirical base for estimating transition probabilities compared to previous studies. Aggregate data giving the distribution of farms across farm types in the population is used in establishing the Markov chain and micro data on the specific movements of sample farms across farm types is used as a priori information in the estimation framework. Transition probabilities are estimated for each of about 100 EU15 regions based on FADN (Farm Accountancy Data Network) data from 1990/1995 to 2005.

The thesis categorises theoretical determinants of farm structural change into the concepts *technology/economies of scale*, *farm household theory*, *path dependency*, *land immobility*, *policy*, and *market conditions*. Functions of the (in part time-varying) transition probabilities are cross-sectionally regressed against explanatory variables picked from these concepts. Two empirical applications, one analysing structural change encompassing all production specialisations and the other one focused on dairy farms are conducted. In both studies significant regional difference in farm structural change are observed. Whereas the expected impact of the *technology/economies of scale* concept is generally confirmed, the effect of the variables from the other concepts on farm structural change remains often ambiguous. Overall, the thesis confirms the widely acknowledged complexity of farm structural change.

Keywords: Farm structural change, Markov chain analysis, FADN data, cross-sectional analysis, regions, EU15.

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Abbreviatons

DFG	Deutsche Forschungsgemeinschaft, German Research Foundation
EAAE	European Association of Agricultural Economics
ESU	European Size Units
EU	European Union
EU15	The 15 member states that constituted the EU from 1995 to 2004
FADN	Farm Accountancy Data Network
NUTS	Nomenclature d'Unités Territoriales Statistiques, Nomenclature of Units for Territorial Statistics of the EU
NUTS 0	Member state level
NUTS I	Bigger parts of a member state (Bundesländer in Germany)
NUTS II	Sub-unit of NUTS I regions
SEAMLESS	System for Environmental and Agricultural Modelling; Linking European Science and Society
SGM	Standard Gross Margin
TPM	Transition Probability Matrix
US	United States of America

Part 1
Overview of the thesis

"No single size distribution or method of analysis can effectively characterise the complexity of farm structure. A sense of the larger context in which structural change will continue to occur is essential."

Stanton, 1993

1.1 Motivation and fundamental research questions

The drastic changes of the farm structure in industrialised countries during the past decades led to plenty of research in this field. Starting with the publication of Cochrane's technology treadmill in 1958, an ever increasing interest in the topic of farm structural change is observed. This is documented by a large amount of studies which have been published in this field, starting with analyses on changes in the US farm structure in the 1960s and soon also turning to European topics. Research on farm structural change in Europe has especially increased during the last ten years documented by a large amount of publications, let alone three EAAE (European Association of Agricultural Economists) seminars[1] which were directly concerned with farm structure issues in the past five years. In Germany, the scientific interest is expressed in the creation of a DFG research group "Structural Change in Agriculture" (2007-2010 and 2010-2013).

Stanton (1993) finds that all farm structure issues are concerned simultaneously with (1) farm businesses, (2) farm households, and (3) agricultural resources. (1) The farm business concept focuses on the business character of farming in the sense that the business as a productive enterprise contributes value-added to the national economy. "These operations combine the services of land,

[1] 96th EAAE seminar "Causes and Impacts of Agricultural Structures" in Tänikon, Switzerland, January 2006; 111th EAAE seminar "Small Farms: Decline or Persistence?" in Canterbury, UK, June 2009; 114th EAAE seminar "Structural Change in Agriculture" in Berlin, Germany, April 2010.

labour, capital, and management in production and sustain profits and losses like any other business" (Stanton, 1993, p. 17). (2) The farm household concept refers to the family farm as it is typical in Western Europe. Decisions and actions taken by the farm household have to be differentiated from decisions and actions taken by the farm business as they might follow from different incentives, values and goals (e.g. Hallam, 1991, Schmitt, 1992, Stanton, 1993). (3) "Fundamental to the organisation of agricultural businesses is the resource base associated with farming in all its many dimensions" (Stanton, 1993, p. 17). For most farms, land is the key component with the other fundamentals labour, capital, and management being organised around it. Farm structure is constructed and farm structural change occurs based on these fundamentals (Stanton, 1993).

Although farm structural change is usually concerned about three major issues (1) the changing distribution in an industry context, (2) production decisions and organisation (keyword: vertical integration), and (3) resource ownership and control (Stanton, 1993), nearly all of public discussion and scientific research in industrialised countries focuses on the examination and explanation of changes in numbers and size of farms (Stanton, 1993, Goddard et al., 1993). Thereby, Stanton (1993, p. 21) finds that "no single size distribution or method of analysis can effectively characterise the complexity of farm structure. A sense of the larger context in which structural change will continue to occur is essential".

The idea of the thesis originates in a large EU-project running from 2005 to 2009, the SEAMLESS project - System for Environmental and Agricultural Modelling; Linking European Science and Society (Van Ittersum et al., 2008). The main aim of the project was the development of a computerised framework for the integrated assessment of agricultural systems and the environment. Therefore, different models from field to global level were connected to each other in a model chain. In this model chain, a structural change module was needed capable of predicting future shares of farms in a large number of multi-dimensional farm types defined by the project. At the same time, the tool should be able to predict the farm type shares for a huge spatial scale - the EU15 - at the level of individual regions.

Following the general observations regarding the scientific treatment of farm structural change presented above and the specific demands of the project, this thesis applies a broad definition of farm structural change describing it as the change of the number of farms in different farm types over time.

As part of the project, a comprehensive literature review was conducted with the main aim of finding a suitable methodological approach to assess and predict farm number changes in multi-dimensional farm types at a broad regional scale. At the same time, also determinants which have proven to be of significance to farm structural change in empirical analyses were reviewed. The literature review was published in the journal *Environmental Science and Policy*[2] and constitutes part 2 of the thesis. While reviewing the literature, it quickly turned out that, so far, structural change analyses in agriculture (and even more beyond agriculture) have been conducted only for a rather limited number of farm types and at a very limited regional scale and that the special farm type and regional scope of the analysis would become the main tasks to accomplish with regard to data availability, methodological approach, theoretical underpinning, and last but not least a comprehensive but clearly arranged presentation of the results.

The literature review reviews many of the currently applied methods to assess farm structural change. It is found that many studies and methods concentrate on one of the several dimensions of farm structural change only. The econometric growth models usually focus on Gibrat's law (the size of a farm and its growth rate are independent of each other) and try to explain farm growth processes, whereas other econometric models (e.g. age cohort analyses) examine net changes in total farm numbers. Only two methods applied in the literature are found to be generally suitable to manage the complexity of the task at hand. Among the econometric models Markov chains and among the simulation models multi-agent systems are able to tackle the multi-dimensionality and interdependency of farm structural change resulting from the competition for resources, specifically land, which requires that some farms decline or exit the sector for others to grow. Due to the enormous requirements of multi-agent models with regard to data and computational resources and the very limited availability of adequate validation procedures, Markov chains are quickly identified as the only methodology being generally suitable to solve the task of the project. However, as the in-depth analysis of Markov chain applications in the literature shows, even this method has previously been applied for a limited farm type and regional scope only. As a result especially from the restricted regional scope of the analyses, also the range of determinants used to explain structural change in Markov chains has been rather limited. Therefore, the other methods are also carefully reviewed with special attention on potential driving factors of structural change in agriculture. The review of the theoretical literature and the hypotheses tested in the more empirical publications revealed that no unified theory of farm structural change exists and that determinants often are expected to have ambiguous impacts. Due to limited space and another focus of the literature review in part 2, theoretical considerations are reviewed and brought together in more detail in part 4 of the thesis. A brief overview is also given in section 1.3. The papers presented in part 3 and 4[3] of the thesis attempt to empirically measure the relevance of the different theories brought up in the literature to the process of farm structural change.

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[2] Zimmermann et al. (2009).

[3] Both papers have been submitted for review to international agricultural economics journals and part 3 and 4 of the thesis constitute first round revisions of the papers originally submitted.

Summarising, the special needs of the project and the literature review brought the attention to several unsolved but fundamental questions concerning farm structural change which are approached in this thesis and which can be brought down to: (1) how changes the farm structure across the different regions of the EU15 and (2) what drives those changes? A third question that arises from the other two is, (3) how can farm structural change be modeled and analysed at such a large scale?

Part 3 of the thesis pays special attention to regional differences of farm structural change in the EU15. They are, for the first time in the agricultural economics literature, systematically analysed and described. The analysis is thereby based on a broad farm typology combining size and specialisation classes developed by the SEAMLESS project. Observing significant regional differences in farm structural change, part 3 builds upon the project work by systematically comparing those differences and making a first step into relating the differences to certain regional characteristics. At the same time, a unique combination of different data types is presented in the methodological approach.

Encouraged by the interesting results of part 3, part 4 concentrates on cross-regional farm structural change in one specialisation class - dairy farming - only. The reduction of the number of farm types to a few size classes makes it possible to observe farm structural change not only cross-regionally but also over time and to systematically test the relevance of different theoretical concepts and their impact on farm structural change.

When the study started in 2005, farm structural change analyses covering more than one region were almost not available. In parallel to the work on the thesis at hand (and probably induced by it), other researchers started exploring cross-regional differences and effects during the past five years. As a result of this and underlining the relevance of the topic, the thesis perfectly fits into the current research landscape which is characterised by regional comparisons (e.g. Huettel and Jongeneel, 2011), cross-regional analyses (e.g. Breustedt and Glauben, 2007, Huettel and Margarian, 2009, Heckelei, 2010), and a general focus on spatial heterogeneity and interaction (e.g. Happe, 2004, Balmann et al., 2010, Margarian, 2010, Weiss, 2010).

The thesis is unique with regard to its farm type and regional scope, the database used, the methodology combining different data types, and its specific cross-regional focus. It is also the first empirical study that explicitly tries to differentiate between the impact of the main theoretical concepts discussed in the literature.

The remaining sections of this introductory part of the thesis are structured as follows: A descriptive section gives an impression of the main structural changes that occurred in Europe in the past and the present and introduces the thinking in farm typologies. A theoretical section briefly summarises the main concepts applied to farm structural change in the literature. It is followed by the summaries of the three main parts of the thesis. From each of these parts the main findings which are important for the flow of the thesis are presented. The final section concludes and gives an outlook into future research in this field.

1.2 Farm structural change in Europe

As this study is the first one which explicitly focuses on regional differences in farm structural change across the whole EU15, the question might arise in how far those differences are actually driven by different historic developments. In fact, path dependency is discussed as one of the main concepts impacting structural change in agriculture (e.g. Balmann, 1995). However, in the agricultural economics literature as well as in part 3 and 4 of the thesis the farm structural change phenomenon is only analysed over a short- to medium-term horizon. For completeness, the following section gives a brief overview of the history and historic differences of farm structural change in (Western) Europe. It is a descriptive excursion with the aim of exploring hints to a potential connection between past and present structural developments. Afterwards, a brief summary is given over recent farm structural changes in the different EU15 regions.

A brief excursion into history

Regionally differing agricultural structures and regionally differing structural developments are not a new phenomenon. Amazing differences in farm structural change across European regions and countries despite similar overall conditions are already reported for the Middle Ages. This phenomenon even led to an extensive scientific debate about their causes among historians from the 1970s to the 1990s. This discussion was later named the ‘Brenner debate’ (Aston, 1987) after Robert Brenner, the author of an intensely discussed article on the historic causes of such differences (Brenner, 1976).

Generally, economic history focuses on property rights and how their distribution changes across European regions and over time. Following the Malthusian theory of population, many authors have argued that as a result of population pressure in the 13th century, competition for land led to a serious degradation of the personal and tenurial status of peasants compared to the landlords' position in Europe which resulted in growing estates of the landlords (Brenner, 1976 and 1982). In the 14th and 15th centuries, in contrast, a population decline resulting from falling productivity, famine and plague led to a drastic reversal of the man/land ratio. The scarcity of peasants not only meant a decline in the level of production, but also in the lords' ability to restrict peasant mobility and peasant freedom in general which in the end determined the fall of serfdom in Western Europe. A repetition of this two-phase movement is observed with increasing population, rising rents, falling wages and a disintegration of peasant holdings in the 16th century and the opposite effect in the 17th century (Brenner, 1976). These being the overall conditions in Europe during the Middle Ages, Brenner (1976) questions if demographic change can be legitimately treated as the cause, let alone the key variable in explaining the class relationships and related farm structural change. Comparing the developments in different European regions, he argues that “different outcomes proceeded from similar demographic trends at different times and in different areas of Europe” (Brenner, 1976, p. 39). For example, he finds that during the 14th and 15th centuries the “parallel trends of declining rents and the rise of peasant freedom” (p. 41) dominated in England, but at the same time a sharpening of landlord controls could be observed in Catalonia and parts of France. With serfdom having ended by the early 16th century in most of Western Europe, in Eastern Europe (particularly in Pomerania, Brandenburg, East Prussia and Poland) a “decline in population from the late 14th century was accompanied by an ultimately successful movement toward imposing extra-economic controls, i.e. serfdom, over what had been, until then, one of Europe’s freest peasantries” (p. 41). Brenner (1982) concludes that “under different property structures and balances of class forces in various European regions, precisely the same demographic and commercial trends yielded widely divergent economic results” (p. 17) and that for this reason the establishment, development and transformation of the class structures “have to be placed at the centre of any interpretation of the long-term evolution of the pre-industrial European economy” (p. 17).

Karayalcin (2010) identifies three regions into which Europe was split at the beginning of the 16th century. Those were basically characterised by a different set of property rights. In Western Europe, particularly in France and Germany serfdom was ended at the end of the mediaeval era leaving peasants with the full legal recognition of their property rights to land. Though their plots were initially relatively large, the rising population and the subdivision of land led to a large class of peasants working on small plots of land at the end of the 16th century. Observing that industrialisation requires large enough domestic markets (Murphy et al., 1989), Karayalcin (2010) finds that the individual landowners did not earn enough to generate sufficient demand to support the new industries. For Eastern Europe the other extreme holds: the second serfdom with a small group of feudal lords siphoning off the income generated in agriculture, no relevant income was available to support industrialisation. In north-western Europe (England and Benelux) the landholding pattern remained in between these two extremes.[4] By the end of the 16th century, land holdings of English farmers averaged around 25 hectares which was substantially larger than for example the plots of French farmers. The English landholdings were neither too small nor in the hand of lords

[4] Table 3.6 in part 3 of the thesis shows that in 1990 the share of large farms was still significantly higher in the United Kingdom, Belgium, Luxembourg, and the Netherlands than in the other member states of the EU15. However, in the 15 years from 1990 to 2005 the share of large farms in France and Germany increased to such an extent that it almost approaches the large farm shares in those countries indicating drastic structural changes.

so “that a reasonably large number of households earned enough income to demand a broader spectrum of goods” (Karayalcin, p. 6). This demand allowed for the expansion of the manufacturing sectors. Karayalcin (2010) follows that property rights mattered in determining the divergent paths taken by the three regions.

Van Zanden (1991) states that until about 1850, real wages of agricultural workers declined in most Western European countries with, at the same time, increasing rental values of land as well as cereal prices. As a result of these developments, farmers were strongly induced to increase production per hectare by using more hired workers and family labour. However, the process of modern economic growth, which had begun in most countries of Western Europe in the first half of the 19th century and which accelerated after 1850, induced increasing scarcity of labour such that real wages of agricultural workers doubled in almost all European countries between 1870 and 1910. The increased labour costs made the continuation of the course of agricultural growth followed before 1870 impossible. According to Van Zanden (1991) a gradual mechanisation of the production process promoting large-scale farming should have been the obvious solution to the rapidly rising labour costs. In fact, precisely the opposite happened. After 1870, large-scale farming based on hired workers gradually disappeared and the rise of the family farm occured in a large number of regions.

In those countries which adapted best to the changing circumstances, the further intensification of agricultural production went together with a rapid growth of labour productivity. Whereas agriculture in Britain played a leading role in European agriculture in the period 1750 to 1880, it suddenly lost its position and stagnated for almost 60 years, until about 1930. Van Zanden (1991) attributes the sudden change after 1870 to the very different farm structure in England compared to most continental countries. The large British holdings still depended on hired workers, whereas continental agriculture was increasingly practiced on small family farms. Being prepared to work on their own land for incomes below the going wage rate, the rapid rise in wage costs after 1870 could not harm these family farms as they were independent of hired workers. Instead they profited from the new land-saving technologies (e.g. chemical fertilisers and purchased feeding stuff) and were able to increase output and productivity in spite of unfavourable economic circumstances. In contrast, the large, capitalist farms in Britain, and perhaps also their continental counterparts in the Paris basin and in Italy, were unable to adapt to these circumstances in a successful way (Van Zanden, 1991). Following these developments, Friedmann (1978) finds that in England the number of both large and small farms decreased, whereas there was an increase in the number of medium-sized farms. He concludes that farm size in England from both directions approached a standard which could be cultivated by family labour at that time. This process was accompanied by political efforts improving property rights for tenants and raising taxes for large estates (Swinnen, 2002). As a result, the vast majority at least of the commercial wheat producers on the world market was organised through family rather than wage labour by 1935.

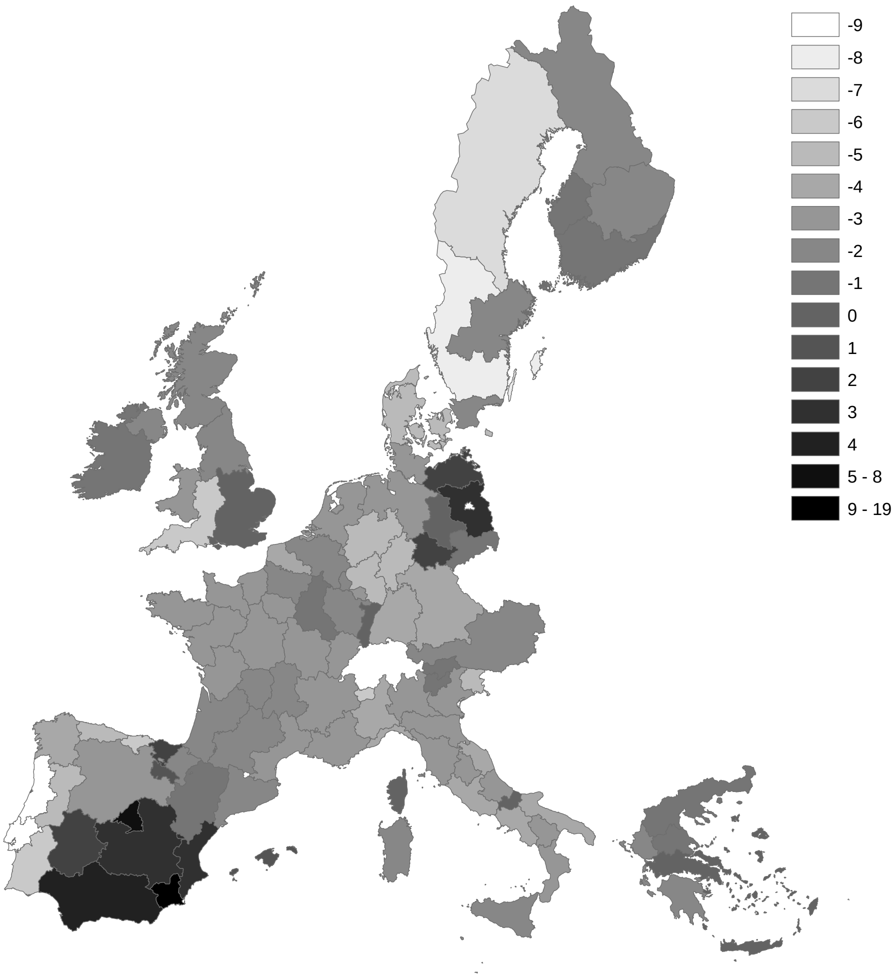
Despite this rather long way to the family farm and the general decline of household production in most branches of industrial economies, Friedmann (1978, p. 550) finds that "the predominance of commercial households in many agricultural branches has been so widely recognised that it ceases to be a matter of theoretical interest" and that "the family farm is treated as a more or less natural basis for agricultural production".

Recent developments and differences

With increasing productivity due to mechanisation and green revolution, farm numbers have been declining and farm sizes have been increasing all across Western Europe for the last 50 years. The thesis at hand analyses farm structural changes from the 1990s to 2005. Overall, the number of farms has decreased by about 30 per cent from 1990 to 2005 in the EU15. The number of farms in the Member States forming the EU before 1995 has decreased from more than 4 million in 1990 to less than 3 million in 2005.[5] In the countries which joined the EU in 1995 (Austria, Sweden, Finland) including East Germany, the number of farms decreased from almost 200,000 in 1995 to less than 160,000 in 2005. Figure 1.1[6] reveals the regional distribution of the average annual rates of farms leaving the sector (exit rates) in the observation period 1990 to 2005 (1995 to 2005 for East Germany, Austria, Sweden and Finland).[7]

[5] Since the analysis in this paper is based on data from the Farm Accountancy Data Network (FADN), here as in FADN, only so-called 'commercial' farms are considered. The FADN data are explained in more detail in section 1.5 and in parts three and four of the thesis.
[6] The figure is also shown in part 3 of the thesis.
[7] The exit rates are calculated by applying the geometric mean to the total number of farms at the beginning and at the end of the observation period.

Figure 1.1: Annual rates of farm number change 1990-2005 [per cent]



Source: Own map based on FADN data.

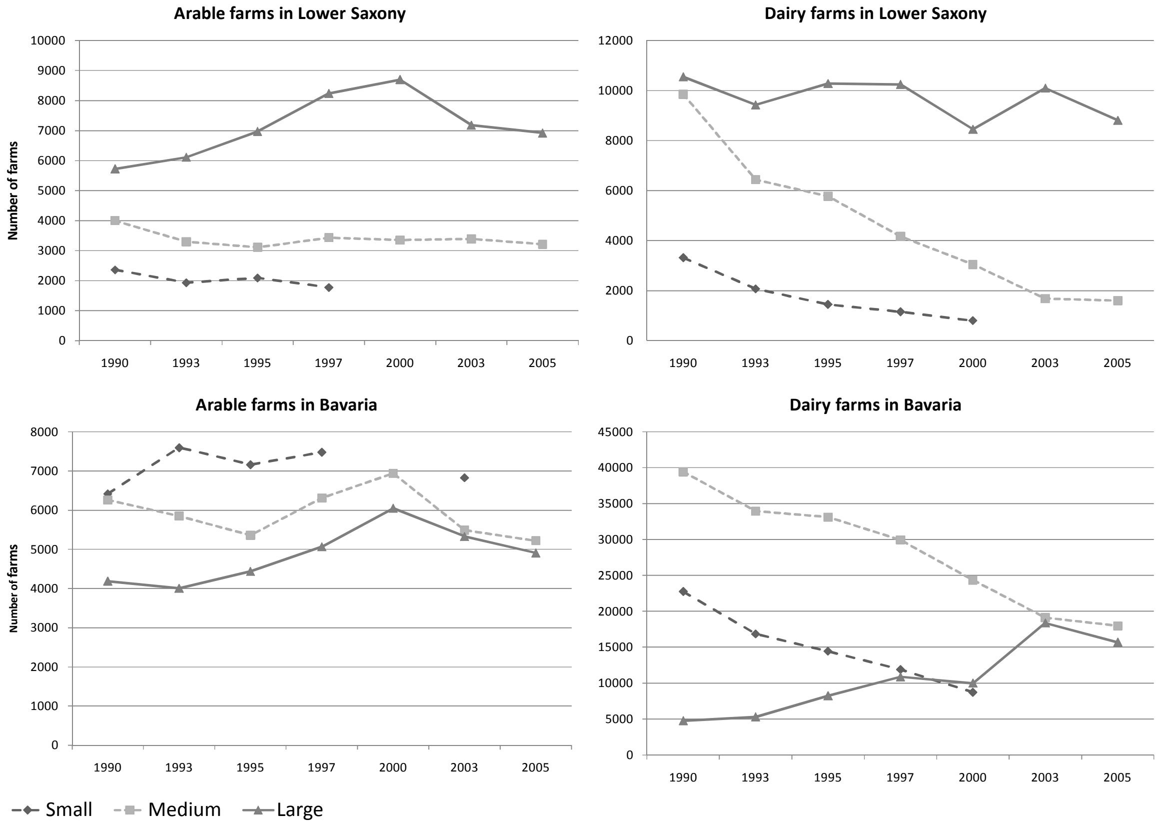
The figure shows considerable variation in the farm number development across regions on the Iberian Peninsula, Scandinavia and Germany, whereas regional farm number change is relatively homogeneous in France and Italy. Most European regions experienced decreasing farm numbers during the time period 1990/1995 to 2005. The highest net exit rates are reported in Portugal and Sweden. The only regions where the number of farms has increased are Central and Southern Spain and, due to historical reasons, parts of East Germany.[8]

Figure 1.2 shows the development of the number of farms in two different specialisation classes for two different German regions from 1990 to 2005. The two upper diagrams give the number of arable farms on the left and the number of dairy farms on the right in Lower Saxony in the North West of Germany. The two lower diagrams give the number of arable farms (again on the left) and the number of dairy farms (on the right) in Bavaria in the South East of Germany. The development of farm numbers is shown for small, medium, and large farms. Small farms are defined as farms with an economic size of up to 16 ESU (European Size Units), medium-sized farms range from 16 to 40 ESU, and large farms are greater or equal to 40 ESU.[9]

[8] The regions with positive growth rates are: Brandenburg, Mecklenburg-Vorpommern, Thueringen in Germany, and Pais Vasco, La Rioja, Baleares, Madrid, Castilla-La Mancha, Comunidad Valenciana, Murcia, Extremadura, Andalucia, Canarias in Spain.

[9] According to FADN, the economic size of a farm is determined by Standard Gross Margins (SGM). "The Standard Gross Margin of a crop or livestock item is defined as the value of output from one hectare or from one animal less the cost of variable inputs required to produce that output" (FADN webpage, 2011). In the period from 1990 to 2005 one ESU corresponded to 1200 Euro.

Figure 1.2: Number of farms in different German regions 1990-2005



Source: Own figure based on FADN data.

Comparing the diagrams for arable and dairy farms in Lower Saxony, it becomes obvious that the number of medium-sized arable farms remained rather stable, whereas the number of medium-sized dairy farms declined drastically in the same period. Similar results are found comparing arable farms and dairy farms in Bavaria: the number of medium-sized arable farms varies within a corridor of 2000 farms, whereas the number of medium-sized dairy farms declined from about 40,000 to less than 20,000 farms. Comparing the same specialisation class between the two regions, a similar development pattern is found for the arable farms. The number of dairy farms, however, tends to slightly decline in Lower Saxony, whereas it clearly increases in Bavaria. Summarising, there obviously exist differences in farm structural change between different specialisation classes as well as differences in the development of the same specialisation class between different regions. This is exemplarily shown here for two specialisation classes and two regions. EU15-wide differences are examined in part 3 and 4 of the thesis.

1.3 Theory of farm structural change

As seen from the historic retrospection and recent developments, farm structural change encompassing regional differences has always occurred and continues until today. However, for the past as well as for the present it is still not very clear what the main drivers of structural developments are. Section 1.2 shows that also the historical literature discusses some key concepts impacting farm structural change (market conditions, policy, technology, farmers' incentives, and path dependency). Here, the existing theoretical concepts are briefly mentioned. They are discussed in more detail in part 4 of the thesis.

A large variety of theoretical and empirical papers discusses farm structural change and its causative factors. Theoretical literature started to occur in the late 1950s. In the beginning, the 'technological treadmill' by Cochrane (1958) was seen as the main driver of farm structural change leading to ever larger farms by favouring economies of scale. The observation of the persistence of small farms in many regions and remaining sectoral heterogeneity led to the development of additional theoretical models complementing the technology/economies of scale concept (e.g. Hallam, 1991, Boehlje, 1992).

Though individual driving factors are often discussed independently of each other (e.g. Goddard et al., 1993, Harrington and Reinsel, 1995), the two most prominent of those models are the farm household theory (Schmitt, 1992, Stanton, 1993) and the concept of path dependency (Balmann, 1995). Rarely, also land immobility as specific characteristic in agriculture is considered (Harrington and Reinsel, 1995). With land being the most important resource in agriculture (Balmann, 1995, Margarian, 2010), land immobility plays a key role in the regional interaction of farmers and the spatial dynamics in agriculture (Mosnier and

Wieck, 2009, Margarian, 2010). As part of the above mentioned theoretical concepts, but due to the difficulty of assigning them to only one of the theories, policy and market conditions are usually independently discussed. Harrington and Reinsel (1995, p. 12) stress that all these mechanisms are to "be combined into a more comprehensive synthesis capable of capturing more of reality". According to them "the empirical tasks of […] researchers are to determine the relative strengths of each of the mechanisms that may be at work in different commodity, regional or temporal settings" (p. 12).

1.4 Review of methods and determinants

In the following, the main findings and conclusions of part 2 are presented according to their relevance for the other parts of the thesis. The extraordinary scope of the analysis with regard to its regional dimension and the number of farm types to be considered demands a suitable methodological approach. Part 2 provides a comprehensive review of the farm structural change literature in order to identify (1) a preferable modelling approach and (2) empirically relevant determinants of farm structural change.

Of all econometric models generally suitable to analyse farm structural change, Markov chain models, models on farm growth, age cohort analyses, and discrete choice models analysing farm succession decisions are reviewed. Within the category of simulation models, multi-agent systems are reviewed as being generally able to analyse farm structural change.

Farm growth models focus on the explanation of farm size, age cohort analyses and farm succession models are used to explain and predict farm numbers. These models are therefore not suitable to analyse structural change in its multidimensional character. Multi-agent systems are very flexible and generally suitable to analyse farm structural change as it is intended here. However, their enormous data and modelling requirements to cover regions Europe-wide preclude them from being considered as suitable approach for the purpose of this thesis. Markov chain models are found to be generally suitable to represent the multidimensional character and to cover a large number of regions, although they have not been applied in such a scope before. Markov chain models are therefore reviewed in detail in part 2 of the thesis in order to find the best approach with regard to the intended scope of the analysis and the data availability.

The other models mentioned above are mainly reviewed with regard to finding determinants of structural change which have proven to be of significance in earlier studies.

The Markov chain concept

Generally, Markov chains describe stochastic processes over time. In the specific case of first-order Markov chains, the outcome of a process in $t+1$ depends solely on the state of the system at time t and is independent of earlier time periods. In the Markov chain concept, transition probabilities are estimated representing the likelihood for a subject to move from a certain state i at time t to another state j in time $t+1$. Developed by and named after the Russian Mathematician Andrei Andreevich Markov in 1907 (Basharin et al., 2004), Markov chains are very broadly applied in almost all disciplines (e.g. informatics, medicine, linguistics, politics etc.) today. In the farm structural change literature, the transition probabilities are used to represent the likelihood of a movement of a farm in a discrete farm type i at time t to another farm type j in the period $t+1$. The process is described as

$$n_{jt} = \sum_{i=1}^{I} n_{it-1} p_{ij} \tag{1.1}$$

with the number of farms n in farm type j at time t depending on the number of farms in all farm types i in the period before $t-1$ multiplied by their respective transition probabilities p_{ij} to move from farm type i to farm type j in a given time period. Additionally, the probability constraints of non-negativity ($p_{ij} \geq 0$) and adding-up to unity ($\sum_j p_{ij} = 1$) must hold.

The transition probabilities are usually collected in a Transition Probability Matrix TPM of dimension $J \times J$:

$$TPM = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1J} \\ p_{21} & p_{22} & \cdots & p_{2J} \\ \vdots & \vdots & \cdots & \vdots \\ p_{I1} & p_{I2} & \cdots & p_{IJ} \end{bmatrix}.$$

Equation (1.1) describes the special case of a stationary Markov chain where the transition probabilities p_{ij} do not change over time. The more general case is described by non-stationary Markov chains in which the transition probabilities denoted by p_{ijt} are allowed to vary over time. The decision of farmers to change from one farm type to another might be driven by certain exogenous variables. Adding a deterministic element to the purely stochastic Markov chain, the relationship between the exogenous variables and the transition probabilities can be expressed by representing the transition probabilities p_{ijt} as functions of those variables Z and respective coefficients β_{ij}.

$$p_{ijt} = f_{ij}(Z_t, \beta_{ij}) \tag{1.2}$$

The literature further distinguishes between micro and macro data Markov chain approaches. In the Markov chain terminology, micro data describe information on the specific movements of farms across farm types. Macro data are aggregate data that give only the information on the number or share of farms in the different farm types at different points in time (Lee et al., 1977). In case of micro data availability the transition probabilities can easily be derived by applying:

$$\hat{p}_{ijt} = m_{ijt} / \sum_{j=1}^{J} m_{ijt} \quad (1.3)$$

with m_{ijt} denoting the number of movements of farms from farm type i to farm type j in time t. If micro data is not available, the transition probabilities have to be estimated by applying a variant of equation (1.1).

Markov chain applications

Markov chain applications analysing farm structural change including conference contributions until 2008 are considered in part 2 of the thesis. The review shows that up to that time only one single region and production orientation is examined in most studies. Exceptions are Rahelizatovo and Gillespie (1999) and Gillespie and Fulton (2001) who consider two respectively 17 American regions in their panel data models. However, they do not focus on the regional differences explicitly. Descriptive comparisons of regional or country-wise differences are provided in Jongeneel et al. (2005) for the Netherlands, Germany, Poland, and Hungary, Tonini (2007) for Poland and Hungary, and a recent publication by Huettel and Jongeneel (2011) for the Netherlands and Germany. Another recent publication by Huettel and Margarian (2009) provides a cross-regional micro data analysis of the West German agricultural sector. A predecessor of the work in this thesis provides a panel data analysis of German farms and has been presented in Zimmermann and Heckelei (2008).

Whereas early Markov chain studies usually rely on micro data, analyses from the end of the 1980s onwards mostly apply macro data approaches. Starting with Judge and Swanson (1961), the first Markov chain application in agricultural economics, stationary approaches dominated the Markov chain literature in the 1960s. With Hallberg (1969) also non-stationary approaches started to appear. Also with regard to estimation techniques a development over time can be observed with the latest macro data studies exclusively applying maximum (e.g. Huettel and Jongeneel, 2011) or cross-entropy (e.g. Karantininis, 2002, Stokes, 2006, Tonini and Jongeneel, 2009) methods following Lee and Judge (1996) and Golan et al. (1996). Those techniques allow including prior information to obtain robust estimates even under limited time series length and for a large number of farm types. Up to now, Karantininis (2002) has estimated transition probabilities for the largest number of farm types. He considers 18 size classes plus an artificial entry/exit class in his analysis of Danish pig farms.

Given the large amount of farm types and the many regions to be considered for the project[10] as well as the special data base available[11], a generalised cross-entropy estimation is identified as the best suitable methodological approach for the work at hand.

Though the formulation of the cross-entropy approach is not directly shown in part 2, it shall be represented here in a general form (non-stationary transition probabilities) in order to avoid repetitions in this overview:

$$\min\left[\sum_i\sum_j\sum_t p_{ijt}\ln\left(p_{ijt}/q_{ijt}\right)+\sum_m\sum_j\sum_t w_{mjt}\ln\left(w_{mjt}/u_{mjt}\right)\right] \qquad (1.4)$$

s.t.

$$y_{jt}=\sum_i y_{it-1}p_{ijt}+\sum_m v_m w_{mjt} \quad \forall j,t \qquad (1.5)$$

The objective function (1.4) minimises the distance between transition probabilities p_{ijt} and prior transition probabilities q_{ijt} both indicating the probability to move from size class i to size class j in time t. Simultaneously, the distance between the error weights w_{mjt} and the prior information on the error weights u_{mjt} is minimised. The objective function is minimised subject to the macro data Markov chain constraints (1.5). These constraints relate the share y of farms in each farm type j at time t to the share of farms in all classes i at time t-1 multiplied by their respective transition probabilities p_{ijt}.[12] The error term is constructed as the product of the support point values v_m and the probabilities w_{mjt} summed over the m support points. Further constraints, non-negativity (p_{ijt},$w_{mjt}\geq0$) and adding-up to unity ($\sum_j p_{ijt}$,=1, $\sum_m w_{mjt}$=1), apply to transition probabilities and error weights.

Empirically relevant determinants of structural change

In part 2 of the thesis the explanatory factors are subdivided into the categories technology, off-farm employment, policy, human capital, demographics, market structure, social setting, and economic environment. Either the whole category or single factors within the categories can also be rearranged according to the theoretical concepts presented in section 1.3 and described in part 4. For example,

[10] Other - frequentist - methods have been tested, but failed in the large-scale application either due to ill-posedness or to other convergence problems connected to the large number of regions.
[11] The database is described in section 1.5 of this overview and again in parts 3 and 4 of the thesis.
[12] The number of farms n in equation (1.1) is substituted here by the share of farms y and an error term is added for estimation purposes.

technology refers to the technology/economies of scale concept, off-farm employment refers to the farm household theory, demographics can be split into the age of the farmers which would belong to the farm household theory and demand shifts which refer to general market conditions.

Most Markov chain studies concentrate on explanatory variables derived from the technology/economies of scale concept and from general market conditions. Apart from those, Chavas and Magand (1988) use sunk costs as proxy for path dependency in their analysis, kinds of land immobility are represented by a population variable in Hallberg (1969) and by the factor drought in Zepeda (1995), some studies also employ policy dummies (e.g. Zepeda, 1995, Rahelizatovo and Gillespie, 1999). Factors referring to the farm household theory have not been used in Markov chain applications so far. As a general rule, theoretically relevant variables with little variation in time are not considered in Markov chain applications since those are usually limited to single or very few regions of analysis. The growth, entry/exit, and farm succession models usually focus on socio-demographic determinants belonging to the wide range of the farm household model.

Multi-agent systems potentially provide the most explicit modelling of farm structural change combining annual and strategic farm decision making, spatial interaction of farms under heterogeneous technologies and farm management, and general economic conditions in a dynamic environment. Experiments with the systems have shown that not only averages, but the distribution of available technologies and managerial capabilities over farms matter for farm structural change, thereby adding to the set of potentially relevant variables to be considered in a Markov chain analysis across a larger number of regions.

1.5 Differences of farm structural change across European regions

Part 3 of the thesis focuses on differences of farm structural change across European regions. It aims at showing (1) in which way structural change differs across EU15 regions referring to size and production orientation and (2) how far certain regional characteristics contribute to those differences. The differences of farm structural change across 101 EU15 regions are described and analysed for the years 1990 to 2005.

Data and their application in the Markov chain approach

The data used in this and the next part stem from the Farm Accountancy Data Network (FADN). FADN comprises data on sample farms in each FADN region. Depending on the country, the FADN regions are adapted from NUTS I and NUTS II regions, but must not necessarily equal them. FADN sample farms are surveyed annually and stay in the sample for a varying number of years. The selection of the FADN farms adheres to certain threshold levels. The threshold levels vary across countries and give the minimum size of a farm to be considered as a 'commercial' farm. As a result, FADN does not represent all farms in a region, but only farms that exceed this threshold level. They are classified into economic size and specialisation classes. Referring to these classes, an aggregation weight is attached to each sample farm which gives the number of similar farms in the regional population which is represented by that sample farm. The aggregation weights are known from bi-to tri-annual censuses, the Farm Structure Survey. Referring to the micro and macro data definitions given above, the movements of sample farms across the farm types represent micro data, whereas the number of farms in the different farm types derived by applying the aggregation weights constitutes the macro data. As shown above, the transition probabilities could easily be derived from the micro data. However, the FADN sample farm data are not sufficient for a pure micro data Markov chain approach since they are based on a rotating panel and the sample is rather small compared to the population entailing significant sampling noise. They nonetheless provide valuable information by giving an indication of the direction of the movements and the amount of farms transitioning between the different farm types. Looking for ways not to lose this information, but at the same time staying consistent with the distribution of farms across the farm types in the population (which is provided by the macro data), the cross-entropy formalism was identified as the best suitable and most flexible estimation method. It allows to combining both data types into one approach by using the micro data as a priori information to the macro data Markov chain estimation.

Farm types

The farm typology used in part 3 of the thesis adheres to the multi-dimensional typology developed in the SEAMLESS project (Anderson et al., 2006), but includes only two dimensions following the FADN typology: economic size and type of farming (specialisation). Three size classes[13] and 10 specialisation classes[14] are taken into account. A farm type is defined as a combination of a certain size and specialisation class. Combining the three size and 10 specialisation classes and adding an artificial entry/exit class, 31 farm types are considered in the empirical analysis.

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[13] Small: until 16 European Size Units (ESU), medium: from 16 to 40 ESU, and large: greater or equal to 40 ESU.

[14] Arable systems; dairy cattle; beef and mixed cattle; sheep, goats, and mixed grazing livestock; pigs; poultry and mixed pigs/poultry; mixed farms; mixed livestock; permanent crops; and horticulture.

Estimation

In part 3 of the thesis, stationary transition probabilities are estimated for each of 101 EU15 regions. The stationary transition probabilities can be understood as averages of non-stationary transition probabilities over time. Referring to equations (1.4) and (1.5), they are estimated by skipping the index t in the transition probabilities p_{ijt} and the prior information q_{ijt}. The prior information q_{ij} is calculated from the micro data according to equation (1.3) and averaging over time. The farm type shares y are derived from the macro data.

For each region a matrix of 31x31 transition probabilities is estimated. For better comparability, the large amount of parameters is reduced by summarising the transition probabilities in mobility indices (Shorrocks, 1978, Jongeneel and Tonini, 2008, Huettel and Jongeneel, 2011). The mobility indices are transformed into continuous intervals and cross-regionally regressed against selected exogenous variables.

Results

Decreasing farm numbers are observed for most of the 101 regions of the EU15. At the same time, regional farm structural change is found to significantly differ in pace and scope and referring to the mobility of farms across size and specialisation classes.

It could be shown that the considered regional characteristics significantly contribute to explaining regional differences, even though some impacts vary when looking at some Member States separately. Referring to the theoretical considerations briefly presented in section 1.3, regional farm size heterogeneity represents the economies of scale concept. The results confirm that under high heterogeneity it is easier for larger, probably more efficient farms to acquire resources from exiting or declining farms. The initial average farm size level proxying path dependency is negatively related to farm exits, but its marginal impact on farm growth is mixed and depends on the initial level itself. A higher share of older farm holders dampens specialisation changes, whereas a high unemployment rate dampens sector exits. Specialisation class changes are positively affected by the share of mixed farms in a region. Difficulties in applying the theoretical concepts to formulate clear and unambiguous hypotheses and in part ambiguous results also reveal the complexity of farm structural change and in the decision-making of the farmers.

1.6 Structural change of European dairy farms

The purpose of part 4 of the thesis is to measure the explanatory relevance and effect of key factors suggested in the theoretical and empirical literature on dairy farm structural change in the EU15 from 1995 to 2005.

Farm types, data, and estimation

This part of the thesis focuses on size classes only, instead of observing general farm types considering several structural dimensions. Four size classes are selected[15] to which an artificial entry/exit class is added. The data used for the analysis is the same as described in the previous section. It is also used in the same way in the Markov chain approach (micro data serves as prior information in the macro data Markov chain approach). The main differences with regard to data are that now only dairy farms are considered and that the time series start in 1995, i.e. five years later in order to achieve a balanced panel.

Instead of stationary, now non-stationary transition probabilities are estimated following equations (1.4) and (1.5). Again, the transition probabilities are estimated for each of the EU15 regions considered (94 regions in this case since not all regions encompass dairy farms). A panel of transition probabilities is formed by combining the non-stationary transition probabilities of the different regions. This panel is transformed into log-odds ratios which are regressed against a large number of exogenous variables representing different theoretical concepts.

Results

The analysis of the transition probabilities shows that there is considerable cross-regional variance dominating variation over time.

In general, the considered explanatory variables significantly affect the log-odds ratios of the transition probabilities in the panel data regression. Elasticities are calculated in order to measure the direct impact of the explanatory variables on the transition probabilities.

The technology/economies of scale concept is clearly and the existence of path dependency is largely confirmed by the data, whereas the results regarding the hypotheses made in the context of the other theoretical concepts remain often ambiguous. A higher unemployment rate is found to hamper structural change because of less off-farm employment opportunities. Policy is included by the representation of differences in the milk quota transfer mechanisms across EU15 countries. It is found that more liberal transfer mechanisms over the market support structural change by limiting farm numbers and enhancing farm size decline, whereas farm growth appears to be facilitated through administrative quota allocation. At times of high milk prices, dairy farm structural change is rather slowed down. The regional milk price differences suggest the existence of concentration processes in regions with higher prices. Uncertainty connected with high price volatility causes farms to refrain from investments. Land immobility is found to play a significant role in farm structural change.

[15] The size classes are defined until 16 ESU, from 16 until 40 ESU, from 40 until 100 ESU, and equal or larger than 100 ESU.

1.7 Conclusions

Summary and results

In the beginning of this overview three research questions were formulated: (1) how changes the farm structure across different EU15 regions, (2) what drives those changes, and (3) how can farm structural change be modeled and analysed at such a large scale as it is required in the study at hand?

Starting with the third question, a Markov chain estimation technology is identified as being the most suitable methodological approach to cover the multi-dimensionality of farm structural change at a large farm type and regional scale. Applying this approach, the main methodological contribution of the thesis lies in its use of the FADN data by combining different data types into one analysis. Thereby, micro data on the movement of sample farms across farm types is used to add information to a macro data Markov chain approach mirroring the farm type distribution in the farm population.

As regards contents and answering research question (1), it is shown that changing agricultural structure is not a new phenomenon and that there exist significant differences across regions and across different size and specialisation classes. In response to research question (2), the existing theoretical concepts on farm structural change are combined and their impact and relevance on EU15-wide structural change is analysed, first, referring to all farms divided into size and specialisation classes and, second, referring to dairy farms divided into size classes. Their impact is measured taking into account specialisation changes, farm size growth and decline, and sector entry and exit at the same time. Overall, the empirical analysis confirms the relevance of the broadly propagated key factors of structural change. Both empirical studies confirm the impact of the technology/economies of scale concept favouring fewer and larger farms and give strong indications on the existence of path dependency. Less off-farm employment opportunities are found to hamper structural change in both studies.

However, it is also found that the impact mechanism of the theoretically identified determinants and their interaction remains sometimes unclear or is ambiguous emphasising the complexity of the system. This is partly due to the fact that the theoretical concepts (e.g. regarding the impact of off-farm employment) already have ambiguous impacts at farm level. Additionally, the interdependency of farm development due to limited regional resources (land) forces the impact of the determinants to be ambiguous when moving from the farm level to the distribution of farms in a region as it is done in this thesis.

Summarising the contribution of the thesis in one sentence, it closes gaps in the literature with regard to bridging micro and macro data in a Markov chain approach and unifying the existing theories in two large-scale empirical analyses of European farm structural change.

Limitations and outlook

Limitations refer to available theoretical foundation, data issues, and methodological approach. Regarding the data source, limitations mainly stem from the inflexibility that is predetermined by the FADN data. The inflexibility refers to the threshold definition of commercial farms, size and specialisation class thresholds and the regional resolution which are all fixed.

With regard to methodology, usually first order Markov chains are applied in the literature as in the thesis as at hand. Thereby, the first order property is generally simply imposed meaning that the stochastic process is modelled assuming that the change of farms from one state to another depends only on the time period before *t*-1 and is independent of earlier time periods.

Another limitation is that, due to the database, the farms are observed in discrete classes and the estimated transition probabilities only refer to these classes. Piet (2008) has shown that a continuous Markov chain approach is much more flexible. However, imposing continuity is still in a development phase and suffers from other rigid assumptions (e.g. the assumption of Gibrat's law) (Piet, 2008).

In the empirical parts of the thesis, a cross-entropy estimation method is applied. Thereby, reference is repeatedly given to a Bayesian estimation of the Markov chain transition probabilities which would allow for a more transparent incorporation of the a priori information from the micro data. Due to the projects' work plan and the large-scale focus of the work it was not possible to develop this estimator in a reasonable amount of time within this thesis. However, the scientific literature in different disciplines (beyond agriculture) has been reviewed for a Bayesian setup of the Markov chain model. The obvious lack of Bayesian type estimations in this field led to another dissertation project within the institute which aims at developing those estimators. In relation to this dissertation project also other projects could be acquired which build upon the experience gained in the work on the thesis at hand.

Earlier versions of the papers presented in part 2 and 3 of the thesis were submitted as deliverables to the SEAMLESS project and are published as project reports (Zimmermann et al., 2006, Zimmermann et al., 2007, Zimmermann et al., 2009). It was initially intended to endogenously embed the structural change module into the SEAMLESS model chain, i.e. forecasts (coming from the SEAMLESS simulation models) on explanatory variables found to impact structural change should be used to update the transition probabilities which in turn lead to updated forecasts on future farm type shares which are again fed into the model chain. In this manner, structural change would become endogenous to policy simulation models allowing to model the impact of rather complex policies on structural change (e.g. changes in direct payments) and at the same time simulate the impact of the adjusted farm type distribution on other sectoral variables. However, due to the complexity of the system it was not possible to establish this link within this thesis. The task of combining policy simulation models with a structural change module remains to be solved in the upcoming projects mentioned above. In the SEAMLESS model chain the stationary transition probabilities are now implemented exogenously.

The complexity of the adjustment processes at aggregate level that is shown in the thesis demands a more unified theory able to explain the distribution of structural characteristics in a geographical entity. The complex and non-linear response of farmers to endogenous and exogenous factors and the decisions taken by them are difficult to grasp in an econometric Markov chain model as it is presented here. In order to better understand these processes – theoretically and empirically, currently progress is being made in the direction of behavioural/experimental economics in combination with agent-based systems (e.g. Margarian, 2010, Balmann et al., 2010). However, also here the complexity of the phenomenon farm structural change and the resulting complexity of the models lead to limitations (e.g. small regional scope, assumptions made regarding the decision processes, restrictions regarding data, modeling and computational resources, lack of validation methods) which currently prevent their application in large-scale analyses as this one. The coexistence and combination of both approaches the econometric and multi-agent models backed by the development of a unified theory appears to be a promising path for future research efforts in understanding farm structural change.

1.8 References

Andersen, E., A.D. Verhoog, B.S. Elbersen, F.E. Godeschalk, and B. Koole (2006). A multidimensional farming system typology. SEAMLESS Report No.12, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org.

Aston, T.H. and C.H.E. Philpin (eds., 1987): The Brenner debate: agrarian class structure and economic development in pre-industrial Europe. Cambridge.

Basharin, G.P., A.N. Langville and A.N. Naumov (2004): The life and work of A.A. Markov. Linear Algebra and Its Applications 386, 3-26.

Boehlje, M. (1992): Alternative Models of Structural Change in Agriculture and Related Industries, Agribusiness 8 (3), 219-231.

Balmann, A. (1995): Pfadabhängigkeiten in Agrarstrukturentwicklungen. Begriff, Ursachen und Konsequenzen. Duncker and Humblot, Berlin.

Balmann, A., K. Kellermann, K. Larsén, S. Sandri and C. Schade (2010): Coordination and Allocation on Land Markets under Increasing Scale Economies and Heterogeneous Actors-an Experimental Study. Paper presented at the 114th EAAE seminar, April 15-16, 2010, Berlin, Germany.

Brenner, R. (1976): Agrarian Class Structure and Economic Development in Pre-Industrial Europe. Past and Present 70, 30-75.

Brenner, R. (1982): The Agrarian Roots of European Capitalism. Past and Present 97, 16-113.

Breustedt, G. and T. Glauben (2007): Driving Forces behind Exiting from Farming in Western Europe. Journal of Agricultural Economics 58 (1), 115-127.

Chavas, J.P. and G. Magand (1988): A Dynamic Analysis of the Size Distribution of Firms: The Case of the US Dairy Industry. Agribusiness 4 (4), 315-329.

Cochrane, W. (1958): Farm Prices: Myth and Reality. University of Minnesota Press, Minneapolis.

FADN webpage (2011): Field of Survey. http://ec.europa.eu/agriculture/rica/methodology1_en.cfm, accessed at 6 July 2011.

Friedmann, H. (1978): World Market, State, and Family Farm: Social Bases of Household Production in the Era of Wage Labor. Comparative Studies in Society and History 20, 545-586.

Gillespie, J.M. and J.R. Fulton (2001): A Markov Chain Analysis of the Size of Hog Production Firms in the United States. Agribusiness 17 (4), 557-570.

Goddard, E., A. Weersink, K. Chen and C.G. Turvey (1993). Economics of structural change in agriculture. Canadian Journal of Agricultural Economics 41, 475-486.

Golan, A., G. Judge and D. Miller (1996). Maximum entropy econometrics. John Wiley and Sons, Chichester.

Hallam, A. (1991): Economies of Size and Scale in Agriculture: An Interpretative Review of Empirical Measurement, Review of Agricultural Economics 13 (1), 155-172.

Hallberg, M.C. (1969): Projecting the Size Distribution of Agricultural Firms - An Application of a Markov Process with Non-Stationary Transition Probabilities. American Journal of Agricultural Economics 51, 289-302.

Happe, K. (2004): Agricultural Policies and Farm Structures - Agent-Based Modelling and Application to EU-Policy Reform. IAMO Studies on the Agricultural and Food Sector in Central and Eastern Europe 30, IAMO, Halle (Saale).

Harrington, D.H. and R.D. Reinsel (1995). A synthesis of forces driving structural change. Canadian Journal of Agricultural Economics 43: 3-14.

Heckelei, T. (2010): Structural Change and Policy Impact Modelling. Invited presentation at the 114th EAAE seminar “Structural Change in Agriculture”, April 2010, Berlin, Germany.

Huettel, S. and R. Jongeneel (2011): How has the EU milk quota affected patterns of herd-size change? European Review of Agricultural Economics, forthcoming.

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

Jongeneel, R., N. Longworth and S. Huettel (2005): Dairy Farm Size Distribution in East and West: Evolution and Sensitivity to Structural and Policy Variables: Case-Studies of the Netherlands, Germany, Poland and Hungary. Paper presented at the 11th EAAE Congress, August 24-27, Copenhagen, Denmark.

Karantininis, K. (2002): Information-based estimators for the non-stationary transition probability matrix: an application to the Danish pork industry, Journal of Econometrics 107, 275-290.

Karayalcin, C. (2010): Property Rights and The First Great Divergence: Europe 1500-1800. Working Paper, Department of Economics, Florida International University, USA.

Lee, T.C., G.G. Judge and A. Zellner (1977): Estimating the parameters of the Markov probability model from aggregate time series data. North-Holland Publishing Company, Amsterdam.

Lee, T.C. and G.G. Judge (1996): Entropy and Cross-Entropy Procedures for Estimating Transition Probabilities from Aggregate Data. In: Berry, D.A., Chaloner, K.M., Geweke, J.K. (Eds.), Bayesian Analysis in Statistics and Econometrics - Essays in Honor of Arnold Zellner. John Wiley and Sons, Inc., New York, pp. 153-164.

Margarian, A. (2010): Coordination and Differentiation of Strategies: The Impact on Farm Growth of Strategic Interaction on the Rental Market for Land. German Journal of Agricultural Economics 59 (3), Special Issue, 202-

216.
Mosnier, C. and C. Wieck (2010): Determinants of spatial dynamics of dairy production: a review. Discussion Paper 2010:2. Institute for Food and Resource Economics, University of Bonn.
Murphy, K.M., A. Shleifer and R. Vishny (1989): Income Distribution, Market Size, and Industrialisation. The Quarterly Journal of Economics 104 (3), 537-564.
Piet, L. (2008): The Evolution of farm size distribution: revisiting the Markov chain model. Paper presented at the 12th EAAE Congress, August 26-29, Ghent, Belgium.
Rahelizatovo, N.C. and J.M. Gillespie (1999): Dairy Farm Size, Entry, and Exit in a Declining Production Region, Journal of Agriculture and Applied Economics 31 (2), 333-347.
Schmitt, G. (1992): Verfügen die Agrarökonomen über eine Theorie des agrarstrukturellen Wandels? Berichte über Landwirtschaft 70, 213-230.
Stanton, B. F. (1993): Farm Structure: Concept and Definition. In: Hallam, A. (ed.), Size, Structure and the Changing Face of American Agriculture, Boulder.
Stokes, J.R. (2006): Entry, Exit, and Structural Change in Pennsylvania's Dairy Sector, Agricultural and Resource Economics Review 35 (2), 357-373.
Swinnen, J.F.M. (2002): Political reforms, rural crises, and land tenure in Western Europe. Food Policy 27, 371-394.
Tonini, A., 2007. Agriculture and Dairy in Eastern Europe after Transition focused on Poland and Hungary, Wageningen, Netherlands.
Tonini, A. and R. Jongeneel (2009): The distribution of dairy farm size in Poland: a Markov approach based on information theory, Applied Economics 41 (1), 55-69.
Van Ittersum, M., F., Ewert, T. Heckelei, J. Wery, J. Alkan Olsson, E. Andersen, I. Bezlepkina, F. Brouwer, M. Donatelli, G. Flichman, L. Olsson, A. Rizzoli, T. van der Wal, J. Wien and J. Wolf (2008): Integrated assessment of agricultural systems - a component-based framework for the European Union (SEAMLESS). Agricultural Systems 96, 150-165.
Van Zanden, J.L. (1991): The first green revolution: the growth of production and productivity in European agriculture, 1870-1914. Economic History Review XLIV (2), 215-239.
Weiss, C. (2010): Agricultural Policy and Structural Change: Analysing (Spatial) Heterogeneity. Invited presentation at the 114th EAAE seminar “Structural Change in Agriculture”, April 2010, Berlin, Germany.
Zepeda, L. (1995): Asymmetry and Nonstationarity in the Farm Size Distribution of Wisconsin Milk Producers: An Aggregate Analysis. American Journal of Agricultural Economics 77 (2), 837-852.
Zimmermann, A., T. Heckelei and I. Pérez Domínguez (2006): Working Paper -

Literature Review of Approaches to Estimate Structural Change. SEAMLESS Report No.16, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org.

Zimmermann, A., T. Heckelei and M. Adenäuer (2007): Report and Code to Simulate Structural Change, SEAMLESS Report No.31, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org.

Zimmermann, A., T. Heckelei and M. Adenaeuer (2009): Methodology and Code to Simulate Structural Change in SEAMLESS-IF: results for SEAMLESS test regions and integration into SEAMLESS-IF, SEAMLESS Report No.36, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org.

Zimmermann, A. and T. Heckelei (2008): Farm Structural Change in German Regions - An Empirical Analysis Using Micro and Macro Data. Poster presented at the XIIth EAAE Congress, August 26-29, Ghent, Belgium.

Zimmermann, A., T. Heckelei and I. Pérez Domínguez (2009): Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants, Environmental Science & Policy 12 (5), 601-618.

Part 2
Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants[16]

Abstract: This paper provides a literature review of methods and determinants relevant for modelling farm structural change within an integrated modelling chain. Environmental and economic impacts at farm level and individual farm responses to agricultural and agri-environmental policies strongly depend on characteristics like farm size, specialisation, and production intensity. Consequently, up-scaling results of corresponding farm type models in ex-ante assessment exercises requires comprehensive and valid predictions of the farm types' future relevance under different scenarios. The paper reviews methods relevant to forecasting farm numbers in classes defined by farm typologies with the objective to identify (1) a preferable modelling approach and (2) empirically relevant determinants. Despite the literature's considerable size, even recent studies are rather limited in scope and typically restricted to a subset of farm types and one or very few regions. With regard to data availability, computational complexity and statistical validation procedures, Markov chain models are identified as the only generally suitable method for a broadly scoped modelling approach across European regions and a differentiated farm typology. However, other research on determinants of farm growth, the number of farm holders, farm succession as well as new multi-agent based simulation approaches hint at relevant explanatory variables previously not considered in Markov chain analyses. Their impact seems testable in more ambitious cross-regional and cross-farm type setups.

Keywords: farm typology, farm structural change, Markov chains, multi-agent systems, transition probabilities.

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2.1 Introduction

In recent years increasing attention is paid to the multifunctional role of agriculture. The development of integrated impact assessment tools (Ewert et al., this issue) is a response to the rising desire of policy makers and stakeholders to properly evaluate – ex ante – the different economic, environmental, and social impacts of policies on the agricultural system. The underlying modelling chains typically capture agri-environmental feedbacks at lower scale through the linking of biophysical and farm type simulation models. The latter represent farm management decisions on land allocation, herd size adjustments and intensity of production subject to available crop and livestock technologies as well as farm resources. More strategic, medium to long term investment decisions to enter or leave the business or to fundamentally change farm size, specialisation or production intensity of the farming system are typically not considered. However, these decisions occur regularly and are highly relevant for the overall impact of policies on the agricultural system, because the implied change in the distribution of farm characteristics (farm structure) not only affects aggregate production at market level, but also changes the relative importance of farm type specific agri-environmental interactions. Therefore, modelling of farm structural adjustments in an ex-ante integrated assessment exercise may also significantly improve the validity of the calculated environmental impacts apart from the relevance for social and economic indicators. As a first step towards establishing a model on farm structural change linked to representative farm type simulation models, the paper reviews the literature on empirical methods aiming to identify a most suitable one for predicting farm structural change in this context. Furthermore, relevant determinants for the model specification shall be identified based on the results of existing empirical studies in order to direct the considerable task of compiling an EU-wide dataset for the empirical analysis.

The research underlying this paper occurred in the context of the SEAMLESS project (Van Ittersum et al., 2008) and is certainly influenced by the decisions made on the overall approach and the specification of the farm simulation tool developed (Louhichi et al., under review), to which a link shall be established with a structural change model. In order to assess economic and environmental aspects of the agricultural sector, a multidimensional farm typology at regional level has been set up in SEAMLESS combining economic size and specialisation classes based on the European standard grouping of farms with an intensity and a land-use dimension (Andersen et al., 2007; Andersen et al., 2006). Ex-post, each class has a certain observable share of farms allowing to weight the modelled farm type specific production responses and related environmental impacts when up-scaling them to higher levels. A dynamic adjustment of these farm type shares for up-scaling to European level and based on ex-ante scenarios has – to our knowledge – not been done in the past. We will see in subsequent sections that existing empirical analyses or simulation models of farm structural change are very limited with respect to the dimensions considered or with respect to regional coverage. In the SEAMLESS model chain, however, prediction of future farm numbers in size and specialisation classes shall eventually allow to aggregate predicted production responses to (European) market level (see Pérez Domínguez et al, this issue) and to up-scale policy induced changes in environmental indicators consistent with the scenario impacts on farm type structures.

The context just explained directly renders the definition of farm structural change relevant for this paper: It is defined as the change of the number of farms within certain farm types. The basic criterion for evaluating and selecting the methods found in the literature is their suitability to robustly perform the prediction of these farm numbers for all EU regions and a minimum number of farm types (30 by the combination of three size and ten specialisation classes) based upon the relevant determinants. As will be discussed further below, only the statistical Markov chain analysis has the potential to fulfil these characteristics. Consequently, the development and recent innovations of this methodology receive significant attention. However, we broaden the review to include analyses based on different methods, as their consideration significantly contributes to the identification of the relevant determinants of farm structural change going beyond those previously considered in Markov chain studies.

Two main methodological categories can be distinguished: econometric models and simulation models. Econometric models comprise Markov chains and various other regression approaches, differentiated by the variable to be explained. The *Markov chain* approach tries to retrieve specific patterns of structural change from historical developments and exploits the obtained results to make forecasts into the future. A large share of the other regression models deals with the phenomenon of *farm growth*. Cohort analyses are mainly used to predict the *number of farm holders* and may help to separate demographical factors from other, mainly economic factors. Models of discrete choice are predominantly applied in this context to analyse *entry/exit decisions* and *farm succession*.

Within the category of simulation models, we restrict our attention to *multi-agent models*. Multi-agents systems with agricultural orientation are mainly employed to understand complex spatial and dynamic processes of farm, or more general, agent interaction, which cannot be handled by traditional modelling concepts, but are of significant relevance for farm structural change. Although various dynamic modelling approaches (recursive dynamic programming or dynamic micro-econometric approaches (Day and Cigno, 1978; Gardebroek and Oude Lansink, 2008)) raise farm-specific structural issues by modelling the use of primary production factors, they are not considered here because a specific contribution to the aim of this paper could not be identified. This literature does currently not – at least not to any meaningful extent in our context – address the interaction of farms in a land restricted environment or add specific determinants relevant to entry/exit, size and specialisation changes beyond the core economic variables typically considered for dynamic analysis of individual firm behaviour.

The next section focuses on the determinants of structural change based on earlier literature reviews and draws some attention to theoretical considerations. In section 2.3, the main developments of Markov chain modelling are presented. Section 2.4 addresses the econometric farm growth, cohort and entry/exit models before multi-agent systems are considered in section 2.5. Section 2.6 summarizes key results and draws conclusions.

2.2 Factors contributing to structural change in agriculture

Most studies on farm structure provide an enumeration of the factors assumed to determine structural change in agriculture. Here, a brief overview of these factors is given, leaving the in-depth discussion to others (see Reimund et al., 1977; Hallam, 1991; Hallam, 1993; Boehlje, 1992; Goddard et al., 1993; Harrington et al., 1995). Factors should not be seen as mutually exclusive but are rather interrelated, as several authors point out (see U.S. Congress, 1985; Van Dijk, 1986; Goddard et al., 1993; Harrington and Reinsel, 1995; Hallam, 1991; Boehlje, 1992). Here we present a non-exhaustive list of the main determinants of structural change derived from theory. Their empirical relevance will be the focus of the subsequent sections.

1) *Technology*. The technology model is based upon the concepts of economies of scale and the adoption and diffusion of technology. It refers to the concept of Cochrane's treadmill (Cochrane, 1958) and focuses on the impact of technological innovation reducing per unit costs of output at the farm level. The first adopters of the new technology will gain from the first-mover advantage as long as output prices remain largely unchanged. But as adoption spreads, prices of farm commodities will fall and competition increases by forcing others to adopt the new technology or to exit the industry, triggering structural adjustments (Harrington and Reinsel, 1995).
2) *Off-farm employment* is handled in two ways. On the one hand, it could be seen as a first step out of the sector. As opportunity costs increase due to better wage levels outside of agriculture, farmers tend to leave the sector until wages equalize (Hallam, 1991) or try to achieve comparable incomes by enlarging the farm business (Harrington and Reinsel, 1995). On the other hand, off-farm employment provides a method to keep on farming at small scales if the off-farm income complements the household income (Goddard et al., 1993; Gebremedhin and Christy, 1996) or farmers are even willing to subsidize their small farm at least in the short-run from other income sources (Harrington and Reinsel, 1995).

3) *Policy*. Structural changes in agriculture are also driven by the general institutional and legal environment as well as by specific public programs which impact the agricultural sector in different ways according to their design. Examples often mentioned apart from agricultural sector policies are tax policies, commodity programs, credit programs, general monetary and fiscal policies, and public research and extension efforts (Harrington and Reinsel, 1995; Goddard et al., 1993; U.S. Congress, 1985).
4) *Human capital* refers to and is influenced by the managerial capability, the level of schooling, and public education programs. It is assumed that an increase in human capital would allow the firm manager to more effectively process information used to allocate the firm's resources and to evaluate new technologies (Boehlje, 1992; Goddard et al., 1993).
5) *Demographics* refer mainly to the age structure of farm operators and the shrinking number of entrants to the farming sector. Although being a consequence rather than a cause of structural change, the age structure is believed to determine the speed of change in a region (Harrington and Reinsel, 1995). Reimund et al. (1977) and Goddard et al. (1993) also point to general changes in the demographical structure which impacts the agricultural sector through changes in the demand of agricultural products.
6) *Market structure* itself influences structural change. This point refers to the Structure-Conduct-Performance approach and is derived from the industrial organization literature (Van Dijk et al., 1986; Boehlje, 1992). The way in which prices are set is determined by the nature of the market, i.e. the degree of market power exercised on the supply or demand side, so that the conduct of the industry is a function of its structure. The development of institutional arrangements, such as vertical integration and cooperatives, has an (so far unclear) impact on structural change as well (Goddard et al., 1993).
7) *Social setting*. Sociological aspects and discussions of structural change in agriculture usually refer to the concept of the family farm (Peterson, 1986; Boehlje, 1992). The sociological model as described by Boehlje (1992) refers to the motivations to maintain a family farm-based agriculture. Boehlje distinguishes between aspects coming from society and the farmer's household. He argues that from the societal perspective the maintenance of a family farm-based agricultural structure is important to efficient production, community viability, and food supply. From the individual perspective the motivations are primarily related to the independent lifestyle, family bonding and relationships. In multigenerational family farm operations the objective is frequently identified as providing an opportunity for a future generation to farm.
8) *Economic environment*. Several sector specific and macroeconomic factors such as input and output prices, demand changes, and the interest rate are supposed to have an impact on structural change (Hallam, 1991; Goddard et al., 1993). However, most of the afore-mentioned points could also be ex-

pressed in economic terms, so that in fact the economic environment could be regarded as the heading subsuming the other factors.

2.3 Markov models

The estimation of Markov chains has a long tradition in the analysis of structural change in agriculture and is a widely accepted approach to predict the number of farms in certain farm types. The section is divided into four parts. Firstly, the general concept of the Markov chains is introduced, then stationary and non-stationary Markov chain studies in the farm structural change literature are discussed and finally the findings are summarized.

Concept

In a Markov chain the movement of firms from a specific firm category (e.g. a farm type) to another one is seen as a stochastic process which can be represented by transition probabilities. Usually, the movement of farms between several farm types is supposed to follow a first order Markov chain, i.e. it is assumed that the probability of the movement of a farm at time t to another farm type in the period $t+1$ is independent of earlier periods.

$$n_{j(t)} = \sum_{i=1}^{N} n_{i(t-1)} p_{ij} \,, \tag{2.1}$$

where the number of farms n in farm type j at time t depends on the number of farms in all farm types i in the period before (t-1) multiplied by their respective transition probabilities p_{ij} to move from farm type i to farm type j in one time period. The probability constraints, non-negativity ($p_{ij} \geq 0$) and summing-up to unity ($\sum_j p_{ij} = 1$) must hold. The single transition probabilities can be collected in a transition probability matrix P ($N \times N$):

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \cdots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{bmatrix}$$

If micro-data is available, i.e. data from which the exact number of movements from one farm type to another can be derived, the elements in P can be estimated as

$$\hat{p}_{ij} = m_{ij} \,/ \sum_{j=1}^{N} m_{ij} \,, \tag{2.2}$$

where m_{ij} denotes the number of movements of firms from state i to state j during the time period under discussion and N is the total number of states. Anderson and Goodman (1957) have shown that the above given approximation of the true p_{ij} is, in fact, the maximum likelihood estimate. If only macro-data, i.e. the number of farms per farm type and year is given, the Markov chain is usually estimated according to equation (2.1) by replacing the number of farms n by farm type shares y and adding an error term.

The estimated transition probabilities can be used to predict future farm numbers in any state:

$$X_t = X_0 P^t, \tag{2.3}$$

where the row vector X_0 is the initial starting state vector or the initial configuration of individuals in the N states, where x_{0i} represents the number of individuals in state i during time period t=0, and the row vector X is the t^{th} configuration vector.

One of the strongest assumptions in this form of the Markov model is that the transition probabilities do not change over time, i.e. they are said to be stationary. This implies that the process of structural change follows the same path until an equilibrium solution is reached. Stationarity may represent a realistic assumption as long as all other factors remain constant, but it does not generally hold for economic phenomena. Changes in exogenous variables require the determination of non-stationary (time-varying) transition probabilities. In the case of micro-data availability non-stationary transition probabilities can be obtained by applying equation (2.2) on an annual base:

$$\hat{p}_{ij(t)} = m_{ij(t)} \,/ \sum\nolimits_{j=1}^{N} m_{ij(t)} \,. \tag{2.4}$$

However, equation (2.4) cannot be used to detect which factors and to what extent these factors have actually influenced the structural process in question. Thus, an econometric model 'behind' the pure Markov chain is required. The non-stationary transition probabilities are, hence, specified as functions of (potentially lagged) exogenous variables and parameters and regressed against these in a second estimation step:

$$p_{ij(t)} = f_{ij}(Z_{(t)}, \beta_{ij}), \tag{2.5}$$

where f_{ij} is the function of the vector of explanatory variables $Z_{(t)}$ and the matrix of parameters β_{ij} which relates the exogenous variables to the transition probabilities. In the case of macro-data, equation (2.5) can directly be substituted into equation (2.1) by changing the stationary p_{ij} to non-stationary $p_{ij(t)}$.

Stationary Markov chain models

Generally, the first Markov chain studies of the agricultural sector deal with micro-data used to estimate stationary transition probabilities via the maximum likelihood method following Anderson and Goodman (1957). Publications which refer to this type of Markov models are Judge and Swanson (1961), Padberg (1962), Stanton and Kettunen (1967), Edwards et al. (1985), and Garcia et al. (1987). Krenz (1964) is the first who estimated a stationary Markov model from macro-data. However, in order to do so he simply applied the micro-data maximum likelihood estimator (2.2) and replaced the single farm movements by farm type shares calculated from the aggregated data. Additionally, a number of constraints had to be imposed to ensure meaningful results. Stavins and Stanton (1980) point to the theoretical limitations of this approach since the behavioural pattern for the farms that should be investigated is, in fact, already postulated beforehand. Also, Lee et al. (1977) and MacRae (1977) have shown that the maximum likelihood function in case of macro-data is in fact rather complex, such that the approach chosen by Krenz suffers from a weak econometric foundation as well. Nonetheless, a similar approach was used later on by Keane (1976), Keane (1991) and Tonini and Jongeneel (2002) and the imposition of constraints on the transition probabilities became rather popular among applied Markov studies. Recent applications of stationary Markov chain models are Jongeneel and Tonini (2008) and Piet (2008). Jongeneel and Tonini introduce mobility indices based on Shorrocks (1978) to the Markov chain literature. The mobility indices give information on mobility level and direction of farms between the different farm types. Piet presents a continuous version of the Markov chain model which gives more insight in the actual distribution of farms and allows the reconstruction of transition probabilities for any size class. The stationary Markov chain models are summarized in the Appendix.

Non-stationary Markov chain models

The non-stationary Markov chain applications in the agricultural economics literature are split into two-step approaches and approaches estimating the Markov chain and the influence of exogenous variables simultaneously. An overview of the non-stationary Markov chain applications is provided in Table 2.1.

Two-step approaches

Hallberg (1969) was the first, who calculated non-stationary transition probabilities in order to predict structural change depending on exogenous variables. The first estimation step follows equation (2.4) and for the second estimation step a restricted least squares procedure is applied. However, the least-squares approach suffers from the fact that it is not possible to ensure the probability constraints when making predictions with the estimated coefficients. Other micro-data models applying two-step procedures are Salkin et al. (1976), Stavins and Stanton (1980), Ethridge et al. (1985), and Rahelizatovo and Gillespie (1999).

Among other modelling exercises, Stavins and Stanton (1980) represent the transition probabilities as multinomial logit functions of explanatory variables and coefficients in the second estimation step. The multinomial logit formulation has the advantage that the probabilities automatically sum to unity and are positive. An ordinary least squares estimator is used to estimate a linearised version of the model.

Rahelizatovo and Gillespie (1999) are the first to conduct a cross-regional analysis where the regional dummy variable reveals a significant influence on most transition probabilities. Other factors significantly affecting structural change among dairy farms in Louisiana are found to be input and output prices, technology expressed as productivity, financial conditions, and agricultural policies that have provided incentives for early retirement and reduction in milk production. Decreasing milk prices are predicted to increase the number of farms quitting the sector. With regard to policy plans to decrease dairy waste disposal into the Tangipahoa River, Rahelizatovo and Gillespie also discuss environmental concerns of the predicted structural change towards larger farm entities. In fact, they predict (without having implemented the relevant policy change in their model) that some producers might discontinue production facing increased investments into waste disposal facilities.

Stokes (2006) employs a generalised cross-entropy estimator (GCE) based on Lee and Judge (1996) and Golan et al. (1996) to estimate time-varying transition probabilities from macro-data. Afterwards the influence of other explanatory variables is analysed by regressing the most interesting transition probabilities against these variables linearly. The prior transition probability matrix for the GCE approach is obtained by firstly estimating a stationary transition probability matrix with a uniform prior. The model is applied to Pennsylvanian dairy farms. Stokes finds that milk prices, price volatility, land values, and the dairy termination program strongly impact the probability for exit from dairying in Pennsylvania. Dairy farm size growth is found to be inhibited by milk price volatility and land values, but responds positively to higher milk prices. Growth and contraction are also positively related to productivity. Concerning the transition probabilities Stokes follows that if the status quo is maintained, there will be fewer, larger dairy farms, with the rate of decline estimated to be about 2.0 percent to 2.5 percent annually over the next two decades. Another contribution of Stokes to the Markov chain literature is the presentation of the linkage between an analytical model of the firm and the Markov chain model saying that as long as the farmers' decisions are consistent with a dynamic planning horizon and the uncertainty faced is Markovian, the size of the firm will also be Markovian as the properties from the underlying sources of uncertainty are inherited through the optimization process.

Simultaneous estimation of Markov chain and exogenous influence

Based on Telser (1963), Disney et al. (1988) are the first in the field of agricultural economics who estimate non-stationary transition probabilities from macro-data. In their study on the hog production industry in southern states of the USA they find that both total farm numbers and the size distribution of pork farms are highly sensitive to different hog-corn price ratio scenarios. A methodologically similar approach was later used by Von Massow et al. (1992).

Chavas and Magand (1988) develop an approach to estimate the probability of net entry and the transition probabilities of the remaining firms separately. Equation (2.1) is therefore redefined as:

$$n_{j(t)} = a_{j(t)} + \sum_{i=1}^{N} n_{i(t-1)} p_{ij(t)}, \qquad (2.6)$$

with $a_{j(t)}$ representing net new entries. As explanatory variables for the transition probabilities pertaining to continuing farms economies of size, sunk costs and market prices are chosen. The vector $a_{j(t)}$ is specified as a function of the same variables with slight adaptations in the variable definition ($a_{j(t)}=f(Z_{j(t-1)},\alpha_j)$). The transition probabilities are estimated within a multinomial logit framework considering four size classes.

Zepeda (1995a) takes up the approach of Chavas and Magand (1988) and models the probability of net new entry separately from the transition probabilities of the existing firms. In her model of Wisconsin dairy farms the milk-feed price ratio is assumed to affect both net new entries and state transitions. The interest rate (to reflect the cost of capital), a dummy policy variable (farmers are paid to exit the sector), the amount of debt and a dummy variable for drought are supposed to influence only net new entries. Zepeda concludes from her analysis that farmers respond symmetrically to price changes when entering or quitting dairy farming, but they are more responsive to price decreases than price increases when changing the herd size. It is also found that under none of the calculated price scenarios any small- or medium-sized farms would exist in the long run. A similar approach has also been applied to hog production firms in the United States in Gillespie and Fulton (2001).

In a second application, Zepeda investigates the influence of technical change on the size distribution of dairy farms (Zepeda, 1995b). The model is applied to four size classes only, without considering entries or exits. As proxy for technical change the milk production per cow and per year is used. Steady state probabilities and elasticities measuring the effect of the explanatory variables on the transition probabilities referred to as ‘probability elasticities’ are calculated. Zepeda finds that increases in the level of technology among continuing dairy farms enhance their ability to stay the same size versus growing in the short run, but in the long run increase the proportion of very large farms.

Karantininis (2002) is the first who applies a generalised cross-entropy (GCE) formalism for a Markov chain estimation of the agricultural sector (Lee and Judge (1996); Golan et al. (1996)). His study focuses on the farm size distribution of Danish hog producers. Although a non-stationary cross-entropy formulation according to equation (2.1) with the probabilities being substituted by equation (2.5) is shown in his article, Karantininis applied an instrumental variables techniques (IV-GCE) developed by Golan and Vogel (2000) in order to determine the impact of exogenous factors on structural change. The IV-GCE procedure is much simpler to apply, but does not allow the estimation of different transition probability matrices for each point in time as possible in traditional non-stationary Markov studies. Nonetheless, the IV-GCE approach is mostly referred to as 'non-stationary', which is thought to reflect the fact that explanatory variables are considered and their impact on the transition probabilities can be measured by elasticities. Using the uniform distribution as prior for the transition probabilities, Karantininis firstly estimates a stationary Markov model which is found to perform rather badly. Information gained from a pre-estimated non-stationary model with a rather simple matrix of prior transition probabilities is introduced as prior information in the main estimation. This second non-stationary model reveals the best overall performance as measured by the pseudo-R^2 of the three Markov models. Karantininis uses pork prices, pork feed prices and input and output prices of other livestock as explanatory variables. Most of the elasticities for pig prices are found to be positive in most of the upper off-diagonals and negative in most of the lower off-diagonal elements meaning that increases in pig prices reduce the probability of firms downsizing, and increase the probability of them increasing in size. Non-stationary Markov chain studies applying IV-GCE estimators according to Karantininis (2002) can also be found in Jongeneel et al. (2005), Tonini (2007), Tonini and Jongeneel (2008), and Huettel and Jongeneel (2008).

Jongeneel (2002) analyses farm structure changes of Dutch dairy farms with a GCE estimator. Unlike Karantininis (2002), Jongeneel estimates time-varying transition probabilities which are simultaneously represented as linear functions of exogenous variables and coefficients.

Summary

Markov chain applications to the agricultural sector advanced from stationary micro-data approaches in the early studies to non-stationary macro-data models related to exogenous factors via two-step or simultaneous estimation procedures. Accordingly, the estimation techniques applied changed from maximum likelihood over linear model specifications to the representation of the transition probabilities as multinomial logit functions. Recently, cross-entropy techniques making use of a priori information given by the researcher and tackling the problem of ill-posedness became popular in Markov chain estimations.

Concerning regional and farm type coverage, with few exemptions only a single region and production orientation (mostly dairy or pig farms) are considered in the Markov chain studies analysed. The maximum number of farm types for which transition probabilities have been estimated is 19 (18 size classes and the artificial entry/exit class; Karantininis, 2002).

As far as estimation results are concerned, most of the more recent studies predict further farm number decreases of small to medium sized farms, whereas the number of large farming entities is mainly predicted to increase. The explanatory variables used in the non-stationary Markov studies relate more or less to the factors contributing to structural change outlined in section 2.2. Most often variables concerning technological change, economic factors like prices and interest rates, and policy variables have been taken into account, whereas human capital or demographical aspects did not appear in any study as explanatory variables. Only Zepeda (1995a) introduces a ‘new’ variable, namely drought, in her analysis.

With regard to the explanatory power of the Markov chains, most authors who conducted stationary as well as non-stationary analyses found that the non-stationary models performed much better in predicting the farm type distribution than the stationary ones (e.g. Hallberg, 1969, Stavins and Stanton, 1980, Von Massow et al., 1992, Karantininis, 2002). The R^2 values tend to attest the models a rather high explanatory power. Where low R^2 values are reported, these mainly refer to single transition probabilities or are attributed to the estimation technique applied (Salkin et al., 1976; Stavins and Stanton, 1980). A number of studies conducting within sample predictions found a good prediction accuracy of the models applied (Hallberg, 1969; Garcia et al. (1987); Zepeda, 1995a and 1995b; Tonini and Jongeneel, 2002). An exemption is Von Massow et al. (1992) who found very high prediction errors in the ‘no production’ class. Out-of-sample predictions conducted by Hallberg (1969) for the stationary model revealed a rather poor fit when compared to the actual values. Stavins and Stanton (1980) found that the out-of-sample predicted distribution showed approximately the correct shape if the multinomial logit model specification was applied to estimate the transition probabilities. In many cross-entropy approaches the incorporated prior information is found to considerably affect the overall quality of the model as indicated by the fact that the final estimates closely follow the prior information matrix.

Table 2.1: Non-stationary Markov studies in the agricultural economics literature

Year	Author	Region	Specialisation	Data type	Time Series	Transition Probabilities	Methodology	Number of States	Dependent Variable	Explanatory Variables	Performance
1969	Hallberg	Pennsylvania, USA	Frozen milk products plants	Micro	1944-1963	Stationary, non-stationary	Maximum likelihood + least squares (2-step)	4 +entry/exit	Firm size (in sales volume)	Wages, population, per capita income, farm-gate price for milk, retail price	R^2: 0.89-0.99
1976	Salkin et al.	Oklahoma, USA	Cotton warehouses	Micro	1964-1973	Stationary, non-stationary	Least squares + geometric model (2-step)	5 + entry/exit	Firm size (in warehouse capacity)	Time	R^2: 0.002-1.0 (linear model), 0.47-1.0 (geometric model)
1980	Stavins and Stanton	New York, USA	Dairy farms	Micro (stationary, 2-step non-stationary), macro (stationary)	1968-1977	Stationary, non-stationary	Maximum likelihood + multinomial logit (2-step)	9 + entry/exit	Firm size (in milk supply)	Milk-feed price ratio	R^2: 0.00-0.70
1985	Ethridge et al.	West Texas, USA	Cotton gin firms	Micro	1967-1979	Stationary, non-stationary	Maximum likelihood + least squares (2-step)	12 (including new entrants, dead gin firms and 5 size classes of inactive and active farms, respectively)	Activity and size (in gin capacity)	Wages, energy costs, plant capacity, technical change	R^2: 0.32-0.72
1988	Disney et al.	Southern states, USA	Pig farms	Macro	1969-1982	Stationary, non-stationary	Minimum absolute deviation	4 (+ entry/exit)	Firm size (in saled market hogs/year)	Hog-corn price ratio	R^2: 0.94-0.97
1988	Chavas and Magand	Different regions, USA	Dairy farms	Macro	1977-1984	Non-stationary	Multinomial logit	4	Net entry; firm size (in herd size)	Economies of size, sunk costs, market prices	R^2: 0.67-0.99

Cont. Table 2.1: Non-stationary Markov studies in the agricultural economics literature

Year	Author	Region	Specialisation	Data type	Time Series	Transition Probabilities	Methodology	Number of States	Dependent Variable	Explanatory Variables	Performance
1992	Von Massow et al.	Ontario, Canada	Pig farms	Macro	1971-1989	Stationary, non-stationary	Minimization of median absolute deviation	5 + entry/exit	Firm size (in number of hogs marketed)	Hog-corn price ratio, interest rate, labour-capital price ratio	Within sample prediction (root mean square error): Stationary 11-33%, 63% (entry/exit); non-stationary 9-20%, 46-62% (entry/exit)
1995a	Zepeda	Wisconsin, USA	Dairy farms	Macro	1972-1992	Non-stationary	Multinomial logit	3	Entry/exit; firm size (in herd size)	Milk-feed price ratio, interest rate, dairy termination program, debt, drought	R^2: 0.9905-0.9986, within sample prediction (error in any year): 2.2-7.2%
1995b	Zepeda	Wisconsin, USA	Dairy farms	Macro	1980-1992	Non-stationary	Multinomial logit	4	Firm size (in herd size)	Milk production per cow (proxy for technical change)	R^2: 0.88-0.99, within sample prediction (error in any year): 2-11% of farms
1999	Rahelizatovo and Gillespie	Louisiana, USA	Dairy farms	Micro	1981-1995	Non-stationary	Maximum likelihood + SUR (2-step)	4 + entry/exit	Firm size (in productivity)	Milk and feed prices, milk production per cow, interest rate, debt/equity ratio, policy dummies, regional dummies	R^2: 0.63-0.80
2001	Gillespie and Fulton	17 US states	Pig farms	Macro	1988-1997	Non-stationary	Multinomial logit	3	Firm size (in number of hogs)	Regional dummies, hog-corn price ratio, interest rate, corporate farm laws, meat processing capacity, percentage of land in farms	R^2: 0.75-0.97
2002	Karantininis	Denmark	Pig farms	Macro	1984-1998	Stationary, non-stationary	GCE, IV-GCE	18 + entry/exit	Firm size (in number of hogs)	Input and output prices of pork and other livestock, fertilizer prices, interest rate	Pseudo-R^2: 0.07, 0.26, 0.49

Cont. Table 2.1: Non-stationary Markov studies in the agricultural economics literature

Year	Author	Region	Specialisation	Data type	Time Series	Transition Probabilities	Methodology	Number of States	Dependent Variable	Explanatory Variables	Performance
2002	Jongeneel	Netherlands	Dairy farms	Macro	1972-1999	Non-stationary	GCE + linear explanation function	3 + entry/exit	Firm size (in herd size)	Milk output, milk price, policy dummy, trend	-
2005	Jongeneel et al.	Netherlands, Germany, Poland, Hungary	Dairy farms	Macro	NL: 1972-2003, W-DE: 1971-2003, E-DE: 1991-2003, PL: 1996-2000, H: 2000/2003	Non-stationary	IV-GCE	NL, E-DE, H: 7 + entry/exit, W-DE: 6 + entry/exit, PL: 4 + entry/exit	Firm size (in herd size)	Trend, milk output, milk price, quota dummy, auction dummy	Pseudo-R^2: NL: 0.84, W-DE: 0.92, E-DE: 0.89, PL: 0.93, H: 0.82
2006	Stokes	Pennsylvania, USA	Dairy farms	Macro	1980-2003	Non-stationary	GCE + SUR (2-step)	6 + entry/exit	Firm size (in herd size)	Milk price, milk price volatility, productivity, interest rates, land values, policy dummy for exit probabilities	-
2007	Tonini	Poland, Hungary	Dairy farms	Macro	PL: 1995-2005, H: 2000-2003	Stationary, non-stationary (PL), stationary (H)	IV-GCE	PL: 8 + entry/exit, H: 7 + entry/exit	Firm size (in herd size)	Trend, milk producer price, price for concentrates for cattle	Pseudo-R^2: PL: 0.048/0.051, H: 0.000
2008	Tonini and Jongeneel	Poland	Dairy farms	Macro	1995-2006	Non-stationary	IV-GCE	8 + entry/exit	Firm size (in herd size)	Trend	Pseudo-R^2: 0.34
2008	Huettel and Jongeneel	Germany, Netherlands	Dairy farms	Macro	W-DE: 1971-2005, E-DE: 1991-2005, NL: 1972-2006	Non-stationary	IV-GCE	W-DE: 6 + entry/exit, E-DE and NL: 7 + entry/exit	Firm size (in herd size)	Milk price, milk yield, policy dummy	Pseudo-R^2: W-DE: 0.82/0.80, E-DE: 0.58, NL: 0.82/0.90

Source: Own table.

2.4 Other econometric models

There exists a vast amount of econometric models apart from Markov chains that deal with structural change in agriculture. These models are characterised by regressions on a number of explanatory variables. The regression analyses can thematically be divided into three model variants. Most of the regression models are related to analysing farm growth, specifically testing Gibrat's law, others are cohort analyses which concern the number of farm holders and the reasons for entering or leaving the sector and the last selected variant of models considers farm succession explicitly. Applications of the model types are summarized in Table 2.2.

Farm growth

Most of the models reviewed in this section try to explain farm growth or size or focus especially on entry and exit of farms to or from the sector. Many of the studies on growth and size distribution of farms rely on a simple stochastic model which is usually a variant of Gibrat's law (Gibrat, 1931). Gibrat's law states that the growth rate of firms is determined by random factors and independent of firm size. The basic equation to test Gibrat's law is:

$$\ln S_{i(t)} - \ln S_{i(t-1)} = \alpha + \beta \ln S_{i(t-1)} + u_{i(t)}\,, \tag{2.7}$$

where $S_{i(t)}$ is the size of firm i at time t, and $u_{i(t)}$ is the random effect. Gibrat's law is true if $\beta=0$ (Weiss, 1999). The main weakness of the law is that systematic factors that are of primary interest from a social science perspective are comprised under the random process. Therefore, the equation given above is often extended to take into account other factors than size as well and on the left hand side of equation (2.7) it is common to include also farm entry and exit (farm survival).

Shapiro et al. (1987) test the relationship between farm size and growth in Canada from 1966 until 1981. They find out that small farms grow faster than large farms implying the rejection of Gibrat's law. Larger farms also experience more stable growth rates in comparison to small farms. Shapiro et al. also find that the probability of exit is greater than the probability of entry at any size, and that the probability of either of them is highest for small farms.

Weiss (1999) takes into account the two interrelated determinants 'entry/exit' and 'firm growth' of continuing farms. He adds a number of other socioeconomic factors to the elementary stochastic model of Gibrat's law in his analysis on Upper Austrian farm households from 1980 to 1990. Factors assumed to have an impact on farm growth and survival are human capital, off-farm employment and other individual and farm-specific characteristics. Weiss splits up his estimation into the branches full-time and part-time farming, but analyses also all farms together. He finds that a large proportion of the variance in the data cannot be explained with the specified econometric model and suggests other important determinants which may have an influence on the unexplained variation (e.g. farm income, farmer's attitude towards risk, etc.). The estimated negative relationship between part-time farming and farm expansion/survival supports the assumption that part-time farming promotes the restructuring of the farm sector. He further finds that the effect of farmer's age on the probability of survival is positive for young farmers and becomes negative for farmers over 51. Moreover, the existence of a farm successor has a positive impact on farm survival. With regard to human capital, agricultural specific schooling and general schooling are examined. An increase in agricultural specific schooling increases the probability of farm survival and farm growth. General schooling has a positive impact on farm survival, but the effect on farm growth is seen to be insignificant.

Weiss furthermore includes aspects concerning the family status of the farmer and derives interesting insights. If the farm operator is married, this has a positive impact on survival and growth of the firm. Also, an increase in the number of family members increases farm survival and growth. If the operator is female, this has a negative impact on farm survival and farm growth. Generally, the effect of all these factors seems to be higher for full-time farms. Gibrat's law is rejected since farm growth is less than proportionate to farm size. As Shapiro et al., Weiss estimates that smaller farms grow faster than larger farms. He determines two "centres of attraction" which suggest a polarisation of growth rates: small and very large farms grow faster than farms in the medium size class.

Bremmer et al. (2004) analyse the structural change in arable farming and horticulture in the Netherlands with regard to farm renewal and farm growth. Renewal covers all changes at the firm requiring the application of new knowledge and includes diversification and innovation. Explanatory variables have been selected in order to reflect personal characteristics of the farm operator, firm structure, and firm performance. The farm operator is characterised by age, time horizon (long if successor exists or age below 50, short otherwise), labour input of family members, off-farm income and education. Firm structure is reflected by the variables soil type, location, farm size, solvency and mechanisation. Profitability is the only variable in the category performance. Personal characteristics are shown to have a weak impact on farm growth. Thus, age, succession, and off-farm income have no influence, and family labour input is negatively correlated with farm growth. Firm development (profitability) is correlated with neither firm growth nor renewal. The results show that firm structure has a larger impact on firm development than personal characteristics and performance. The degree of mechanization has the largest marginal impact on both farm growth and renewal, since a high degree of mechanization implies high investments in the past, encouraging firm renewal and firm growth. Firm growth is found to be independent of firm size. However, the authors conclude that the present models do not provide a satisfactory explanation for firm growth and renewal. In general, a large proportion of no-changes is predicted correctly, whereas the occurrence of growth and renewal is predicted incorrectly. According to the authors this might be due to data limitations as most firms provided only five or six observations and firm growth and renewal took place in a limited number of years. For further research they suggest to include the decision making process in the model. Separate estimation of the model for arable farming and protected horticulture shows that firm size has a positive impact on firm growth in arable and a negative impact in horticultural farming.

Sumner and Leiby (1987) analyse effects of human capital on size and growth. Their study employs a sample of southern dairy farms in the United States. Variables included are age (supposed to reflect general experience, life-cycle, and cohort effects), experience (measures the tenure of the farm operator, where, for a given age, more dairy experience means less general experience), schooling (representative for general human capital), and management (as an indicator of dairy-specific information or techniques). Cohort analyses (see below) are conducted for age, experience, and schooling cohorts. From the econometric analysis the authors conclude that the considered variables indeed may affect farm size and growth. However, the effects remain unclear and further work in this field is suggested.

Number of farm holders

Farmers of a certain gender and occupational category (full-time, part-time, hired, family) belonging to a cohort, i.e. group, are defined by specifying the period during which they were born. Their number can be followed and simulated through time by cohort analyses (De Haen and Von Braun, 1977). This method depends on population dynamics and the life cycle of farmers. Projections are made by assuming that historical patterns of changes in the number of farmers by age cohort will continue into the future (Olson and Stanton, 1993). The basic equation for an age cohort analysis is:

$$H_{a+1}(t+1) = H_a(t)\, ps_{a,a+1}\, pe_{a,a+1} - NA_{a,a+1}(t, t+n)\,, \tag{2.8}$$

where $H_{a(t)}$ is the number of holders in the cohort of age a at time t, $ps_{a,a+1}$ is the probability to survive during age interval a to $a+1$, $pe_{a,a+1}$ is the probability to maintain the earning capacity during age interval a to $a+1$, and NA is the non-autonomous change of the cohort size. Age cohort analyses in agriculture are usually used to predict labour developments (De Haen and Von Braun, 1977). With a cohort analysis the autonomous changes in the farm structure can be separated from non-autonomous changes. Autonomous events are demographic factors such as ageing, death, disability, and retirement through ageing. Non-autonomous changes are those changes that can be attributed to all other factors (e.g. new entrants, change of occupation, early retirement). They are usually interpreted as arising from changes in social and economic circumstances. The autonomous component of the decrease in the number of farmers in a specific age cohort can be inferred from general population statistics. The residuals (the non-autonomous change) that follow from the cohort analysis are then explained using econometric methods which may include several explanatory variables that were already outlined in the previous sections. De Haen and Von Braun (1977) predicted that for the work force decrease in West Germany a considerable part (about 60 %) are due to age, death, and disability.

EU-wide age cohort analyses have been carried out within the SEAMLESS project by Garvey (2006). Garvey (2006) finds that for the explanation of the non-demographic part, i.e. the non-autonomous change of the number of farm holders, only the regional unemployment rate appears to be useful. His analysis shows that a percentage point increase in regional unemployment generally leads to a 1.5 percentage point increase in net-entry to the farming sector among young farmers. For farmers between 35 and 55 years a 0.8 percent increase of net-entry is found in case of a one percentage point increase of the unemployment rate. In general, net-entry among young farmers appears to be more sensitive to regional unemployment changes than entry or exit for more middle-aged farmers.

The age cohort approach could theoretically be used in analyses of structural change to approximate the number of farms in a region. However, this approach makes sense for regions in which one farm corresponds to one farm holder (family farm structure). For regions where this is not the case, e.g. in Eastern Europe, the age cohort approach is not suitable. Furthermore, the methodology is not suitable for modelling aggregate change of farm numbers in specialisation and size classes as the underlying decisions are mainly determined by other factors than age structure.

Farm succession

In the context of farming systems, models of discrete choice have mainly been used to explain switches from conventional to organic farming (a literature review is provided by Acs et al., 2005). However, there exist a number of studies that concentrate on the estimation of farm survival by analysing the probability of farm succession. These studies are normally formulated as problems of discrete choice where the model generally includes characteristics of the individual (e.g. age, number and age of children) and relative attributes of competing choices (e.g. expected utility). Examples are the studies by Kimhi and Nachlieli (2001) and Pietola et al. (2003). Generically, we can represent a discrete choice model according to the following formula (Pietola and Heikkilä, 2006):

$$y_i^* = \alpha + \beta z_i + u_i \quad \text{where } y_i = 1 \text{ if } y_i^* > 0, \text{ else } y_i = 0 . \tag{2.9}$$

y_i^* is a latent response variable defined in practice and unobservable. What we observe is the dummy variable y_i representing a certain choice. From the previous relations the choice probability relation and the likelihood function can be derived.

Kimhi and Nachlieli (2001) estimated a binary choice model for Israeli farms in which a variable w_t is defined as the tendency to declare a successor in period t. The model was estimated via probit and SNP (semi-nonparametric) methods. The age of the farm owner, an education dummy, off-farm employment, the age difference between farm owner and eldest child, the number of daughters and sons, a regional dummy, farm size, a production dummy, and a dummy for an already existing (declared) successor served as explanatory variables. Four different R^2-based measures revealed values between 50 and 80 per cent. Kimhi and Nachlieli (2001) found that the probability of having a successor rises with the age of the operator (up to age 68), his/her level of schooling, and age of the oldest child. The number of children and the parents' off-farm employment did not have a significant influence on the probability of succession. Also, succession probabilities were found to be much higher in farms located in Northern regions of the country and fruit or vegetable farms have higher probabilities for succession than farms with more land and/or poultry enterprises.

Pietola et al. (2003) analysed the timing and type of exit from farming in relation to early retirement programmes in Finland. Three choice alternatives were assumed: exit and close down of the farm operation, exit and transfer of the farm to a new entrant, or the continuation of farming. These three alternatives are mutually exclusive such that two binary indicators (exit and transfer) were used to identify them, whereas the third choice of continuation was observed if neither exit nor transfer occurred. McFadden's R^2 was 0.68 and 0.65 for two estimated models (a model which controls for serial correlation by simulating the sequence of interrelated choice probabilities using the Geweke-Hajivassiliou-Keane (GHK) simulation technique and multinomial probit, respectively). Explanatory variables were the farmer's age, a regional dummy, land and forest area, output prices, subsidy rates, the level of saved pension, a dummy which indicates the expiration of an early retirement programme, and a dummy for the presence of a spouse. However, some parameters associated with prices and subsidies were not significant at the five percent level. The results of the study suggest that the timing and type of exit decision respond elastically to farmer and farm characteristics and the political and economic environment. More specifically it is predicted that an increase of the minimum age of eligibility for early retirement will first slow down structural development, since farmers cannot exit as early as before. However, as the exit decision is delayed and the farmers' age increases, the probability of transferring the farm to a new entrant will decrease. This result is in line with Kimhi and Nachlieli (2001), who predict a decreasing probability for farm succession for farms with farm holders being older than 68 years as well.

Table 2.2: Overview of other (than Markov) econometric models

Analysis	Year	Region	Focus	Time period	Dependent	Explanatory	Performance
				Farm growth			
Bremmer et al.	2004	Netherlands	Arable farming and horticulture	1990-2000	Farm renewal/ farm growth	Farmer's age, succession, off-farm employment, firm size, family labour input, solvency, mechanisation, profitability	R^2: 0.36/0.30 (both); 0.28/0.33 (arable); 0.78/0.32 (horticulture)
Shapiro et al.	1987	Canada	All specialisations	1966-1981	Firm size; entry/exit	Firm size	R^2: 0.10-0.80
Sumner and Leiby	1987	Southern USA	Dairy farms	1982, 1977, 1987	Firm size and growth	Farmer's age, experience, schooling, management	
Weiss	1999	Upper Austria	All specialisations	1980-1990	Entry, exit, firm growth	Farm size, human capital, off-farm employment, farmer's age, farmer's family status	
				Number of holders (age cohort analyses)			
De Haen and Von Braun	1977	West German regions	All specialisations	1965-1975	Number of holders	Autonomous events, non-autonomous events	
Garvey	2006	EU15	All specialisations	1995-2000	Number of holders	Autonomous events, non-autonomous events	R^2: 0.47-0.63
				Farm succession (discrete choice analyses)			
Kimhi and Nachlieli	2001	Israel	All specialisations	1994-1995	Tendency to declare a successor in period t	Farmer's age, education, off-farm employment, age difference between holder and eldest child, number of children, regional dummy, farm size, production dummy, dummy for declared successor	R^2: 0.49-0.83
Pietola et al.	2003	Finland	All specialisations	1993-1998	Exit and close down; exit and transfer to new entrant; continuation	Farmer's age, regional dummy, land and forest area, output prices, subsidy rates, saved pension, expiry of early retirement programme, marital status	R^2 (McFadden): 0.65-0.68

Source: Own table.

2.5 Multi-agent systems

Recently, agent-based systems became popular in the field of quantitative agricultural sector analysis, where they are used especially in the modelling of land-use and land-cover changes. Usually, these models combine two key components: (1) a cellular model representing the landscape and (2) an agent-based model that describes decision-making and interactions of the actors in the system (Parker et al., 2003). Since our objective lies specifically in the modelling of changing farm numbers rather than in the analysis of land-use changes, land-use/cover models are not reviewed here. Reviews of land-use/cover models can for instance be found in Parker et al. (2003), Berger and Parker (2002, pp.27), Parker and Berger (2002, pp.79), or Robinson et al. (2007). A thorough literature review of multi-agent systems in agriculture is also provided by Happe (2004).

Agent-based systems differ from conventional mathematical programming or econometric models mainly in the way that global equilibrium conditions are not employed and thus a top-down perspective is avoided. Instead agent-based models allow a bottom-up perspective on the subject under study in the way that human decision making and the interaction between different agents (behavioural rules) as well as the environment (general framework and conditions) can be modelled explicitly by the researcher. In this sense, agent-based models provide substantial flexibility and can for instance be used to conduct computational (thought) experiments (Parker et al., 2002; Berger et al., 2002; Happe, 2004; Robinson et al., 2007). The implemented decision rules result in a particular property of agent-based systems which is called self-organisation and means the ability of multi-agent systems to generate complex structures that change endogenously. In the same manner the speed of change is determined endogenously and not imposed externally (Happe, 2004, p. 21). All these properties make agent-based modelling interesting for the analysis of structural change as well, where they are mainly used to detect system inherent properties which may either hamper or accelerate farm structure changes.

The disadvantages of agent-based models, however, are closely interrelated with the advantages described before. The most outstanding one is the danger of over-specification of the model. The great flexibility nearly automatically leads to a greater complexity and the researcher might be tempted to represent the real world as close as possible. This refers particularly to processes where human decision making is involved (Happe, 2004; Couclelis, 2002). Another disadvantage that arises from the increased complexity is given by the data requirements if the system shall be calibrated to a specific region with real-world data. This particularly concerns the accessibility to individual farm accountancy data which often is available only for aggregates of selected farm variables. Another shortcoming is the current lack of methodologies to statistically validate the responses of the system to changes in institutional or economic conditions (Parker et al., 2003, p.

327). These shortcomings could be partially addressed by reflecting behavioural and parameter uncertainty through simulations under different specifications allowing to represent the plausible range of model outcomes. Another opportunity might be the use of meta-models (Happe, 2004) to describe the relationship between parameter settings and model results using regression techniques.

The only agent-based model in the agricultural economics literature which is specifically applied to analyse farm structural change is AgriPoliS (Happe, 2004; Happe et al. 2006; Happe et al., 2008). With a precursor model of AgriPoliS Balmann (1994 and 1997) could demonstrate the existence of path dependencies in agricultural structures by use of a cellular automaton.

In Happe (2004) AgriPoliS has been calibrated to the small German region Hohenlohe. Two types of agents, farm agents and market agents, are distinguished with one farm agent corresponding to one farm. The objective function of each farm agent is assumed to be farm household income maximisation (farm and off-farm income) which is subject to specific constraints referring to factor endowments (land, labour, fixed assets, liquidity), the situation on input and output markets, policies, and overall framework conditions (opportunities for off-farm employment, interest rate levels, access to credit). Farm agents differ mainly with respect to specialisation, farm size, factor endowment, production technology, personal characteristics of the farmer and managerial ability. The most important actions undertaken by a farm agent are renting land, investment, production, farm accounting, and the decision whether to quit farming or to stay in the sector. However, agent interactions occur only indirectly by competing on factor and product markets which are managed by the market agents. The spatial dimension of AgriPoliS is represented by a cellular automaton. Typical farms are modelled and up-scaled to represent the regional characteristics of the test region. Farm typologies depend on the farm type (professional vs. non-professional), specialisation and size (Happe, 2004).

AgriPoliS is calibrated to the base year 2000/2001 considering the political framework conditions of the Agenda 2000 reform package. Two sets of policies are analysed with regard to structural change. These policies are compared with respect to their impact on and the pace of structural change and their impact on factor use, farm size, incomes, efficiency and governmental expenses. Here only the effects on farm structure are briefly reviewed.

The first group of policies comprises three different options: (1) a retirement payment scheme, (2) fully decoupled single farm payments and (3) a stepwise phasing out of direct payments. Each of the policies is hypothesized to facilitate structural adjustment. It is found that, as expected, policies providing incentives for small farms to withdraw from the sector lead to significantly larger farms. Also, the pace of structural adjustment differs substantially between the three policy scenarios in the sense that policies providing incentive payments cause stronger adjustment reactions right after the policy change (decoupling and retirement payments) compared to a policy introducing gradual changes (phasing out). Dairy and beef cattle production seem to cease in the long-run irrespective of the policy environment. In all policy scenarios, the dominant position of granivore farms grows despite of the downward trend in product prices.

The second set of policies analysed comprise three ways of decoupling direct payments: (1) a mixed payment (decoupled single farm payment combined with a low area payment), (2) a regional single area payment, and (3) an only partly decoupled single farm payment. Regarding farm size, structural change takes place in all policy scenarios, but a significant shift right after the policy change can only be observed in case of the mixed payment. For this scenario the share of farms above 50 ha is significantly higher than in the other scenarios. However, with the exception of the regional premium scenario the gap between the scenarios closes over time. Regarding farm specialisation, it is outlined that the importance of granivore farms is common to all policy scenarios, but the relative importance of intensive livestock farming is pronounced in the mixed decoupling scenario.

For model validation systematic variations on model parameters are introduced and exploited by a statistical meta-modelling exercise. The results show that technological change, interest rate levels and managerial ability have a significant impact on structural change. Particular emphasis is given to the distribution of managerial ability by varying the heterogeneity of these skills and it was found that this does significantly affect the farm responses to different interest rate scenarios.

2.6 Conclusions

This paper presented a literature review on empirical models of farm structural change in the context of predicting farm type numbers within an integrated modelling chain for ex-ante impact assessment. The objective was to identify a generally suitable and robust methodology to predict numbers of farms based on relevant determinants for at least 30 farm type classes and all regions in the EU. In addition, the review aimed at a general overview on the empirical relevance of potential determinants for model specification to give direction for the significant task of data compilation in preparing the envisaged empirical analysis.

Modelling methods

Regarding the suitability of methods to model farm structural change in the context set out, it can be first noted that neither the contributions explicitly considered in this review nor those surveyed but left out, aimed at such a comprehensive modelling exercise as envisaged for the SEAMLESS modelling chain (see Introduction). The econometric models apart from the Markov chain each only aim to explain and predict a limited dimension of farm structural change as defined here, either related to farm size (farm growth models) or farm numbers (cohort analyses or exit/entry models). Straightforward extensions to incorporate multiple dimensions and the required representation of interdependencies between farms or farm types are not available nor immediately recognisable without leaving the basic methodological approach of those studies. We can therefore exclude these methodological approaches for the considered task. The Markov chain studies are generally limited to a narrow subset of farm specialisations and restrict their attention to single or very few regions. Multi-agent systems are rather comprehensive regarding the farm types considered, but existing systems are restricted to very few and small regions due to the considerable requirements on data as well as specification and validation time.

The Markov chain and the multi-agent systems are in principle able to endogenously predict farm numbers within a given differentiated farm typology as long as data sources and model specification allow a corresponding classification, i.e. a definition of desired class boundaries according to size and specialisation. The multi-agent systems have the clear advantage that the model specification does not generally restrict the type of classification applied to modelling results. As long as the variables characterizing the individual farms in the system are distributed similarly to the underlying “real-world” population, any classification based on these variables is potentially valid. Contrary to this, Markov chain models are estimated based on a pre-defined classification and the interpretation of estimation results and predictions are restricted to this specific choice. A redefinition of the farm typology in the integrated modelling chain requires a re-estimation of the Markov model based on the new classes. However, this might be a minor disadvantage if we consider that regular updates of the estimation are anyway required as time progresses and new data become available.

The crucial deficiency of multi-agent systems in view of the task ahead are the enormous data and modelling resources required to cover regions Europe-wide. Although this reason alone can be seen as prohibitive, it should also be noted that the state of the literature on multi-agent systems is not far enough to provide adequate procedures for validation of modelling results on farm structural change as needed for an ex-ante exercise of policy impact assessment. First approaches using meta-models based on systematic experiments with the system provide initial progress in this respect. However, solid evidence on the validity of model responses regarding farm structural change is currently not delivered. Furthermore, the analysis of substantial ex-post experiments seems required comparing modelling results with actual structural developments. By design, the Markov chain analysis provides at least an ex-post statistical validation through the assessment of model fit, prediction error and measures on the influence of exogenous determinants. If data availability allows, even an out-of-sample test can be straightforwardly implemented. Like any other statistical or econometric approach it is, however, not guarded against future changes in the underlying mechanisms of farm structural change which would render estimates based on past observations invalid.

In view of the discussion above, we are left with the Markov chain approach as the only suitable methodology from the set of possible choices. It should be clear by now that this choice is not a decision on a generally best method to model structural change. It is only a conclusion with respect to the limited definition of structural change and the scope of the prediction exercise considered here. There does not exist a model or methodology which is best for all purposes. Even having decided on the general method, the review of the Markov chain literature shows considerable variety with respect to specific approaches applied and the above mentioned limitations of scope. Apart from data availability, it seems that computational requirements exponentially increasing with farm types and observations currently restrict extensions of the analyses in relevant directions. However, recent developments in estimation based on cross-entropy formulations provide opportunities for a more broadly scoped estimation exercise as they allow including prior information to obtain robust estimates even under a limited time series length. For example, observations on class transitions in farm sample data could provide reference probabilities in a Markov chain approach based on macro-data. Furthermore, newly presented two-step procedures are likely able to avoid computational impossibilities when trying to simultaneously estimate non-stationary transition probabilities across size and specialisation classes.

Determinants of structural change

Turning to the second objective of the paper, we briefly discuss findings on empirically relevant determinants of farm structural change based on the research reviewed. Existing Markov chain models mainly identify statistical relevance of technological change, government programs, and prices of outputs and inputs related to the specific farm specialisation class considered. Price variables typically capture incentives within the class (key output prices) and those of alternative uses of the resources (land values and interest rates). The limitation to single or very few regions of analysis explains that theoretically relevant variables with little variation in time were not considered. For example, climate and soil characteristics are left out although they strongly determine the set of technologies available to the farms. Also, the Markov chain literature is focused on transitions across size classes but largely ignores specialisation classes. Consequently, a broader analysis incorporating different classes of main production orientation or farming system intensity could render variables with variations across the spatial domain much more relevant.

In the regression analyses of farm growth and exit/entry decisions, a different and large set of variables is employed with a strong emphasis on socio-demographic determinants. Variables selected and found statistically significant in both types of analyses have a considerable overlap because continuation and growth is the alternative decision to exiting the sector. Farmer's age and education as well as farm size appear relevant in most of the studies presented. The very few cohort analyses focus on autonomous demographical drivers of labour use in agriculture. The key lesson to be learned here is the importance of the age-structure of farm holders for the aggregate exit pattern of farms confirming the significance of farmer's age in strategic decisions on farm continuation. This variable as well as measures on education are so far ignored in Markov chain analyses and could be relevant for cross regional variation in aggregate exit decisions. Although important aspects of farm structural change were identified by the considered farm growth, exit/entry and cohort analyses, the conceptual lack of interaction between farms or farm types makes it difficult to infer deeper general insight or aggregate impacts. Despite their theoretical importance for the strategic farm decisions modelled, the conditions outside of agriculture (job opportunities, interest rates, alternative uses of land, etc.) rarely proved to have statistical influence or were not even considered. Again, most likely a limited variation of these variables due to the small regional coverage might explain this observation.

Multi-agent systems potentially provide the most explicit modelling of farm structural change combining annual and strategic farm decision making, spatial interaction of farms under heterogeneous technologies and farm management, and general economic conditions in a dynamic environment. Experiments with the systems have shown that not only averages, but the distribution of available technologies and managerial capabilities over farms matter for farm structural change, thereby adding to the set of potentially relevant variables to be considered in a Markov chain analysis across a larger number of regions.

Overall we can conclude that the number and type of relevant determinants for farm structural change identified in a single empirical analysis very much depends on the specific objective and scope of analysis regarding regional and farm type coverage and differentiation. The estimation of Markov chain models of farm structural change for all of Europe could theoretically be done by following most Markov chain approaches presented here simply performing a separate analysis for each specialisation class and region. However, a more interesting contribution to the literature could be obtained by using recent methodological developments and push the extension in the regional and farm type domain as far as computationally possible. This would provide possibilities to incorporate and test the impact of determinants which previously had to be ignored and potentially improve reliability and scenario dependency of farm structural changes in an integrated modelling chain.

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2.7 References

Acs, S., Berentsen, P.B.M., Huirne, R.B.M., 2005. Modelling Conventional and Organic Farming: A Literature Review. NJAS Wageningen Journal of Life Sciences 53 (1), 1-18.

Andersen, E., Elbersen, B., Godeschalk, F., Verhoog, D., 2007. Farm management indicators and farm typologies as a basis for assessments in a changing policy environment. Journal of Environmental Management 82, 353-362.

Andersen, E., Verhoog, A.D., Elbersen, B.S., Godeschalk, F.E., Koole, B., 2006. A multidimensional farming system typology. SEAMLESS Report No. 12, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org, 30 pp.

Anderson, T.W., Goodman, L.A., 1957. Statistical Inference about Markov Chains. Annals of Mathematical Statistics 28, 89-110.

Balmann, A., 1995. Pfadabhängigkeiten in Agrarstrukturentwicklungen. Begriff, Ursachen und Konsequenzen, Duncker and Humblot, Berlin.

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

Berger, T., Goodchild, M., Janssen, M.A., Manson, S.M., Najlis, R.,Parker, D.C., 2002. Methodological Considerations for Agent-Based Modeling of Land-Use and Land-Cover Change. In: Parker, D.C., Berger, T., Manson, S.M., McConnell, W.J. (Eds.), Agent-Based Models of Land-Use and Land-Cover Change. LUCC Report Series No. 6, Irvine, California, USA, pp. 7-25.

Berger, T., Parker, D.C., 2002. Examples of Specific Research. In: Parker, D.C., Berger, T., Manson, S.M., McConnell, W.J. (Eds.), Agent-Based Models of Land-Use and Land-Cover Change. LUCC Report Series No. 6, Irvine, California, USA, pp. 27-35.

Boehlje, M., 1992. Alternative Models of Structure Change in Agriculture and Related Industries. Agribusiness 8 (3), 219-231.

Bremmer, J., Oude Lansink, A.G., Olson, K.D., Baltussen, W.H., Huirne, R.B., 2004. Analysis of Farm Development in Dutch Agriculture and Horticulture. In: Bremmer, J. (Ed.), Strategic Decision Making and Firm Development in Dutch Horticulture. PhD-thesis, Wageningen University and Agricultural Economics Research Institute, Wageningen, Netherlands, pp. 23-39.

Chavas, J.P., Magand, G., 1988. A Dynamic Analysis of the Size Distribution of Firms: The Case of the US Dairy Industry. Agribusiness 4 (4), 315-329.

Cochrane, W., 1958. Farm Prices: Myth and Reality, University of Minnesota Press, Minneapolis.

Couclelis, H., 2002. Why I No Longer Work with Agents: A Challenge for ABMs of Human-Environment Interactions. In: Parker, D.C., Berger, T., Manson, S.M., McConnell, W.J. (Eds.), Agent-Based Models of Land-Use and Land-Cover Change. LUCC Report Series No. 6, Irvine, California, USA, pp. 3-5.

Day, R.H., Cigno, A., 1978. Modelling Economic Change: The Recursive Programming Approach, North-Holland, Amsterdam.

De Haen, H., Von Braun, J., 1977. Mobility of Agricultural Labour and Fluctuating Regional Labour Markets: A Demographic and Economic Analysis with Application to West-Germany. European Review of Agricultural Economics 4 (3), 215-243.

Disney, W.T., Duffy, P.A., Hardy, W.E.J., 1988. A Markov Chain Analysis of Pork Farm Size Distributions in the South. Southern Journal of Agricultural Economics 20, 57-64.

Edwards, C., Smith, M.G., Peterson, R.N., 1985. The Changing Distribution of Farms by Size: A Markov Analysis. Agricultural Economics Research 37 (4), 1-16.

Ethridge, D.E., Roy, S.K., Myers, D.W., 1985. A Markov Chain Analysis of Structural Changes in the Texas High Plains Cotton Ginning Industry. Southern Journal of Agricultural Economics 7 (2), 11-20.

Ewert, F., van Ittersum, M.K., Bezlepkina, I., Therond, O., Andersen, E., Belhouchette, H., Bockstaller, C., Brouwer, F., Heckelei, T., Janssen, S., Knapen, R., Kuiper, M., Louhichi, K., Alkan Olsson, J., Turpin, N., Wery, J., Wien, J.E., Wolf, J. (this issue): A methodology for integrated assessment of policy impacts in agriculture.

Garcia, P., Offutt, S.E., Sonka, S.T., 1987. Size Distribution and Growth in a Sample of Illinois Cash Grain Farms. American Journal of Agricultural Economics 69 (2), 471-476.

Gardebroek, C., Oude Lansink, A., 2008. Dynamic microeconometric approaches to analysing agricultural policy. Paper presented at the 107th EAAE Seminar “Modelling of Agricultural and Rural Development Policies”, January 29-February 1, 2008, Seville, Spain.

Garvey, E., 2006. Estimations of Labour Inputs using FADN Data, SEAMLESS Report No. 15, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org, 35 pp, ISBN no. 90-8585-043-6.

Gebremedhin, T.G., Christy, R.D., 1996. Structural Changes in U.S. Agriculture: Implications for Small Farms. Journal of Agricultural and Applied Economics 28 (1), 57-66.

Gibrat, R., 1931. Les Inégalités Economique, Sirey, Paris.

Gillespie, J.M., Fulton, J.R., 2001. A Markov Chain Analysis of the Size of Hog Production Firms in the United States. Agribusiness 17 (4), 557-570.

Goddard, E., Weersink, A., Chen, K., Turvey, C.G., 1993. Economics of Structural Change in Agriculture. Canadian Journal of Agricultural Economics 41, 475-86.

Golan, A., Judge, G., Miller, D., 1996. Maximum Entropy Econometrics, John Wiley and Sons, Chichester.

Golan, A., Vogel, S., 2000. Estimation of non-stationary social accounting matrix coefficients with supply side information. Economic Systems Research 12, 447-471.

Hallam, A., 1991. Economies of Size and Scale in Agriculture: An Interpretative Review of Empirical Measurement. Review of Agricultural Economics 13 (1), 155-172.

Hallam, A., 1993. Empirical Studies of Size, Structure, and Efficiency in Agriculture. In: Hallam, A. (Ed.), Size, Structure, and the Changing Face of American Agriculture. Westview Press, Boulder, Colorado, pp. 204-231.

Hallberg, M.C., 1969. Projecting the Size Distribution of Agricultural Firms - An Application of a Markov Process with Non-Stationary Transition Probabilities. American Journal of Agricultural Economics 51, 289-302.

Happe, K., 2004. Agricultural Policies and Farm Structures - Agent-Based Modelling and Application to EU-Policy Reform. IAMO Studies on the Agricultural and Food Sector in Central and Eastern Europe 30, IAMO, Halle (Saale), URL: http://www.iamo.de/dok/sr_vol30.pdf.

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

Happe, K., Kellermann, K., Balmann, A., 2006. Agent-based analysis of agricultural policies: an illustration of the agricultural policy simulator AgriPoliS, its adaptation, and behaviour. Ecology and Society 11 (1): 49. URL: http://www.ecologyandsociety.org/vol11/iss1/art49/.

Harrington, D.H., Reinsel, R.D., 1995. A Synthesis of Forces Driving Structural Change. Canadian Journal of Agricultural Economics Special Issue 43, 3-14.

Huettel, S., Jongeneel, R., 2008. Structural Change in the Dairy Sectors of Germany and the Netherlands – A Markov Chain Analysis. Paper presented at the 12th EAAE Congress, August 26-29, Ghent, Belgium.

Jongeneel, R., 2002. An Analysis of the Impact of Alternative EU Dairy Policies on the Size Distribution of Dutch Dairy Farms: An Information Based Approach to the Non-Stationary Markov Chain Model. Paper presented at the 10th EAAE Congress, August 28-31, Zaragoza, Spain.

Jongeneel, R., Longworth, N., Huettel, S., 2005. Dairy Farm Size Distribution in East and West: Evolution and Sensitivity to Structural and Policy Variables: Case-Studies of the Netherlands, Germany, Poland and Hungary. Paper presented at the 11th EAAE Congress, August 24-27, Copenhagen, Denmark.

Jongeneel, R., Tonini, A., 2008. Dairy Quota and Farm Structural Change: A Case Study on the Netherlands. Paper presented at the 107th EAAE Seminar, January 29-February 1, Seville, Spain.

Judge, G.G., Swanson, E.R., 1961. Markov Chains: Basic Concepts and Suggested Uses in Agricultural Economics. Agricultural Experiment Station Research Report AERR-49. University of Illinois. Department of Agricultural Economics, Urbana, Illinois.

Karantininis, K., 2002. Information-based estimators for the non-stationary transition probability matrix: an application to the Danish pork industry. Journal of Econometrics 107, 275-290.

Keane, M., 1976. Projections of Change in Creamery Supplier Structure. Irish Journal of Agricultural Economics and Rural Sociology 6 (2), 177-184.

Keane, M., 1991. Changes in the Size Structure of Irish Dairy Farms. Irish Journal of Agricultural Economics and Rural Sociology 14, 67-74.

Kimhi, A., Nachlieli, N., 2001. Intergenerational Succession in Israeli Family Farms. Journal of Agricultural Economics 52 (2), 42-58.

Krenz, R.D., 1964. Projection of Farm Numbers for North Dakota with Markov Chains. Agricultural Economics Research 16, 77-83.

Lee, T.C., Judge, G.G., Zellner, A., 1977. Estimating the Parameters of the Markov Probability Model from Aggregate Time Series Data, North-Holland Publishing Company, Amsterdam.

Lee, T.C., Judge, G.G., 1996. Entropy and Cross-Entropy Procedures for Estimating Transition Probabilities from Aggregate Data. In: Berry, D.A., Chaloner, K.M., Geweke, J.K. (Eds.), Bayesian Analysis in Statistics and Econometrics - Essays in Honor of Arnold Zellner. John Wiley and Sons, Inc., New York, pp. 153-164.

Louhichi, K., Janssen, S., Li, H., Borkowski, N., Kanellopoulos, A., van Ittersum, M. K., Flichman, G., Hengsdijk, H., Zander, P., Blanco Fonseca, M., Stokstad, G., Athanasiadis, I., Rizzoli, A. E., Huber, D., in review. A generic Farming System Simulator (FSSIM) for modelling European arable farming sectors. In: Brouwer, F. M., van Ittersum, M. K. (Eds.), Environmental and agricultural modelling: integrated approaches for policy impact assessment.

MacRae, E.C., 1977. Estimation of Time-Varying Markov Processes with Aggregate Data. Econometrica 45 (1), 183-198.

Olson, K.D., Stanton, B.F., 1993. Projections of Structural Change and the Future of American Agriculture. In: Hallam, A. (Ed.), Size, Structure, and the Changing Face of American Agriculture. Westview Press, Boulder, Colorado, pp. 587-627.

Padberg, D.I., 1962. The Use of Markov Processes in Measuring Changes in Market Structure. Journal of Farm Economics 44 (1), 189-199.

Parker, D.C., Berger, T., Manson, S.M., McConnell, W.J., 2002. Agent-Based

Models of Land-Use and Land-Cover Change. LUCC Report Series No. 6, Irvine, California, USA.

Parker, D.C., Berger, T., 2002. Synthesis and Discussion. In: Parker, D.C., Berger, T., Manson, S.M., McConnell, W.J. (Eds.), Agent-Based Models of Land-Use and Land-Cover Change. LUCC Report Series No. 6, Irvine, California, USA, pp. 79-88.

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. Annals of the Association of American Geographers 93 (2), 314-337.

Peterson, E.W.F., 1986. Agricultural Structure and Economic Adjustment. Agriculture and Human Values 3 (4), 6-15.

Pérez Domínguez, I., Bezlepkina, I. V., Heckelei, T., Oude Lansink, A., Romstad, E., & Kanellopoulos, A. (this issue). Capturing price impacts of farm level policies: A statistical extrapolation approach using biophysical and farm resource characteristics.

Piet, L., 2008. The Evolution of farm size distribution: revisiting the Markov chain model. Paper presented at the 12th EAAE Congress, August 26-29, Ghent, Belgium.

Pietola, K., Heikkilä, A., 2006. Possibilities to Switch into Capital-Intensive Technologies in Small Scale Dairy Production. Contributed paper, 96th EAAE Seminar, January 10-11, Tänikon, Switzerland.

Rahelizatovo, N.C., Gillespie, J.M., 1999. Dairy Farm Size, Entry, and Exit in a Declining Production Region. Journal of Agriculture and Applied Economics 31 (2), 333-347.

Reimund, D.A.; Moore, C.V.; Martin, J.R., 1977. Factors Affecting Structural Change in Agricultural Subsectors: Implications for Research. Southern Journal of Agricultural Economics 9 (1), 11-19.

Robinson, D.T, Brown, D.G., Parker, D.C., Schreinemachers, P., Janssen, M.A., Huigen, M., Wittmer, H., Gotts, N., Promburom, P., Irwin, E., Berger, T., Gatzweiler, F., Barnaud, C., 2007. Comparison of empirical methods for building agent-based models in land use science. Journal of Land Use Science 2 (1), 31-55.

Salkin, M.S., Just, R.E., Cleveland, J.O.A., 1976. Estimation of Nonstationary Transition Probabilities for Agricultural Firm Size Projection. Annals of Regional Science 10, 71-82.

Shapiro, D., Bollman, R.D., Ehrensaft, P., 1987. Farm Size and Growth in Canada. American Journal of Agricultural Economics 69 (2), 477-483.

Shorrocks, A.F., 1978. The Measurement of Mobility. Econometrica 46 (5), 1013-1024.

Stanton, B.F., Kettunen, L., 1967. Potential Entrants and Projections in Markov Process Analysis. Journal of Farm Economics 49, 633-642.

Stavins, R.N., Stanton; B. F., 1980. Using Markov Models to Predict the Size Distribution of Dairy Farms, New York State, 1968-1985. Cornell University. Department of Agricultural Economics, Ithaca, New York.

Stokes, J.R., 2006. Entry, Exit, and Structural Change in Pennsylvania's Dairy Sector. Agricultural and Resource Economics Review 35 (2), 357-373.

Sumner, D.A., Leiby, J.D., 1987. An Econometric Analysis of the Effects of Human Capital on Size and Growth among Dairy Farms. American Journal of Agricultural Economics 69 (2), 465-470.

Telser, L.G., 1963. Least-Squares Estimates of Transition Probabilities. In: Christ, D.F. (Ed.), Measurement in Economics: Studies in Mathematical Economics and Econometrics in Memory of Yehuda Grunfeld. Stanford University Press, Stanford, pp. 270-292.

Tonini, A., Jongeneel, R., 2002. Dairy farm size restructuring in Poland and Hungary. In: Hinners-Tobraegel, L, Heinrich, J. (Eds.), Agricultural Enterprises in Transition: Parallels and Divergences in Eastern Germany, Poland and Hungary. Studies on the Agricultural and Food Sector in Central and Eastern Europe Vol. 15, Wissenschaftsverlag, Kiel, pp. 317-339.

Tonini, A., 2007. Agriculture and Dairy in Eastern Europe after Transition focused on Poland and Hungary, Wageningen, Netherlands.

Tonini, A., Jongeneel, R., 2008. The Distribution of Dairy Farm Size in Poland: A Markov Approach based on Information Theory. Applied Economics 40, 1-15.

U.S. Congress, O.o.T.A., 1985. Factors Contributing to Structural Change in Agriculture. In: U.S. Congress, O.o.T.A. (Ed.), Technology, Public Policy, and the Changing Structure of American Agriculture: A Special Report for the 1985 Farm Bill. Technology, Public Policy, and the Changing Structure of American Agriculture: A Special Report for the 1985 Farm Bill. Washington, DC, pp. 107-118.

Van Dijk, G., Hoogervorst, N., Bauwens, N., Tijdink, T., 1986. A Framework for Agricultural Structural Policy Analysis. Sociologia Ruralis 16 (2), 109-127.

Van Ittersum, M., Ewert, F., Heckelei, T., Wery, J., Alkan Olsson, J., Andersen, E., Bezlepkina, I., Brouwer, F., Donatelli, M., Flichman, G., Olsson, L., Rizzoli, A., Van der Wal, T., Wien, J., Wolf, J., 2008. Integrated Assessment of Agricultural Systems - A Component-based Framework for the European Union (SEAMLESS). Agricultural Systems 96, 150-165.

Von Massow, M., Weersink, A., Turvey, C.G., 1992. Dynamics of Structural Change in the Ontario Hog Industry. Canadian Journal of Agricultural Economics 40, 93-107.

Weiss, C.R., 1999. Farm Growth and Survival: Econometric Evidence for Individual Farms in Upper Austria. American Journal of Agricultural Economics 81, 103-116.

Zepeda, L., 1995a. Asymmetry and Nonstationarity in the Farm Size Distribution of Wisconsin Milk Producers: An Aggregate Analysis. American Journal of Agricultural Economics 77 (2), 837-852.

Zepeda, L., 1995b. Technical Change and the Structure of Production: A non-stationary Markov Analysis. European Review of Agricultural Economics 22, 41-60.

2.8 Appendix

Table 2.3: Stationary Markov studies in the agricultural economics literature

Year	Author	Region	Specialisation	Type of Data	Time Series	Methodology	Number of States	Dependent Variables	Performance
1961	Judge and Swanson	Illinois, USA	Pig farms	Micro	1946-1958	Maximum likelihood	6 + entry/exit	Firm size (in number of litters of hogs)	-
1962	Padberg	California, USA	Wholesale fluid milk industry	Micro	1950-1955, 1955-1960	Maximum likelihood	3 + entry/exit	Firm size (in market shares)	-
1964	Krenz	North Dakota, USA	All farms	Macro	1935-1960	Maximum likelihood	6 + entry/exit	Firm size (in acres)	-
1967	Stanton and Kettunen	New York, USA	Dairy farms	Micro	1960-1964	Maximum likelihood	3 + entry/exit	Firm size (in herd size)	-
1976	Keane	South of Ireland	Dairy farms	Macro	1968-1973	Maximum likelihood	6 + entry/exit	Firm size (in milk supply)	-
1985	Edwards et al.	USA	All farms	Micro	1974-78	Maximum likelihood	8; 8 + entry/exit	Firm size (by acres, value of sales, tenure, standard industrial classification)	-
1987	Garcia et al.	Illinois, USA	Cash grain farms	Micro	1976-1985	Maximum likelihood	11 for each size measure (entry/exit not considered)	Firm size (gross value of farm product/tillable acres)	Within sample prediction (average root mean square error): 3.1/11.7%
1991	Keane	Dairy co-operative society, Ireland	Dairy farms	Macro	1983-1989	Maximum likelihood	7 + entry/exit	Firm size (in milk supply)	-
2002	Tonini and Jongeneel	Poland	Dairy farms	Macro	1981/1987, 1998-2001	Maximum likelihood	4 + entry/exit, 6 + entry/exit	Firm size (in herd size)	Within sample prediction (average prediction error): 0.25%
2008	Jongeneel and Tonini	Netherlands	Dairy farms	Macro	1972-2006	GCE	7 + entry/exit	Firm size (in herd size)	Pseudo-R^2: 0.33-0.38
2008	Piet	France	All farms	Macro	1980-2005	Nonlinear least-squares	Continuous	Firm size (in utilised agricultural area)	R^2: 0.99

Source: Own table.

Part 3
Differences of farm structural change across European regions[17]

Abstract: Challenges arising from the EU policy focus on rural development lead to an increased demand for farm structure analyses at a regional level. The study's aim is to show (1) which way structural change differs across EU15 regions referring to size and production orientation and (2) how far certain regional characteristics contribute to those differences. A Markov chain analysis combining sample and aggregate data is used to identify regionally different development paths. Significant regional differences are observed regarding the farm number development in general and with respect to size and specialisation classes. A cross-sectional analysis shows that region-specific structural variables partially explain those differences.

Keywords: Farm structural change, Markov chain analysis, mobility indices, cross sectional analysis.

3.1 Introduction

The EU policy focus on rural development leads to an increased interest in farm structural change at a regional level. General economic developments as well as recent fundamental reforms of the Common Agricultural Policy significantly impact on the European farm structure. Although a decline of total farm numbers continues to be the general observation, important differences exist across regions. Regional differences of farm structural change under similar overall conditions in Europe have long been observed and are extensively discussed in the economic history literature. Brenner (1976) describes such regional differences in Europe during the Middle Ages until 1800. Emphasizing the very similar overall conditions in Europe already at these times, he argues that most of the differences

[17] This part is the first round revision of a paper submitted to an international agricultural economics journal as Zimmermann, A. and T. Heckelei: Differences of farm structural change across European regions.

are likely to be caused by regionally specific characteristics. His article provoked a still continuing scientific discussion (e.g. Karayalcin, 2010) which was later called the "Brenner debate" (Aston et al., 1987). Though the phenomenon of regionally differing structural developments has long been described, the agricultural economics literature only very recently started to explore and to explain those differences. In comparing English and Spanish rural restructuring processes, Hoggart and Paniagua (2001a and 2001b) discover significant differences and explicitly call for analysing the cross-national dimension. Breustedt and Glauben (2007) identify determinants which cause regionally differing exit rates of farms in Western Europe.

Defining structural change as the change of the number of farms in different farm types over time, we are particularly interested in Markov chain studies which allow estimating probabilities not only for sector entries and exits but also for the movement of farms across other farm types (e.g. size increases and decreases, changes to other production specialisations). Among the Markov chain studies, Rahelizatovo and Gillespie (1999) are the first who pay attention to regional differences in farm structural change. They estimate a two-region panel data model for dairy farms in Louisiana (USA) and represent the regional characteristics by dummy variables. Gillespie and Fulton (2001) estimate a panel data model for hog farms with dummy variables representing 17 states of the USA. Zimmermann and Heckelei (2008) quantify the regional impact on structural change in the German Bundesländer by estimating a fixed effects model. Huettel and Margarian (2009) explain differences in farm structural change across West German regions with a cross-sectional[18] Markov chain approach. We explicitly aim at (1) identifying the differences in farm structural change across regions in Western Europe and (2) identifying key factors that likely cause these differences.

More particularly, the paper analyses differences in the farm structure development across farm types and 101 EU15 regions in the years 1990 to 2005. We apply a Markov chain approach in order to derive regional structural development patterns (which are expressed in transition probabilities and summarised in mobility indices adapted from Jongeneel and Tonini, 2008). Afterwards the regional development patterns (in form of the mobility indices) are compared to each other and cross-sectionally regressed against a set of region-specific explanatory variables.

Since Judge and Swanson (1961) used a Markov chain approach to predict the development of pig farms in Illinois, Markov chain estimations have often been applied in the farm structural change literature (recent literature reviews are provided by Piet (2008) and Zimmermann et al., 2009). By far the most Markov chain studies in agriculture focus on structural developments within one region.

[18] Their focus is on the cross-sectional effects, they additionally compare two time periods (1999-2003 and 2003-2007) to each other.

Often, stationary transition probabilities are estimated, i.e. the structural developments are averaged over time (recent examples are Jongeneel and Tonini, 2008 and Piet, 2008). Other studies estimate non-stationary transition probabilities which vary over time (e.g. Zepeda, 1995a and 1995b and Stokes, 2006). Stationary transition probabilities can be used to describe the general direction of structural change over a certain time period. Additionally, non-stationary probabilities can be used to describe changes in the structural change process itself. Furthermore, non-stationary transition probabilities are often regressed against other time-dependent variables which are assumed to influence structural change. Apart from the time-dependency of structural change, very few studies pay attention to differing structural developments across regions (cf. studies mentioned above: Rahelizatovo and Gillespie, 1999, Gillespie and Fulton, 2001, Zimmermann and Heckelei, 2008, Huettel and Margarian, 2009).

We conduct a cross-sectional analysis across 101 EU-15 regions. Whereas the influence of time-dependent variables on structural change has been tested in many Markov chain studies[19], we explicitly focus on the detection of regional characteristics and their impact on the structural change process. In line with the agricultural economics literature we chose five variables representing regional characteristics: the initial farm structure is represented by the initial farm size (in the agricultural economics literature it is often tested against Gibrat's law which states the independence of farm size and its growth rate), farm size heterogeneity (Harrington and Reinsel, 1995, Huettel and Margarian, 2009) and the share of mixed farms. Additionally, the farm holders' age (Harrington and Reinsel, 1995, Pietola et al., 2003) and the regional unemployment rate (Goddard et al., 1993, Harrington and Reinsel, 1995) are considered.

According to the data type used, one distinguishes between micro and macro data Markov chain approaches. In the Markov chain terminology, micro data describe detailed information on the movement of farms across farm types (e.g. size classes) over time (Lee et al., 1977). Most of the early Markov chain approaches rely on such kind of data (e.g. Judge and Swanson, 1961, Padberg, 1962, Hallberg, 1969). Macro data, in the Markov chain terminology, describe aggregate data that comprise time series on the number of farms in different farm types (Lee et al., 1977). Since micro data are mostly not available, macro data dominate the Markov chain literature (e.g. Disney et al., 1988, Zepeda, 1995a and 1995b, Karantininis, 2002, Stokes, 2006). The Farm Accountancy Data Network (FADN) grants access to both data types, though the micro data on FADN sample farms is not sufficient for a full micro data Markov chain approach. The macro data is

[19] Variables often tested with regard to this aspect are input-output price ratios (e.g. Disney et al., 1988, Zepeda, 1995a, Karantininis, 2002), productivity measures (e.g. Zepeda, 1995b, Rahelizatovo and Gillespie, 1999), policy variables (e.g. Zepeda, 1995a, Rahelizatovo and Gillespie, 1999) and macroeconomic variables as wages (e.g. Hallberg, 1969, Ethridge et al., 1985) or interest rates (e.g. von Massow et al., 1992, Zepeda, 1995a, Rahelizatovo and Gillespie, 1999, Karantininis, 2002).

derived from bi- or tri-annual censuses, the Farm Structure Survey. Macro data can also be recovered by applying the weights attached to the sample farms in FADN.[20] Since the not fully representative micro data nonetheless provide valuable information on the magnitude of movements of farms across certain farm types, we chose to combine both data types in our estimation approach. The combination of the micro and the macro data is accomplished by using the micro data as prior information in a macro data cross-entropy estimation approach.

According to Goddard et al. (1993), the definition of structural change in the agricultural economics literature has generally narrowly focused on the number and size of farms. Almost all Markov chain applications in agriculture define structural change as the change of the number of farms in certain size classes. Additionally to the size classes mostly also sector entries and exits are considered. Given that Markov processes can generally be used to describe the movement of economic agents across a number of discrete states over time (MacRae, 1977), Ethridge et al. (1985) do not stick to the size classes but also consider activity classes in their analysis.

Considering the whole farm population represented by FADN and acknowledging potentially different underlying dynamics concerning specialisation changes, we distinguish between size and specialisation class changes. Specifically, we distinguish between an entry/exit class, three size and ten specialisation classes. Combining the size and specialisation classes, i.e. each specialisation is divided into three size classes and adding the entry/exit class, we arrive at 31 farm types to be considered in our empirical analysis. This goes far beyond the number of classes that has been considered so far in Markov chain studies. Karantininis (2002) applied a Markov chain procedure to 19 classes, the other Markov chain studies vary between three (e.g. Zepeda, 1995a) and twelve classes (Ethridge, 1985).

Summarising, our approach differs from previous Markov studies in three ways: 1) We explicitly focus on regional differences in farm structural change and their determinants. Considering the whole EU15, the analysis has an unprecedented cross-sectional scope (101 regions across the EU15) which significantly increases the observed variance in farm type transitions and brings new determinants into play; 2) farm type transitions observed at micro level are used as prior information in a macro data estimation approach; and 3) not only size, but also different specialisation classes are considered distinguishing 30 farm types (plus one entry/exit class) and thereby significantly exceeding the number of farm types considered up to now.

In the next section the data base is explained and general farm structure developments are summarized, followed by the description of the methodological

[20] Details are provided in: http://ec.europa.eu/agriculture/rica/methodology3_en.cfm, accessed at 28 February 2011.

approach. Thereafter the results and the analysis of the relationship between structural variables and the mobility indices are presented. The final section concludes.

3.2 European farm structure

This section introduces the farm typology and the data used throughout the document and gives an overview of the differences in European farm structure development from 1990 to 2005.

Farm typology

We use an adapted version of the multi-dimensional farm typology presented in Andersen et al. (2006) which was developed based on the FADN data. Our farm typology comprises two dimensions: a size and a specialisation dimension. According to FADN and the farm typology of Andersen et al. (2006), farm size is measured in economic terms (European Size Units). We distinguish three size categories: a small size category until 16 ESU (Small), a medium size category from 16 to 40 ESU (Medium) and a large size category greater or equal to 40 ESU (Large). The specialisation classes as defined by Andersen et al. (2006) are based on the European Community farm typology. Ten specialisation classes are considered: 1) arable systems, 2) dairy cattle, 3) beef and mixed cattle, 4) sheep, goats, and mixed grazing livestock, 5) pigs, 6) poultry and mixed pigs/poultry, 7) mixed farms, 8) mixed livestock, 9) permanent crops, 10) horticulture. As in case of the size classes, the specialisation classes are defined in economic terms, specifically by the standard gross margin shares of farming activities. The exact definition is given in the appendix (Table 3.5). A farm type is defined as a combination of a certain size and a certain specialisation class. Combining our three size and ten specialisation classes, we thus arrive at 30 farm types to be considered in the empirical analysis.

Data

The main data used throughout the document stem from the Farm Accountancy Data Network (FADN). The FADN database uses sample farms in order to represent the European farm structure. In FADN, only ‘commercial’ farms, which exceed a certain country specific size threshold, are considered.[21] Weighting factors define the number of farms which is represented by each FADN sample farm. The weighting factors are calculated according to three stratification criteria: region, economic size and specialisation. A farm type is a combination of a certain eco-

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[21] The threshold value is country-specific and defined in terms of economic size (http://ec.europa.eu/agriculture/rica/methodology1_en.cfm, accessed at 28 February 2011).

nomic size and a specialisation class. The weighting factors are derived from bi- to tri-annual censuses (the Farm Structure Survey). FADN has its own regional resolution such that FADN regions only roughly refer to NUTS I and II regions or their aggregates.[22] This analysis uses FADN data for the EU15 from 1990 to 2005. In 2005, about 57,000 sample farms were used to represent approximately 3 million 'real' farms in the EU15. For the Markov chain estimations information of sample farm movements across different farm types (a combination of both size and specialisation classes) as well as the aggregated data on the number of farms (represented by the sample farms) in different time periods is used. The information on observed transitions of sample farms is called micro data in the Markov chain terminology (Lee et al., 1977). The aggregate data which gives the actual number of farms in the different farm types (as surveyed in the Farm Structure Survey) is named macro data.

Generally, the availability of micro data would allow for a simple calculation of transition probabilities, a so-called micro data Markov chain approach. However, the FADN micro data is not sufficient for such an approach since: (1) FADN data is based on a rotating panel. The FADN sample farms arbitrarily enter, exit and probably re-enter the sample. As a result of this policy, the data on sector entries and exits of sample farms is not meaningful at all. (2) The FADN micro data constitutes a, compared to the population, small sample with corresponding sampling noise. However, it still represents a unique and valuable source of information. Our approach combines both data types: the observed movements of sample farms across the farm types (micro data) is used as a priori information, whereas the total number of farms derived by applying the weighting factors (macro data) is used as data for the Markov chain constraint (see detailed estimation description in section 3.3).

Farm structure development

This subsection provides a descriptive analysis of the differences in farm structural change across the European regions.

Farm number development

The number of farms in the Member States forming the EU before 1995 has decreased from more than 4 million in 1990 to less than 3 million in 2005.[23] In the

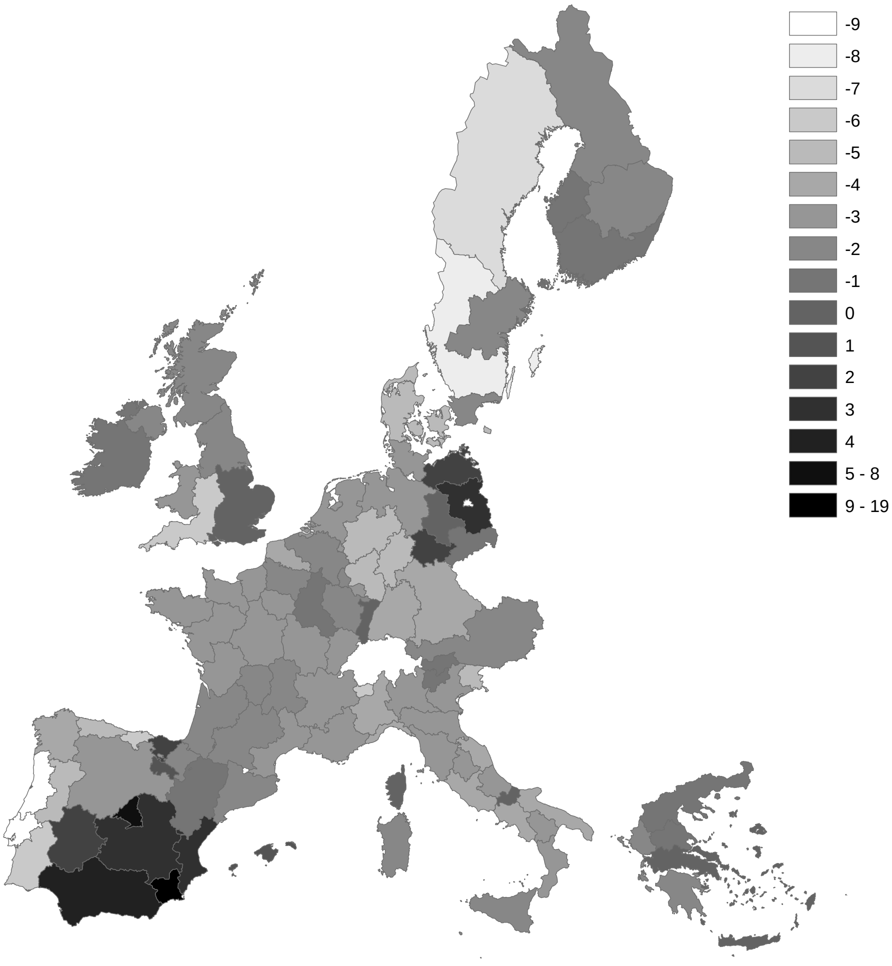
[22] Though the FADN weighting factors are derived from the Farm Structure Survey, the number of farms represented by FADN (i.e. the FADN single farms multiplied by their weighting factors) is not equal to the publicly available Farm Structure Survey farm numbers. This is due to two effects: (1) in FADN only 'commercial' farms are considered, and (2) the FADN regions differ from the NUTS II level at which the Farm Structure Survey is based.

[23] Since the analysis in this paper is based on data coming from the Farm Accountancy Data Network (FADN), here as in FADN, only so-called 'commercial' farms are considered.

countries which joined the EU in 1995 (Austria, Sweden, Finland) including East Germany, the number of farms decreased from almost 200,000 in 1995 to less than 160,000 in 2005. Figure 3.1 reveals the regional distribution of the average annual rates of farms leaving the sector (exit rates) for the observation period 1990 to 2005 (1995 to 2005 for East Germany, Austria, Sweden and Finland).[24]

[24] The exit rates are calculated by applying the geometric mean to the total number of farms at the beginning and at the end of the observation period.

Figure 3.1: Average annual rates of farm number change 1990-2005 [per cent][25]



Source: Own calculation based on FADN data.

The figure shows considerable variation in the farm number development across regions on the Iberian Peninsula, Scandinavia and Germany, whereas regional farm number change is relatively homogeneous in France and Italy. Most Europe-

[25] Switzerland, Andorra and the German city states Berlin, Hamburg, and Bremen are not considered.

an regions experienced decreasing farm numbers during the time period 1990/1995 to 2005. The highest net exit rates are reported in Portugal and Sweden. The only regions where the number of farms has increased are Central and Southern Spain and, due to historical reasons, parts of East Germany.[26] Before the German reunification, farms were organised in collectives in East Germany. After the reunification, the collectives were partly split and new farms occurred which explains the raise in farm numbers in East Germany. One explanation for a growing number of farms in Spain could be that farms formerly classified as not commercial farms exceed the monetary FADN threshold value and hence newly appear in the FADN statistics.[27] This is supported by Hoggart and Paniagua (2001b) who find that in fact agriculture in rural Spain is characterised by a growth in full-time farm engagement.

Development of the size classes

In the United Kingdom, Belgium, Luxembourg, the Netherlands, Denmark and Sweden large farms already represented the majority of farms in 1990 and their share still gained importance till 2005 (Table 3.6 in the appendix). In France and Germany the status of the largest size class changed from medium-sized farms in 1990 to large farms in 2005. Medium-sized farms remain the most important group in Austria and Finland, whereas the farm structure in the South European countries and Ireland was and still is dominated by small farms.

Development of the specialisation classes

In most countries either arable or dairy farms represent the largest specialisation class in terms of the proportion of farms (Table 3.7 in the appendix). In South European countries dairy farming is less important. Instead, the share of permanent crop farms is very high. Generally, the farm structure is less diversified in the European South than in the North. In Southern Europe, the majority of farms is classified as arable or permanent crop farms. The share of the dairy farming specialisation class has significantly decreased in all European countries except Austria. Usually, the decline of the share of dairy farms coincides with an increase of the share of cattle keeping farms. In Austria, for which the persistence of small dairy farming is repeatedly reported (e.g. Kirner et al., 2009), the share of dairy farms increased from 27 per cent in 1995 to 39 per cent in 2005.[28] In Finland and in Sweden the share of arable farms increased drastically in the same

[26] The regions with positive growth rates are: Brandenburg, Mecklenburg-Vorpommern, Thueringen in Germany, and Pais Vasco, La Rioja, Baleares, Madrid, Castilla-La Mancha, Comunidad Valenciana, Murcia, Extremadura, Andalucia, Canarias in Spain.

[27] The same holds for exits. Farms exiting the sector could also be farms that just decline in size and do not reach the threshold size anymore.

[28] For Austria, an increase of medium and especially large dairy farms is reported in the FADN data, whereas the number of small Austrian dairy farms decreases only slowly.

time period (by 21 per cent in Finland and 17 per cent in Sweden). In Spain and in Portugal, a remarkable increase of the share of permanent crop farms took place (by 23 and 13 per cent, respectively).

Combination of size and specialisation classes

The combination of size and specialisation classes results in 30 farm types. Table 3.1 gives an overview of the development of these farm types.

Table 3.1: Overview of the development of the farm types

Farm type		Share of farms in EU15 [per cent]		Average growth rates across regions (1990-2005) [per cent]				
Specialisation	Size class	2005	Δ to 1990	Mean	Standard deviation	Median	10%-Quantile	90%-Quantile
Arable crops	Small	16.14	-7.62	-25.3	40.6	-5.67	-100.00	1.62
	Medium	6.48	1.20	-0.3	6.1	-1.05	-6.78	6.37
	Large	6.41	2.64	0.7	16.5	1.40	-2.18	11.15
Sheep, goats	Small	2.74	-1.76	-39.3	45.4	-9.16	-100.00	-0.94
	Medium	2.19	0.90	-13.2	35.7	0.35	-100.00	6.52
	Large	1.18	0.80	-12.6	39.6	3.30	-100.00	11.64
Permanent crops	Small	23.33	2.43	-25.1	42.2	-3.17	-100.00	5.24
	Medium	5.32	2.21	-4.5	25.2	-0.56	-8.85	10.55
	Large	3.59	2.01	2.6	15.8	2.29	-2.23	16.42
Dairy	Small	1.04	-4.19	-57.0	43.9	-100.00	-100.00	-7.43
	Medium	3.25	-1.94	-18.0	31.4	-7.46	-100.00	0.89
	Large	6.06	2.74	4.3	15.0	2.34	-2.73	18.89
Beef, mixed cattle	Small	3.71	0.06	-29.3	43.5	-6.53	-100.00	3.53
	Medium	2.17	0.58	-2.2	17.5	0.55	-8.42	10.46
	Large	1.52	0.87	2.9	15.2	4.69	-2.59	11.80
Pigs	Small	0.08	-0.07	-65.0	44.8	-100.00	-100.00	-3.41
	Medium	0.27	-0.05	-45.9	46.1	-13.96	-100.00	-1.70
	Large	1.06	0.57	-11.3	33.9	0.23	-100.00	7.02
Poultry	Small	0.07	-0.05	-62.9	44.4	-100.00	-100.00	-3.78
	Medium	0.13	0.02	-22.1	36.8	-2.65	-100.00	3.13
	Large	0.46	0.33	-0.4	22.1	2.05	-6.99	17.26
Mixed farms	Small	2.33	-2.33	-38.2	45.1	-8.71	-100.00	-0.50
	Medium	1.72	-0.45	-10.5	26.4	-4.45	-11.50	4.54
	Large	2.63	1.02	-0.3	12.7	0.44	-4.40	6.36
Mixed livestock	Small	0.94	-0.98	-46.8	45.1	-18.05	-100.00	-1.94
	Medium	0.42	-0.38	-25.1	37.8	-10.25	-100.00	4.33
	Large	0.81	0.21	-8.5	27.2	-0.59	-11.84	5.44
Horticulture	Small	1.03	0.02	-44.3	49.1	-10.29	-100.00	3.96
	Medium	1.26	0.39	-10.1	29.7	-2.98	-9.35	5.81
	Large	1.68	0.80	-0.8	20.4	1.94	-4.19	11.50
Total	Total	100.00		-1.8	4.8	-2.52	-4.83	1.61

Source: Own calculation based on FADN data.

The by far largest farm types in terms of their share of the number of farms were small permanent crop farms and small arable farms in 2005. Both farm types are mainly located in the South European countries, where the number of farms is extraordinarily high compared to the North European countries. The mean growth rates[29] and their standard deviation show that there exist significant differences in the structural development of the farm types across the regions. The average growth rates of the different farm types are evaluated in terms of the median and the 10 and 90 per cent quantiles across the regions. The differences between the quantiles indicate the very different development paths across the observed regions. The median growth rates picture a clear pattern: they are positive for the large size class apart from the mixed livestock specialisation and negative for the small and medium size classes apart from medium-sized sheep and goat farms and medium-sized beef farms which are slightly positive. The 10 per cent quantiles are negative for all farm types and indicate the total disappearance for the majority of farm types. The 90 per cent quantiles are mostly positive. They are negative for the smallest size class in all mixed and livestock breeding specialisation classes except small beef farms. In case of pig farming the 90 per cent quantile is even negative for the medium size class.

3.3 Methodology

A Markov chain estimation approach is chosen to analyse farm number changes in the different farm types. Beginning with Judge and Swanson (1961), the estimation of Markov chains has a long tradition in the analysis of structural change in agriculture (literature reviews are provided by Stavins and Stanton, 1980, Zepeda, 1995a, Zepeda, 1995b, Karantininis, 2002, Piet, 2008 and Zimmermann et al., 2009). The scope of our application is unique with respect to the number of regions and farm types considered. Furthermore, for the first time observed farm type transitions from micro data are used as a priori information within a macro data Markov chain approach. Summarizing the estimated transition probabilities, mobility indices according to Shorrocks (1978) and as recently again suggested and adapted by Jongeneel and Tonini (2008) and Huettel and Jongeneel (2011) are calculated. They allow for better comparison across European regions and provide the statistical basis for a cross-sectional regression analysis.[30]

[29] The growth rates are calculated by applying the geometric mean to the number of farms in the respective farm types at the beginning and at the end of the observation period.

[30] Technically, we speak of a two-step solution. First, transition probabilities are estimated. They are summarized in mobility indices which are (after transformation to continuous intervals), in a second step, regressed against explanatory variables. Unfortunately, we are not able to exploit potential correlations between first and second step errors in the two-step approach. However, we are not aware of any methodology that is applicable in a simultaneous approach of our dimension in the literature (not even considering our objective to combine two data sources) and our own preliminary

The sections below describe the general concept of Markov chains, explain the estimation procedure and present the calculation of the mobility indices.

The Markov chain model

A stationary first order Markov chain is described as

$$n_{jt} = \sum_{i=1}^{I} n_{it-1} p_{ij} \tag{3.1}$$

where the number of farms *n* in farm type *j* at time *t* is the sum over the number of farms in all farm types *i* in the period before (*t-1*) multiplied by their respective transition probabilities p_{ij}. Hence, a transition probability p_{ij} gives the likelihood for a farm to move from farm type *i* to farm type *j* in one time period ($i,j=1,\ldots,J$).[31] It is common to collect the single transition probabilities in a transition probability matrix *P* ($J \times J$):

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1J} \\ p_{21} & p_{22} & \cdots & p_{2J} \\ \vdots & \vdots & \cdots & \vdots \\ p_{I1} & p_{I2} & \cdots & p_{IJ} \end{bmatrix}.$$

Non-negativity ($p_{ij} \geq 0$) and adding-up conditions for the probabilities in each row of the matrix ($\sum_j p_{ij}=1$) must hold. If only macro data, i.e. data where only the number of farms per farm type and year is given, is available, the Markov chain is usually estimated by replacing the number of farms *n* in equation (3.1) by farm type shares *y* and adding an error term *e*:

$$y_{jt} = \sum_{i=1}^{I} y_{it-1} p_{ij} + e_{jt} \tag{3.2}$$

In the case of micro data availability, the transition probabilities can easily be derived by the following equation (Anderson and Goodman, 1957):

$$p_{ij} = \frac{m_{ij}}{\sum_{j=1}^{J} m_{ij}} \tag{3.3}$$

where the number of movements of farms m_{ij} from farm type *i* to farm type *j* is divided by the number of movements from farm type *i* to all farm types *j*.

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trials on a simultaneous approach failed at considerably smaller dimensions for computational reasons.

[31] In our case each farm type is a combination of a size and a specialisation class as described above.

Estimation of the transition probabilities

As described above, the FADN database mainly consists of micro data from sample farms. However, due to several reasons (cf. section 3.2) the FADN micro data is not sufficient for a full micro data Markov chain approach. The weighting factors attached to the FADN data allow reproducing the farm type distribution (the weighting factors are derived from the Farm Structure Survey, a bi- to tri-annual census). Given this 'real' distribution (the macro data) and the valuable information on transitions of the sample farms (the micro data), we present an estimation approach to efficiently combine both data types. The main idea behind our approach is to use the micro data as prior information to the macro data Markov chain estimation. Note that this approach is consistent in the sense that if the size of the micro sample approaches the population, then the estimated transition probabilities will converge to the a priori transition probabilities as the underlying observed transitions generate the macro data.

The only approach available allowing to incorporate a priori information in estimating transition probabilities for a large number of farm types is a cross-entropy estimator (Golan et al., 1996, Karantininis, 2002, Stokes, 2006) which we also use here.[32] The same estimation procedure is applied to each of the 101 regions. Transition probabilities are calculated for 30 farm types plus an artificial entry/exit class, i.e. we arrive at 31 x 31 transition probabilities for each of the 101 regions. For each region data from 1990 to 2005, that means 15 transitions are available.[33,34] 465 data points (15 transitions times 31 farm types) are available to estimate 930 transition probabilities (31 x 30 observing adding-up conditions), a lack of 465 degrees of freedom.[35] However, since we set transition probabilities for which not a single transition in the micro data was observed to zero, the number of transition probabilities to be estimated decreases significantly in most regions which automatically leads to an increase in the degrees of freedom. On average across the regions, 280 degrees of freedom are available with a maximum of 407 and a minimum of 38 degrees of freedom.

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[32] Alternative Bayesian estimators are not fully developed at this point. Building on the work of Martin (1967), Lee et al. (1977) are the first to derive a Bayesian estimator for micro and macro data based stationary Markov chain approaches. MacRae (1977), however, shows that their statistical assumptions do not correspond to the true nature of the data generation process. She derives the correct specification of the likelihood function and shows that the vector of state proportions is distributed as a sum of multinomials rather than a multinomial. Taking this into account, Storm and Heckelei, (2011) developed a Bayesian estimator, but it is not applicable to a problem of our size at this point.

[33] For East Germany, Austria, Sweden and Finland only time series from 1995 to 2005 are available.

[34] Since the Farm Structure Survey and its weights are updated only every two to three years, the farm numbers between these years are interpolated.

[35] For East Germany, Austria, Sweden and Finland with a limited number of only 10 transitions (data from 1995 to 2005), the lack of degrees of freedom is 620 (31 x 30 transition probabilities to be estimated minus 31 farm types x 10 transitions).

$$\min\left[\sum_{i=1}^{I}\sum_{j=1}^{J} p_{ij}\ln\left(p_{ij}/q_{ij}\right)+\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{t=1}^{T} w_{mjt}\ln\left(w_{mjt}/u_{mjt}\right)\right] \quad (3.4)$$

s.t.

$$y_{jt}=\sum_{i=1}^{I} y_{it-1}p_{ij}+\sum_{m=1}^{M} v_m w_{mjt} \quad (3.5)$$

The objective function (3.4) minimises the distance between the estimated transition probabilities p_{ij} and the a priori information on the transition probabilities q_{ij} and the distance between the error weights w_{mjt} and the a priori information on the error weights u_{mjt}. The Markov constraint (3.5) relates the farm type shares y at time t to the farm type shares at time $t\text{-}1$ multiplied by the respective transition probabilities. The error term is constructed as the product of the m-dimensional vector of supports v and the error weights for each farm type and time period w. Additional constraints establish non-negativity ($p_{ij},w_{mjt}\geq 0$) and ensure adding-up to unity of the estimated probabilities ($\sum_j p_{ij}=1$, $\sum_m w_{mjt}=1$).

We use the micro data to construct the prior transition probability matrix (TPM). Our a priori information is composed by applying equation (3.3) to the micro data of each region and averaging across years ($q_{ij}=\sum_t m_{ijt}/\sum_t\sum_j m_{ijt}$ with m_{ijt} being the movement of a sample farm from farm type i to farm type j in one time period). Hence, the movements of the sample farms across the farm types are used to determine the prior transition probabilities. In case that not a single transition is observed, the associated transition probability is set to zero. Since the micro data does not provide information on sector entries or exits cruder assumptions had to be made with regard to the entry/exit prior information. Regarding sector exits an average annual exit rate was calculated depending on the total number of farms at the beginning and at the end of the observation period. This exit rate was applied to all farm types in a region and transformed into an exit probability (such that the prior transition probabilities add up to one in each row). The prior probability for sector entries was set to a value close to zero (1E-10). Empirical evidence from the literature shows that entry probabilities are usually not zero for all size classes even though they are generally small. Karantininis (2002) for example detects positive entry probabilities for the smallest as well as for medium and large size classes for Danish pork farms. Huettel and Jongeneel (2011) detect positive entry probabilities for Dutch and West German dairy farms to the medium and large size classes.[36] Our results show that the estimation procedure could deal well with

[36] Additionally, one should keep in mind that entry in case of the FADN data does not necessarily mean that new farms are set up. More likely is a growth process of smaller, formerly 'not commercial' farms which then exceed the FADN threshold and thus newly appear in the FADN farm population.

the prior entry/exit information in that the final estimates regarding entry and exit probabilities vary significantly across farm types.

Using a priori information coming from observed transitions of sample farms we go far beyond other Markov chain studies. Karantininis (2002) starts by constructing a prior transition probability matrix of uniform probabilities and further develops the matrix by setting certain off-diagonal elements to zero (entry and exit probabilities are kept at the initial uniform value) and increasing the diagonal prior probabilities accordingly. Stokes (2006) uses a uniform prior TPM in order to estimate stationary transition probabilities. The estimated stationary TPM is then used as a priori information for a non-stationary Markov chain approach. Admitting weaknesses in comparability, Tonini and Jongeneel (2009) derive their a priori information for dairy farm size development in Poland from other Markov chain analyses. Earlier Markov chain studies which use frequentist estimation methods and therefore do not rely on a priori information restrict the probabilities to certain ranges as well. In fact, those constraints are much more restrictive as they are fixed and cannot be adjusted in the estimation process as it is possible in the cross-entropy formalism. Zepeda (1995b) for example assumes that farms can change by only one size class within one period.

The prior information on the error weights, u_{mjt}, is uniformly distributed with m=3, i.e. u_{mjt}=1/3. Following Tonini and Jongeneel (2009) and Golan et al. (1996, p. 88), the vector of supports is set according to the 3-sigma-rule of Pukelsheim (1994). This means defining v as v=-3σ,0,3σ with σ being the standard deviation of y_j. By applying the 3-sigma-rule, we acknowledge that each farm type share can be characterized by a different variance over time. The specification of common support bounds for each farm type would lead to very large bounds even for farm types with small variances. As a result, the estimates of the transition probabilities for those farm types would converge closely to the respective a priori information and underutilize the information from the macro-data in the Markov chain constraint (Tonini and Jongeneel, 2009).[37] A bootstrap procedure according to Mittelhammer et al. (2000, p. 728) is applied in order to derive standard errors for the estimated transition probabilities.

Mobility indices

The movements across entry, exit, size and specialisation classes are estimated simultaneously. Combining the 10 specialisation classes with the three size classes introduced above results in a total of 30 farm types to which an artificial entry/exit class is added. Due to their dimension, the resulting 31×31 transition

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[37] For some regions the support bounds had to be widened in order to (numerically) solve the problem. For 63 regions the three-sigma rule was applied (v=-3σ,0,3σ). For 15 regions v was multiplied by 1.1, in 4 cases by 1.2 and in 19 cases by 1.3.

probability matrices are difficult to meaningfully compare between the 101 regions. Hence, mobility indices according to Shorrocks (1978) are calculated to provide summary type information suitable for the subsequent cross-sectional analysis. Denoting the matrix of estimated transition probabilities as $\hat{P}$, the overall mobility index is defined as

$$M^{ov} = \left[J - tr(\hat{P}) \right] \Big/ (J-1) \tag{3.6}$$

If farms do not change the farm type at all, the overall mobility M^{ov} is equal to zero and we speak of immobility. Perfect overall mobility with a value of one occurs if the average probability of remaining in the same category is not larger than the one of moving to any category (1/J).

The overall mobility can be decomposed into partial mobility indices according to Jongeneel and Tonini (2008) and Huettel and Jongeneel (2011):

$$M^{exit} + M^{entry} + M^{s+} + M^{s-} + M^{spec} = M^{ov} \tag{3.7}$$

M^{exit} is defined as the part of overall mobility associated with going out of business, M^{entry} with new or re-entry to the market, M^{s+} with increase in size, M^{s-} with decrease in size, and M^{spec} with the move to another specialisation class. The size mobilities refer to size class changes within each specialisation class. The mobility index for specialisation class changes denotes changes from one specialisation to another. It does not specifically reflect size class changes taking place simultaneously.

The partial mobility indices (M^{part}) are calculated according to formula:

$$M^{part} = \sum_i \sum_k \hat{p}_{ik} \Big/ (J-1) \tag{3.8}$$

with $\hat{p}_{ik}$ being the respective probabilities in the exit or entry class, for size increases or declines or specialisation changes. Let the set Z contain the ordered size classes z=1,...,3 and the set C specialisations c=1,...,10. Consequently, each farm type i,k corresponds to a unique pair (z^i,c^i) and (z^k,c^k), respectively, or is equal to the entry/exit category J=31. Denoting the correspondence as i~(z^i,c^i) and k~(z^k,c^k) allows characterising partial mobility indices by the different definitions of i and k:

M^{exit}: i=1,...,30; k=31

M^{entry}: i=31; k=1,…,30

M^{s+}: i~(z^i,c^i) *with* z^i=1,2 *and* c^i=1,…,10; k~(z^k,c^k) *with* $z^k > z^i$ *and* $c^k = c^i$

M^{s-}: i~(z^i,c^i) *with* z^i=2,3 *and* c^i=1,…,10; k~(z^k,c^k) *with* $z^k < z^i$ *and* $c^k = c^i$

M^{spec}: i~(z^i,c^i) *with* z^i=1,…,3 *and* c^i=1,…,10; k~(z^k,c^k) *with* z^k=1,…,3 *and* $c^k \neq c^i$.

3.4 Results on the regional farm type mobility

In describing the results of the outcome of the estimation of the transition probabilities and the resulting mobility indices this section contributes to the identification of differences in farm structural developments across the European regions. In order to focus on those differences, generally moments or quantiles of the distribution of transition probabilities and mobility indices across the regions are given.

Transition probabilities

Table 3.2 shows the average transition probability matrix in which the transition probabilities are averaged across the 101 regions. The first row of small, italic numbers below the mean transition probabilities give the standard deviation of the transition probabilities across the regions. As typical for transition probability matrices, the elements on the diagonal are relatively high reflecting the high probability to remain in the same farm type as in the year before. High probabilities can also be found for changes to other size classes within the same specialisation class. These probabilities are arranged in blocks around the main diagonal (for better visibility the diagonal is shaded). Mostly, non-zero probabilities exist also for changes between the mixed farms and mixed livestock farms and the other farm types. Changes are rare between livestock producing specialisations (especially pig and poultry farming) and other farm types and between horticulture and other farm types. The probabilities to move into the exit class are generally relatively high, whereas the probabilities for entering the sector are typically close to zero.

Stokes (2006) tested against the hypothesis that the probabilities are zero. In our case, it is not tested against the hypothesis that the probabilities are zero because from the a priori information we already know that those actually estimated are not zero.[38] A bootstrap procedure (Mittelhammer et al., 2000, p. 728) with 250 repetitions is used to approximate the standard errors for the estimated transition probabilities. The mean standard errors averaged across the regions are given in each second row of small, italic numbers in Table 3.2. The mean standard error across all regions for all elements on the diagonal is 0.0254, for the off-diagonal elements it is 0.0013, for entry 0.0006 and for exit it is 0.0048.

[38] As said above, only transition probabilities for which transitions are actually observed in the period of analysis are estimated. Probabilities for which the prior information from the FADN sample farms is zero are eliminated from the estimation.

Table 3.2: Average transition probabilities, standard deviation and mean standard errors across regions

Farm type		Variable[a]	Arable			Sheep and goats			Permanent crops			Dairy			Beef		
			Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Arable	Small	Mean probability	0.74837	0.09510	0.01157	0.00018	0.00016	0.00000	0.03101	0.00478	0.00036	0.00120	0.00008	0.00036	0.00042	0.00001	0.00000
		Standard deviation	*0.27041*	*0.20488*	*0.09678*	*0.00066*	*0.00139*	*0.00000*	*0.07112*	*0.02578*	*0.00304*	*0.00792*	*0.00039*	*0.00264*	*0.00258*	*0.00014*	*0.00000*
		Mean standard error	*0.02381*	*0.01168*	*0.00097*	*0.00026*	*0.00014*	*0.00001*	*0.00665*	*0.00142*	*0.00027*	*0.00019*	*0.00005*	*0.00012*	*0.00029*	*0.00002*	*0.00000*
	Medium	Mean probability	0.06515	0.76902	0.05340	0.00053	0.00004	0.00003	0.00835	0.01737	0.00154	0.00002	0.00004	0.00016	0.00073	0.00017	0.00004
		Standard deviation	*0.06049*	*0.13671*	*0.03831*	*0.00281*	*0.00029*	*0.00026*	*0.02346*	*0.03098*	*0.00438*	*0.00017*	*0.00028*	*0.00074*	*0.00472*	*0.00141*	*0.00030*
		Mean standard error	*0.01413*	*0.02599*	*0.01247*	*0.00016*	*0.00006*	*0.00002*	*0.00203*	*0.00415*	*0.00060*	*0.00003*	*0.00004*	*0.00006*	*0.00018*	*0.00010*	*0.00005*
	Large	Mean probability	0.01213	0.07376	0.80857	0.00192	0.00065	0.00037	0.00101	0.00555	0.02670	0.00000	0.00036	0.00005	0.00150	0.00019	0.00034
		Standard deviation	*0.08697*	*0.07216*	*0.16227*	*0.01711*	*0.00356*	*0.00309*	*0.00931*	*0.01785*	*0.10278*	*0.00000*	*0.00322*	*0.00027*	*0.01311*	*0.00112*	*0.00201*
		Mean standard error	*0.00081*	*0.01194*	*0.02241*	*0.00040*	*0.00014*	*0.00018*	*0.00008*	*0.00087*	*0.00441*	*0.00000*	*0.00003*	*0.00003*	*0.00018*	*0.00004*	*0.00012*
Sheep and goats	Small	Mean probability	0.00553	0.00048	0.00007	0.75911	0.05812	0.00091	0.00135	0.00003	0.00002	0.01236	0.00455	0.00004	0.02298	0.00365	0.00000
		Standard deviation	*0.01598*	*0.00225*	*0.00047*	*0.25181*	*0.14091*	*0.00685*	*0.00695*	*0.00023*	*0.00019*	*0.06500*	*0.02511*	*0.00041*	*0.05804*	*0.03041*	*0.00000*
		Mean standard error	*0.00128*	*0.00023*	*0.00014*	*0.02798*	*0.01169*	*0.00072*	*0.00020*	*0.00003*	*0.00003*	*0.00230*	*0.00075*	*0.00000*	*0.00475*	*0.00107*	*0.00000*
	Medium	Mean probability	0.00580	0.00223	0.00028	0.06728	0.69046	0.02637	0.00052	0.00004	0.00019	0.01447	0.02790	0.00718	0.00640	0.02997	0.00493
		Standard deviation	*0.04744*	*0.01674*	*0.00127*	*0.10905*	*0.26557*	*0.05287*	*0.00524*	*0.00039*	*0.00147*	*0.05652*	*0.13847*	*0.05275*	*0.02320*	*0.08312*	*0.03172*
		Mean standard error	*0.00075*	*0.00024*	*0.00009*	*0.01303*	*0.03320*	*0.00959*	*0.00012*	*0.00001*	*0.00002*	*0.00125*	*0.00226*	*0.00028*	*0.00110*	*0.00505*	*0.00098*
	Large	Mean probability	0.00100	0.00006	0.00010	0.00019	0.07362	0.70613	0.00000	0.00000	0.00005	0.00000	0.00463	0.04092	0.00022	0.01102	0.02700
		Standard deviation	*0.00915*	*0.00059*	*0.00100*	*0.00106*	*0.12717*	*0.31182*	*0.00000*	*0.00000*	*0.00046*	*0.00000*	*0.03362*	*0.15442*	*0.00219*	*0.06303*	*0.07556*
		Mean standard error	*0.00006*	*0.00001*	*0.00003*	*0.00004*	*0.01077*	*0.02547*	*0.00000*	*0.00000*	*0.00001*	*0.00000*	*0.00054*	*0.00251*	*0.00006*	*0.00101*	*0.00353*
Permanent crops	Small	Mean probability	0.02439	0.00451	0.00055	0.00031	0.00000	0.00000	0.84724	0.05888	0.01424	0.00005	0.00003	0.00000	0.00000	0.00003	0.00000
		Standard deviation	*0.04176*	*0.01895*	*0.00413*	*0.00176*	*0.00000*	*0.00000*	*0.21561*	*0.15569*	*0.07601*	*0.00037*	*0.00030*	*0.00002*	*0.00000*	*0.00034*	*0.00000*
		Mean standard error	*0.00541*	*0.00146*	*0.00018*	*0.00015*	*0.00001*	*0.00000*	*0.02150*	*0.00943*	*0.00233*	*0.00003*	*0.00001*	*0.00001*	*0.00004*	*0.00002*	*0.00001*
	Medium	Mean probability	0.00739	0.01642	0.01462	0.00002	0.00003	0.00000	0.04906	0.81090	0.06232	0.00002	0.00000	0.00000	0.00004	0.00000	0.00000
		Standard deviation	*0.01997*	*0.02465*	*0.10145*	*0.00019*	*0.00018*	*0.00000*	*0.12324*	*0.20897*	*0.11748*	*0.00019*	*0.00000*	*0.00000*	*0.00044*	*0.00000*	*0.00000*
		Mean standard error	*0.00176*	*0.00376*	*0.00131*	*0.00000*	*0.00004*	*0.00000*	*0.00782*	*0.02314*	*0.01091*	*0.00002*	*0.00000*	*0.00000*	*0.00002*	*0.00000*	*0.00000*
	Large	Mean probability	0.00201	0.00482	0.02328	0.00014	0.00005	0.00001	0.00714	0.05203	0.88462	0.00001	0.00000	0.00000	0.00057	0.00010	0.00009
		Standard deviation	*0.00967*	*0.01235*	*0.09933*	*0.00101*	*0.00045*	*0.00015*	*0.02450*	*0.06723*	*0.13408*	*0.00007*	*0.00000*	*0.00000*	*0.00571*	*0.00105*	*0.00088*
		Mean standard error	*0.00036*	*0.00079*	*0.00346*	*0.00013*	*0.00001*	*0.00002*	*0.00083*	*0.00867*	*0.01561*	*0.00001*	*0.00000*	*0.00000*	*0.00022*	*0.00001*	*0.00001*
Dairy	Small	Mean probability	0.01415	0.00054	0.00001	0.01452	0.00029	0.00000	0.00002	0.00002	0.00000	0.73161	0.10252	0.00017	0.03435	0.00271	0.00000
		Standard deviation	*0.04414*	*0.00317*	*0.00014*	*0.06874*	*0.00152*	*0.00000*	*0.00016*	*0.00021*	*0.00000*	*0.23466*	*0.17679*	*0.00090*	*0.06387*	*0.01266*	*0.00000*
		Mean standard error	*0.00157*	*0.00016*	*0.00001*	*0.00273*	*0.00014*	*0.00000*	*0.00000*	*0.00006*	*0.00000*	*0.02065*	*0.01235*	*0.00021*	*0.00742*	*0.00123*	*0.00000*
	Medium	Mean probability	0.00432	0.00243	0.00044	0.00134	0.00717	0.00011	0.00003	0.00001	0.00000	0.04061	0.76627	0.06724	0.01465	0.02419	0.00300
		Standard deviation	*0.01317*	*0.01395*	*0.00361*	*0.00558*	*0.03109*	*0.00065*	*0.00028*	*0.00012*	*0.00000*	*0.10580*	*0.15300*	*0.06976*	*0.04193*	*0.03234*	*0.00726*
		Mean standard error	*0.00104*	*0.00063*	*0.00009*	*0.00022*	*0.00182*	*0.00011*	*0.00000*	*0.00001*	*0.00000*	*0.00742*	*0.02661*	*0.01550*	*0.00377*	*0.00704*	*0.00191*
	Large	Mean probability	0.00076	0.00100	0.00079	0.00001	0.00148	0.00428	0.00597	0.00000	0.00034	0.00096	0.04558	0.86302	0.00012	0.00444	0.01760
		Standard deviation	*0.00453*	*0.00394*	*0.00289*	*0.00011*	*0.01113*	*0.02290*	*0.05862*	*0.00000*	*0.00339*	*0.00611*	*0.06520*	*0.11136*	*0.00046*	*0.01086*	*0.03116*
		Mean standard error	*0.00008*	*0.00046*	*0.00036*	*0.00001*	*0.00020*	*0.00135*	*0.00048*	*0.00000*	*0.00012*	*0.00012*	*0.00951*	*0.02100*	*0.00021*	*0.00140*	*0.00688*
Beef	Small	Mean probability	0.02644	0.00038	0.00019	0.03902	0.00392	0.00024	0.00028	0.00000	0.00000	0.05152	0.00560	0.00054	0.70930	0.06005	0.00041
		Standard deviation	*0.08335*	*0.00269*	*0.00195*	*0.09612*	*0.03303*	*0.00243*	*0.00227*	*0.00000*	*0.00000*	*0.11605*	*0.01414*	*0.00514*	*0.24281*	*0.12516*	*0.00326*
		Mean standard error	*0.00289*	*0.00009*	*0.00005*	*0.00746*	*0.00071*	*0.00030*	*0.00003*	*0.00000*	*0.00000*	*0.00583*	*0.00145*	*0.00019*	*0.03014*	*0.01089*	*0.00022*
	Medium	Mean probability	0.00449	0.00277	0.00055	0.00298	0.01687	0.00085	0.00134	0.00000	0.00008	0.00762	0.07926	0.00693	0.05392	0.67989	0.03912
		Standard deviation	*0.02349*	*0.01157*	*0.00316*	*0.01173*	*0.03465*	*0.00347*	*0.01344*	*0.00000*	*0.00078*	*0.02815*	*0.11320*	*0.01382*	*0.05931*	*0.19867*	*0.04728*
		Mean standard error	*0.00033*	*0.00057*	*0.00008*	*0.00039*	*0.00375*	*0.00028*	*0.00006*	*0.00000*	*0.00002*	*0.00061*	*0.00942*	*0.00114*	*0.01050*	*0.02949*	*0.00870*
	Large	Mean probability	0.00104	0.00324	0.00044	0.00000	0.00562	0.01047	0.00000	0.00000	0.00000	0.00000	0.03608	0.10440	0.00310	0.07996	0.64312
		Standard deviation	*0.01042*	*0.02346*	*0.00220*	*0.00000*	*0.02952*	*0.03031*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.14722*	*0.14471*	*0.02505*	*0.16799*	*0.28929*
		Mean standard error	*0.00002*	*0.00025*	*0.00016*	*0.00000*	*0.00064*	*0.00280*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00221*	*0.01158*	*0.00024*	*0.00761*	*0.02819*
Pigs	Small	Mean probability	0.00387	0.00014	0.00000	0.00382	0.00000	0.00000	0.00433	0.00000	0.00947	0.00010	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.02839*	*0.00102*	*0.00000*	*0.03081*	*0.00000*	*0.00000*	*0.04354*	*0.00000*	*0.09515*	*0.00101*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
		Mean standard error	*0.00054*	*0.00002*	*0.00000*	*0.00039*	*0.00000*	*0.00000*	*0.00036*	*0.00000*	*0.00002*	*0.00002*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
	Medium	Mean probability	0.01195	0.00032	0.00023	0.00244	0.00000	0.00030	0.00062	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.09984*	*0.00321*	*0.00199*	*0.01922*	*0.00000*	*0.00301*	*0.00509*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
		Mean standard error	*0.00026*	*0.00006*	*0.00008*	*0.00041*	*0.00000*	*0.00007*	*0.00012*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
	Large	Mean probability	0.00217	0.00121	0.00083	0.00000	0.00020	0.00000	0.00044	0.00030	0.00036	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.01812*	*0.00516*	*0.00463*	*0.00000*	*0.00198*	*0.00000*	*0.00331*	*0.00301*	*0.00268*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
		Mean standard error	*0.00038*	*0.00040*	*0.00017*	*0.00000*	*0.00004*	*0.00000*	*0.00009*	*0.00005*	*0.00007*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
Poultry	Small	Mean probability	0.00357	0.00097	0.00000	0.00000	0.00000	0.00000	0.00265	0.00108	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.02756*	*0.00726*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.01879*	*0.01081*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
		Mean standard error	*0.00054*	*0.00019*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00031*	*0.00021*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
	Medium	Mean probability	0.00529	0.00000	0.00000	0.00000	0.00000	0.00000	0.00138	0.00000	0.00000	0.00117	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.03250*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.01144*	*0.00000*	*0.00000*	*0.01176*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
		Mean standard error	*0.00070*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00023*	*0.00000*	*0.00000*	*0.00022*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
	Large	Mean probability	0.00960	0.00566	0.00168	0.00000	0.00000	0.00000	0.00000	0.00284	0.00052	0.00000	0.00000	0.00130	0.00000	0.00005	0.00966
		Standard deviation	*0.03912*	*0.02646*	*0.01379*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.01559*	*0.00523*	*0.00000*	*0.00000*	*0.01231*	*0.00000*	*0.00053*	*0.09711*
		Mean standard error	*0.00179*	*0.00076*	*0.00025*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00043*	*0.00008*	*0.00000*	*0.00000*	*0.00012*	*0.00000*	*0.00001*	*0.00000*
Mixed farms	Small	Mean probability	0.12202	0.02319	0.00033	0.02293	0.00345	0.00000	0.01380	0.00197	0.00000	0.00828	0.00174	0.00000	0.04921	0.00159	0.00006
		Standard deviation	*0.12567*	*0.10136*	*0.00162*	*0.05054*	*0.01508*	*0.00000*	*0.03694*	*0.01183*	*0.00000*	*0.02362*	*0.00864*	*0.00000*	*0.12523*	*0.00618*	*0.00062*
		Mean standard error	*0.01623*	*0.00326*	*0.00014*	*0.00493*	*0.00107*	*0.00000*	*0.00198*	*0.00056*	*0.00000*	*0.00180*	*0.00061*	*0.00000*	*0.00890*	*0.00102*	*0.00006*
	Medium	Mean probability	0.01839	0.05962	0.00844	0.00663	0.01863	0.00143	0.00109	0.00923	0.00125	0.01125	0.01844	0.00272	0.00949	0.02225	0.00238
		Standard deviation	*0.03173*	*0.05606*	*0.01324*	*0.01616*	*0.02826*	*0.00513*	*0.00346*	*0.04484*	*0.00526*	*0.07075*	*0.03684*	*0.00805*	*0.04485*	*0.02805*	*0.00812*
		Mean standard error	*0.00333*	*0.01050*	*0.00213*	*0.00108*	*0.00464*	*0.00068*	*0.00011*	*0.00178*	*0.00034*	*0.00164*	*0.00274*	*0.00075*	*0.00192*	*0.00583*	*0.00110*
	Large	Mean probability	0.00142	0.01889	0.05587	0.00000	0.01152	0.01680	0.00006	0.00824	0.01655	0.00003	0.00490	0.02447	0.00003	0.00237	0.01552
		Standard deviation	*0.00732*	*0.05446*	*0.05450*	*0.00000*	*0.04062*	*0.03193*	*0.00059*	*0.05144*	*0.08623*	*0.00026*	*0.02766*	*0.03930*	*0.00032*	*0.00836*	*0.03290*
		Mean standard error	*0.00014*	*0.00304*	*0.00905*	*0.00000*	*0.00171*	*0.00327*	*0.00000*	*0.00092*	*0.00227*	*0.00001*	*0.00099*	*0.00425*	*0.00002*	*0.00065*	*0.00488*
Mixed livestock	Small	Mean probability	0.03966	0.00524	0.00000	0.03393	0.00309	0.00000	0.00066	0.00018	0.00039	0.02318	0.01057	0.00000	0.03660	0.00132	0.00000
		Standard deviation	*0.10263*	*0.03873*	*0.00000*	*0.07996*	*0.01537*	*0.00000*	*0.00448*	*0.00135*	*0.00387*	*0.10405*	*0.09574*	*0.00000*	*0.12196*	*0.00487*	*0.00000*
		Mean standard error	*0.00340*	*0.00066*	*0.00000*	*0.00510*	*0.00078*	*0.00000*	*0.00012*	*0.00006*	*0.00006*	*0.00173*	*0.00040*	*0.00000*	*0.00497*	*0.00056*	*0.00000*
	Medium	Mean probability	0.00686	0.02550	0.00323	0.00843	0.02591	0.00120	0.00083	0.00000	0.00025	0.00174	0.03660	0.00358	0.00328	0.05538	0.00062
		Standard deviation	*0.02051*	*0.10876*	*0.01610*	*0.02242*	*0.04924*	*0.00425*	*0.00633*	*0.00000*	*0.00254*	*0.00583*	*0.08523*	*0.01249*	*0.01323*	*0.15711*	*0.00356*
		Mean standard error	*0.00063*	*0.00154*	*0.00051*	*0.00120*	*0.00347*	*0.00032*	*0.00006*	*0.00000*	*0.00004*	*0.00016*	*0.00366*	*0.00045*	*0.00041*	*0.00539*	*0.00013*
	Large	Mean probability	0.00000	0.00583	0.01207	0.00000	0.00332	0.02106	0.00000	0.00000	0.00008	0.00000	0.00158	0.03835	0.00000	0.00738	0.03386
		Standard deviation	*0.00000*	*0.02471*	*0.04035*	*0.00000*	*0.01906*	*0.06948*	*0.00000*	*0.00000*	*0.00083*	*0.00000*	*0.00659*	*0.07481*	*0.00000*	*0.04143*	*0.09193*
		Mean standard error	*0.00000*	*0.00087*	*0.00130*	*0.00000*	*0.00019*	*0.00368*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00021*	*0.00559*	*0.00000*	*0.00062*	*0.00445*
Horticulture	Small	Mean probability	0.06812	0.00331	0.00154	0.00027	0.00000	0.00001	0.00300	0.00170	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.14689*	*0.01555*	*0.01547*	*0.00276*	*0.00000*	*0.00005*	*0.01576*	*0.01629*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00002*	*0.00000*	*0.00000*
		Mean standard error	*0.00989*	*0.00057*	*0.00037*	*0.00006*	*0.00000*	*0.00005*	*0.00058*	*0.00059*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00003*	*0.00000*	*0.00000*
	Medium	Mean probability	0.05274	0.03275	0.00288	0.00051	0.00000	0.00000	0.00785	0.00033	0.00014	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
		Standard deviation	*0.14588*	*0.08108*	*0.01471*	*0.00490*	*0.00000*	*0.00000*	*0.03529*	*0.00241*	*0.00099*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
		Mean standard error	*0.00574*	*0.00510*	*0.00062*	*0.00009*	*0.00000*	*0.00000*	*0.00190*	*0.00021*	*0.00008*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
	Large	Mean probability	0.01017	0.04321	0.05253	0.00000	0.00000	0.00000	0.00420	0.00714	0.00205	0.00000	0.00004	0.00024	0.00000	0.00050	0.00000
		Standard deviation	*0.03160*	*0.13220*	*0.15597*	*0.00000*	*0.00000*	*0.00000*	*0.01768*	*0.06131*	*0.01810*	*0.00000*	*0.00027*	*0.00202*	*0.00000*	*0.00492*	*0.00000*
		Mean standard error	*0.00184*	*0.00457*	*0.00556*	*0.00000*	*0.00000*	*0.00000*	*0.00078*	*0.00043*	*0.00049*	*0.00000*	*0.00002*	*0.00004*	*0.00000*	*0.00010*	*0.00000*
Entry		Mean probability	0.00052	0.00071	0.00040	0.00060	0.00133	0.00076	0.00049	0.00049	0.00077	0.00038	0.00046	0.00021	0.00074	0.00092	0.00059
		Standard deviation	*0.00245*	*0.00180*	*0.00124*	*0.00163*	*0.00311*	*0.00178*	*0.00234*	*0.00130*	*0.00217*	*0.00209*	*0.00182*	*0.00055*	*0.00240*	*0.00218*	*0.00129*
		Mean standard error	*0.00044*	*0.00043*	*0.00037*	*0.00066*	*0.00086*	*0.00064*	*0.00043*	*0.00043*	*0.00049*	*0.00028*	*0.00032*	*0.00020*	*0.00050*	*0.00055*	*0.00038*

Cont. Table 3.2: Average transition probabilities, standard deviation and mean standard errors across regions

Farm type		Variable[a]	Pigs			Poultry			Mixed farms			Mixed livestock			Horticulture			Exit
			Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	
Arable	Small	Mean probability	0.00003	0.00017	0.00002	0.00001	0.00017	0.00068	0.02901	0.02176	0.00042	0.00373	0.00001	0.00000	0.00618	0.00395	0.00218	0.03810
		Standard deviation	*0.00021*	*0.00158*	*0.00011*	*0.00012*	*0.00149*	*0.00669*	*0.10062*	*0.12245*	*0.00413*	*0.02335*	*0.00012*	*0.00000*	*0.02055*	*0.02400*	*0.01117*	*0.05677*
		Mean standard error	*0.00007*	*0.00009*	*0.00006*	*0.00002*	*0.00021*	*0.00026*	*0.00517*	*0.00228*	*0.00008*	*0.00163*	*0.00004*	*0.00001*	*0.00197*	*0.00149*	*0.00110*	*0.00829*
	Medium	Mean probability	0.00002	0.00002	0.00009	0.00000	0.00008	0.00010	0.00375	0.02872	0.00376	0.00052	0.00062	0.00020	0.00098	0.00472	0.00802	0.03179
		Standard deviation	*0.00022*	*0.00017*	*0.00041*	*0.00000*	*0.00083*	*0.00079*	*0.01145*	*0.07685*	*0.00722*	*0.00240*	*0.00200*	*0.00092*	*0.00424*	*0.01312*	*0.04004*	*0.07307*
		Mean standard error	*0.00014*	*0.00001*	*0.00014*	*0.00000*	*0.00002*	*0.00013*	*0.00112*	*0.00575*	*0.00140*	*0.00025*	*0.00040*	*0.00012*	*0.00028*	*0.00174*	*0.00192*	*0.00574*
	Large	Mean probability	0.00000	0.00009	0.00045	0.00000	0.00000	0.00014	0.00019	0.00353	0.02386	0.00004	0.00047	0.00099	0.00000	0.00265	0.01022	0.02427
		Standard deviation	*0.00000*	*0.00095*	*0.00381*	*0.00000*	*0.00000*	*0.00101*	*0.00106*	*0.00791*	*0.03621*	*0.00044*	*0.00403*	*0.00281*	*0.00000*	*0.01386*	*0.03856*	*0.04950*
		Mean standard error	*0.00002*	*0.00003*	*0.00016*	*0.00000*	*0.00000*	*0.00011*	*0.00010*	*0.00121*	*0.00617*	*0.00001*	*0.00009*	*0.00074*	*0.00001*	*0.00074*	*0.00316*	*0.00458*
Sheep and goats	Small	Mean probability	0.00001	0.00000	0.00001	0.00008	0.00000	0.00000	0.06075	0.01291	0.00000	0.01637	0.00158	0.00000	0.00042	0.00069	0.00020	0.03781
		Standard deviation	*0.00005*	*0.00000*	*0.00008*	*0.00077*	*0.00000*	*0.00000*	*0.13487*	*0.06161*	*0.00000*	*0.04141*	*0.00630*	*0.00000*	*0.00417*	*0.00498*	*0.00194*	*0.06570*
		Mean standard error	*0.00009*	*0.00000*	*0.00001*	*0.00005*	*0.00000*	*0.00000*	*0.00851*	*0.00185*	*0.00001*	*0.00458*	*0.00071*	*0.00000*	*0.00007*	*0.00048*	*0.00007*	*0.00707*
	Medium	Mean probability	0.00000	0.00000	0.00003	0.00000	0.00000	0.00000	0.00680	0.05624	0.00801	0.00231	0.01140	0.00114	0.00000	0.00000	0.00000	0.03005
		Standard deviation	*0.00000*	*0.00000*	*0.00031*	*0.00000*	*0.00000*	*0.00000*	*0.02618*	*0.15546*	*0.02605*	*0.01109*	*0.03096*	*0.00707*	*0.00000*	*0.00000*	*0.00000*	*0.03784*
		Mean standard error	*0.00000*	*0.00000*	*0.00001*	*0.00000*	*0.00000*	*0.00000*	*0.00093*	*0.00561*	*0.00250*	*0.00036*	*0.00253*	*0.00047*	*0.00000*	*0.00000*	*0.00000*	*0.00462*
	Large	Mean probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00460	0.07709	0.00000	0.00089	0.02486	0.00000	0.00000	0.00000	0.02762
		Standard deviation	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.02541*	*0.20280*	*0.00000*	*0.00673*	*0.08669*	*0.00000*	*0.00000*	*0.00000*	*0.06860*
		Mean standard error	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00078*	*0.00534*	*0.00000*	*0.00030*	*0.00447*	*0.00000*	*0.00000*	*0.00000*	*0.00372*
Permanent crops	Small	Mean probability	0.00000	0.00001	0.00004	0.00002	0.00000	0.00000	0.00182	0.00009	0.00000	0.00003	0.00000	0.00000	0.00849	0.00025	0.00151	0.03752
		Standard deviation	*0.00000*	*0.00009*	*0.00034*	*0.00019*	*0.00000*	*0.00000*	*0.00516*	*0.00042*	*0.00001*	*0.00029*	*0.00000*	*0.00000*	*0.07785*	*0.00116*	*0.01448*	*0.08231*
		Mean standard error	*0.00000*	*0.00009*	*0.00005*	*0.00002*	*0.00000*	*0.00000*	*0.00080*	*0.00018*	*0.00000*	*0.00006*	*0.00000*	*0.00000*	*0.00149*	*0.00020*	*0.00038*	*0.00806*
	Medium	Mean probability	0.00000	0.00000	0.00003	0.00000	0.00000	0.00003	0.00106	0.00720	0.00016	0.00009	0.00005	0.00000	0.00004	0.00133	0.00363	0.02554
		Standard deviation	*0.00000*	*0.00000*	*0.00033*	*0.00000*	*0.00000*	*0.00024*	*0.00430*	*0.06062*	*0.00058*	*0.00058*	*0.00040*	*0.00000*	*0.00033*	*0.01325*	*0.02524*	*0.05320*
		Mean standard error	*0.00000*	*0.00000*	*0.00003*	*0.00000*	*0.00000*	*0.00008*	*0.00023*	*0.00177*	*0.00027*	*0.00007*	*0.00002*	*0.00003*	*0.00010*	*0.00058*	*0.00053*	*0.00463*
	Large	Mean probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00021	0.00000	0.00046	0.00185	0.00000	0.00000	0.00001	0.00000	0.00053	0.00057	0.02149
		Standard deviation	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00151*	*0.00000*	*0.00293*	*0.00936*	*0.00000*	*0.00000*	*0.00010*	*0.00000*	*0.00332*	*0.00255*	*0.02406*
		Mean standard error	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00012*	*0.00000*	*0.00014*	*0.00078*	*0.00000*	*0.00000*	*0.00001*	*0.00000*	*0.00027*	*0.00036*	*0.00437*
Dairy	Small	Mean probability	0.00004	0.00000	0.00000	0.00000	0.00000	0.00000	0.03987	0.01287	0.00000	0.01307	0.00243	0.00000	0.00000	0.00000	0.00000	0.03081
		Standard deviation	*0.00035*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.06954*	*0.05698*	*0.00000*	*0.02918*	*0.01267*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.04232*
		Mean standard error	*0.00009*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00501*	*0.00236*	*0.00000*	*0.00243*	*0.00048*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00472*
	Medium	Mean probability	0.00013	0.00003	0.00004	0.00000	0.00000	0.00000	0.00575	0.01706	0.00291	0.00107	0.00555	0.00222	0.00067	0.00000	0.00000	0.03277
		Standard deviation	*0.00132*	*0.00028*	*0.00042*	*0.00000*	*0.00000*	*0.00000*	*0.01784*	*0.03045*	*0.00773*	*0.00367*	*0.01123*	*0.00871*	*0.00674*	*0.00000*	*0.00000*	*0.05024*
		Mean standard error	*0.00004*	*0.00001*	*0.00002*	*0.00000*	*0.00000*	*0.00001*	*0.00140*	*0.00344*	*0.00115*	*0.00052*	*0.00157*	*0.00100*	*0.00007*	*0.00000*	*0.00000*	*0.00602*
	Large	Mean probability	0.00000	0.00000	0.00018	0.00000	0.00000	0.00004	0.00006	0.00318	0.02141	0.00000	0.00099	0.00570	0.00000	0.00012	0.00000	0.02197
		Standard deviation	*0.00000*	*0.00000*	*0.00128*	*0.00000*	*0.00000*	*0.00028*	*0.00037*	*0.01094*	*0.04194*	*0.00000*	*0.00940*	*0.02153*	*0.00000*	*0.00119*	*0.00002*	*0.01910*
		Mean standard error	*0.00000*	*0.00000*	*0.00010*	*0.00000*	*0.00000*	*0.00005*	*0.00004*	*0.00089*	*0.00549*	*0.00000*	*0.00028*	*0.00268*	*0.00000*	*0.00002*	*0.00003*	*0.00490*
Beef	Small	Mean probability	0.00009	0.00000	0.00000	0.00001	0.00000	0.00000	0.05004	0.00805	0.00009	0.01676	0.00062	0.00000	0.00122	0.00000	0.00020	0.02501
		Standard deviation	*0.00094*	*0.00000*	*0.00000*	*0.00015*	*0.00000*	*0.00000*	*0.07496*	*0.02374*	*0.00091*	*0.04090*	*0.00293*	*0.00000*	*0.01223*	*0.00000*	*0.00200*	*0.02239*
		Mean standard error	*0.00001*	*0.00000*	*0.00000*	*0.00003*	*0.00000*	*0.00000*	*0.00770*	*0.00205*	*0.00002*	*0.00343*	*0.00026*	*0.00000*	*0.00070*	*0.00000*	*0.00002*	*0.00423*
	Medium	Mean probability	0.00000	0.00005	0.00000	0.00000	0.00000	0.00002	0.00815	0.04587	0.00560	0.00201	0.01752	0.00114	0.00000	0.00000	0.00000	0.02297
		Standard deviation	*0.00000*	*0.00053*	*0.00000*	*0.00000*	*0.00000*	*0.00017*	*0.02041*	*0.06309*	*0.01941*	*0.00957*	*0.04598*	*0.00394*	*0.00000*	*0.00000*	*0.00000*	*0.02056*
		Mean standard error	*0.00000*	*0.00001*	*0.00000*	*0.00000*	*0.00000*	*0.00004*	*0.00151*	*0.00759*	*0.00113*	*0.00022*	*0.00343*	*0.00031*	*0.00000*	*0.00000*	*0.00000*	*0.00288*
	Large	Mean probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00482	0.07341	0.00000	0.00176	0.01160	0.00000	0.00000	0.00001	0.02094
		Standard deviation	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00001*	*0.00000*	*0.01875*	*0.13750*	*0.00000*	*0.01085*	*0.02781*	*0.00000*	*0.00000*	*0.00006*	*0.01961*
		Mean standard error	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00001*	*0.00000*	*0.00058*	*0.01035*	*0.00000*	*0.00036*	*0.00253*	*0.00000*	*0.00000*	*0.00003*	*0.00228*
Pigs	Small	Mean probability	0.77668	0.07565	0.01431	0.00016	0.00000	0.00000	0.04374	0.00690	0.00000	0.03296	0.00400	0.00000	0.00000	0.00000	0.00250	0.02138
		Standard deviation	*0.32612*	*0.20860*	*0.09911*	*0.00141*	*0.00000*	*0.00000*	*0.14852*	*0.03817*	*0.00000*	*0.13079*	*0.02283*	*0.00000*	*0.00000*	*0.00000*	*0.02512*	*0.06383*
		Mean standard error	*0.01946*	*0.00928*	*0.00158*	*0.00016*	*0.00000*	*0.00000*	*0.00335*	*0.00080*	*0.00000*	*0.00224*	*0.00077*	*0.00000*	*0.00000*	*0.00000*	*0.00026*	*0.00360*
	Medium	Mean probability	0.04688	0.72055	0.08267	0.00000	0.00050	0.00030	0.01601	0.03685	0.00331	0.00169	0.02587	0.01116	0.00000	0.00000	0.00000	0.03835
		Standard deviation	*0.14195*	*0.28549*	*0.12958*	*0.00000*	*0.00329*	*0.00283*	*0.07322*	*0.09377*	*0.01144*	*0.00852*	*0.09910*	*0.09768*	*0.00000*	*0.00000*	*0.00000*	*0.10426*
		Mean standard error	*0.01023*	*0.02800*	*0.01502*	*0.00000*	*0.00037*	*0.00010*	*0.00126*	*0.00437*	*0.00052*	*0.00040*	*0.00264*	*0.00023*	*0.00000*	*0.00000*	*0.00000*	*0.00489*
	Large	Mean probability	0.00028	0.05782	0.78756	0.00000	0.00000	0.00087	0.00355	0.00783	0.05976	0.00000	0.00205	0.04407	0.00000	0.00000	0.00001	0.03069
		Standard deviation	*0.00193*	*0.16074*	*0.27597*	*0.00000*	*0.00000*	*0.00538*	*0.03572*	*0.02444*	*0.16456*	*0.00000*	*0.01185*	*0.14577*	*0.00000*	*0.00000*	*0.00007*	*0.08916*
		Mean standard error	*0.00017*	*0.01035*	*0.02371*	*0.00000*	*0.00000*	*0.00037*	*0.00039*	*0.00166*	*0.00668*	*0.00000*	*0.00066*	*0.00564*	*0.00000*	*0.00000*	*0.00000*	*0.00507*
Poultry	Small	Mean probability	0.00204	0.00000	0.00000	0.73881	0.10334	0.03470	0.03253	0.01045	0.00000	0.01806	0.00124	0.00000	0.00000	0.00193	0.00135	0.04728
		Standard deviation	*0.02049*	*0.00000*	*0.00000*	*0.34792*	*0.23229*	*0.13698*	*0.15418*	*0.09960*	*0.00000*	*0.08502*	*0.01242*	*0.00000*	*0.00000*	*0.01938*	*0.01360*	*0.12865*
		Mean standard error	*0.00042*	*0.00000*	*0.00000*	*0.02347*	*0.01304*	*0.00521*	*0.00271*	*0.00010*	*0.00000*	*0.00245*	*0.00026*	*0.00000*	*0.00000*	*0.00040*	*0.00027*	*0.00761*
	Medium	Mean probability	0.00000	0.00030	0.00174	0.04774	0.72272	0.09112	0.01458	0.04108	0.00373	0.01903	0.00529	0.00636	0.00000	0.00000	0.00000	0.03848
		Standard deviation	*0.00000*	*0.00260*	*0.01001*	*0.13222*	*0.32126*	*0.19287*	*0.08707*	*0.13720*	*0.03190*	*0.09124*	*0.02763*	*0.06391*	*0.00000*	*0.00000*	*0.00000*	*0.08257*
		Mean standard error	*0.00000*	*0.00012*	*0.00031*	*0.01153*	*0.03073*	*0.01311*	*0.00176*	*0.00509*	*0.00030*	*0.00270*	*0.00105*	*0.00101*	*0.00000*	*0.00000*	*0.00000*	*0.00726*
	Large	Mean probability	0.00000	0.00000	0.00474	0.00392	0.02579	0.82370	0.00418	0.00889	0.04294	0.00031	0.00473	0.02944	0.00000	0.00036	0.00000	0.01970
		Standard deviation	*0.00000*	*0.00000*	*0.02114*	*0.02023*	*0.07025*	*0.24017*	*0.02785*	*0.03283*	*0.13492*	*0.00314*	*0.01763*	*0.11633*	*0.00000*	*0.00357*	*0.00000*	*0.03403*
		Mean standard error	*0.00000*	*0.00000*	*0.00068*	*0.00236*	*0.00773*	*0.02108*	*0.00084*	*0.00219*	*0.00411*	*0.00005*	*0.00123*	*0.00407*	*0.00000*	*0.00009*	*0.00000*	*0.00343*
Mixed farms	Small	Mean probability	0.00280	0.00099	0.00006	0.00091	0.00157	0.00046	0.62464	0.06415	0.00016	0.01735	0.00294	0.00000	0.00050	0.00018	0.00005	0.03467
		Standard deviation	*0.01335*	*0.00454*	*0.00060*	*0.00512*	*0.00710*	*0.00335*	*0.24241*	*0.12781*	*0.00113*	*0.03168*	*0.00701*	*0.00000*	*0.00272*	*0.00119*	*0.00053*	*0.10097*
		Mean standard error	*0.00143*	*0.00054*	*0.00001*	*0.00059*	*0.00084*	*0.00026*	*0.02794*	*0.00950*	*0.00007*	*0.00489*	*0.00098*	*0.00000*	*0.00014*	*0.00014*	*0.00001*	*0.00308*
	Medium	Mean probability	0.00002	0.00544	0.00373	0.00133	0.00246	0.00126	0.03033	0.65745	0.05178	0.00299	0.02011	0.00200	0.00117	0.00298	0.00035	0.02537
		Standard deviation	*0.00017*	*0.01543*	*0.00972*	*0.00829*	*0.00918*	*0.00640*	*0.03248*	*0.14048*	*0.06757*	*0.00964*	*0.02853*	*0.00447*	*0.00950*	*0.02789*	*0.00213*	*0.02562*
		Mean standard error	*0.00006*	*0.00201*	*0.00155*	*0.00089*	*0.00179*	*0.00102*	*0.00587*	*0.02995*	*0.01110*	*0.00064*	*0.00559*	*0.00112*	*0.00019*	*0.00084*	*0.00028*	*0.00284*
	Large	Mean probability	0.00047	0.00048	0.01422	0.00000	0.00064	0.00264	0.00088	0.04667	0.71621	0.00000	0.00212	0.01803	0.00000	0.00066	0.00039	0.01991
		Standard deviation	*0.00475*	*0.00410*	*0.03548*	*0.00000*	*0.00545*	*0.00772*	*0.00882*	*0.10768*	*0.17894*	*0.00000*	*0.00755*	*0.02706*	*0.00000*	*0.00523*	*0.00273*	*0.01807*
		Mean standard error	*0.00005*	*0.00012*	*0.00408*	*0.00000*	*0.00058*	*0.00125*	*0.00009*	*0.00577*	*0.02778*	*0.00000*	*0.00065*	*0.00620*	*0.00000*	*0.00020*	*0.00015*	*0.00265*
Mixed livestock	Small	Mean probability	0.00496	0.00563	0.00000	0.00360	0.00062	0.00040	0.12119	0.00502	0.00032	0.64949	0.03038	0.00000	0.00004	0.00000	0.00000	0.02352
		Standard deviation	*0.01933*	*0.02656*	*0.00000*	*0.02323*	*0.00435*	*0.00347*	*0.17770*	*0.01627*	*0.00318*	*0.31477*	*0.10596*	*0.00000*	*0.00042*	*0.00000*	*0.00000*	*0.03882*
		Mean standard error	*0.00198*	*0.00102*	*0.00000*	*0.00127*	*0.00068*	*0.00018*	*0.01100*	*0.00142*	*0.00004*	*0.02512*	*0.00419*	*0.00000*	*0.00002*	*0.00000*	*0.00000*	*0.00343*
	Medium	Mean probability	0.00074	0.01312	0.00925	0.00013	0.00329	0.00624	0.01597	0.11133	0.00772	0.02521	0.57442	0.03683	0.00000	0.00000	0.00005	0.02228
		Standard deviation	*0.00681*	*0.03025*	*0.05391*	*0.00116*	*0.01793*	*0.03748*	*0.05616*	*0.16404*	*0.01916*	*0.06417*	*0.27820*	*0.06466*	*0.00000*	*0.00000*	*0.00051*	*0.02211*
		Mean standard error	*0.00006*	*0.00386*	*0.00173*	*0.00020*	*0.00152*	*0.00220*	*0.00143*	*0.01142*	*0.00141*	*0.00363*	*0.02983*	*0.00733*	*0.00000*	*0.00000*	*0.00002*	*0.00212*
	Large	Mean probability	0.00000	0.00124	0.03380	0.00000	0.00002	0.00245	0.00000	0.02339	0.09275	0.00000	0.02983	0.66097	0.00000	0.00000	0.00397	0.02804
		Standard deviation	*0.00000*	*0.00919*	*0.08619*	*0.00000*	*0.00017*	*0.00752*	*0.00000*	*0.10693*	*0.12455*	*0.00000*	*0.09118*	*0.25647*	*0.00000*	*0.00000*	*0.03974*	*0.05003*
		Mean standard error	*0.00000*	*0.00017*	*0.00563*	*0.00000*	*0.00001*	*0.00108*	*0.00000*	*0.00147*	*0.01190*	*0.00000*	*0.00460*	*0.03282*	*0.00000*	*0.00000*	*0.00013*	*0.00413*
Horticulture	Small	Mean probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00552	0.00000	0.00000	0.00036	0.00000	0.00000	0.78399	0.08726	0.02576	0.01917
		Standard deviation	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00002*	*0.00000*	*0.04163*	*0.00000*	*0.00000*	*0.00338*	*0.00000*	*0.00000*	*0.25379*	*0.17208*	*0.10954*	*0.02628*
		Mean standard error	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00005*	*0.00001*	*0.00160*	*0.00000*	*0.00000*	*0.00007*	*0.00000*	*0.00000*	*0.02886*	*0.01446*	*0.00358*	*0.00395*
	Medium	Mean probability	0.00008	0.00000	0.00000	0.00000	0.00000	0.00000	0.00032	0.00010	0.00026	0.00000	0.00000	0.00000	0.03395	0.75966	0.07424	0.03419
		Standard deviation	*0.00076*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00256*	*0.00105*	*0.00260*	*0.00000*	*0.00000*	*0.00000*	*0.07206*	*0.22920*	*0.09388*	*0.08137*
		Mean standard error	*0.00014*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00006*	*0.00004*	*0.00007*	*0.00000*	*0.00000*	*0.00000*	*0.01019*	*0.03261*	*0.01869*	*0.00561*
	Large	Mean probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00045	0.00073	0.00215	0.00000	0.00000	0.00000	0.00839	0.05330	0.78281	0.03209
		Standard deviation	*0.00000*	*0.00000*	*0.00000*	*0.00149*	*0.00000*	*0.00000*	*0.00387*	*0.00552*	*0.01198*	*0.00000*	*0.00000*	*0.00000*	*0.05278*	*0.07813*	*0.24699*	*0.06559*
		Mean standard error	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00006*	*0.00010*	*0.00068*	*0.00000*	*0.00000*	*0.00000*	*0.00148*	*0.01385*	*0.02675*	*0.00622*
Entry		Mean probability	0.00015	0.00062	0.00073	0.00051	0.00057	0.00050	0.00032	0.00063	0.00057	0.00073	0.00042	0.00043	0.00075	0.00109	0.00082	0.98178
		Standard deviation	*0.00049*	*0.00236*	*0.00165*	*0.00149*	*0.00123*	*0.00089*	*0.00149*	*0.00157*	*0.00183*	*0.00378*	*0.00105*	*0.00135*	*0.00248*	*0.00317*	*0.00202*	*0.01534*
		Mean standard error	*0.00026*	*0.00039*	*0.00063*	*0.00041*	*0.00046*	*0.00042*	*0.00036*	*0.00045*	*0.00037*	*0.00068*	*0.00037*	*0.00039*	*0.00071*	*0.00098*	*0.00067*	*0.00527*

Source: Own calculation based on FADN data 1990-2005; a: all measures calculated across regions.

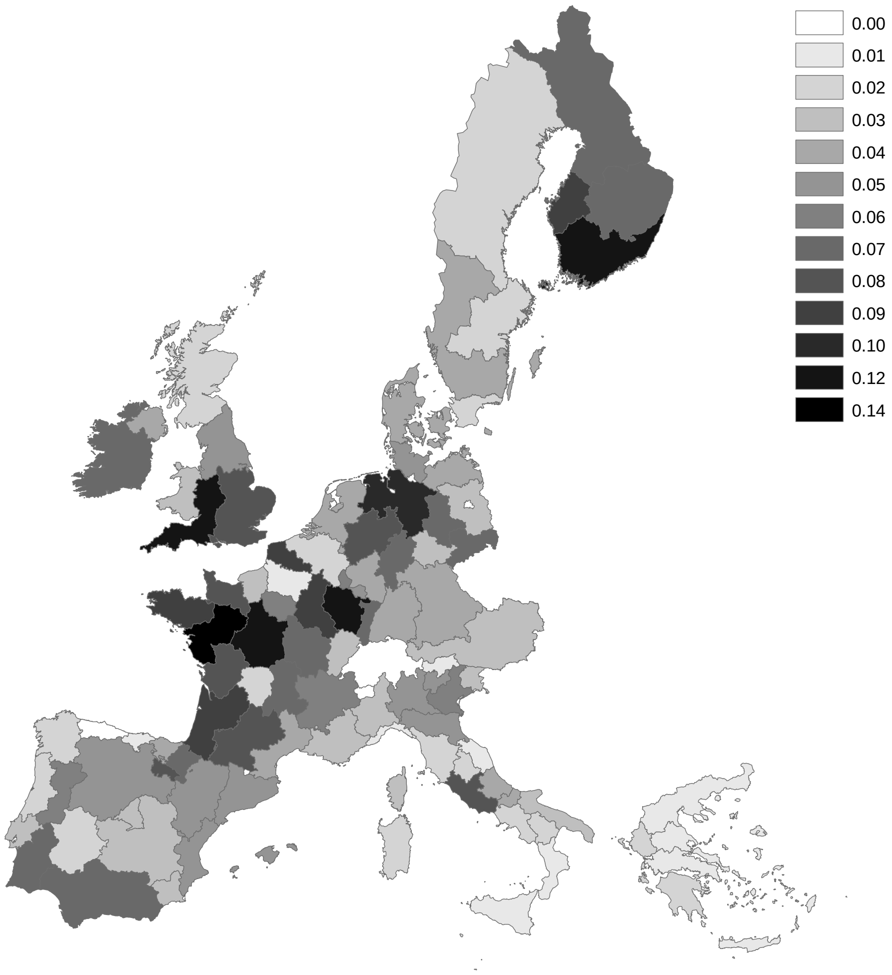
Mobility indices

In the following, we present a descriptive analysis of the mobility indices, restricting the attention to size and specialisation class changes as market entry and exit are already sufficiently considered in section 3.2 on the farm number development.

The overall mobility comprises all off-diagonal transition probabilities in the transition probability matrix, i.e. the likelihood for all possible farm type changes. It is the sum of the partial mobility indices. Overall mobility is very high (above the 90 per cent quantile of 0.3810) in many parts of Italy, especially in the North and in Portugal. It is high in Scandinavia, in West and North Spain, in West France, South England, and West Germany. In East Germany, the Netherlands, and partly in the North of France and of Spain farms are relatively unlikely to change their actual farm type (mobility index below the 10 per cent quantile of 0.1389). The median of the overall mobility index across regions is 0.2578. As the overall mobility gives a general indication of the structural volatility in a region but does not provide insight into the direction of structural change, it is neither shown nor further analysed in the paper.

The analysis of farm size changes distinguishes between size increases and size decline. Figure 3.2 shows the mobility to change to a larger size class per region.

Figure 3.2: Mobility for size increases 1990-2005 [index]



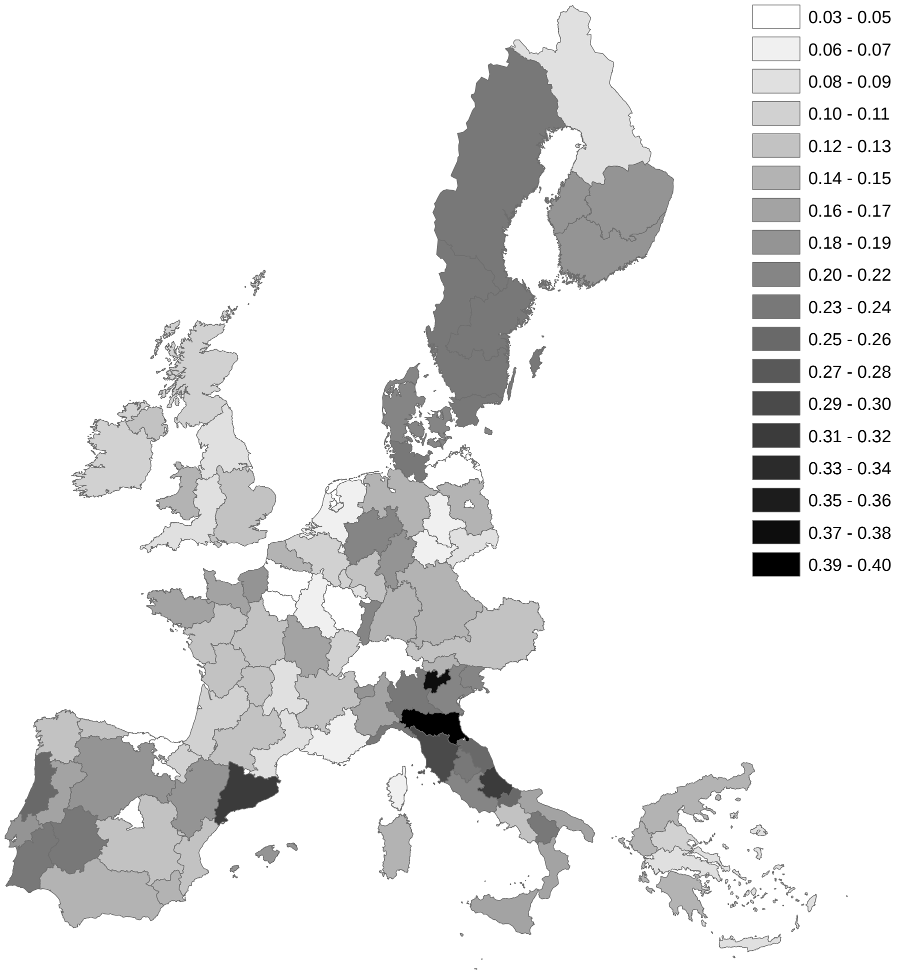
Source: Own calculation based on FADN data.

Increasing farm sizes are found in all European regions, though the mobility values for farm size increases are generally higher in the central part of the EU15. The median of the mobility to increase in size across regions is 0.0425. The probability to increase in size is very high (above the 90 per cent quantile of 0.0875) in Finland, Northwest Germany, Southern England and in large parts of France. In Southern Europe, especially Greece and South Italy, the mobility index is below the 10 per cent quantile of 0.0132 indicating that farms are less likely to increase in size in these regions.

Generally, the mobility values for a decline in farm size are much lower than the values for size increases. The median across the regions is 0.0301. Compared to farm size increases which take mainly place in the central part, declining farm sizes can be found at the border zones of the EU15. The countries with the highest mobility indices (above the 90 per cent quantile of 0.0659) for farm size decline are Portugal, Italy, Greece, and Finland. In Finland already high values of the mobility for size increases could be found. In the central part of the EU15, and here especially in Northern France and East Germany, farms are very unlikely to change to lower size classes (mobility index below the 10 per cent quantile of 0.0071). Surprisingly, farm size decline seems to take place mainly in regions which are already dominated by small scale farming. This effect might at least partly be due to the fact that many small farms are kept as hobby or part-time businesses in the Mediterranean countries (Lianos and Parliarou, 1986, Hoggart and Paniagua, 2001). In Portugal, Spain, Italy, Greece and Sweden, the mobility to decrease in size usually is higher than the mobility for size growth. In Finland, the mobility of size increases is higher.

Figure 3.3 shows the mobility index for specialisation class changes. Due to the high amount of specialisation classes, the share of specialisation class changes on the overall mobility is rather high in most regions. The median of the mobility index for specialisation changes across the regions is 0.1474.

Figure 3.3: Mobility to change the specialisation class 1990-2005 [index]



Source: Own calculation based on FADN data.

Farms are most likely to change their specialisation class in Italy, Portugal and West and North Spain (mobility index above the 90 per cent quantile of 0.2295). The share of the mobility for specialisation class changes of the overall mobility is highest in Italian regions (65 per cent compared to the European average share of specialisation class changes of 56 per cent). In order to answer the question to which farm types the farms change to, the transition probability matrices and regional farm type shares are analysed. Generally, specialisation changes are likely to happen between dairy and beef farming and various specialisation classes and the mixed and mixed livestock specialisations. Farms are less likely to change their specialisation class in East Germany, Northern France, the Netherlands and Northern Spain (mobility index below the 10 per cent quantile of 0.0621).

3.5 Relationship between structural variables and mobility indices

It has been shown above that there exist considerable differences in structural change across the European regions. Given that the overall political conditions are rather similar for all of these regions under the Common Agricultural Policy, other – regionally specific – reasons must be responsible for this result. Based on explicitly formulated hypotheses, the relationship between structural variables and the mobility indices is investigated by means of a multiple regression. The mobility indices derived above are transformed from the zero-one to a continuous interval and serve as dependent variable. The structural variables discussed below are used as explanatory variables in OLS (Ordinary Least Squares) regressions. The regressions are accomplished at EU15 level and also for Member States with a reasonably large number of regions to conduct cross-sectional analyses. These Member States are Germany (13 regions), France (22 regions), Spain (17 regions) and Italy (21 regions). For each of the mobility indices a separate regression is set up. All mobility indices (for exits, for changes to larger size classes, changes to smaller size classes, specialization class changes) are regressed against a constant, the initial farm size, farm size heterogeneity and farmers' age. The mobility for sector exits (M^{exit}) is additionally regressed against the unemployment rate and the mobility for specialization class changes is additionally regressed against the share of mixed farms in a region. The mobility to enter the sector is not considered because it is almost zero in most regions.

Hypotheses

From a vast amount of factors which potentially might lead to the regional differences in structural change, we have chosen five variables for a closer examination in this respect. Acknowledging that structural change is path dependent (Balmann, 1995) we assume that the initial farm structure significantly determines structural developments in a region. We characterise the initial farm structure by the initial farm size, farm size heterogeneity and the share of mixed farms in a region. Among others, Harrington and Reinsel (1995) point to the relevance of the farmers' age to structural change. Finally, the unemployment rate as proxy for off-farm employment opportunities is assumed to affect sector exits (e.g. Goddard et al., 1993). Hypotheses are made concerning the relationship between the aforementioned structural variables and the mobility indices. They are described in the following and an overview of the expected signs is given in the third column of Table 3.4. A descriptive analysis of the explanatory variables is given in Table 3.3 and in the results section.

Farm size

Conflicting theories exist on the relationship between farm size and structural change. Gibrat's law states that the size of a firm and its growth rate are independent, whereas other authors stipulate the existence of scale economies (e.g. Hallam, 1991, Boehlje, 1992, Goddard et al., 1993, Harrington and Reinsel, 1995) and path dependency in agriculture (Balmann, 1995). Empirical evidence is found for and against Gibrat's law. Shapiro et al. (1987) and Weiss (1999) reject Gibrat's law for Canada and Upper Austria, whereas it is, with limitations, supported by Kostov et al. (2006) and Piet (2008) for Northern Ireland and France, respectively. Melhim et al. (2009) detect a correlation between farm size and production diversification. We formulate the following hypotheses with regard to the relationship between farm size and regional differences in structural change:

1. We suppose that a more consolidated farm structure at the beginning of the period (expressed in a higher average farm size) would lead to less sector exits (M^{exit}) compared to regions where small-scale farming still dominates the agricultural sector.
2. Concerning the relationship between initial size and the mobility for changes into higher size classes (M^{s+}) a positive sign is expectable. This could be explained with an ongoing growth process steered by technical change and scale economies (e.g. Hallam, 1991, Boehlje, 1992, Goddard et al., 1993, Harrington and Reinsel, 1995), which led to larger farm sizes in the past, but still has potential for more growth based on a favourable distribution of shrinking and growing farms in the regions. The farm size heterogeneity is therefore used as another explanatory variable. The respective hypotheses are formulated in the following section on the farm size heterogeneity.0.
3. Complementary to hypothesis 1. and 2., we expect that the larger the initial size, the lower is the mobility for changes into smaller size classes (M^{s-}).
4. For the relationship between the initial size and the mobility for specialisation changes (M^{spec}) two alternatives can be thought of:
   a. On the one hand one could imagine that the higher the initial size, the more has been invested in the past in certain production technologies and the lower is the probability to change the specialisation class due to path dependency.
   b. On the other hand it could be assumed that holders of large farms who generally contribute a larger share to the corresponding farm household income act 'more economically' than small scale farmers, i.e. might be willing to alter specialisation more rapidly if suggested by changed prod-

uct and factor market conditions in order to improve returns to primary factors. This would lead to a positive relationship between farm size and specialisation class changes.

Farm size heterogeneity

Besides the correlation between initial farm size and structural change, we assume a relationship between the heterogeneity of farm size and structural change. Up to now, this aspect has seldom been analysed in the literature, though for example Harrington and Reinsel (1995) discuss different potential implications of sectoral heterogeneity. Huettel and Margarian (2009) find a relationship between both variables. Based on Harrington and Reinsel (1995) we assume that a higher regional heterogeneity in farm size mirrors differences in the production efficiency. The existence of large differences in the production efficiency would allow more efficient farms to acquire resources of less efficient farms. This process would generally lead to accelerated structural adjustments. Following, our hypotheses are formulated:

5. The more heterogeneously farm size is distributed in a region, the easier resources of shrinking or exiting farms are taken over by larger farms. If less efficient farms go out of business, the mobility of sector exits (M^{exit}) will be rather high.
6. The higher the heterogeneity, the more likely are takeovers of resources from smaller farms leading to higher mobility values for farm size growth (M^{s+}).
7. If heterogeneity is high and large farms take over resources of smaller farms, the smaller farms may either go out of business as argued in hypothesis 5. or decline. If we assume that at least a part of the smaller farms just declines (instead of leaving the sector altogether), this would lead to high mobility values for changes into smaller size classes (M^{s-}) as well.
8. Regarding the connection between farm size heterogeneity and the mobility of specialisation changes (M^{spec}), we expect that the process of structural change where relatively large farms take over the resources of smaller farms leads to generally higher mobility values for specialisation class changes. Large farms probably specialise during the growth process and small farms change their specialisation while changing to part-time farming or moving to some niche production.

Farmers' age

Since farmers usually do not quit and change to another business during their active working age, the farmers' age is widely conceived as one of the main drivers of structural change (e.g. Harrington and Reinsel, 1995, Weiss, 1999, Pietola et al., 2003). Farms are much more likely to lower farming activities or go out of business as soon as the farmer retires or dies and there is no successor willing to continue farming. This effect is also exploited in age cohort analyses in order to identify farm structural change in terms of the total number of farms (e.g. De Haen and Von Braun, 1977). Our hypotheses regarding the relationship between farmers' age and regional differences in farm structural change are:

9. The higher the share of farmers being older than 55 years in a region, the higher will be the mobility value for sector exits (M^{exit}),
10. the lower should be the mobility values for changes into higher size classes (M^{s+}),
11. and the higher are the mobility values for changes to smaller size classes (M^{s-}),
12. Regarding the relationship between farmers' age and specialisation class changes, again two contradictory hypotheses can be developed:
    a. On the one hand, one could argue that the higher the share of farmers being older than 55 years is in a region, the less specialisation changes take place (M^{spec}). This is due to the fact that older farmers are probably less flexible in changing the type of business.
    b. On the other hand, retired farmers might continue a less intensive farming activity. This would lead to more specialisation changes.

Share of mixed farms

The relationship between the degree of specialisation and structural change has rarely been analysed in the literature.

13. Based on the descriptive analysis, we assume that the higher the share of mixed farms is in a region, the higher will be the mobility for specialisation class changes (M^{spec}). This is due to the fact that mixed farms can easier focus on one of their activities (which would lead to a reclassification of the specialisation type) than more specialised farms are able to switch their specialisation (due to sunk costs and path dependency).

Unemployment rate

14. In the theoretical and empirical literature, the opportunity for off-farm employment in a region has proven to be an important driver for structural change in that better off-farm employment opportunity raises the probability of farm sector exits (e.g. Harrington and Reinsel, 1995, Weiss, 1999). A higher unemployment rate in a region implies less opportunity for off-farm employment which in turn leads to small exit rates and lower mobility values for sector exits (M^{exit}).

Results

This section aims at identifying the impact of assumed key factors on regionally different structural developments across Europe. It provides results of the regression of the mobility indices against the explanatory variables discussed above. The regression analyses are accomplished at EU15 and at Member State level for countries with a reasonably large number of regions (Germany, France, Spain, and Italy). The cross-regional mobility indices are regressed against the explanatory factors discussed above. Table 3.3 displays averages and standard deviations (small values below the averages) for every structural variable used in the regression at EU15 level and for the four Member States considered.

Table 3.3: Averages and standard deviations of the structural variables

Variable	Definition of the variable	Measure	EU	DE	FR	ES	IT
Initial farm size	Average ESU/Farm 1990[a] [per cent]	Mean	37.7	117.3	41.2	11.5	13.4
		Standard deviation	52.8	111.1	14	8.2	5.3
Heterogeneity	Gini coefficient 1990[b] [index]	Mean	0.374	0.409	0.296	0.356	0.475
		Standard deviation	0.1	0.1	0	0.1	0.1
Age	Share of farmers > 55 years (average 1990/1991)[b] [per cent]	Mean	26.2	27.9	17.2	29.3	34.3
		Standard deviation	11.9	5.9	4.9	11.3	12.4
Mixed farms	Share of mixed farms 1990[b] [per cent]	Mean	12.5	25.5	14.2	4.9	9.2
		Standard deviation	9.3	7.8	8.4	6.5	4.9
Unemployment	Unemployment rate[c] [per cent]	Mean	8.6	10.5	9	11.9	7.3
		Standard deviation	4.1	5.6	2.4	3.8	4.8

Source: Own calculation, a: data from the public FADN database, b: based on FADN data, c: EUROSTAT[39].

Concerning the categories initial farm size and farm size heterogeneity, different measures are suitable a-priori. To represent the initial farm size we considered the average economic size per farm and the average Utilized Agricultural Area (UAA) per farm, both in the beginning of the observation period. We chose the definition based on economic size units given the differences in relevance of land resources between the specialisations. For the measure on farm size heterogeneity we picked a Gini coefficient weighted by specialisation shares (motivated further below). The farmers' age is expressed by the regional share of farmers being older than 55 years as those are the ones considered to leave the sector within the following 10 to 15 years. The opportunity for off-farm employment is represented by the regional unemployment rate. The share of mixed farms is used as a measure of production diversification in a region.

The mobility indices representing the dependent variable in the regressions are transformed from the zero-one interval to a continuous interval by the inverse of the standard normal distribution. An ordinary least squares (OLS) estimator is applied to regress the transformed mobility indices against the structural variables. In case of the EU15, we have 101 observations (from the 101 regions). For

[39] Averages from 1990 to 2005. Source: http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/regional_statistics/data/database, tables reg_lfh3unrt and reg_lfu3rt, downloaded in November 2009

Germany 13 regions, for France 22 regions, for Spain 17 regions and for Italy 21 regions are considered. Depending on the type of mobility, four to five explanatory variables (including the constant) are used in the regressions (four in case of the size mobilities and five in case of the exit and specialisation change mobilities). Accordingly, the degrees of freedom vary from eight (country: Germany, mobility: M^{exit} or M^{spec}) to 97 (country: EU15, mobility: M^{s+} or M^{s-}).

Table 3.4 shows the results of the regression of the mobility indices against the structural variables. The R^2 measures are generally surprisingly high for a cross-sectional analysis, though they just give an impression how well the variance in the transformed mobility indices is explained by the structural variables. For a better overview, the discussion of the results is divided into subsections.

Table 3.4: Estimated coefficients

Mobility	Variable	Expected sign	EU (101 regions)	DE (13 regions)	FR (22 regions)	ES (17 regions)	IT (21 regions)
M^{exit}	Constant		7.49 **	19.127 **	-1.192 **	-19.293	-2.618 ***
	Average ESU/Farm 1990	-	-0.041 **	-0.098 ***	0.015 **	0.668	-0.026 *
	Gini coefficient	+	11.078	116.513 ***	0.796	53.347	2.811 **
	Share of farmers > 55 years	+	-0.182 **	-0.976 ***	-0.067 ***	-0.225	-0.001
	Unemployment rate	-	-1.464 ***	-3.888 ***	-0.059 **	-1.99 *	-0.023 *
	R^2		0.319	0.959	0.54	0.204	0.334
M^{s+}	Constant		-1.631 ***	-1.572 ***	-1.901 ***	-2.495 ***	-3.342 ***
	Average ESU/Farm 1990	+	0.001 *	-0.002 **	0.001	0.013	0.015
	Gini coefficient	+	-0.055	1.395 **	1.383	1.624 *	2.786 **
	Share of farmers > 55 years	-	-0.006 **	-0.013	-0.005	-0.002	-0.005
	R^2		0.065	0.413	0.046	0.214	0.386
M^{s-}	Constant		-1.038	-5.4	-1.892 ***	-2.428 ***	-2.077 ***
	Average ESU/Farm 1990	-	-0.027 ***	-0.019	-0.02 ***	-0.001	-0.021 **
	Gini coefficient	+	-0.917	-6.921	1.437	1.405 ***	1.194 *
	Share of farmers > 55 years	+	0.005	0.197	0.004	0.004	0.001
	R^2		0.172	0.116	0.563	0.612	0.318
M^{spec}	Constant		-1.671 ***	-1.365 ***	-1.564 ***	-2.69 ***	-1.155 ***
	Average ESU/Farm 1990	- / (+)	-0.004 ***	-0.001	-0.013 ***	0.008	0.019 **
	Gini coefficient	+	1.41 ***	-0.78	1.247	2.898 ***	-0.021
	Share of farmers > 55 years	-	0	0.013	0.014	0.008	0.002
	Share of mixed farms	+	0.015 ***	0.009	0.017 **	0.021 **	0.004
	R^2		0.432	0.621	0.43	0.697	0.216

Source: Own calculation based on FADN data. Significance levels: ***: 1 per cent, **: 5 per cent, *: 10 per cent.

Initial farm size

The average economic size per farm (in ESU) in the initial observation year was highest in Germany, close to the European average in France and far below the European average in Italy and in Spain (Table 3.3). In the case of the EU15, Germany and Italy, the initial farm size has, as expected, a significantly negative impact on the mobility of sector exits: the higher the farm size was at the beginning of the observation period, the lower is the probability to exit the sector due to a more consolidated farm structure. For France and Spain a positive relationship between the initial farm size and mobility of sector exits is found, though the coefficient is not significant in the Spanish case. Huettel and Margarian (2009) find in an analysis on structural change of West German farms that the higher the inital share of small farms was in a region, the lower are the exit probabilities for small farms and the higher are the exit probabilities for larger farms. Foltz (2004) finds for dairy farms in Connecticut that a small farm size is per se not significant for sector exits. While testing Gibrat's Law for Upper Austrian farms, Weiss (1999) observes a highly significant impact of the initial farm size on both farm survival (i.e. exit) and farm growth. Supporting our results, he finds that an increase in the initial farm size leads to higher survival probabilities.

Concerning the relationship between initial farm size and the mobility for changes to larger size classes, a positive coefficient was expected. The regression results show that at EU15 level the relationship is significantly positive, whereas in Germany a significantly negative relationship is found. This might be caused by the fact that in regions where the average farm size was already very large at the beginning of the observation period (as for example in East Germany), further farm size increases might just not be detected because there are only three size classes with the largest size class having no upper bound. Our assumption of a negative sign for the connection between the initial farm size and the mobility for changes to smaller size classes is confirmed by the data. Contrary to our results, Huettel and Margarian (2009) find in their analysis on West German farms that the mobility to change to larger size classes is highest in regions which are characterised by a small average farm size. A high initial share of small farms corresponds to higher probabilities for farm size growth in their analysis. Weiss (1999) reports two turning points: the impact of the initial farm size is negative for farms below and above the turning points, whereas it is positive for medium-sized farms. The different dynamics observed by Weiss (1999) are moreover correlated to the farmers' off-farm employment status.

As argued in the hypotheses, the initial farm size is positively as well as negatively connected with the mobility for specialisation class changes.

Farm size heterogeneity

We use a weighted Gini coefficient to represent farm size heterogeneity. The weighted Gini coefficient takes into account the relative importance of a farm type in a region. It is constructed by calculating Gini coefficients based on the economic farm size distribution for each specialisation class individually and weighting the specialisation class Gini coefficients by the share of farms falling into the respective specialisation classes. Afterwards, it is averaged across the specialisation classes in order to derive a singular heterogeneity measure per region. Gini coefficients are generally defined between 0 and 1. The higher the Gini coefficient, the more heterogeneously is farm size distributed in a region.

The weighted Gini coefficients for Italy and Germany are above and the coefficients for Spain and France are below the European average (Table 3.3).

As expected, farm size heterogeneity has a positive impact on the mobility for sector exits. Concerning the relationship between the farm size heterogeneity and the mobility for changes to larger size classes, the coefficients are, as expected, positive for Germany, France, Spain, and Italy. They are negative at EU15 level, though not significantly. As expected, the Gini coefficient has a positive impact (where significant) on the mobility for changes to smaller size classes and on the mobility for specialisation class changes. Huettel and Margarian (2009) distinguish between Gini coefficients at two different points in time. They generally found a higher mobility with increasing Gini coefficients which is in line with our results.

Farmers' age

The share of farmers being older than 55 years in the FADN sample at the beginning of the observation period is used as explanatory variable. Clear differences across the regions are detected. On European average, 26.2 per cent of the farmers in FADN are older than 55 in the beginning of the observation period. This value is only slightly higher in Germany and about 3 per cent and 8 per cent in Spain and Italy, respectively. In France only 17.2 per cent of the farm holders are older than 55 years.

We assumed that the higher the share of farmers being older than 55 years is in the beginning of the observation period, the higher would be the mobility for sector exits. Surprisingly, the data exhibit that this share has a negative impact on the mobility for sector exits. It was further assumed that the share of farmers older than 55 years would negatively affect the mobility of changes to larger size classes. This is verified by the data, though the coefficient is significant only at EU15 level. For the mobility to smaller size classes and the mobility for specialisation class changes, the share of farmers being older than 55 is not significant. Unfortunately, we do not have any information on farm succession. While simultaneously controlling for the existence of a successor, Weiss (1999) finds a positive effect of age on the probability of survival for young farmers in Upper Austria and a negative effect once it exceeds 51 years. He observes a similar pattern regarding farm growth rates: a younger age promotes farm growth (up to 34 years), whereas a negative relationship exists for older farmers and farm growth. Bremmer et al. (2004) cannot find an influence of neither the farmers' age nor the existence of a successor on growth of Dutch arable and horticulture farms.

Share of mixed farms

The share of mixed farms is especially high in Germany, close to the European average of 12.5 per cent in France, and relatively small in Spain and Italy.

We assumed that the higher the share of mixed farm is in a region, the higher would be the mobility for specialisation class changes. This relationship is generally confirmed by the data.

Unemployment

In Italy, the average of the official unemployment rate is lowest, followed by France. In Germany the unemployment rate is a little and in Spain it is well above the European average of 8.6 per cent (Table 3.3). It was expected that good off-farm employment opportunities let farmers give up the farming business more easily, whereas a high unemployment rate leads them to stay in farming as long as possible. This effect can be shown in all considered cases (EU15, Germany, France, Spain, and Italy). Our results are supported by Weiss (1999) who observes a significantly lower probability of survival for part-time compared to full-time farms.

3.6 Conclusions

The purpose of the paper was 1) to identify differences in farm structural change across EU15 regions and 2) to identify the impact of key factors on those differences.

In a first part, the differences of farm structural change across 101 EU15 regions are described for the years 1990 to 2005.

A generalized cross-entropy Markov chain estimation is conducted in order to derive transition probabilities which indicate the likelihood for a farm to change from one farm type to another in a certain period. The cross-entropy technique is employed in order to combine micro data representing movements of sample farms across the farm types and macro data which correctly mirror the distribution of farms across the farm types and which is derived from census data.

Transition probabilities are estimated for size and specialisation class changes. The information contained in the transition probabilities is summarized in mobility indices. Distributional measures of both the transition probabilities and the mobility indices are used to demonstrate the regionally different structural development paths. The analysis confirms the often stated observation of decreasing farm numbers for most regions of the EU15. Large differences are however found in pace and scope of the farm number decline and referring to the mobility of farms across size and specialisation classes.

In order to understand what determines the cross-sectional variation in farm structural change, the mobility indices representing general directions of structural change (amount of sector exits, size class changes and specialisation class changes) are cross-sectionally regressed against a number of structural variables.

It could be shown that the considered regional characteristics significantly contribute to explaining regional differences, even though some impacts vary when looking at some Member States separately. Initial average farm size levels are negatively related to farm exit mobility but their marginal impact on upward size mobility is mixed and depends on the initial level itself. Exit and size mobility generally increase with initial farm size heterogeneity in the regions. The share of farmers above the age of 55 has surprisingly little, and if significant, negative impacts on exit mobility, but dampens specialisation changes. Regional unemployment rates show the strong and expected negative impact on exits. Specialisation changes are more likely to happen with an increasing initial share of mixed farms.

Overall we find that farm structural variables caused by structural change processes antedating our time period of analysis contribute substantially to explaining current regional variations in farm sector adjustments. This generally confirms strong path dependency of the structural change process. The current analysis is constrained by limited socio-demographic information on the farm household such as on the existence of successors. Indicators on institutional differences in regional succession laws and land transfer could further explain observed processes. A more explicit model of farm structural change, however, would very quickly force the analyst to reduce the scope with respect to included regions and farm types thereby also changing the observed variance to be explained.

The contributions of the paper to the existing literature on structural change in agriculture lie in: (1) the focus on regional differences in farm structural change and their determinants, (2) the combination of micro and macro data in estimating the transition probabilities and (3) the multidimensionality of the farm typology. The significant contribution of regional characteristics in explaining regional differences of farm structural change stresses the importance of considering regional aspects in the policy making process. This would support decentralized policies as they are intended in the EU rural development program.

3.7 References

Andersen, E., Verhoog, A.D, Elbersen, B.S., Godeschalk, F.E. and Koole, B. (2006). A multidimensional farming system typology. SEAMLESS Report No.12, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, www.SEAMLESS-IP.org.

Anderson, T.W. and Goodman, L.A. (1957). Statistical Inference about Markov Chains. Annals of Mathematical Statistics 28: 89-110.

Aston, T.H. and Philpin, C.H.E. (1985): The Brenner debate: agrarian class structure and economic development in pre-industrial Europe. Cambridge University Press, Cambridge.

Balmann, A. (1995). Pfadabhängigkeiten in Agrarstrukturentwicklungen. Begriff, Ursachen und Konsequenzen. Duncker and Humblot, Berlin, Germany.

Boehlje, M. (1992). Alternative Models of Structural Change in Agriculture and Related Industries. Agribusiness 8: 219-231.

Bremmer, J., Oude Lansink, A.G., Olson, K.D., Baltussen, W.H. and Huirne,R.B. (2004). Analysis of farm development in Dutch agriculture and horticulture. In Bremmer, J. (ed), Strategic decision Making in firm development in Dutch horticulture. Wageningen University and Agricultural Economics Research Institute, Netherlands, 23-39.

Brenner, R. (1976): Agrarian Class Structure and Economic Development in Pre-Industrial Europe. Past and Present 70: 30-75.

Breustedt, G. and Glauben, T. (2007). Driving Forces behind Exiting from Farming in Western Europe. Journal of Agricultural Economics 58: 115-127.

De Haen, H. and Von Braun, J. (1977). Mobility of agricultural labour and fluctuating regional labour markets: a demographic and economic analysis with application to West-Germany. European Review of Agricultural Economics 4: 215-243.

Disney, W.T., Duffy, P.A. and Hardy, W.E.J. (1988). A Markov chain analysis of pork farms size distributions in the South. Southern Journal of Agricultural Economics 20: 57-64.

Ethridge, D.E., Roy, S.K. and Myers, D.W. (1985). A Markov chain analysis of structural changes in Texas high plains cotton ginning industry. Southern Journal of Agricultural Economics 7: 11-20.

Foltz, J.D. (2004): Entry, Exit, and Farm Size: Assessing an Experiment in Dairy Price Policy. American Journal of Agricultural Economics 86: 594-604.

Goddard, E., Weersink, A., Chen, K. and Turvey, C.G. (1993). Economics of structural change in agriculture. Canadian Journal of Agricultural Economics 41: 475-486.

Golan, A., Judge, G. and Miller, D. (1996). Maximum entropy econometrics. John Wiley and Sons, UK: Chichester.

Hallam, A. (1991). Economies of size and scale in agriculture: an interpretative review of empirical measurement. Review of Agricultural Economics 13:

155-172.
Hallberg, M.C. (1969). Projecting the size distribution of agricultural firms – an application of a Markov process with non-stationary transition probabilities. American Journal of Agricultural Economics 51: 289-302.
Harrington, D.H. and Reinsel, R.D. (1995). A synthesis of forces driving structural change. Canadian Journal of Agricultural Economics 43: 3-14.
Hennis, M. (2001). Europeaniziation and globalization: the missing link. Journal of Common Market Studies 5: 829-850.
Hoggart, K., and Paniagua, A. (2001a). What rural restructuring? Journal of Rural Studies 17: 41-62.
Hoggart, K. and Paniagua, A. (2001b). The restructuring of rural Spain? Journal of Rural Studies 17: 63-80.
Huettel, S. and Jongeneel, R. (2011). How has the EU milk quota affected patterns of herd-size change? European Review of Agricultural Economics, forthcoming.
Huettel, S. and Margarian, A. (2009). Structural change in the West German agricultural sector. Agricultural Economics 40, supplement: 759-772.
Jongeneel, R. and Tonini, A. (2008). Dairy quota and farm structural change: a case study on the Netherlands. In: Proceedings of the 107th EAAE Seminar, 30 January-1 February 2008, Sevilla, Spain.
Judge, G.G. and Swanson, E.R. (1961). Markov Chains: Basic Concepts and Suggested Uses in Agricultural Economics. Agricultural Experiment Station Research Report AERR-49. University of Illinois, Department of Agricultural Economics, Illinois, USA.
Karantininis, K. (2002). Information-based estimators for the non-stationary transition probability matrix: an application to the Danish pork industry. Journal of Econometrics 107: 275-290.
Karayalcin, C. (2010): Property Rights and The First Great Divergence: Europe 1500-1800. Working Paper, Department of Economics, Florida International University, USA.
Kirner, L., Hambrusch, J. and Ortner, K.M. (2009). The persistence of small dairy farms in Austria from an economic perspective. 111th EAAE Seminar, June 26-27, Canterbury, UK.
Kostov, P., Patton, M., Moss, J and McErlean, S. (2006). Does Gibrat's law hold amongst dairy farmers in Northern Ireland? MPRA Paper No. 3370.
Lee, T.C., Judge, G.G. and Zellner, A. (1977). Estimating the parameters of the Markov probability model from aggregate time series data. North-Holland Publishing Company, Amsterdam.
Lianos, T.P. and Parliarou, D. (1986). Farm size structure in Greek agriculture. European Review of Agricultural Economics 13: 233-248.
MacRae, E.C. (1977). Estimation of time-varying Markov processes with aggregate data. Econometrica 45: 183-198.

Martin, J.J. (1967). Bayesian Decision Problems and Markov Chains. John Wiley and Sons, Inc., New York.

Melhim, A., O' Donoghue, E.J. and Shumway, C.R. (2009). Do the Largest Firms Grow and Diversify the Fastest? The Case of U.S. Dairies. Review of Agricultural Economics 31: 284-302.

Mittelhammer, R.C., Judge, G.G. and Miller, D.J. (2000): Econometric Foundations. Cambridge University Press, USA.

Padberg, D.I. (1962). The use of Markov processes in measuring changes in market structure. Journal of Farm Economics 44: 189-199.

Piet, L. (2008). The evolution of farm size distribution: revisiting the Markov chain model. Paper presented at the 12th EAAE Congress, August 26-29, Ghent, Belgium.

Pietola, K., Väre, M. and Oude Lansink, A. (2003). Timing and Type of Exit from Farming: Farmer's Early Retirement Programmes in Finland. European Review of Agricultural Economics 30: 99-116.

Pukelsheim, F. (1994). The three sigma rule. The American Statistician 48: 88-91.

Rahelizatovo, N.C. and Gillespie, J.M. (1999). Dairy farm size, entry, and exit in a declining production region. Journal of Agriculture and Applied Economics 31: 333-347.

Shapiro, D., Bollman, R.D. and Ehrensaft, P. (1987). Farm size and growth in Canada. American Journal of Agricultural Economics 69: 477-483.

Shorrocks, A. F. (1978). The measurement of mobility. Econometrica 46: 1013-1024.

Stavins, R. N. and Stanton, B.F. (1980). Using Markov Models to Predict the Size Distribution of Dairy Farms, New York State, 1968-1985. Cornell University, Department of Agricultural Economics, Ithaca, New York.

Stokes, J.R. (2006). Entry, exit, and structural change in Pennsylvania's dairy sector. Agricultural and Resource Economics Review 35: 357-373.

Storm, H. and Heckelei, T. (2011). Bayesian estimation of non-stationary Markov models combining micro and macro data. Working Paper. Institute for Food and Resource Economics, University of Bonn, Germany.

Tonini, A. and Jongeneel, R. (2009). The distribution of dairy farm size in Poland: a Markov approach based on information theory. Applied Economics 41: 55-69.

Von Massow, M., Weersink, A. and Turvey, C.G. (1992). Dynamics of structural change in the Ontario hog industry. Canadian Journal of Agricultural Economics 40: 93-107.

Weiss, C.R. (1999). Farm Growth and Survival: Econometric Evidence for Individual Farms in Upper Austria. American Journal of Agricultural Economics 81: 103-116.

Zepeda, L. (1995a). Asymmetry and nonstationarity in the farm size distribution of Wisconsin milk producers: An Aggregate Analysis. American Journal of Agricultural Economics 77: 837-852.

Zepeda, L. (1995b). Technical change and the structure of production: a non-stationary Markov analysis. European Review of Agricultural Economics 22: 41-60.

Zimmermann, A. and Heckelei, T. (2008): Farm Structural Change in German Regions - An Empirical Analysis Using Micro and Macro Data. Poster presented at the XIIth EAAE Congress, August 26-29, Ghent, Belgium.

Zimmermann, A., Heckelei, T. and Pérez Domínguez, I. (2009). Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants. Environmental Science & Policy 12: 601-618.

3.8 Appendix

Table 3.5: Types in the specialisation dimension with definitions and reference to codes in the Community typology

Specialisation type	EU-Code	Definition
Arable systems	1 + 6	>2/3 of Standard Gross Margin (SGM) from arable or (>1/3 of SGM from arable and/or permanent crops and/or horticulture)
Dairy cattle	4.1	>2/3 of SGM from dairy cattle
Beef and mixed cattle	4.2 + 4.3	>2/3 of SGM from cattle and <2/3 of SGM from dairy cattle
Sheep, goats and mixed grazing livestock	4.4	>2/3 of SGM from grazing live-stock and <2/3 of SGM from cattle
Pigs	5.01	>2/3 of SGM from pigs
Poultry and mixed pigs/poultry	5.02 + 5.03	>2/3 of SGM from pigs and poultry and <2/3 of SGM from pigs
Mixed farms	8	All other farms
Mixed livestock	7	>1/3 and <2/3 of SGM from pigs and poultry and/or >1/3 and <2/3 of SGM from cattle
Permanent crops	3	>2/3 of SGM from permanent crops
Horticulture	2	>2/3 of SGM form horticultural crops

Source: Andersen et al. 2006.

Table 3.6: Shares of farms in the size classes per Member State [per cent]

Country	Year	Small	Medium	Large
UK	1990	18.4	32.7	49.0
	2005	2.3	33.9	63.7
FR	1990	19.3	49.4	31.2
	2005	6.7	28.4	64.9
DE	1990	27.1	46.0	26.9
	2005	0.0	37.1	62.9
IT	1990	79.8	13.7	6.6
	2005	63.6	23.2	13.2
BL	1990	0.0	44.2	55.8
	2005	0.0	23.3	76.7
LU	1990	7.1	44.7	48.2
	2005	11.7	22.2	66.1
NL	1990	0.0	27.6	72.4
	2005	0.0	21.7	78.3
DK	1990	33.6	28.8	37.5
	2005	23.2	27.0	49.7
IR	1990	64.6	25.0	10.4
	2005	64.1	21.5	14.4
EL	1990	90.9	8.6	0.5
	2005	84.6	13.4	1.9
ES	1990	85.2	12.1	2.7
	2005	65.8	21.3	12.9
PT	1990	94.7	3.9	1.4
	2005	81.4	11.3	7.3
AT	1995	45.2	45.3	9.5
	2005	33.7	46.0	20.2
FI	1995	41.0	50.4	8.7
	2005	25.3	41.2	33.6
SE	1995	27.9	36.0	36.1
	2005	31.7	32.1	36.1

Source: Own calculation based on FADN data.

Table 3.7: Shares of farms in the specialisation classes per Member State [per cent]

Country	Year	Arable	Sheep and goats	Permanent crops	Dairy	Beef	Pigs	Poultry	Mixed farms	Mixed livestock	Horticulture
UK	1990	24	23	1	26	11	2	1	9	1	3
	2005	31	18	1	21	14	2	2	8	1	3
FR	1990	27	5	14	21	13	1	0	11	4	3
	2005	29	6	17	16	13	1	1	11	3	3
DE	1990	17	0	7	42	4	1	0	18	8	2
	2005	23	1	7	33	8	3	0	17	5	4
IT	1990	40	3	39	5	2	0	0	6	2	2
	2005	36	4	44	4	3	1	0	4	1	4
BL	1990	11	0	3	31	14	6	1	14	9	10
	2005	15	0	5	19	20	10	0	13	7	11
LU	1990	1	0	11	67	7	0	0	9	4	0
	2005	4	3	12	40	25	1	0	9	4	0
NL	1990	14	2	5	39	5	8	3	4	4	16
	2005	15	11	6	32	3	6	3	5	3	15
DK	1990	48	0	1	21	1	5	0	19	4	2
	2005	58	1	1	14	1	4	1	16	1	2
IR	1990	3	24	0	31	38	0	0	3	0	0
	2005	3	23	0	18	51	0	0	4	0	0
EL	1990	39	7	45	0	1	0	0	5	1	1
	2005	39	7	43	0	1	0	0	5	2	2
ES	1990	34	9	25	14	6	1	1	5	2	3
	2005	24	5	48	3	6	1	1	5	2	5
PT	1990	38	6	21	5	4	1	0	15	8	3
	2005	27	7	34	7	6	1	0	8	5	6
AT	1995	17	1	8	27	22	4	0	13	7	0
	2005	18	2	9	39	13	6	0	9	3	0
FI	1995	22	1	0	53	3	7	0	10	3	0
	2005	43	1	1	33	4	2	0	10	0	4
SE	1995	33	3	0	37	6	1	0	19	0	0
	2005	50	0	0	27	6	2	0	12	1	1

Source: Own calculation based on FADN data.

Part 4
Structural change of European dairy farms – a cross-regional analysis[40]

Abstract: Previous analyses of dairy farm structural change focused on the variation over time in one or a very small number of regions. Here we present an EU15-wide, cross-sectional analysis of the farm number development in different size classes. The purpose is to measure the explanatory relevance and effect of key factors suggested in the theoretical and empirical literature. Apart from the unprecedented scope, the underlying Markov chain analysis also contributes by combining observed transitions in micro data with macro data on farm numbers. Results show widely significant impacts of most considered explanatory variables, but also reveal the complexity of the underlying processes.

Keywords: structural change, dairy farms, Markov chain analysis, cross-sectional, EU15.

4.1 Introduction

Plenty of empirical and theoretical papers exist discussing farm structural change and its causative factors. Whereas initially the 'technological treadmill' model (Cochrane, 1958) in combination with the economies of size concept was seen as the main driver of structural change in agriculture, additional theoretical models were then developed in order to complement the technology and economies of size argument and to better capture the reality of structural change with a persistence of small farms and remaining sectoral heterogeneity (e.g. Hallam, 1991, Boehlje, 1992). Though individual driving forces are often discussed independently from each other (e.g. Goddard et al., 1993, Harrington and Reinsel,

[40] This part is the first round revision of a paper submitted to an international agricultural economics journal as Zimmermann, A. and T. Heckelei: Structural change of European dairy farms – a cross-regional analysis.

1995), in principle two strands of theory can be distinguished apart from the technology model (Boehlje, 1992): the theory of the farm household (Schmitt, 1992) and the concept of path dependency (Balmann, 1995). Rarely, also land immobility as specific characteristic in agriculture is considered (Harrington and Reinsel, 1995). Harrington and Reinsel (1995, p. 12) stress that all these mechanisms are to “be combined into a more comprehensive synthesis capable of capturing more of reality”. According to them (p. 12) the empirical task of researchers is “to determine the relative strengths of each of the mechanisms that may be at work in different commodity, regional or temporal settings”.

Our empirical analysis sets out to measure the explanatory relevance and effect of the above mentioned key factors on dairy farm structural change in the EU15 from 1995 to 2005.

In previous analyses, the structural development of dairy farms has mostly been analysed over time in one specific region (e.g. Stokes, 2006 and Zepeda, 1995a and 1995b), though recent studies found significant differences in structural change especially between regions (Rahelizatovo and Gillespie, 1999, Jongeneel et al., 2005, Huettel and Jongeneel, 2011). Rahelizatovo and Gillespie (1999) estimate a panel data model considering two different regions in Louisiana, USA which are represented by dummy variables. Other dairy farm Markov chain studies derive differences between regions, but do not analyse their potential causes explicitly. Examples are Jongeneel et al. (2005) presenting a combined analysis of structural changes in the dairy sector in four European countries and Huettel and Jongeneel (2011) comparing structural developments in Germany and the Netherlands. We use a panel dataset of 94 regions covering the whole EU15. The cross-sectional approach allows us to incorporate explanatory variables representing regional characteristics which have not been analysed in the literature before.

Defining structural change as the change of the number of farms in different size classes[41], a Markov chain approach is suitable to derive structural development patterns over time and across regions (Zimmermann et al., 2009). We employ a two-step Markov chain estimation in order to derive those patterns and to relate them to the explanatory variables. The first step, the pure Markov chain estimation, is a stochastic approach to assess the change of the number of farms in discrete classes. In the Markov chain formalism, transition probabilities characterising the likelihood of a farm to move from one size class to another are estimated. Markov chain approaches can be divided according to the data type employed to estimate the transition probabilities. One distinguishes between micro and macro data approaches. Micro data describe observed movements of farms across the size classes, macro data comprise information on the number of farms in different

[41] There are many ways to define structural change (e.g. Goddard et al, 1993). Goddard et al. (1993) find that most studies in agriculture focus on the number and size of farms.

size classes over time. Though micro data with direct observations on class transision are generally better suited to derive the transition probabilities, they are rarely available. Therefore, most of the more recent Markov chain studies rely on macro data (e.g. Zepeda 1995a and 1995b, Karantininis, 2002, Stokes, 2006, Tonini and Jongeneel, 2009, Huettel and Jongeneel, 2011).

We use Farm Accountancy Data Network (FADN) data to estimate the transition probabilities. The data comprise observed transitions, i.e. micro data of sample farms. Since the FADN sample is a rotating panel and contains sampling noise the information in the micro data are limited. However, attached to the sample farms are weights derived from bi- to tri-annual censuses (Farm Structure Survey, FSS) which indicate how many structurally similar farms are represented by each FADN sample farm. Weighting the sample farms leads to the number of farms per size class in the farm population. Thus, FADN provides macro data as well, providing additional information to estimate the transition probabilities. Due to the special data base we are able to combine both data types in our Markov chain estimation and thereby increase the precision of the estimates compared to a separate data use. Technically, we estimate an macro data Markov chain using micro data as prior information. We use a generalised cross-entropy framework similar to Karantininis (2002) and Stokes (2006) to estimate non-stationary transition probabilities covering the years 1995 to 2005 for each of the 94 EU15 regions distinguishing four size classes plus an entry/exit class.

In the second estimation step, the transition probabilities are transformed into log-odds ratios and linearly regressed against region-specific and time-dependent variables derived from the theoretical and empirical literature. This two-step procedure is similar to Stavins and Stanton (1980), Rahelizatovo and Gillespie (1999) and Stokes (2006).

Summarizing, our model adds to the existing literature on dairy farm structural change in three ways: (1) We combine micro data on transitions between size classes from the Farm Accountancy Data Network (FADN) with macro data on the total number of farms in different size classes. (2) The structural development of dairy farms is shown for 94 regions of the EU15 going far beyond previous approaches with respect to the cross-sectional scope. (3) For the first time, we analyse the relationship between certain regional (and time-dependent) characteristics and the different structural development patterns.

The paper is structured as follows: Section 4.2 introduces the data and the size classes used for the analysis and gives an overview of the structural developments in the dairy farm sector from 1995 to 2005. Section 4.3 explains the methodological approach and section 4.4 describes the results on the transition probabilities. In section 4.5 hypotheses on factors supposed to affect structural change are formulated. Section 4.6 gives the results regarding the explanatory variables' impact on the transition probabilities and section 4.7 summarises and concludes.

4.2 Structural developments of dairy farms across Europe

This section gives an overview of the structural development of dairy farms in the observation period. Before doing so, the data used throughout the analysis and the applied farm typology are introduced.

Data and size classes

Farm Accountancy Data Network (FADN) data are used throughout the study to determine micro and macro data. FADN comprises data on sample farms in each FADN region and for each combination of size and specialisation classes present in the region. The FADN regions are similar, but not equal to NUTS I and NUTS II regions.[42] The sample farms are surveyed annually and stay in the sample for a varying number of years. To each sample farm an aggregation weight is attached representing the number of similar farms (according to economic size and type of farming) in the FADN region known from a generally tri-annual census (the Farm Structure Survey). The aggregation weights allow recovering the distribution of farms across size and types of farming in the farm population (i.e. the macro data) for every Farm Structure Survey (FSS)[43] year. Macro data in between the FSS years are interpolated.

One could estimate the transition probabilities in the Markov chain approach from the micro data alone. However, the FADN sample farm data are not sufficient for a pure micro data Markov chain approach since they are based on a rotating panel and the sample is rather small compared to the population which entails considerable sampling noise. But more generally, it is simply poor econometrics to not use all available data information. Therefore, we combine the data on the transitions of sample farms between classes (the micro data) from FADN with the number of farms represented by the sample farms (the macro data), the information of which is provided by the Farm Structure Survey.

The selection of the FADN farms adheres to certain threshold levels. The threshold levels vary across countries and give the minimum size of a farm to be considered as a 'commercial' farm. As a result, FADN does not represent all farms in a region, but only farms that exceed this threshold level.

Our analysis considers only farms that are classified as 'specialist milk' (farms in this type of farming acquire more than two thirds of their standard gross margin from dairy cattle). We distinguish four size classes. In order to keep representativeness, size classes are defined according to the ES6 grouping of the

[42] Please note that this is a relatively large scale which has to be kept in mind when analysing the results based on micro-level arguments (due to heterogeneity within regions).
[43] The FSS data themselves are not available in the regional and size class resolution needed for our analysis. They also do not offer information on the movement of farms across size classes (micro data).

FADN data[44]. The FADN size classes are defined in economic terms (European Size Units – ESU). The smallest three size classes of the ES6 grouping are aggregated since they are sparely occupied in EU15 regions. The exact definition and the share of farms in each size class is given in Table 1. We observe EU15 farms at a regional level in the time period 1995 to 2005. An entry/exit class is added to the four size classes. Please note that the entry/exit class also implies farms that are considered 'not commercial', i.e. they are below the size threshold or that come from or change to other specialisations.

Table 4.1: Size class definition

Size class	Definition (ESU)	Share of farms (per cent)
SIZE 1	Country-specific - <16	21.5
SIZE 2	16 - <40	34.4
SIZE 3	40 - <100	33.1
SIZE 4	>= 100	11.0

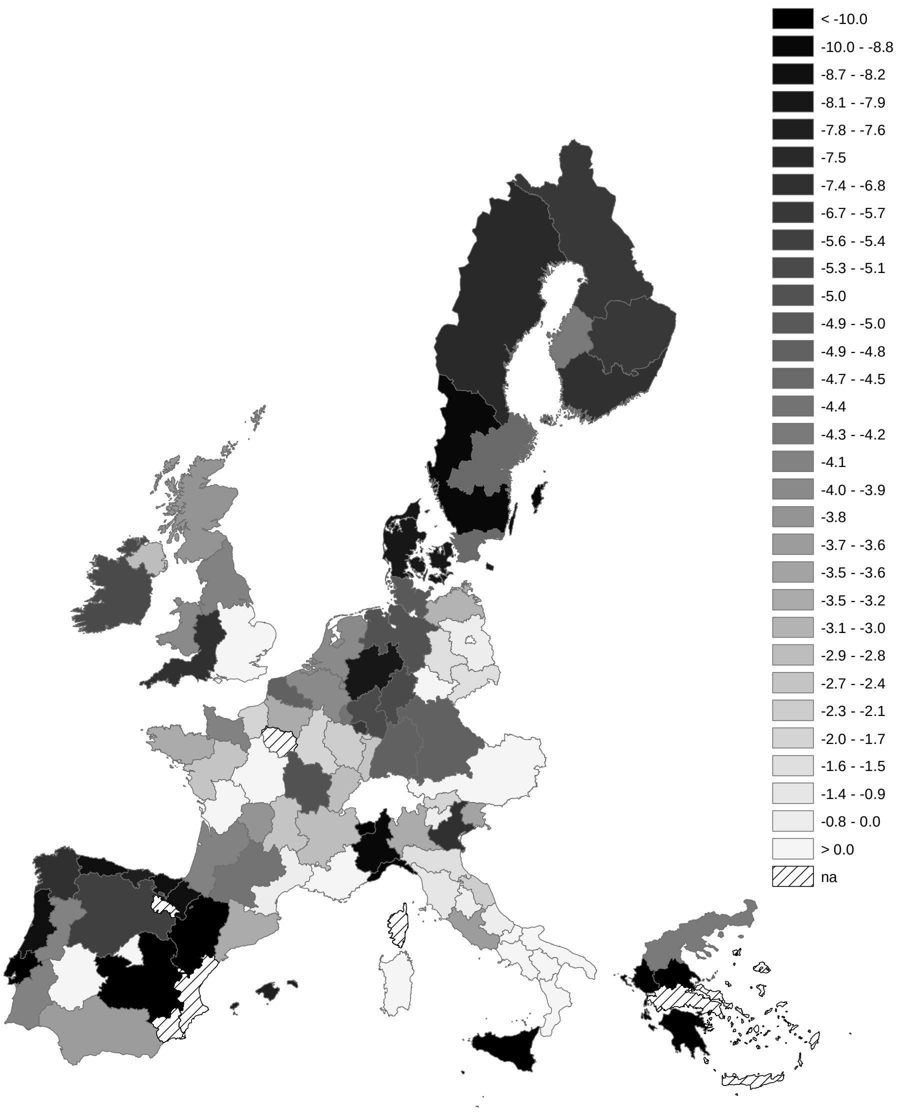
Source: Own table based on FADN data.

Main structural developments

Generally, the number of dairy farms in the EU15 has declined drastically in the observation period. Figure 1 shows the average annual change of dairy farm numbers from 1995 to 2005 in the EU15 FADN regions.

[44] http://ec.europa.eu/agriculture/rica/diffusion_en.cfm.

Figure 4.1: Average annual change rate of dairy farms 1995-2005 [per cent][45]



Source: Own figure based on FADN data.

The average annual rate of change for the EU15 regions is -3.9 per cent. The decline was strongest in Scandinavia, West Germany, and large parts of Spain. Due

[45] For the hatched regions data on dairy farming were not available or not sufficient. They are not considered in the analysis.

to historically large farms the number of farms only slightly decreases in East Germany which is also the main milk producing region in the EU15. Looking at the development of the number of farms in the different size classes we find an average annual farm number decrease of 13.3 per cent in SIZE 1. The standard deviation of the average annual change rate across the regions is 10.5. The number of farms in SIZE 2 decreased by approximately 5.5 per cent with large differences across the regions (the standard deviation is 9.2). On average across the European regions, dairy farm numbers increased in size classes three and four. The larger the size class, the higher the rates of farm number increase. The average annual rates are 4.0 per cent (standard deviation: 10.5) in SIZE 3, and 12.7 per cent in SIZE 4 (standard deviation: 13.4).

4.3 Markov chain approach

Transition probabilities are estimated in order to identify the different regional development paths. Each transition probability represents the likelihood of a farm to move from one size class to another. The transition probabilities are derived in a Markov chain estimation framework. Technically, Markov chains have long been used for the analysis of structural change (a recent literature review is provided by Zimmermann et al., 2009). We are particularly interested in the determinants leading to regionally different structural development patterns. Therefore, the transition probabilities are represented as a function of exogenous variables. In order to estimate these non-stationary transition probabilities various estimation approaches were tested. Particularly, an instrumental variable generalised cross-entropy approach according to Golan and Vogel (2000) and Karantininis (2002) and a simultaneous generalised cross-entropy estimation framework with the transition probabilities being represented as multinomial logit functions of coefficients and explanatory variables have been explored. However, general convergence difficulties due to the regional dimension of the problem eventually led us to use a two-step procedure[46]. In the first step, time-varying transition probabilities are derived which are then regressed against a set of exogenous variables. Similar approaches were applied by Stavins and Stanton (1980) and Stokes (2006).

[46] The disadvantage of the two step approach is that it potentially reduces efficiency as there is no trade-off between first and second step errors. The advantage is that we are able to perform a cross sectional analysis of the dimension offered. Note that high-dimensional non-linear optimisation problems are prone to exhibit convergence problems. We are rather certain that the tested specifications were correct as they recovered know transition probabilities in a test with generated data in the expected.fashion. Moreover, the dimensions of the estimation problems in Golan and Vogel (2000) and Karantininis (2002) were far smaller than in our case.

Transition probabilities (step 1)

The Markov chain literature distinguishes between micro data and macro data estimation approaches. If micro data are available, transition probabilities can easily be derived by dividing the number of movements of farms from one size class to another by the total number of movements from the same size class to all other size classes. However, often micro data are not available and one has to rely on macro data. Several estimation techniques have been developed in order to derive transition probabilities from macro data only. As argued already above, we chose to combine both data types which is done by estimating an macro data Markov chain approach incorporating the micro data as prior information. Apart from Bayesian approaches which are not yet available for Markov chain approaches of this dimension (Storm and Heckelei, 2011), cross-entropy techniques are suitable for the combination of two different data sources (Robilliard and Robinson, 2003) as well as for the solution of ill-posed problems. In the recent farm structural change literature, cross-entropy approaches have often been used to estimate transition probabilities (Karantininis, 2002, Stokes, 2006, Tonini and Jongeneel, 2009). We adapt Karantininis' (2002, p. 278) stationary generalized cross-entropy Markov chain formulation to the estimation of time-varying transition probabilities. In applying a two-step procedure we follow Stokes (2006).

The objective function (4.1) minimises the distance between transition probabilities p_{ijt} and the prior transition probabilities q_{ijt} both indicating the probability to move from size class i to size class j in time t. Simultaneously, the distance between the error weights w_{mjt} and the prior information on the error weights u_{mjt} is minimised.

$$\min\left[\sum_i\sum_j\sum_t p_{ijt}\ln\left(p_{ijt}/q_{ijt}\right)+\sum_m\sum_j\sum_t w_{mjt}\ln\left(w_{mjt}/u_{mjt}\right)\right] \tag{4.1}$$

s.t.

$$y_{jt}=\sum_{i=1} y_{it-1}p_{ij}+\sum_{m=1} v_m w_{mjt} \quad \forall j,t \tag{4.2}$$

The objective function is minimised subject to the Markov constraints (4.2). These constraints relate the share y of farms in each farm size class j at time t to the share of farms in all classes i at time t-1 multiplied by their respective transition probabilities p_{ijt}. The error term is constructed as the product of the support point values v_m and the probabilities w_{mjt} summed over the m support points. Further constraints, non-negativity ($p_{ijt}, w_{mjt} \geq 0$) and summing-up-to-unity ($\sum_j p_{ij}=1$, $\sum_m w_{mjt}=1$), apply to transition probabilities and error weights.

The shares y are derived from the macro data. The prior probabilities q are derived from the micro data, i.e. the movements of the FADN sample farms.[47] Prior probabilities are generally calculated as the number of observed transitions from one size class to another over the number of all transitions in the sample ($q_{ijt}=m_{ijt}/\sum_j m_{ijt}$ with the movement m_{ijt} of a sample farm from size class i to size class j in one time period). Exceptions are the prior probabilities for entry and exit. Both cannot be derived from the micro data due to the rotating panel character of the FADN sample. The prior probabilities on farm entry are set to 1E-10. For the prior probabilities on sector exits the following procedure is followed: an average exit rate is calculated based on the geometric mean between the total number of farms from the macro data in t and in t-1. This exit rate is applied to all size classes and transformed into an exit probability. The prior information on the error weights is uniformly distributed with u=1/m and m=3. In order to reflect different variances of the size class shares, the support bounds are set similar to the three sigma rule of Pukelsheim (1994) (Golan et al., 1996, p. 88, Tonini and Jongeneel, 2009, p. 58). To derive as much information as possible from the macro data, the support bounds are set very narrowly: v is set to $v=[-(1E\text{-}3)\sigma,0,(1E\text{-}3)\sigma]$ with σ being the standard deviation of y.

The time-varying transition probabilities are derived for each of the 94 regions separately. For each year from 1995 to 2005 a separate matrix of transition probabilities is derived (the structure of the transition probability matrix is explained in section 4.4). Depending on the four size classes plus the entry/exit category, each transition probability matrix contains five times five probabilities, which are estimated from five observations in each year. The degrees of freedom DF per region are calculated as: $DF=J\times T-J\times(J-1)\times T$. That means the estimation of each region lacks 150 degrees of freedom (a lack of 15 degrees of freedom per time period).

Regression analysis of the transition probabilities (step 2)

The regional and time-varying transition probabilities obtained in the Markov chain estimation step shall now be explained by a set of explanatory variables. More precisely, the transition probabilities are represented as multinomial logit function of the exogenous variables Z differentiated by time t and region r and the coefficients to be estimated β (MacRae, 1977, Zepeda, 1995b):

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[47] Using a priori information coming from observed transitions of sample farms we go far beyond other Markov chain studies. Karantininis (2002) and Stokes (2006) build upon a matrix of uniform transition probabilities which is further modified either by setting certain off-diagonal elements to zero and increasing the diagonal prior probabilities accordingly (Karantininis, 2002) or by pre-estimating a stationary Markov chain model, the results of which are used as prior information in the non-stationary formulation (Stokes, 2006). Tonini and Jongeneel (2009) derive their a priori information from other Markov chain analyses. Earlier Markov chain studies using frequentist estimation methods restrict the probabilities to certain ranges as well (e.g. Zepeda, 1995b).

$$p_{ijtr} = \frac{\exp\left(Z_{itr}\beta_{ij}\right)}{1+\sum_{k=1}^{s-1}\exp\left(Z_{itr}\beta_{ik}\right)},\ i=1,\ldots,s \quad j=1,\ldots,s-1 \tag{4.3}$$

$$p_{istr} = \frac{1}{1+\sum_{k=1}^{s-1}\exp\left(Z_{itr}\beta_{ik}\right)},\ \text{i=1,…,s} \tag{4.4}$$

The equations are linearised by transforming the transition probabilities into log-odds ratios (Stavins and Stanton, 1980; Greene, 2003). The exit class is taken as reference class *s*.

$$\ln\left(\frac{p_{ijtr}}{p_{istr}}\right) = \mathbf{z}_{itr}\boldsymbol{\beta}_{ij} \tag{4.5}$$

For i=1,2,…,s and j=1,2,…,s-1.

Since the estimated coefficients indicate marginal effects on the log-odds ratios and are difficult to interpret, the direct influence of the exogenous variables on the transition probabilities is evaluated in form of probability elasticities (Zepeda, 1995b; Greene, 2003). The probability elasticities measure the effect of a one per cent change in the *i*th explanatory variable on each transition probability:

$$E_{ijtr}^{p} = \frac{\partial p_{ijtr}}{\partial Z_{itr}}\frac{Z_{itr}}{p_{ijtr}} = \left(\beta_{ij}\,p_{ijtr} - p_{ijtr}\sum_{k=1}^{s-1}p_{iktr}\beta_{ik}\right)\frac{Z_{itr}}{p_{ijtr}} \tag{4.6}$$
$$\text{for } i=1,\ldots,s \quad j=1,\ldots,s-1$$

$$E_{istr}^{p} = \frac{\partial p_{istr}}{\partial Z_{itr}}\frac{Z_{itr}}{p_{istr}} = -\left(p_{istr}\sum_{k=1}^{s-1}p_{iktr}\beta_{ik}\right)\frac{Z_{itr}}{p_{istr}},\quad i=1,\ldots,s \tag{4.7}$$

4.4 Results on the transition probabilities (from step 1)

Transition probability matrix

The estimated transition probabilities can be collected in a transition probability matrix P (J×J):

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1J} \\ p_{21} & p_{22} & \cdots & p_{2J} \\ \vdots & \vdots & \cdots & \vdots \\ p_{I1} & p_{I2} & \cdots & p_{IJ} \end{bmatrix}.$$

Table 4.2 shows the probabilities as averages over time and over region. In addition, their standard deviations separated by time and regional dimension are presented.

Table 4.2: Average transition probabilities and standard deviations across regions and time

	SIZE 1	SIZE 2	SIZE 3	SIZE 4	EXIT
SIZE 1	0.8209	0.0775	0.0088	0.0065	0.0862
Std. dev. region	*0.1317*	*0.075*	*0.0143*	*0.0129*	*0.0766*
Std. dev. time	*0.0474*	*0.0386*	*0.0054*	*0.0051*	*0.0573*
SIZE 2	0.0186	0.8221	0.0764	0.0062	0.0768
Std. dev. region	*0.028*	*0.0723*	*0.0525*	*0.0153*	*0.0525*
Std. dev. time	*0.009*	*0.0314*	*0.0263*	*0.0037*	*0.0364*
SIZE 3	0.0042	0.034	0.8879	0.0248	0.049
Std. dev. region	*0.012*	*0.0441*	*0.0635*	*0.028*	*0.0327*
Std. dev. time	*0.005*	*0.0081*	*0.0286*	*0.0111*	*0.0295*
SIZE 4	0.0048	0.0036	0.0343	0.923	0.0344
Std. dev. region	*0.0143*	*0.0095*	*0.0427*	*0.0664*	*0.0338*
Std. dev. time	*0.0041*	*0.0041*	*0.0141*	*0.0322*	*0.0225*
ENTRY	0.018	0.0267	0.0313	0.0197	0.9043
Std. dev. region	*0.0317*	*0.0334*	*0.0318*	*0.0294*	*0.0875*
Std. dev. time	*0.0174*	*0.0243*	*0.0327*	*0.0215*	*0.0881*

Source: Own calculation based on FADN data.

The probabilities show much more variability across regions than across time. On average the standard deviation across time is only about half as high as the standard deviation across the regions. However, the standard deviation across time is almost as high as the standard deviation across regions concerning entry and exit probabilities. The matrix reveals a typical pattern. The highest values on the diagonal represent the probabilities to remain in the same size class as in the year before. Probabilities adjacent to the diagonal are next in size indicating that transitions to neighbouring size classes are relatively more frequent. Furthermore, all size classes show relevant probabilities to exit. However, they are consistently decreasing with the size class. The entry probabilities for all size classes are comparable to other dairy farm studies in Europe and the USA (Huettel and Jongeneel, 2011, Stokes, 2006). Note, that there are three possibilities of farm entry and exit: total entry/exit to or from outside the agricultural sector, entry/exit of farms below the size threshold, and entry/exit to or from dairy farming from or to other specialisation classes.

4.5 Determinants and hypotheses

Deviating from existing studies, this paper combines time-variant factors considered to impact structural change with region-specific determinants explaining the regional development of dairy farm sizes. According to the literature, the determinants are divided into the sections technology/economies of scale, farm household theory, path dependency, policy, market conditions, and land immobility.[48] Their expected impact is formulated in hypotheses. A descriptive overview of the determinants and the expected signs concerning the impact on respective transition probabilities is given in Table 4.3. The table distinguishes between probabilities to stay in the initial size class (stagnation), probabilities on changes to larger size classes (growth), probabilities on changes to smaller size classes (decline), entry and exit. Additionally to the below described explanatory factors, a constant and a trend variable are considered in the estimation.

[48] Emphasising the complexity of structural change, most of the factors are interdependent of each other and especially the policy and market condition determinants could also be part of one or several of the theoretical concepts (technology/economies of scale, farm household, path dependency, land immobility). However, for the analysis at hand the division into those six categories proved to be most efficient.

Table 4.3: Hypotheses and descriptive analysis of explanatory variables

Theoretical concept	Explanatory variable	Type of variable	Years	Descriptive analysis			Hypotheses				
Theoretical concept	Explanatory variable	Type of variable	Years	Mean	Standard deviation	Source	Stagnation	Growth	Decline	Entry	Exit
Technology / economies of scale	Milk yield (kg/cow)	regional	average 1995-2004	5567.01	1032.13	FADN	-	+	-		
	Gini coefficient of dairy farm size	regional	1995	0.31	0.12	FADN	-	+	+		+
Farm household	Unemployment rate (per cent)	regional	average 1995-2004	8.65	4.48	EUROSTAT[1]	+/-	+/-	-		+/-
	Share of farmers > 62 years (per cent)	regional	1995	7.30	8.23	FADN	-	+	+		+
Path dependency	Initial size (ESU)	regional	1995	40.52	39.68	FADN	+/-	+/-	-		-
	Stocking density (Livestock units/forage ha)	regional	1995	3.00	3.68	FADN	+	+	-		-
Policy	Quota implementation scheme 1 (most liberal)	dummy				Baldock et al. (2008)	-	+	+	-	+
	Quota implementation scheme 2 (rather liberal)	dummy				Baldock et al. (2008)	-	+	+	-	+
Market conditions	Milk price over time (deviation from regional average) (€/kg)	time	1995-2004	0.00	0.02	FADN	+	-	-	+	-
	Average milk price (€/kg)	regional	average 1995-2004	0.33	0.05	FADN	+	-	-	+	-
	Milk price coefficient of variation (€/kg)	regional	average 1995-2004	0.05	0.03	FADN	+/-	-	+	-	+
Land immobility	Share of grassland (per cent)	regional		37.47	20.76	CAPRI database[2]	-	-	+	-	+
	Population density (population/km2)	regional	average 1995-2004	161.28	178.33	EUROSTAT[3]	-		-		-
	Population growth (per cent)	regional	average 1995-2004	0.30	0.49	EUROSTAT[4]	-	-	+	-	+

1 Source of unemployment rate: http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/regional_statistics/data/database, tables reg_lfh3unrt and reg_lfu3rt, downloaded in November 2009.

2 Share of grassland: Britz and Witzke (2008). Original data from the Farm Structure Survey (EUROSTAT: http://epp.eurostat.ec.europa.eu/portal/page/portal/agriculture/legislation).

3 Population density: http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/regional_statistics/data/database, table reg_d3dens, downloaded in November 2009.

4 Population growth: http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/regional_statistics/data/database, table reg_d2jan, downloaded in November 2009.

Technology/economies of scale

Technical change is generally assumed to play a major role in farm structural change and is closely related to the concept of economies of scale (e.g. Cochrane, 1958, Boehlje, 1992, Harrington and Reinsel, 1995). It is widely acknowledged that technical change reduces per unit costs of output by shifting the farm's marginal cost function down and/or to the right and, hence, provides an incentive to adopt the new technology (e.g. Hallam, 1991, Goddard et al., 1993, Harrington and Reinsel, 1995). Technology diffusion leads to increased sector output and falling prices. Farmers unwilling or unable to adopt the new technology are squeezed out of the sector leaving resources to be acquired by the innovating producers (Harrington and Reinsel, 1995). In European dairy farming the main competitive resources are land and milk quota (Huettel and Jongeneel, 2011). Harrington and Reinsel (1995) argue that many technological changes require a certain minimum production size to be profitably adopted such that larger farms are in a better position to innovate. Goddard et al. (1993, p. 479) find that "the presence of increasing returns to size at low or moderate levels, particularly for livestock operations (Hallam, 1991), implies that firms of this size must either leave the industry or grow to a size consistent with minimum long run average cost. Therefore, growth in firm size is a natural consequence of economies of size".

We use the milk yield in order to reflect regional technology differences. In other Markov chain studies on dairy farm structural change, it is often used to represent technical change over time (Zepeda, 1995b). The Gini coefficient as measure of farm size heterogeneity in a region is used to reflect the assumed relationship between growing farms on the one hand and declining/exiting farms on the other. The following hypotheses are developed:

Hypotheses regarding the milk yield

Since distributional effects and initial farm size are controlled for in the analysis and farm size is measured in economic terms, we would expect that a higher milk yield leads to larger farm sizes. Accordingly, we expect a positive relationship between milk yield and changes to larger size classes and a negative effect between milk yield and changes to lower size classes.

Hypotheses regarding farm size heterogeneity

Regional farm size heterogeneity is measured in terms of regional Gini coefficients which are calculated based on the economic size of the farms. The Gini coefficient is bounded between zero and one. The higher the Gini coefficient, the more heterogeneously is farm size distributed in a region. Due to the theoretical mechanism described above, we expect that a higher farm size heterogeneity in a region leads to accelerated structural change compared to regions with a more homogeneous distribution of farm size. Farm size heterogeneity is expected to enhance resource reallocation between farms and thereby generally increase the upward and downward transition probabilities.

Farm household theory

The observation that the technology/economies of scale theory is not able to explain a large part of the reality of farm structural change (e.g. the persistence of small farms) led to a discussion of other factors that might impact the process (Hallam, 1991, Boehlje, 1992, Schmitt, 1992). An often repeated argument is that other than the initially assumed purely economic motives must play a role. Hallam (1991, p. 167), for example, argues that non-financial goals and values of farmers significantly impact structural developments. He supposes that producers who intrinsically value the farming lifestyle will accept lower returns to labor and management and thus make smaller farms with higher economic costs fully compatible with larger low cost farms (Hallam, 1991, p. 167). These ‘cultural’ and/or psychological aspects are sometimes subsumed under the term ‘farm household theory’ (e.g. Schmitt, 1992, Mann, 2003). Apart from the accepted lower returns to labor and management, often off-farm work is seen as a way to continue farming even under difficult economic conditions (e.g. Hallam, 1991, Goddard et al., 1993). Goddard et al. (1993, pp. 481-482), for example, feel that off-farm employment could serve to counter the trend towards fewer and larger farms by (1) reducing the amount of farm income required to meet a certain level of purchasing power, (2) allowing firms to operate at sizes not consistent with minimum cost, and (3) stabilizing total household income enabling smaller farms to better handle input and output price fluctuations.

However, an opposing strand of argumentation is that farming is related to wage levels outside the agricultural sector in the sense that “if wage levels outside of agriculture are on the rise, then farmers may tend to leave the sector until wages equalize” (Hallam, 1991, 9. 167). Harrington and Reinsel (1995) also acknowledge the opportunity of off-farm employment in complementing household income. But contrary to the argument that off-farm employment helps stabilizing the sector, they argue that “farm consolidations and structural change will continue as long as nonfarm opportunities continue to improve” (p. 5). They further specify that a worsening of off-farm employment opportunities can slow down farm consolidation which in a way contradicts the idea that better off-farm employment opportunities would lead to less sector exits.

Another factor often assumed to be related to the pace of farm structural change is the farmers’ age and the successor question. As both are connected to the valuation of the farming lifestyle and off-farm employment opportunities, we discuss them in relation to the farm household theory. Since farms most often close down if the farmer retires (and a successor does not exist), the farmers’ age is one of the most important factors driving structural change (e.g. Weiss, 1999, De Haen and Von Braun, 1977, Pietola et al., 2003, Happe et al., 2004). This effect is for example used in age cohort analyses explaining and predicting farm numbers (e.g. De Haen and Von Braun, 1977) and in agent-based models where the inter generational transition is assumed to take place after a certain number of years and opportunity costs of labour are raised for the next generation (Happe, 2004).

Hypotheses regarding the unemployment rate

Summarizing the arguments described above, better off-farm employment opportunities can be seen as either slowing down structural change due to cross-subsidization of the farming business or as accelerating structural change in the sense of farm number decline and farm growth due to higher opportunity costs.

Since the opportunity for off-farm work cannot be directly observed, we include the unemployment rate as proxy variable. The higher the unemployment rate in a region, the lower is the probability to find off-farm work. Following the first strand of argumentation, a higher unemployment rate would dampen the opportunity to complement household income and accelerate farm structural change by forcing more farms to leave the sector (exit probabilities increase) giving way for growth processes of others (probabilities to change to larger size classes increase). Consistent with this argumentation, the probabilities to change to smaller size classes would decrease. Following the second strand of argumentation, a higher unemployment rate and resulting lower off-farm employment opportunities would hamper structural change by decreasing sector exits and farm size decline which in turn leads to more stagnation and less potential for growth.

Hypotheses regarding the farmers' age

For our analysis, we use the regional share of farmers being older than 62 years in the beginning of the observation period as explanatory variable. We assume that the higher the share of farmers being older than 62 years was, the more likely are declines and exits (of smaller farm sizes) increasing the growth opportunities of remaining farms.

Path dependency

Harrington and Reinsel (1995, p. 5) hypothesize that, "once made, investments tend to become fixed over wide ranges of rates of return between the acquisition costs of expanding capacity and the salvage value of reducing capacity". They speak of 'capital immobility' and follow that neither investment nor disinvestment occurs. Balmann (1995) finds local optima of farm size and assumes that for small farm in local optima the transition to the 'real' optimum entails transition costs. Local optima are stable if the transition costs are sunk costs (Balmann, 1995, Mann, 2003). Consequently, the initial farm size is used as explanatory variable representing path dependency.[49] We further employ the initial stocking density as a measure of intensity. It serves as proxy for investments that have been made into dairy farming.

Hypotheses regarding the initial farm size

According to the path dependency argument, both high as well as low initial farm sizes tend to be stable in the short and medium run. Consequently, unambiguous hypotheses cannot be developed regarding farm size stagnation probabilities. The expected impact of the initial farm size on the probabilities to change to larger size classes is ambiguous as well. On the one hand, larger initial average farm size might be a result of large investments and resulting strong growth processes in a region and this might continue. On the other hand one could argue that in regions with already larger farms and high technology level, pressures and ability for further growth decrease. Consequently, no definite hypothesis on the sign of the impact is stated for farm size growth. We hypothesize that initial farm size is negatively related to farm size decline and sector exit. Due to path dependency, it is rather unlikely that farms which have grown to a certain size again decrease in size or exit the sector altogether. In some cases (for example England), however, also decreasing farm sizes due to multiple succession schemes are reported (Burton and Walford, 2005).

Hypotheses regarding the initial stocking density

A high stocking density is assumed to result from former investments (especially into barn capacity). The higher the stocking density was at the beginning of the observation period, the less probable are farm size decline or exit. Stagnating or even growing farm sizes are instead more likely.

Policy

Though policy impacts on structural change are generally discussed as being ambiguous (Harrington and Reinsel, 1995), Huettel and Jongeneel (2011) find that the literature suggests that the milk quota is more likely to hamper structural change in the dairy farm sector. Differences are, however, expected with regard to the milk quota implementation scheme in the different EU member states (Huettel and Jongeneel, 2011). Generally, it is expected that the more liberal the transfer mechanism, the higher is the pace of structural change.

According to Baldock et al. (2008, p. 38) we divide the member states into four categories thought to represent the different implementation regimes. The report by Baldock et al. (2008) distinguishes between the following key aspects:

[49] Please note that not the initial farm size per farm, but the average initial farm size per region is measured. The mean initial size might have some implications following from aggregation.

quota mobility between regions, market transactions with or without land, and administrative reallocations. In the time period relevant for our analysis, we are able to distinguish three categories of countries: (1) The most liberal system is characterised by quota transfer through market transactions and the transfer of quota between regions is allowed. This system is applied in the United Kingdom, the Netherlands, Sweden, Greece, Denmark, Portugal, Austria and Luxembourg. (2) A rather liberal system is applied in Finland, Italy, Germany, and Spain. In these countries the quota is transferred through the market, but quota mobility between regions is not allowed. (3) The strictest regime does not allow quota transfers between regions and the quota is reallocated by administrative means. This regime is applied in Belgium, Ireland, and France.

Hypotheses regarding the milk quota implementation regime

In the estimation, the most restrictive regime (3) is used as reference and dummies are used representing the most liberal (1) and rather liberal system (2). Compared to the reference scenario, we expect that both the most and the rather liberal system enhance structural change leading to higher probabilities of farm growth, decline and exit. The effects are expected to be stronger for the most liberal system than for the rather liberal system.

Market conditions

In the long run, there exists a strong interdependency between input and output prices and the concepts of technical change and economies of scale. In the medium and short run (and/or if we consider tradable goods in a rather liberal trade environment), prices may be assumed to be more exogenous and to significantly impact structural change (e.g. Goddard et al., 1993). We consider three aspects of the milk price in order to represent market conditions: (1) the milk price development over time, (2) regional price differences, and (3) regional differences in the milk price volatility. In the literature, the milk price is the most frequently used variable to explain structural changes in the dairy sector (e.g. Stavins and Stanton, 1980; Chavas and Magand, 1988; Rahelizatovo and Gillespie, 1999; Stokes, 2006).

Hypotheses regarding milk price development over time

Over time, high milk prices lead to less pressure on the farms which results in generally low probabilities for changes into other size classes and for exits (e.g. Breustedt and Glauben, 2007). However, since farm size is measured in economic terms, high milk prices are expected to lead to farm size growth, i.e. higher probabilities to change to larger size classes. The sector entry could also be positively affected.

Hypotheses regarding different milk price levels across regions

Considerable milk price differences exist between regions. Again, we argue that the farm structure tends to remain rather stable with high milk prices.

Hypotheses regarding milk price volatility

Apart from the general price level also price volatility is expected to impact farm structure development. The higher the milk price volatility, the more risky is dairy farming, and the more likely is it that farms exit the sector. Regarding the transition between size classes one could argue that a higher price volatility and thus uncertainty causes farms to refrain from investments generally leading to fewer changes to other size classes (Stokes, 2006). Farms might also decide to decline in size and seek off-farm employment. Entry should be negatively affected (Goddard et al., 1993, Stokes, 2006).

Land immobility

Following Ricardo and von Thünen, the adaptation of land to different agricultural and non-agricultural uses is determined by soil quality, climate, location with respect to market, infrastructure, etc. (Harrington and Reinsel, 1995). Summarizing the aforementioned factors Harrington and Reinsel (1995) speak of 'land immobility' which is thought to impact farm structural change. Natural resources or market distance measures are usually not part of structural change analyses (with the exception of Zepeda 1995a, who includes the factor 'drought' in her analysis). They play, however, a significant role in the spatial dynamics of dairy production (Mosnier and Wieck, 2010).

We use the share of grassland in a region as proxy for natural resources and the population density and growth as proxies for market distance.

Hypotheses regarding the share of grassland

A high share of grassland indicates less fertile areas. As livestock production is often located in less fertile areas (Mosnier and Wieck, 2010), one could get the idea that the higher the share of grassland in a region, the less likely are farm exits and the more likely are farm size increases due to a higher relative competitiveness of livestock production compared to other production types. Experience, however, shows that the dynamics move into another direction. Especially in regions with a very high grassland share, farms in general and also dairy farms are more likely to disappear and/or decline (for example if farming is continued as tourist attraction or as part-time business). Especially intensification (which is likely to go hand in hand with farm size growth) usually takes place in more fertile areas due to the better access to concentrated feeding stuff. Thus, a negative correlation between the share of grassland and farm growth and entry, and a positive correlation between the share of grassland and farm decline and exit is predicted.

Hypotheses regarding market distance

Generally, farms located close to main transportation axes in plane areas are advantaged compared to farms in remote or mountainous areas (Mosnier and Wieck, 2010, Limao and Venables, 2001). In dairy farming the market distance is especially important regarding the milk collection scheme. According to Mosnier and Wieck (2010) dairy farms tend to be located in populated areas in order to benefit from public infrastructure. Thus, a negative impact of the population density on farm size decline and exit is assumed. However, with increasing population growth, the increased non-agricultural competition on land might lead to a different picture: the larger the population growth rates, the less farm growth and the more farm decline and exits are observed (Foltz, 2004).

4.6 Regression results (from step 2)

A panel data regression is used in order to identify the relationship between transition probabilities and the explanatory variables discussed in section 4.5. Combining the time and the regional dimension leads to a panel of 10 (years)*94 (regions) observations per log-odds ratio. 16 explanatory variables are considered.

A pooled regression model is used to establish the relationship between the log-odds ratios of the transition probabilities and the explanatory variables. A descriptive analysis of the explanatory variables was presented in Table 4.3. The coefficient estimates and their significance for the regression of the log-odds ratios are given in Table 4.4. The probability elasticities (equations (4.6) and (4.7)) are evaluated at the variable means and given in Table 4.5.[50] The majority of the estimates is highly significant. The average R^2 of the regressions is 0.119 with the minimum value being 0.032 and a maximum value of 0.277. In the following, we will restrict interpretations mainly to the probability elasticities as they better reflect the overall impact of the determinants on transition probabilities. Only elasticities based on significant estimates are interpreted.

[50] Since the elasticities are evaluated at their means, consistent results within the regions or the time periods might sometimes lead to strange results after averaging them. Generally, apparently contradictory effects are also found in other Markov chain studies (e.g. Karantininis, 2002).

Table 4.4: Estimated coefficients

Category of transition probability	Log-odds ratio	Constant	Trend	Milk yield	Gini coefficient	Unemployment rate	Age	Initial size	Stocking density	Quota dummy 1 (most liberal)	Quota dummy 2 (rather liberal)	Milk price over time	Milk price across regions	Milk price coefficient of variation	Share of grasslanc	Population densit	Population growt	R2
Own size	p11 /p1e	13.187 ***	0.360 ***	-0.002 ***	-21.321 ***	0.083	-0.063	0.123 ***	0.095	-2.141 *	-3.735 ***	3.816	31.231 ***	-18.731	0.002	0.009 ***	-1.219 *	0.184
	p22 /p2e	4.009	0.012	-0.001 **	2.348	0.336 ***	0.066 *	-0.002	0.139 *	-0.440	-0.167	7.093	21.824 ***	-4.621	-0.034 **	0.001	-0.047	0.067
	p33 /p3e	21.888 ***	-0.334 ***	-0.002 ***	-2.673	0.273 ***	0.102 ***	0.013	0.146 *	-1.682 *	-1.158	24.792 *	8.929	8.355	-0.079 ***	-0.002	0.575	0.120
	p44 /p4e	37.211 ***	-0.601 ***	-0.003 ***	-4.133	0.382 ***	0.022	-0.017 *	0.183 **	0.489	1.967 **	11.042	-21.272 ***	20.927 *	-0.026 *	-0.005 ***	0.441	0.195
Entry	pe1 /pee	-17.565 ***	-0.173 **	-0.001 ***	3.420	0.131 *	0.065 **	-0.020 **	-0.036	1.389 *	2.018 ***	18.426 *	9.563 *	13.515	-0.028 **	-0.003 **	0.376	0.114
	pe2 /pee	-17.528 ***	-0.211 **	-0.001 **	2.104	0.129 *	0.101 ***	0.004	-0.045	-1.342	-0.197	23.596 **	11.428 *	15.991	-0.034 **	-0.004 **	0.648	0.057
	pe3 /pee	-14.779 ***	0.013	-0.001 **	6.399 **	0.125	0.038	0.009	-0.058	-2.725 **	-1.053	22.251 *	2.608	10.916	-0.046 ***	-0.002	0.641	0.044
	pe4 /pee	-23.178 ***	0.253 ***	0.001 *	8.870 ***	0.060	0.024	0.019 **	-0.074	-4.413 ***	-1.696 **	1.709	0.059	7.526	-0.046 ***	-0.001	0.130	0.083
Growth	p12 /1e	0.671	-0.236 **	-0.001 ***	4.768	0.075	-0.079 **	0.009	-0.011	-0.025	1.573 *	20.810	5.936	-25.288 *	0.027 *	0.003	0.674	0.032
	p13 /p1e	-14.238 ***	0.268 ***	0.000	-12.369 ***	0.044	0.000	0.086 ***	0.192 **	-3.811 ***	-1.680 **	1.580	27.913 ***	-10.959	-0.007	0.007 ***	0.173	0.141
	p14 /p1e	-16.299 ***	0.364 ***	0.000	-14.644 ***	0.070	-0.030	0.095 ***	0.127 *	-2.866 ***	-1.476 *	5.859	34.841 ***	-28.341 **	-0.004	0.006 ***	0.969	0.164
	p23 /p2e	-12.772 ***	-0.122	0.001 **	16.045 ***	0.118	-0.015	-0.011	0.025	-5.488 ***	-4.232 ***	43.253 **	19.427 **	-8.143	0.014	-0.005 **	0.893	0.051
	p24 /p2e	-15.996 ***	-0.005	0.000	5.331 *	0.297 ***	0.083 **	0.019 *	0.174 **	-4.494 ***	-2.868 ***	10.579	25.308 ***	0.737	-0.069 ***	-0.002	-0.787	0.101
	p34 /p3e	-17.952 ***	0.092	0.001 **	-0.425	0.102	0.109 **	0.041 ***	0.033	-2.489 **	-3.583 ***	38.350 **	26.818 ***	6.811	-0.040 **	0.000	0.496	0.060
Decline	p21 /p2e	-7.844 *	-0.087	-0.002 ***	12.563 ***	0.279 ***	0.040	-0.054 ***	0.014	3.203 ***	2.929 ***	14.796	15.403 **	8.519	-0.024 *	-0.003	-1.928 **	0.155
	p31 /p3e	-0.942	-0.317 ***	-0.002 ***	-2.207	0.276 ***	0.177 ***	0.007	0.144 *	-1.277	0.544	12.843	9.691	17.858	-0.079 ***	-0.005 ***	1.000	0.175
	p32 /p3e	-7.911 **	0.000	0.000	3.103	0.004	0.060	-0.010	-0.052	0.579	0.704	17.268	19.516 **	-8.941	-0.039 **	-0.008 ***	1.422 *	0.042
	p41 /p4e	10.432 ***	-0.504 ***	-0.003 ***	-0.915	0.381 ***	0.068 **	-0.019 **	0.249 ***	-0.002	2.505 ***	-0.056	-11.900 **	30.322 **	-0.030 **	-0.005 ***	1.205 **	0.277
	p42 /p4e	12.762 ***	-0.501 ***	-0.003 ***	-1.665	0.329 ***	0.068 **	-0.007	0.229 ***	0.149	3.276 ***	-5.690	-16.443 **	22.924 **	-0.034 **	-0.005 ***	0.906	0.255
	p43 /p4e	-0.046	-0.006	-0.001 ***	-1.574	0.120	0.073 **	0.019 **	0.185 **	0.658	1.408 *	-33.130 ***	-3.557	40.485 ***	-0.015	0.001	1.092 *	0.074

Source: Own estimation based on FADN data. Significance levels: ***: 1 per cent, **: 5 per cent, *: 10 per cent.

Table 4.5: Mean transition probability elasticities over time and across regions

Category of transitio probability	Transition probability	Constant	Trend	Milk yield	Gini coefficient	Unemployment rate	Age	Initial size	Stocking density	Quota dummy 1 (most liberal)	Quota dummy 2 (rather liberal)	Milk price over time	Milk price across regions	Milk price coefficint of variation	Share of grassland	Population density	Population growth
Own size	p11	2.5428	0.4144	-1.1748	-1.2391	0.0671	-0.0468	0.5526	0.0050	-0.0685	-0.4902	-0.0058	1.5230	-0.0630	-0.0599	0.1711	-0.1048
	p22	1.9336	0.0735	-1.0929	-0.3446	0.3747	0.0878	0.0372	0.0070	0.0648	0.1084	-0.0042	0.6350	-0.0226	-0.2254	0.0932	-0.0130
	p33	3.1709	-0.2230	-1.4106	-0.1221	0.2337	0.0454	0.0026	0.0055	-0.0296	-0.0490	-0.0024	-0.1205	0.0568	-0.2366	-0.0055	0.0010
	p44	2.7692	-0.2553	-0.8681	-0.0824	0.1786	-0.0117	-0.0674	0.0019	0.0031	0.0410	-0.0084	-0.4656	-0.0062	-0.0428	-0.0592	-0.0046
	pee	1.7015	0.0085	0.2851	-0.1609	-0.1026	-0.0500	-0.0357	0.0017	0.0187	0.0189	0.0011	-0.1924	-0.0668	0.1228	0.0364	-0.0126
Exit	p1e	-10.6440	-1.5663	8.1979	5.3456	-0.6525	0.4124	-4.4269	-0.0259	0.4099	1.5362	-0.0058	-8.6384	0.9234	-0.1338	-1.2877	0.2616
	p2e	-2.0751	0.0064	3.8953	-1.0697	-2.5315	-0.3963	0.1115	-0.0383	0.1632	0.1989	-0.0042	-6.4659	0.2207	1.0617	-0.0570	0.0011
	p3e	-18.7169	1.6144	10.5751	0.7034	-2.1271	-0.6978	-0.5085	-0.0421	0.3462	0.5795	-0.0024	-3.0256	-0.3832	2.7368	0.3716	-0.1719
	p4e	-34.4421	3.0498	15.1791	1.1940	-3.1237	-0.1740	0.6047	-0.0577	-0.1062	-1.0262	-0.0084	6.4556	-1.1084	0.9255	0.7040	-0.1371
Entry	pe1	-15.8633	-0.9451	-5.9809	0.8953	1.0257	0.4254	-0.8284	-0.0101	0.3291	1.1137	0.0011	2.9192	0.6450	-0.9300	-0.4795	0.1005
	pe2	-15.8269	-1.1514	-4.0483	0.4890	1.0113	0.6874	0.1406	-0.0131	-0.2811	-0.0882	0.0011	3.5259	0.7754	-1.1522	-0.5423	0.1824
	pe3	-13.0778	0.0807	-4.3090	1.8155	0.9796	0.2246	0.3421	-0.0171	-0.5899	-0.5525	0.0011	0.6562	0.5081	-1.5972	-0.2830	0.1802
	pe4	-21.4763	1.4012	3.2952	2.5786	0.4152	0.1235	0.7504	-0.0223	-0.9671	-0.9015	0.0011	-0.1733	0.3296	-1.5939	-0.1686	0.0267
Growth	p12	-9.9725	-2.8649	2.2352	6.8183	-0.0015	-0.1643	-4.0503	-0.0293	0.4042	2.3895	-0.0058	-6.7070	-0.4084	0.8850	-0.8529	0.4644
	p13	-24.8816	-0.0901	6.2437	1.5256	-0.2743	0.4133	-0.9527	0.0366	-0.4416	0.6249	-0.0058	0.4435	0.3462	-0.4094	-0.0892	0.3135
	p14	-26.9431	0.4383	5.9948	0.8230	-0.0471	0.1931	-0.5670	0.0155	-0.2305	0.7352	-0.0058	2.6975	-0.5692	-0.2818	-0.2706	0.5531
	p23	-14.8473	-0.6642	8.5769	3.8856	-1.5112	-0.5080	-0.3308	-0.0302	-1.0628	-2.0972	-0.0042	-0.1451	-0.2081	1.5686	-0.9377	0.2696
	p24	-18.0708	-0.0222	1.1702	0.5768	0.0401	0.2106	0.8871	0.0184	-0.8408	-1.3573	-0.0042	1.7686	0.2596	-1.5305	-0.3747	-0.2357
	p34	-36.6688	2.1212	16.0702	0.5721	-1.2436	0.1007	1.1562	-0.0313	-0.2098	-1.3646	-0.0024	5.7002	-0.0245	1.2205	0.3631	-0.0228
Decline	p21	-9.9192	-0.4706	-6.0454	2.8103	-0.1191	-0.1018	-2.0809	-0.0337	0.8788	1.7879	-0.0042	-1.4543	0.6694	0.1448	-0.5142	-0.5787
	p31	-19.6592	-0.1300	-1.9967	0.0217	0.2621	0.5955	-0.2073	0.0048	0.0608	0.8745	-0.0024	0.1275	0.5573	-0.2055	-0.3607	0.1288
	p32	-26.6275	1.6144	9.2733	1.6619	-2.0937	-0.2610	-0.8985	-0.0589	0.4755	0.9617	-0.0024	3.3243	-0.8541	1.2882	-0.9263	0.2556
	p41	-24.0100	0.2769	-1.4395	0.9113	0.1664	0.3219	-0.1645	0.0233	-0.1066	0.3328	-0.0084	2.5838	0.4885	-0.1850	-0.1320	0.2251
	p42	-21.6806	0.2967	-1.6398	0.6798	-0.2824	0.3241	0.3153	0.0167	-0.0729	0.7513	-0.0084	1.1056	0.0989	-0.3319	-0.1352	0.1353
	p43	-34.4885	3.0187	7.7905	0.7080	-2.0819	0.3621	1.3882	0.0025	0.0408	-0.2624	-0.0084	5.2982	1.0238	0.3701	0.8456	0.1912

Source: Own estimation based on FADN data. Negative values are shaded.

Technology/economies of scale

Milk yield

As expected, the milk yield negatively affects the own size probabilities and positively affects the probabilities to change to larger size classes and sector exits. Farm size decline is, as expected, negatively affected with the exception of changes from the largest to the next smaller size class. Overall, the results confirm the presence of technical change and its relationship to economies of scale.

Other Markov chain analyses confirm the observation that higher milk productivity per cow positively affects farm size growth (Stokes, 2006; Rahelizatovo and Gillespie, 1999; Chavas and Magand, 1988). Zepeda (1995b) by contrast found that the milk production per cow had no measurable impact on farm size.

Farm size heterogeneity

The estimated impact of farm size heterogeneity on the transition probabilities is in line with our expectation that higher farm size heterogeneity would accelerate the process of structural change by facilitating resource takeovers of more efficient farms from less efficient farms: The transition probabilities to remain in the same size class are negatively affected, the exit probabilities are positively affected (except the probability to exit from the second smallest size class), and farm growth is positively affected. Regarding farm size decline only one coefficient is significant (the appropriate elasticity is positive).[51] Huettel and Margarian (2009) employ Gini coefficients representing regional farm size heterogeneity at two different points in time explaining Markov chain transition probabilities of West German farms. In line with our results, they report generally higher mobilities with increasing farm size heterogeneity in a region.

Farm household

Unemployment rate

Following ambiguous theoretical reasoning in the literature, our hypotheses regarding the effect of the unemployment rate on farm structural change were not clear-cut. Results show that the regional unemployment rate positively affects the own size transition probabilities – the higher the unemployment rate, the more likely are farms to remain in the same size category as in the period before. In line with this observation, sector exits are negatively affected. The only significant

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[51] Please note that the Gini-coefficient measure has limitations with respect to being able to target farm interdependency in regions within our generally fairly large FADN regions.

estimate regarding farm size growth leads to a positive elasticity between the unemployment rate and probability to change from the second smallest to the largest size class. The impact on changes to smaller size classes is ambiguous, farm entry is positively affected. Summarizing, the effects on the own size probabilities, sector exits and entries would support the second strand of argumentation presented in section 4.5: structural change is dampened by low off-farm employment opportunities which contradicts the assumptions of the farm household theory. The effect on farm size remains unclear. Breustedt and Glauben (2007) find that a high share of part-time farms negatively affects net exit rates in the EU, the unemployment rate is positively correlated with sector exits in their analysis.

Age

Contrary to our assumption, the share of farmers being older than 62 years at the beginning of the observation period positively affects the own size probabilities and negatively affects sector exits. Entry is positively affected. In line with our expectations, farm size decline is positively affected, whereas the effect on farm size growth remains ambiguous. There are two limitations concerning the use of the age variable in our analysis: (1) Apart from the age, also information on a potential successor should be considered since the existence of a successor would likely alter the farmers’ behaviour significantly. This data was however not available. (2) The age data comes from the FADN sample farms and its regional representativeness cannot be confirmed (the FADN weights cannot be applied to establish regional representativeness concerning the farmers' age).

Breustedt and Glauben (2007) employ the share of farm holders aged 44 years or older as explanatory variable in their analysis on exit rates of Western European farms. In line with our results, they report a negative relationship between a higher share of older farms and the exit rates. They explain this finding by the fact that the higher the share of older farmers in a region, the less likely are those to exit farming due to lower opportunity costs. Weiss (1999) finds age to be nonlinearly connected to farm growth and exit for farms in Upper Austria. Contrary to our results and the results of Breustedt and Glauben (2007) he finds that if age exceeds fifty-one years, the probability for sector exit rises. Younger farmers are found to be more likely to increase their farming business than older farmers (Weiss, 1999).

Path dependency

Initial farm size

As expected, the own size probabilities are ambiguously affected by the initial size of farms. The same holds for farm growth: the existence of path dependency is confirmed in the way that with a larger initial farm size, the probability for small farms to change to larger size classes is significantly dampened, whereas larger farms are more likely to grow further. Contrary to our expectations, the probabilities for farm size decline are ambiguously affected as well: Changes from the second smallest and the largest size class to the smallest size class are negatively affected, whereas there is a positive correlation between the initial farm size and a change from the largest to the second largest size class. We also assumed a negative relationship between initial size and sector exits. This is not unambiguously confirmed by the results. Farms in the second smallest and the largest size class seem to be more likely to exit and farms in the smallest and the second largest are less likely to exit with higher initial farm size. Breustedt and Glauben (2007) find in their analysis on the driving forces of exits from farming in Western Europe that a larger initial farm size reduces net exit rates. Weiss (1999) finds a highly significant impact of the initial farm size on farm growth and sector exits. The higher the initial farm size, the lower the exit probabilities. Weiss (1999) finds two turning points regarding the size-growth relationship, but generally suggests that small farms grow faster than larger ones.

Stocking density

Confirming the existence of path dependency, the results support our expectations regarding positive elasticities on own size and growth probabilities and negative effects on sector exits. We expected, however, that farm size decline would be negatively affected by a high stocking density which is not supported by the results.

Policy

We expected that the more liberal quota implementation schemes 1 and 2 would facilitate structural change compared to the reference scenario. This hypothesis is largely confirmed by the elasticities for own-size, exit, entry, and decline. Regarding farm growth, we expected that the more liberal quota regimes would positively affect the probabilities to change to larger size classes. This effect is not confirmed for the most liberal system. The elasticities are mainly negative indicating that farm growth is dampened compared to the most restrictive regime. Comparing the rather liberal with the most restrictive system with regard to farm growth, a mixed effect can be observed. If the quota is transferred through the market, but not tradable across regions farm growth seems to be facilitated for small farms, but it is hampered for medium-sized and large farms. Another expectation was that structural change would be the more enhanced the more liberal the quota implementation scheme is designed. This effect is not confirmed comparing the elasticities between the most and the rather liberal system. Summarising, the results indicate that quota regimes allowing for the quota reallocation through market transactions support structural change in form of limiting farm numbers and enhancing farm size decline. Farm growth, however, seems to be better facilitated through administrative quota allocation. Compared to the difference between administrative or market transfer of the milk quota, there are only small differences between quota only tradable within regions and those also tradable across regions in a country.

Market conditions

Milk price over time

We expected that the milk price over time would be positively correlated with farm size growth. However, changes to larger size classes are negatively affected. In line with our expectation farm size decline is negatively affected as well. Our hypotheses are further supported by negative exit and positive entry elasticities. High milk prices over time seem to generally slow down structural change in the dairy sector. If the price pressure is low, there is no reason for rather inefficient farms to leave the sector such that more efficient farms are unable to acquire additional resources (mainly land and quota, Huettel and Jongeneel, 2011).

Breustedt and Glauben (2007) and Stokes (2006) support our finding by reporting a negative relationship between output prices and exit rates. A positive effect on entry probabilities is also confirmed by Stokes (2006) for dairy farms in Pennsylvania. Stokes (2006) finds a positive effect of the milk price on upward and a negative effect on downward probabilities.

Milk price across regions

The elasticities concerning the impact of the average milk price across regions confirm our hypotheses with regard to positive entry and mostly negative exit signs. The impact on the own size probabilities, on farm growth and decline is mixed, though there is a strong tendency for a positive effect on growth and decline which is contrary to the development over time. This effect might be the result of concentration processes in regions with high milk prices.

Milk price volatility

The results show that farm size growth is negatively affected by a higher milk price volatility supporting the assumption that higher uncertainty causes farms to refrain from investments. As expected, farm size decline is positively affected. Contrary to our expectations, the impact on sector exits is mixed and sector entries are positively affected. This could be influenced by other (input) prices, information on which was not available for our analysis.

Stokes (2006) states a positive relationship between the milk price volatility and exits from all size classes. Stokes (2006) confirms negative effects on the growth probabilities. Where significant, entry and decline probabilities are negatively affected in his analysis.

Land immobility

Share of grassland

Supporting our hypotheses, the own size probabilities are negatively affected by a higher grassland share, exit is mostly positively, and entry is negatively affected. Our expectations are not confirmed regarding farm size growth and decline. In both cases, the observed effect is ambiguous, potentially indicating that with an increasing share of grassland the reduction of competitiveness compared to other regions is partially compensated by the increase of competitiveness between different specialisations within the region. Wieck and Heckelei (2007) find that a higher grassland share is associated with higher marginal costs.

Population density

The effect of the population density on own size probabilities is ambiguous, small farms tend to stay in their size class, whereas the probability for large farms to remain in their size class decreases with increasing population density. In line with our expectations, farm size decline and entry are negatively affected. The effect on exits is mixed. Breustedt and Glauben (2007) describe a positive relationship between the population density and exit rates.

Population growth

The estimates concerning the own size probabilities are almost not affected by the population growth variable. The estimates concerning farm growth and sector entry are not significant at all. The expected positive relationship between population growth and farm size decline is confirmed for larger farms, but it does not hold for farms coming from the second smallest size class. The effect on exits is mixed: small farms are more likely to exit, larger farms are less likely to exit with increasing population growth. Foltz (2004) found a negative impact of the population change on the probability of staying in business and the probability of growing in size.

4.7 Conclusions

The theory discusses several concepts related to farm structural change which imply partly contradictory and/or ambiguous impacts of determinants on regional farm size distributions. The most prominent ones are the technology/economies of scale concept, the farm household theory and path dependency. Additionally, market conditions, policies, and land immobility are relevant for structural change. The paper tries to measure the explanatory relevance and to differentiate the effect of factors representing those theories and concepts for explaining regional differences in dairy farm size structural change across the EU15 from 1995 to 2005.

To derive the regional development patterns, non-stationary transition probabilities are calculated region-wise in a generalised cross-entropy Markov chain framework. Afterwards, a panel data regression on the transition probabilities is conducted in order to identify the aforementioned time- and region-dependent drivers of structural change. The contributions to the existing literature on dairy farm structural change are: (1) the combination of micro and macro data in the calculation of the non-stationary transition probabilities, (2) the unprecedented regional scope, and (3) the cross-sectional focus in explaining the transition probabilities.

The analysis of the transition probabilities shows that there is considerable cross-regional variance dominating variation over time. In general, the considered variables significantly affect the log-odds ratios of the transition probabilities in the panel data regression. Elasticities are calculated in order to measure the direct impact of the explanatory variables on the transition probabilities.

Summarising and simplifying the results, the technology/economies of scale concept represented by the milk yield and the Gini coefficient measuring farm size heterogeneity is clearly confirmed by the data, whereas the results regarding our hypotheses in the context of other theoretical concepts are often ambiguous. A higher unemployment rate, for example, hampers structural change because of less off-farm employment opportunities. In the farm household theory it is often assumed that off-farm employment would dampen structural change because farmers are willing to cross-subsidise their business in order to stay in farming. The existence of path dependency is largely confirmed by the results. Regarding policy impacts, more liberal quota transfer mechanisms are found to support structural change in form of limiting farm numbers and enhancing farm size decline, whereas farm growth is facilitated through administrative quota allocation. Following the observation that time variation is lower than regional variation, the estimates regarding the milk price over time are generally less significant. At times of high milk prices, structural change seems to be generally slowed down in the dairy sector. The results regarding regional milk price differences suggest that there exist concentration processes in regions with high milk prices. A high milk price volatility is related to higher uncertainty and causes farms to refrain from investments. Land immobility plays a significant role in farm structural change.

Overall, the analysis confirms the relevance of the broadly propagated key factors of structural change, though the direction of their impact is sometimes ambiguous. This result is however not surprising. The ambiguity appears at least for two reasons: (1) Some determinants such as off-farm employment opportunities already theoretically have ambiguous impacts at farm level; (2) When moving from farm level to the development of farm size distributions in a region, the impact of all determinants is forced to be ambiguous in some sense, simply by the interdependency of farm development due to limited regional resources, the most important of which is agricultural land. The obvious complexity of the underlying adjustment processes at aggregate level leaves plenty of room for further research in this area. Progress on a more unified theory able to explain the *distribution of structural characteristics* in a geographical entity would probably be the biggest step forward. However, methodological and data innovations leading to a continuous representation of observed distributions without the compromise of uniform classes across units of observations or more robust estimation approaches to investigate non-linear relationships between determinants could also contribute to a better understanding of cross sectional differences.

4.8 References

Baldock, D., J. Barley, A. Burrell, D. Colman, K. Hart, P. Pointereau, and P. Silcock (2008): Evaluation of the environmental impact of milk quotas. Final deliverable report, Alliance Environment.

Balmann, A. (1995): Pfadabhängigkeiten in Agrarstrukturentwicklungen. Begriff, Ursachen und Konsequenzen. Berlin: Duncker and Humblot.

Boehlje, M. (1992): Alternative Models of Structural Change in Agriculture and Related Industries, Agribusiness 8 (3), 219-231.

Breustedt, G. and T. Glauben (2007): Driving Forces behind Exiting from Farming in Western Europe. Journal of Agricultural Economics 58 (1), 115-127.

Britz, W. and P. Witzke (Eds.) (2008): CAPRI model documentation 2008: Version 2. Available at: www.capri-model.org.

Burton, R.J.F. and N. Walford (2005): Multiple succession and land divison on family farms in the South East of England: A counterbalance to agricultural concentration? Journal of Rural Studies 21, 335-347.

Chavas, J. P. and G. Magand (1988): A Dynamic Analysis of the Size Distribution of Firms: The Case of the US Dairy Industry, Agribusiness 4 (4), 315-329.

Cochrane, W. (1958): Farm Prices: Myth and Reality. Minneapolis: University of Minnesota Press.

De Haen, H. and J. Von Braun (1977): Mobility of Agricultural Labour and Fluctuating Regional Labour Markets: A Demographic and Economic Analysis with Application to West-Germany, European Review of Agricultural Economics 4 (3), 215-243.

Foltz, J.D. (2004): Entry, Exit, and Farm Size: Assessing an Experiment in Dairy Price Policy, American Journal of Agricultural Economics 86 (3), 594-604.

Goddard, E., A. Weersink, K. Chen and C.G. Turvey (1993): Economics of Structural Change in Agriculture, Canadian Journal of Agricultural Economics 41, 475-86.

Golan, A., G. Judge and D. Miller (1996): Maximum Entropy Econometrics. Chichester: John Wiley and Sons.

Golan, A. and S.J. Vogel (2000): Estimation of non-stationary social accounting matrix coefficients with supply side information, Economic Systems Research 12, 447-471.

Greene, W.H. (2003): Econometric Analysis. New Jersey: Prentice Hall.

Hallam, A. (1991): Economies of Size and Scale in Agriculture: An Interpretative Review of Empirical Measurement, Review of Agricultural Economics 13 (1), 155-172.

Happe (2004): Agricultural policies and farm structures. Agent-based modeling and application to EU-policy reform. Studies on the Agricultural and

Food Sector in Central and Eastern Europe Vol. 30. IAMO, Halle.
Happe, K., A. Balmann and K. Kellermann (2004): The Agricultural Policy Simulator (AgriPoliS) - An Agent-Based Model to study Structural Change in Agriculture (Version 1.0). Discussion Paper No. 71. IAMO, Halle.
Harrington, D.H. and R.D. Reinsel (1995): A Synthesis of Forces Driving Structural Change, Canadian Journal of Agricultural Economics 43, 3-14.
Huettel, S. and R. Jongeneel (2011): How has the EU milk quota affected patterns of herd-size change? European Review of Agricultural Economics, forthcoming.
Huettel, S. and A. Margarian (2009): Structural change in the West German agricultural sector. Agricultural Economics 40, supplement, 759-772.
Jongeneel, R., N. Longworth and S. Huettel (2005): Dairy Farm Size Distribution in East and West: Evolution and Sensitivity to Structural and Policy Variables: Case-Studies of the Netherlands, Germany, Poland, and Hungary. Paper presented at the 107th EAAE Seminar, January 29 – February1, Seville, Spain.
Karantininis, K. (2002): Information-based estimators for the non-stationary transition probability matrix: an application to the Danish pork industry, Journal of Econometrics 107, 275-290.
Limao, N. and A.J. Venables (2001): Infrastructure, geographical disadvantage, transport cost, and trade, The World Bank Economic Review 15 (3), 451-479.
MacRae, E.C. (1977): Estimation of Time-Varying Markov Processes with Aggregate Data, Econometrica 45 (1), 183-198.
Mann, S. (2003): Theorie und Empirie agrarstrukturellen Wandels? Agrarwirtschaft 52 (3), 140-148.
Mosnier, C. and C. Wieck (2010): Determinants of spatial dynamics of dairy production: a review. Discussion Paper 2010:2. Institute for Food and Resource Economics, University of Bonn.
Pietola, K., M. Väre and A. Oude Lansink (2003): Timing and Type of Exit from Farming: Farmer's Early Retirement Programmes in Finland, European Review of Agricultural Economics 30 (1), 99-116.
Pukelsheim, F. (1994): The three sigma rule, The American Statistician 48 (2), 88-91.
Rahelizatovo, N.C. and J.M. Gillespie (1999): Dairy Farm Size, Entry, and Exit in a Declining Production Region, Journal of Agriculture and Applied Economics 31 (2), 333-347.
Robilliard, A.-S. and S. Robinson (2003): Reconciling Household Surveys and National Accounts Data using a Cross Entropy Estimation Method, Review of Income and Wealth 49 (3), 395-406.
Schmitt, G. (1992): Verfügen die Agrarökonomen über eine Theorie des agrarstrukturellen Wandels? Berichte über Landwirtschaft 70, 213-230.

Stavins, R.N. and B.F. Stanton (1980): Using Markov Models to Predict the Size Distribution of Dairy Farms, New York State, 1968-1985. Department of Agricultural Economics, Cornell University.

Stokes, J.R. (2006): Entry, Exit, and Structural Change in Pennsylvania's Dairy Sector, Agricultural and Resource Economics Review 35 (2), 357-373.

Storm, H. and T. Heckelei (2011): Bayesian estimation of non-stationary Markov models combining micro and macro data. Working Paper, Institute for Food and Resource Economics, University of Bonn.

Tonini, A. and R. Jongeneel (2009): The distribution of dairy farm size in Poland: a Markov approach based on information theory, Applied Economics 41 (1), 55-69.

Weiss, C.R. (1999): Farm Growth and Survival: Econometric Evidence for Individual Farms in Upper Austria, American Journal of Agricultural Economics 81, 103-116.

Wieck, C. and T. Heckelei (2007): Determinants, differentiation, and development of short-term marginal costs in dairy production: an empirical analysis for selected regions of the EU, Agricultural Economics 36 (2), 203-220.

Zepeda, L. (1995a): Asymmetry and Nonstationarity in the Farm Size Distribution of Wisconsin Milk Producers: An Aggregate Analysis, American Journal of Agricultural Economics 77 (2), 837-852.

Zepeda, L. (1995b): Technical Change and the Structure of Production: A non-stationary Markov Analysis, European Review of Agricultural Economics 22, 41-60.

Zimmermann, A., T. Heckelei and I. Pérez Domínguez (2009): Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants, Environmental Science & Policy 12 (5), 601-618.