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Ex-ante measurement of redistributive effects of agricultural policy in western Germany

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Related publications:

Parts of this thesis have been presented as *work in progress* at several scientific conferences. Furthermore, one article based on this thesis has been published in a peer-reviewed international journal. Below, a list of these papers is given, together with the respective sections of this thesis they rely on.

Journal article:

1) Deppermann, A., Grethe, H., Offermann, F. (2014), Distributional effects of CAP liberalisation on western German farm incomes – an ex-ante analysis. *European Review of Agricultural Economics*, 41(4), 605-626, doi:10.1093/erae/jbt034.

   Section: 4.1; 5.1.2.1; 5.3.3.

Conference papers:

2) Deppermann. A., Grethe, H., Offermann, F. (2010), Farm Level Effects of EU Policy Liberalization: Simulations Based on an EU-Wide Agricultural Sector Model and a Supply Model of the German Agricultural Sector, Contributed Paper at the 114th EAAE Seminar "Structural Change in Agriculture", Berlin, April 2010. http://purl.umn.edu/61083 (also published in German as: Deppermann, A., Grethe, H., Offermann, F. (2011), Effekte einer EU-Agrarmarktliberalisierung auf Betriebsebene: Simulationen anhand eines europäischen Agrarsektormodells und eines Angebotsmodells für den deutschen Agrarsektor, in: Weingarten, P., Banse, M., Gömann, H., Isermeyer, F., Nieberg, H., Offermann, F., Wendt, H. (eds.), *Möglichkeiten und Grenzen der wissenschaftlichen Politikanalyse*, Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e. V., 46, 371-384.).
   Sections: 3.2.4; 4.2.
3) Deppermann, A., Grethe, H., Offermann, F. (2011), An ex-ante analysis of distributional effects of the CAP on western German farm incomes, Contributed paper at the 122nd EAAE Seminar "Evidence-based Agricultural and Rural Policy Making: Methodological and Empirical Challenges of Policy Evaluation", Ancona, February 2011. (a similar version is published as: Deppermann, A., Grethe, H., Offermann, F. (2011), Distributional effects of the CAP on western German farm incomes and regional farm income disparity, Contributed paper at the XIIIth EAAE Congress "Change and Uncertainty", Zurich, Switzerland, August/September 2011.).
   Section: 5.1.2.1.
4) Deppermann, A., Offermann, F., Grethe H. (2013), Distributional Impacts of Agricultural Policy in West Germany – from the Sectoral Level to the Single Farm, Contributed paper at the 133th EAAE Seminar "Developing integrated and reliable modelling tools for agricultural and environmental policy analysis", Chania, Crete, June 2013.
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Declaration:

Andre Deppermann is the lead author of the above listed publications which evolved under his coordination. Concepts were developed mainly by him and were intensively discussed with his co-authors. Model adaptions and simulations were done by Andre Deppermann, except for all technical adaptions and scenario calculations with the FARMIS model. Frank Offermann carried these out in the above listed publications as well as for all other scenarios presented in this thesis. Furthermore, the ESIM-FARMIS interface and the micro model, which required specific knowledge of the FARMIS model, were developed in collaboration with Frank Offermann. Interpretation of the results and the drafting of texts were done by Andre Deppermann and intensively discussed with the co-authors.

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Abbreviations

ABM	Agent based model
AF	Arable farms
BA	Bayern
BW	Baden-Württemberg
CAP	Common Agricultural Policy
CGE	Computable general equilibrium
DF	Dairy farms
DP	Direct payment
ESIM	European Simulation Model
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
FADN	Farm Accountancy Data Network
FAPRI	Food and Agricultural Policy Research Institute
FARMIS	Farm Modelling Information System
FFI	Family farm income
GAMS	General Algebraic Modeling System
GDP	Gross domestic product
GIS	Geographic information system
GL	Grazing livestock farms
HE	Hessen
MF	Mixed farms
NUTS	Nomenclature des unités territoriales statistiques
NR	Nordrhein-Westfalen
NS	Niedersachsen
OECD	Organisation of Economic Co-operation and Development
PC	Permanent crop farms
PD	Pigout-Dalton transfer principle
PE	Partial equilibrium
PMP	Positive mathematical programming
PP	Pig and poultry farms
PSE	Producer support estimate
RHG	Representative household group
RP	Rheinland-Pfalz
SAM	Social accounting matrix
SH	Schleswig-Holstein
SL	Saarland

Executive summary

In recent decades, agricultural support of the European Common Agricultural Policy (CAP) has increasingly shifted from market price support measures to budgetary payments. This development has made support more visible and has raised public attention to the distribution of support, which in turn increased political awareness of the topic. Fittingly, the European Commission (2012, p. 8f) states in its *Report on the Distribution of Direct Aids to Agricultural Producers for the financial year 2011* that “direct payments have lost their compensatory character over time and have increasingly become a support ensuring a certain farm income stability” and that “the proposals for the CAP after 2013 […] aim to reduce the discrepancies between the levels of payments obtained after full implementation of the current legislation, between farmers, regions and Member States”.

This interest regarding redistributive effects of agricultural policy is also reflected in the scientific literature. Most of the literature in this field, however, is ex-post and static in nature. Despite the undoubted usefulness and importance of ex-post analyses, they are of limited use when it comes to the evaluation of policies that are planned to be implemented in the future. Since the outcomes of future policy reforms cannot be tested in a laboratory counterfactual situations have to be constructed artificially.

Simulation models are tools frequently used for the ex-ante analysis of policy reforms. In other scientific areas, e.g. poverty analysis or tax reform analysis, it is quite common to assess impacts of macroeconomic shocks on income distribution on a national scale by the application of behavioural ex-ante models and referring to the level of individual incomes. The level of aggregation is particularly important in the analysis of redistributive effects since heterogeneity is exactly the parameter under consideration and the first best level of disaggregation for inequality analysis is the individual level. Hence, methods were developed to commonly analyse impacts of macroeconomic shocks on an aggregate and individual level by combining outputs of macro models with individual data; mostly large population or household surveys.

Similar tools for the measurement of impacts of sectoral or macroeconomic policies on the individual farm income level are less frequent for the agricultural sector and, apart from few exceptions, ex-ante studies of redistributive effects of agricultural policy are rare.

Yet, in general, ex-ante policy impact analysis in the agricultural sector has a long tradition. The combination of models to jointly assess effects at different levels of aggregation and taking behavioural effects into account is very common. Most of the model chains, however, take farm groups or average farms into account rather than accounting for effects at the individual farm level. Some attempts have been made to combine macro or sectoral models with micro models, which incorporate the behaviour of individual farms. Such research, however, is often restricted to the analysis of certain types of farms. In general, ex-ante analyses of redistributive effects among individual farms on a supra-regional level in the sense of evaluating a counterfactual distribution of income with regard to a reference distribution of income including an assessment of progressivity or related concepts can hardly be found for the agricultural sector.

Against this background, the main objective of this work is to develop a tool that is able to consistently assess impacts of agricultural policy on individual farm incomes, thereby building on existing modelling approaches and thus, taking behavioural effects into account for the ex-ante analysis of redistributive effects of agricultural policy. Subsequently, different liberalization scenarios are defined and a detailed analysis of redistributive effects is carried out for the western German agricultural sector by the application of methodologies borrowed from the field of tax progressivity analysis. Thereby, several contributions to the understanding of modelling inequality effects are made, methodologically as well as empirically.

The modelling system consists of three layers. At the sectoral and the meso-level two previously developed large scale models are applied. The European Simulation Model (ESIM) is an agricultural sector model with a strong focus on the CAP. It depicts the world agricultural sector – though in different degrees of regional disaggregation – and quantifies effects of agricultural policy at the European and member state level. It is, however, unable to estimate intra-sectoral income changes at the farm level. The Farm Modelling Information System (FARMIS) is a more disaggregate model that depicts the German agricultural sector in great detail. It applies 628 homogenous farm groups and is used in the modelling chain to estimate impacts on the intra-sectoral distribution of income at the meso-level. The two models at the sectoral and meso-level are consistently linked via an iterative solution process. After convergence is achieved between ESIM and FARMIS, the integrated results are further processed in a micro model, estimating impacts at the individual farm level. The micro model has been developed for this study, is static in nature, and relies on the results of the meso-model.

After changes in individual incomes are calculated as a first step by the modelling system for different scenarios, model results are analysed in a second step by the application of a methodology for the measurement of redistributive effects that was originally developed for the analysis of tax reforms. Based on the comparison and decomposition of relative and absolute Gini coefficients, detailed redistributive impacts of changes in agricultural policy are presented. This methodology is applied for the first time in an ex-ante analysis of redistributive effects in the agricultural sector to the best knowledge of the author. For the analysis, scenario results for the year 2020 are evaluated relative to the income distribution of a reference scenario where the CAP is still in place in 2020.

To account for different conceptual impacts of inequality analysis on results, the analysis is carried out at different aggregation levels, for different income classifications, and for income data generated in a static way in comparison to data generated by the modelling system.

It can be stated that inequality effects are robust with regard to the conceptual differences tested for, at least in terms of the direction of inequality changes. All calculated liberalization scenarios lead to decreasing absolute income differences among western German farms in 2020 because high-income farms lose higher absolute amounts of money than small-income farms. Relative to their Baseline incomes, however, low-income farms tend to lose a higher share compared to high-income farms which leads to increasing relative inequality due to liberalization. Only one exemption from this pattern of results exists: if grouped results are disaggregated and total household income is considered instead of family farm income.

With regard to the different policy instruments, it turns out that the abolishment of market price support is more progressive in absolute terms and less regressive in relative terms than the abolishment of direct payments. This is because income reductions caused by the abolishment of market price support is more unequally distributed (a higher share of losses in the upper tail of the distribution and a lower share in the lower tail) than losses caused by the abolishment of direct payments.

Additionally, a decomposition of inequality effects of CAP liberalization by subgroups is carried out in this work. When the Gini coefficient is decomposed, three inequality components can be defined: inequality within subgroups, inequality between subgroup means and a term that arises when distributions of subgroups are overlapping. From the overlapping term the state of segregation of the farm population with regard to subgroups can be derived. Furthermore, a more detailed picture of the underlying processes of inequality changes can be revealed with this methodology.

The analysis is carried out with regard to different grouping criteria. In a first analysis, subgroups refer to farm types while in a second analysis, subgroups refer to the region a farm is located in. Based on this analysis, the importance of the group of dairy farms for inequality effects is discovered.

Even though the defined minimum requirement of a CAP reform (a positive redistributive effect in absolute terms) is fulfilled in all conducted scenarios, it is difficult to give policy recommendations based solely on these analyses since redistributive effects are only one concern of agricultural policy. The developed modelling tool mainly is suited to observe (unintended) distributional effects of CAP reforms, which is not intended to be the sole decision criterion, but rather to complement other policy analyses.

In summary, this work provides an innovative combination and extension of different simulation models, which enables the ex-ante measurement of income changes for individual farms. This information in turn facilitates the measurement of redistributive effects in the agricultural sector taking behavioural effects into account. The new modelling system is able to answer questions which might become more relevant for coming reforms of the CAP. In combination with advanced methodologies for the measurement of redistributive effects and for the decomposition of inequality indices, the tool can provide valuable contributions to the development and design of agricultural policy.

Zusammenfassung

Verschiedene Reformen der letzten Jahrzehnte haben die Ausgestaltung der Gemeinsamen Agrarpolitik (GAP) der Europäischen Union grundlegend verändert. Traditionelle Instrumente der Marktpreisstützung wurden in zunehmendem Maße durch Direktzahlungen an landwirtschaftliche Betriebe ersetzt. Diese Entwicklung führte zu einer erhöhten Transparenz in der politischen Stützung des Agrarsektors und rückte die Frage der Verteilung von Subventionen stärker in den Fokus des öffentlichen Interesses. Die Verteilungsaspekte der europäischen Agrarpolitik fanden daraufhin verstärkt Eingang in den politischen Diskurs und wurden unter anderem von der Europäischen Kommission in ihrem *Bericht zur Verteilung der Direktzahlungen an Landwirte für das Geschäftsjahr 2011* aufgegriffen.

Das gesteigerte Interesse an den Verteilungswirkungen der Agrarpolitik spiegelt sich auch in der wissenschaftlichen Fachliteratur wieder. Der Großteil der wissenschaftlichen Arbeiten zu diesem Thema besteht jedoch aus ex-post Analysen und wurde ohne Einbeziehung von möglichen Verhaltensänderungen einzelner landwirtschaftlicher Betriebe in Reaktion auf agrarpolitische Maßnahmen und ihre Effekte durchgeführt. Trotz des unbestrittenen Nutzens von ex-post Analysen sind diese jedoch nur von eingeschränktem Wert für die Evaluation der Folgen politischer Reformen vor ihrer Umsetzung. Da politische Reformen vorab jedoch nicht in einer neutralen Umgebung getestet werden können, müssen kontrafaktische Situationen durch die Anwendung von Modellen künstlich erzeugt werden.

Für diese Art der Politikfolgenabschätzung wird regelmäßig auf Simulationsmodelle zurückgegriffen. In anderen wissenschaftlichen Bereichen – beispielsweise in der Analyse von Armutseffekten oder in der Analyse von Steuerreformen – ist es gängige Praxis, die Auswirkungen makroökonomischer Veränderungen auf die individuelle Einkommensverteilung eines Landes durch die Anwendung von Simulationsmodellen vorab zu bewerten. Für die Bewertung von Verteilungseffekten ist die Aggregationsstufe des verwendeten empirischen Modells essentiell. Da die Heterogenität der Einkommen bewertet werden soll, ist die First-Best-Aggregationsstufe für die Analyse von Verteilungseffekten der individuelle Einkommensbezieher. Folglich wurden Methoden für die simultane Modellierung von Auswirkungen makroökonomischer Änderungen auf hoch aggregiertem und individuellem Level entwickelt. Für diese Art von Analysen werden häufig Ergebnisse aus Makromodellen mit umfangreichen Haushaltsdatensätzen kombiniert.

Ähnliche Instrumente für die Bemessung von Auswirkungen sektoraler oder makroökonomischer Politiken auf die Höhe individueller Einkommen gibt es weniger oft für die Analyse des Agrarsektors. Von seltenen Ausnahmen abgesehen, sind ex-ante Studien zu den Wirkungen von Agrarpolitik auf die individuelle Einkommensverteilung im Agrarsektor kaum zu finden.

Grundsätzlich gibt es jedoch eine lange Tradition in der Entwicklung von Modellen für die Politikfolgenabschätzung im Agrarsektor. Auch die kombinierte Nutzung von verschiedenen Einzelmodellen für die gemeinsame, konsistente Bewertung von Politikszenarien auf verschiedenen Aggregationsstufen ist üblich. Die meisten Modell-Kombinationen beziehen sich jedoch auf die Auswertung von Betriebsgruppen oder Durchschnittsbetrieben als niedrigste Aggregationsstufe. Es existieren einige Ansätze, die Makromodelle mit Mikromodellen verknüpfen, die ihrerseits Verhaltensanpassungen einzelner Betriebe abbilden. Viele dieser Studien beschränken sich jedoch auf die Abbildung von bestimmten Betriebstypen oder Regionen. Grundsätzlich ist festzuhalten, dass bislang nur sehr wenige überregionale ex-ante Analysen von betriebsindividuellen Verteilungseffekten durchgeführt wurden. Unter einer Analyse von Verteilungseffekten ist dabei eine vergleichende Bewertung verschiedener Einkommensverteilungen unter Zuhilfenahme von Konzepten zur Progressivitätsmessung oder verwandter Konzepte zu verstehen.

Vor diesem Hintergrund ist es Ziel der vorliegenden Arbeit, eine Analysemethode zur simultanen und konsistenten Bewertung von agrarpolitisch induzierten Einkommensverteilungswirkungen auf aggregierter und betriebsindividueller Ebene im Agrarsektor zu entwickeln. Dabei wird auf bereits bestehende Einzelmodelle zur Politikfolgenabschätzung zurückgegriffen. Mit der entwickelten Methode werden verschiedene Liberalisierungsszenarien der europäischen Agrarpolitik ausgewertet. Eine detaillierte Analyse von Auswirkungen auf die betriebsindividuelle Einkommensverteilung wird für den westdeutschen Agrarsektor präsentiert. Dabei werden verschiedene methodische und empirische Beiträge zum Verständnis der ex-ante Modellierung von Verteilungseffekten geleistet.

Das in der vorliegenden Arbeit entwickelte Modellsystem besteht aus drei verschiedenen Stufen. Auf der sektoralen Ebene und dem Meso-Level kommen zwei bereits existierende Modelle zur Politikfolgenabschätzung zum Einsatz. Das „European Simulation Model“ (ESIM) ist ein Agrarsektormodell mit einem starkem Fokus auf die europäische Agrarpolitik. Das Modell wird zur Quantifizierung von agrarpolitisch induzierten Effekten auf europäischer Ebene sowie auf Ebene der Mitgliedstaaten verwendet. Aufgrund seiner hohen Aggregationsebene kann das Modell jedoch nicht zur Bestimmung von intra-sektoralen Einkommensänderungen verwendet werden. Hierzu wird das „Farm Modelling Information System“ (FARMIS) hinzugezogen. Letzteres operiert auf einer niedrigeren Aggregationsstufe und bildet die Produktionsseite des deutschen Agrarsektors in größerem Detail ab. In dem Modell werden 628 homogene Betriebsgruppen verwendet, um intra-sektorale Einkommensänderungen auf dem Meso-Level abzubilden.

Die beiden Modelle werden in einem iterativen Prozess miteinander verlinkt. Nachdem Konvergenz zwischen ESIM und FARMIS erreicht ist, werden die Ergebnisse für die 628 Betriebsgruppen in einem Mikromodell weiter disaggregiert. Das Mikromodell wurde für die vorliegende Studie entwickelt. Es handelt sich um ein statisches Modell, das keine eigenen

Verhaltensänderungen einzelner Betriebe abbildet und eng auf das FARMIS Modell abgestimmt ist.

Die in einem ersten Schritt unter Anwendung des Modellsystems simulierten betriebsindividuellen Einkommensänderungen werden in einem zweiten Schritt analysiert. Zu diesem Zweck wird eine Methode zur Messung von Verteilungseffekten angewendet, die ursprünglich für die Analyse von Steuerreformen entwickelt wurde. Basierend auf einem Vergleich und einer Zerlegung von relativen und absoluten Gini-Koeffizienten können detaillierte Aussagen über die Auswirkungen von agrarpolitischen Reformen auf die Einkommensverteilung im Agrarsektor getroffen werden. Diese Methode wird nach bestem Wissen des Autors zum ersten Mal im Zusammenhang mit einer ex-ante Analyse für den Agrarsektor verwendet. Auswirkungen verschiedener Reformszenarien auf die Einkommensverteilung im Agrarsektor werden für das Jahr 2020 mit Bezug auf die Einkommensverteilung eines Referenzszenarios bewertet, in welchem die GAP nach aktuellem Stand im Jahr 2020 implementiert ist.

Um den Einfluss verschiedener methodischer Ansätze auf die Ergebnisse abzuschätzen, wird die Analyse für verschiedene Aggregationslevel, verschiedene Einkommensklassifizierungen und verschiedene Arten der Berechnung von Einkommensänderungen (statisch versus modellbasiert) durchgeführt.

Bezüglich der Ergebnisse kann konstatiert werden, dass die getesteten konzeptionellen Unterschiede mit einer Ausnahme keinen Einfluss auf die Richtung der Verteilungseffekte haben. Die simulierten Szenarien, die einen Abbau der Agrarpolitik beinhalten, führen zu einer Verringerung von absoluten Einkommensunterschieden zwischen westdeutschen Betrieben im Jahr 2020. Betriebe, die im Referenzszenario ein hohes Einkommen erzielen, verlieren durch eine Liberalisierung absolut gesehen mehr Einkommen, als Betriebe mit geringerem Einkommen in der Referenzsituation. Relativ gesehen verlieren jedoch Betriebe mit geringerem Einkommen einen größeren Anteil ihres Referenzeinkommens in 2020 als Betriebe mit höherem Referenzeinkommen. Dieses führt zu einer Vergrößerung von relativer Ungleichheit, aber zu einer Verringerung von absoluter Ungleichheit. Für die Abschaffung der Marktpreisstützung wird eine stärkere Progressivität in absoluten Werten und eine weniger starke Regressivität in relativen Werten gemessen, als für die Abschaffung von Direktzahlungen.

Zusätzlich werden in der vorliegenden Arbeit die Effekte auf die sektorale Einkommensverteilung in Effekte für einzelne Untergruppen zerlegt. Durch die Zerlegung des Gini-Koeffizienten können drei Ungleichheits-Komponenten unterschieden werden: Ungleichheit in den einzelnen Untergruppen, Ungleichheit zwischen den Durchschnittseinkommen der Untergruppen und eine Komponente für die Überschneidung der Einkommensverteilungen einzelner Untergruppen. Anhand der letzten Komponente kann der Grad der Segregation verschiedener Untergruppen bestimmt werden. Außerdem wird durch die Zerlegung ein detaillierteres Bild der zugrundeliegenden Verteilungsprozesse gezeichnet.

Die Zerlegung in Ungleichheits-Komponenten wird anhand verschiedener Kriterien getestet. Für eine erste Analyse werden Untergruppen nach Betriebstypen und für eine zweite Analyse nach Regionen gebildet. Basierend auf dieser Methode werden beispielsweise starke Einflüsse der Gruppe der Milchviehbetriebe auf die Gesamtverteilung aufgedeckt.

Obwohl die definierte Mindestanforderung an eine GAP-Liberalisierung – ein ausgleichender absoluter Verteilungseffekt – in allen Szenarien erfüllt wird, können Politikempfehlungen auf der Basis der Modellergebnisse nur eingeschränkt hergeleitet werden, da die Verteilungswirkung von Agrarpolitik nur ein Bewertungskriterium unter Vielen ist. Die in der vorliegenden Arbeit entwickelte Methode ist hauptsächlich geeignet zur Quantifizierung von (unbeabsichtigten) Effekten auf die Einkommensverteilung. Ergebnisse sollten allerdings in Kombination mit Kennzahlen verwendet werden, die eine Erreichung weiterer agrarpolitischer Ziele wiederspiegeln.

Zusammenfassend lässt sich sagen, dass die vorliegende Arbeit eine innovative Kombination und Erweiterung verschiedener bestehender Simulationsmodelle präsentiert, die eine ex-ante Messung betriebsindividueller Einkommensänderungen ermöglicht. Die mit dem Modellsystem generierten Ergebnisse wiederum ermöglichen eine Evaluierung von agrarpolitisch induzierten Effekten auf die Einkommensverteilung im Agrarsektor unter der Berücksichtigung von Anpassungseffekten auf betrieblicher Ebene. Auf Grundlage des Modellsystems können Umverteilungsfragen beantwortet werden, deren Bedeutung für zukünftige GAP-Reformen weiter zunehmen dürfte.

1 Introduction[1]

In its early years, the European Common Agricultural Policy (CAP) was designed to foster production and ensure food security, predominantly through high commodity prices, border protection and export subsidies. After serious problems such as overproduction, high administrative costs, and environmental damages were experienced in the 1970s and 80s, fundamental reforms were implemented. Due to a series of reforms, starting with the McSharry reform in 1992, the CAP became more market oriented. Classical market price support measures as intervention prices and export subsidies were gradually reduced and replaced by budgetary payments, so called “direct payments” (DPs). DPs were initially introduced to compensate farmers for declining market price support and were coupled to production. In 2003 it was decided to decouple most of the payments from production since decoupled payments are assumed to be less market distorting than coupled payments (European Commission, 2013).

Moreddu (2011) argues that due to this shift from market price support measures to budgetary payments, agricultural support becomes more visible and consequently, the distribution of support among farmers has gained more public attention. Fittingly, the European Commission (2012, p. 8) states in its annual *Report on the Distribution of Direct Aids to Agricultural Producers* that “direct payments have lost their compensatory character over time and have increasingly become a support ensuring a certain farm income stability” and Schmid et al. (2006, p. 2) argue that the CAP “has evolved from an *allocative* towards a *distributive* policy”. Increasing public interest in the distribution of agricultural support and the question of ‘who gets what’ is reflected by media coverage (e.g. tagesschau.de, 2009) and in the specialized press (e.g. Agra-Europe, 2013, p. 3). Thus, equity issues in the agricultural sector also increasingly become an area of political concern. The European Commission (2012, p. 8f) e.g. claims that “the proposals for the CAP after 2013 […] aim to reduce the discrepancies between the levels of payments obtained after full implementation of the current legislation, between farmers, regions and Member States”. Already in 1998 OECD ministers of agriculture agreed that, among other criteria, measures of agricultural policy should be equitable (OECD, 1998).

Besides growing public and political interest, there are also good economic reasons to analyse the effects of agricultural policy on income distribution in the agricultural sector. Mishra et al. (2009) for instance refer to links between farm income inequality and technology adaption, productivity, sector growth, and further social issues such as family health.

This interest is also reflected in the scientific literature (see Section 5.2). However, most of the literature regarding redistributive effects of agricultural policy is ex-post and static in nature. Several studies focus on the distribution of direct payments (e.g. Keeney, 2000; El

[1] Parts of this section are identical with parts of chapter 1 in Deppermann et al. (2013).

Benni and Finger, 2012). Fewer authors also take effects of market price support into account and aim to assess redistributive effects of the whole system of agricultural support (e.g. Allanson, 2006; 2008; Moreddu, 2011). Furthermore, some attempts are made to evaluate impacts of possible future reforms of EU agricultural policy on individual farm incomes at the national level in an ex-ante way, but without taking any behavioural effects into account (e.g. Severini and Tantari , 2013).

Yet, despite the undoubted usefulness and importance of ex-post analyses, they are of limited use when it comes to the evaluation of "distributional impacts of policies or policy designs that *do not currently exist*, but that *might* exist in the future" (Bourguignon and Ferreira, 2003 p. 123). For such an exercise, counterfactual situations have to be constructed. In the best case, incentive effects of individuals are taken into consideration since they "respond to policy changes by changing their own actions" and thus, "counterfactual[s] must rely on some representation of […] behaviour" (ibidem, p. 124).

Simulation models account for behavioural effects, but the measurement of inequality is highly sensitive to the aggregation of individual data and the traditional approach of applying few representative groups within a simulation model turned out to be inadequate due to unobservable changes in inner-group inequality (Bourguignon et al., 2005; Savard, 2005). The share of total inequality that is accounted for by measuring inequality between groups is expected to increase with the number of subgroups a population is divided into, other factors being equal (Shorrocks and Wan, 2005). Still, as Elbers et al. (2005) empirically find, even a relatively high number of subgroups may coincide with a high within-group inequality component.[2]

In other scientific areas, e.g. poverty analysis or tax reform analysis, it is quite common to assess impacts of macroeconomic shocks on income distributions on a national scale by the application of behavioural ex-ante models and referring to the level of individual incomes. To this end, methods were developed to commonly analyse impacts of macroeconomic shocks on an aggregate and individual level by combining outputs of macro models with individual data; mostly large population or household surveys. Different approaches are extensively reviewed in section 2.3.3 of this study.

Similar tools for the measurement of impacts of sectoral or macroeconomic policies on the individual farm income level are less frequent for the agricultural sector. An example is a tool presented in Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007), which combine a computable general equilibrium (CGE) model with a large-scale farm household survey. However, the link to the micro level is established through identical changes for all farm households in labour allocation, consumption and production and thus heterogeneity mainly is introduced by farm specific differences in initial income sources. Other attempts are made to combine macro or sectoral models with micro models, which incorporate the

[2] However, it shall be mentioned that in their work still a relatively high number of individuals is embedded in an average group.

behaviour of individual farms; however, such research is often restricted to the analysis of specific types of farms. Some model chains, however, do include a high number of individual farms (e.g. Louhichi and Valin, 2012) and might be extendable to represent the whole sector. Furthermore, in principle, the LEI model funnel presented by van Tongeren (2000) and Woltjers et al. (2011) would enable the analysis of macroeconomic impacts on individual farm incomes via the Financial-Economic Simulation model (FES), which is an FADN[3]-based, non-behavioural accounting model on the single farm level. However, the analysis of redistributive effects[4] among individual farms on a supra-regional level has not been conducted so far, to the best knowledge of the author with any of these models. Income effects rather are reported in more aggregated form for specific farm types or regions.

Further tools worth mentioning are models, which depict farms at regional or farm type level, e.g. the CAPRI model (Britz and Witzke, 2012). These kinds of models are suitable to assess income changes at a certain level of disaggregation but not on the single farm level.

Yet, even though ex-ante studies which explicitly aim at the estimation of redistributive effects of agricultural policy are rare, in general, ex-ante policy impact analysis in the agricultural sector has a long tradition. The combination of models to mutually assess effects at different levels of aggregation, taking behavioural effects into account, is very common (see section 2.3.2 for a review of different linking approaches).

Against this background, the main objective of this work is to develop a tool that is able to consistently assess impacts of agricultural policy on individual farm incomes, thereby building up on existing modelling approaches and thus, taking behavioural effects into account for the ex-ante analysis of redistributive effects of agricultural policy. Subsequently, different liberalization scenarios are defined and a detailed analysis of redistributive effects is carried out for the western German agricultural sector by the application of methodologies borrowed from the field of tax progressivity analysis. In doing so, several contributions to the understanding of modelling inequality effects are made, methodologically as well as empirically.

The modelling system consists of three layers. At the sectoral and the meso-level two previously developed large scale models are applied. The European Simulation Model (ESIM, Grethe, 2012) is an agricultural sector model with a strong focus on the CAP. It depicts the world agricultural sector – though in different degrees of disaggregation – and quantifies effects of agricultural policy at the European level. However, it is unable to estimate intra-sectoral income changes at the farm level. The Farm Modelling Information System (FARMIS, Osterburg et al., 2001; Bertelsmeier, 2005; Offermann et al., 2005) is a more disaggregate model that depicts the German agricultural sector in great detail. It applies 628

[3] Farm Accountancy Data Network
[4] The term 'redistributive effects' in this case explicitly refers to the evaluation of a new income distribution with regard to another income distribution and the assessment of progressivity or related concepts. It does not refer to the pure calculation of income changes in different regions or for different farm types, as for example presented in Louhichi and Valin (2012).

homogenous farm groups and is used in the modelling chain to estimate impacts on the intra-sectoral distribution of income at the meso-level. The two models at the sectoral and meso-level are consistently linked via an iterative solution process.

The ESIM model depicts the German agricultural sector through *representative individuals* (Kirman, 1992) for supply and demand, not differentiating between the different actors within the sector. Thus, ESIM is clearly exposed to the critics regarding the representative individuals approach, especially in terms of aggregation biases. Due to its more disaggregated structure, the FARMIS model is able to incorporate individual behaviour in more detail. Particularly, biophysical constraints and individual differences e.g. in terms of factor endowments can be accounted for. Nevertheless, due to the application of farm groups rather than single farms, results also are supposed to be biased by aggregation, however, to a far lesser extent than in ESIM. Thus, due to the consistent combination of the two models the aggregation bias in ESIM probably will be relaxed. The determination of the impact of the joint application of the models on the results is one sub-goal of this study. To this end, differences in the reaction of both stand-alone models to the same price changes will be discussed in chapter 4.2 before mutual results are presented.

After convergence is achieved between ESIM and FARMIS, the mutual results are subsequently further processed in a micro model which estimates impacts at the individual farm level. The micro model has been developed for this study, is static in nature, and relies on the results of the meso-model. Comparability between corporate and family farms cannot be ensured when using family farm income (FFI) as an indicator for income. Thus, due to the dominance of corporate farms in eastern Germany, results regarding the measurement of inequality are presented for western Germany only.

The methodology for the measurement of inequality in this study is traditionally developed and applied in the field of tax analysis. Based on the comparison and decomposition of Gini coefficients, detailed redistributive impacts of changes in agricultural policy are presented. Inter alia, different measures of agricultural policy (DPs vs. market price support) are assessed regarding their redistributive impacts and different concepts of inequality (relative vs. absolute) are applied.

Due to an application of data at different aggregation levels (farm groups vs. individual farms) the magnitude of the aggregation bias regarding inequality parameters due to data grouping is assessed. Furthermore, to assess the relevance of links between market income and agricultural support, a static analysis is conducted and compared to the model based analysis. In addition, analyses for different concepts of income (i.e. family farm income vs. total farm household income) are compared regarding their redistributive outcomes. Results are discussed with reference to existing insights from the scientific literature.

Furthermore, a detailed analysis of inequality effects with regard to farm types and regions is presented. To this end, the overall farm population is subdivided into farm type and regional groups, respectively. Subsequently, the Gini inequality index is decomposed with regard to these groups. Thereby, effects can be distinguished with respect to within-group inequality, between-groups inequality, and an overlapping term. The latter is conceptually closely related to stratification characteristics of the overall farm population and to the best knowledge of the author, the methodology is applied for the first time in agricultural sector impact analysis.

The present study consists of seven chapters. Following this introduction, in *Chapter 2* the theoretical background for this study is provided and relevant literature for the combination of models depicting different levels of aggregation is reviewed. In *Chapter 3* the modelling chain which is established and applied afterwards in this work is described in detail. Scenario descriptions and sectoral results are provided in *Chapter 4*. *Chapter 5* is dedicated to introducing the methodology which is applied for the measurement of inequality and redistribution. Furthermore, literature which is concerned with the distributional effects of agricultural policy in the agricultural sector is reviewed and subsequently, redistributive effects are presented for different liberalization scenarios in western Germany. In *Chapter 6* a subgroup decomposition of inequality effects is presented. In *Chapter 7* the work is summarized and concluded.

2 Heterogeneity and Simulation Model Coupling – Theoretical Considerations and State of the Art

The endeavour of the following lines is to give a meaning to the term ‘simulation model’. Thereafter, potential problems of utilizing aggregated data in simulation models are discussed. One possible way to overcome these problems and to simultaneously assess impacts at the macro and micro level is the combination of different stand-alone models. A subsequent literature review is presented on the coupling of models for the purposes of agricultural sector analysis and the measurement of inequality impacts.

2.1 Simulation modelling

Empirical models are suited for the evaluation of political reforms in complex environments. Models are able to reduce complexity by abstracting to a certain degree from reality and by focusing on the problem area under consideration.

If a policy reform is already implemented, ex-post analyses can generate valuable insights on the outcomes of that reform. However, if information on the possible outcomes of a reform is desired as basis for decision-making before a reform is implemented, ex-ante analysis is required. Since in economics the outcome of policy reforms can hardly be tested in a laboratory, a simulation of the likely outcomes can serve as a substitute to provide the desired information. Thus, conducting ex-ante analyses means answering ‘what if’ questions by generating a counterfactual situation that can be compared to the status quo or to other simulated scenarios. Consequently, to generate a counterfactual situation as realistic as possible, the behaviour of actors under consideration needs to be taken into account and incentive effects should be incorporated (Peichl, 2009; Bourguignon and Ferreira, 2003).

To conclude, simulation models generally are tools for the execution of ex-ante analyses and at best, take behavioural effects into account. However, the latter is not an inevitable condition since certain questions may require information on first-round effects. Furthermore, no model can account for *all* behavioural effects. From this perception, a static model may simply be seen as a variation of a behavioural model that assumes constant behaviour.

The impacts of a policy reform may have various dimensions. In the absence of the ‘world model’ (van Tongeren et al., 2001), specific policy simulation tools exist in various fields of research, are concerned with different problems, and are conducted at different levels of aggregation. To concretize the very broad definition of simulation models given above, in the following, different types of models, which are frequently applied for ex-ante policy evaluations in the agricultural sector, are introduced. Subsequently, micro-simulation models, which are typically applied for the analysis of redistributive effects, are introduced. Only model types which are relevant for the work at hand and those that are closely related are discussed since manifold approaches of simulation models exist and the field is very fragmented. Thus, several other modelling approaches which by definition also are simulation models are not explicitly mentioned in this overview.

One model type, which is, among applications in many other research fields, regularly utilised for economic ex-ante analyses of agricultural policies, is the CGE model. CGE models rely on general equilibrium theory. They depict all sectors and agents (households, firms and government) of an economy and their interrelations, though mostly on a high level of aggregation. The reactions of agents are specified by underlying functional forms and exogenously implemented behavioural parameters. Furthermore, optimizing behaviour of agents is assumed. The objective of the models is to evaluate the impacts of changes in exogenous parameters on endogenous variables, for example on prices and quantities. For this purpose the models are calibrated to a consistent dataset which was observed at one point in time. This procedure ensures that observed data are replicated when the model is solved for the base period. For the generation of counterfactual scenarios, one or more exogenous parameters are changed and the system is forced to find a new equilibrium with newly calculated endogenous variables (Hertel et al., 2007; Peichl, 2009).

Other frequently applied models are partial equilibrium (PE) models. Similar to CGE models, in PE models behaviour is determined by functional forms and behavioural parameters. Also, optimizing behaviour of agents is assumed and the models are calibrated to observed base year data. However, in contrast to general equilibrium models, partial models only depict one sector of the economy. For the agricultural sector of an industrialized country, the underlying assumption is that the sector is so small that no feedback effects exist to other sectors of the economy. Thus, macroeconomic indicators and other variables like the rate of technical progress are introduced exogenously. The advantage of partial equilibrium modes of the agricultural sector is that interrelations between demand and supply of agricultural products can be depicted in greater detail (van Tongeren et al., 2001).

The third model type is well established at the farm level and is based on programming approaches. Models in this category are also partial models since only the agricultural sector is considered. Mostly, only the supply side is modelled or the programming model is combined with a demand component to endogenously account for price effects in agriculture, as well (see e.g. CAPRI, Britz and Witzke, 2012). The basic concept of programming models relies on the depiction of several farm groups which are represented by an objective function that is optimized under several constraints. This approach, in general, allows for a more disaggregated and detailed depiction of agricultural production compared to equilibrium models.

For the analysis of policy induced redistributive effects, micro-simulation models frequently are applied. Micro-simulation models are “microanalytic partial models focusing on one side (usually the household side) of markets” (Peichl, 2009, p. 305) and “allow simulating the effects of a policy on a sample of economic agents […] at the individual level” (Bourguignon and Spadaro, 2006, p. 77). When applied for the analysis of redistributive effects they mostly are based on large population or household surveys. Bourguignon et al. (2008b) differentiate between models with micro accounting and models with behavioural micro simulation. The first group of models are static models and do not allow for the adjustment of consumption or production when prices are changed and thus, only first-round effects are taken into consideration. The latter models take behavioural effects into account to a certain degree and often rely on econometric approaches.

A subcategory of micro-simulation models which frequently is applied in the analysis of the agricultural sector is subsumed under the term ‘agent based models’ (ABM). ABMs aim to model behaviour of individual farms (agents) and their interaction with each other. The ABM approach usually relies on income maximizing behaviour of the agents and builds on mathematical programming techniques. It allows for the integration of detailed economic factors (like e.g. transaction costs) or of non-economic factors that have impacts on individual behaviour (Kremmydas, 2012). Most of the ABMs depicting the agricultural sector are applied on a regional scale, though exemptions are available: The SWISSland model (Mack et al., 2011) e.g. depicts the whole Swiss agricultural sector. However, ABMs have rarely been applied for the analysis of redistributive effects in the agricultural sector, so far.

In general, models operating at a high level of aggregation typically depict the economy in a less detailed manner. However, variables may change their nature at different levels of aggregation, i.e. being exogenous at the individual level but endogenous at the macro level (Laborte et al, 2007). The trade-off between generality and scope on the one side and detailedness on the other can be observed in many modelling exercises (e.g. Gohin and Moschini, 2006). In the following sections, biases that trace back to the aggregation of data are discussed in more detail before the coupling of different stand-alone models is discussed as one possibility to overcome this trade-off.

2.2 Heterogeneity and aggregation

Depending on the type of aggregation, different types of biases may occur. Potential biases of empirical models due to the utilization of aggregated data will be discussed briefly in the next section. Subsequently, the specific problems of data aggregation with regard to the analysis of distributional effects will be presented.

2.2.1 Aggregation biases in simulation modelling

Depending on the type of model and the particular aggregation of the underlying data, different types of errors presumably occur in modelling exercises. One can distinguish between individual aggregation, special aggregation, product or sectoral aggregation, and temporal aggregation of data.

When data over *individuals* are aggregated, the heterogeneity of the base population needs to be taken into account to draw reliable inferences on aggregate reactions on parameter changes e.g. in the political environment of a sector (e.g. Stoker, 1993). Heterogeneity of farms might stem from various sources, such as different returns to scale, environmental constraints, or management abilities, which can be subsumed under the term production technology. Usually, equilibrium models apply behavioural parameters which are econometrically estimated or rely on expert knowledge to determine the intensity of reactions of their implemented agents. Even if these parameters take heterogeneity fully into account, they cannot account for a likely changing composition of individual farms which presumably leads to changing marginal reactions of the aggregate. Furthermore, policies designed to have different impacts on certain types of farms (e.g. the currently discussed capping of direct payments for the post-2013 phase of the Common Agricultural Policy of the EU) can hardly be depicted in models which work with highly aggregated data. Thus, a highly aggregated model might lead to considerably differing results compared to a model operating at a disaggregated level. A similar argument counts for the depiction of bio-physical or environmental constraints which might be binding for some individual farms but not for others.

Spatial aggregation errors are virtually all a special sub-type of individual aggregation errors as individual characteristics related to a regional component are taken into account. Different adjustment reactions might be caused in different regions due to region-specific constraints in production (e.g. environmental requirements) or regionally designed policy measures (e.g. the regional model of direct payments in Europe). Different regions might face different prices (e.g. due to transportation costs). An aggregation over regions excludes this and may therefor lead to biased results.

Other biases might occur in models due to aggregation over different *products* or *sectors*. When combining different products or factors to a common aggregate one implicitly treats them as perfect substitutes, which certainly leads to stronger biases the more heterogeneous the products are.

Narayanan et al. (2010) describe the disadvantages of using sectoral aggregated data for trade policy analysis in CGE models. They argue that product specific tariffs and policies cannot properly be depicted in models with highly commodity-wise aggregated data as many products are not explicitly identified. Further, they find aggregation biases due to “false competition”. This term refers to a situation where “two countries that do not compete in a third market at the disaggregated level (e.g. one exports engine blocks and one auto transmissions), may appear as competitors at an aggregate (auto parts) level” (Narayanan et al., 2010, p. 755).

Data aggregation over *time* has not been widely discussed explicitly in relation with simulation modelling. Nevertheless, it is clearly of interest when dealing with seasonable labour or harvesting periods for example. Furthermore, time and adjustment processes are crucial parameters in the analysis of policy reforms (van Tongeren, 2000) since short run effects may be oppositional to long run effects.

Clearly, in more disaggregated models lower aggregation biases are expected *ceteris paribus*. Building models in a more disaggregate way, however, often comes at the cost of restricting the scope of the area depicted in the model.

Findings on the importance of aggregation biases in empirical work, however, are ambiguous. Shumway and Davis (2001) for example review nine studies[5] focusing either on individual or commodity-wise aggregation and find that the majority report small inferential errors due to aggregation. The authors also found, however, that including distributional information about individuals generally reduces the existing error of aggregation over individuals. Wu and Adams (2002) argue that the prediction accuracy of aggregate models is not necessarily problematic, especially if over-predictions for some individuals are compensated by under-predictions for others. However, other studies like e.g. Charteris and Winchester (2010), Narayanan et al. (2010) or Bektasoglu et al. (2012) find serious problems due to sectoral aggregation and large impacts on simulation results.

2.2.2 Data aggregation and measurement of inequality[6]

In general the measurement of inequality is highly sensitive to the aggregation of data since heterogeneity is exactly the parameter under consideration. The impact of the information loss due to aggregation becomes most obvious in the extreme case when there is only one aggregate group used for simulation (e.g. with the representative individual approach). Without any information on the distribution of a certain variable – let’s assume income – an inequality measurement is impossible.

Consider a population being divided into k mutually exclusive groups and I^{total} representing an additively decomposable[7] income inequality index of the form:

(1) $$I^{total} = I^{within} + I^{between}$$

where I^{within} is a (weighted) sum of income inequality inside the k groups and $I^{between}$ the inequality between subpopulation means (Deutsch and Silber, 1999). In the extreme case of just one representative group, all the desired information would be hidden in I^{within} whereas only $I^{between}$ would be measurable, but without any meaning in this case. Obviously, inequality inside of aggregated groups is not observable and thus, the loss on information generates a downward bias in the measurement of overall inequality by only incorporating grouped income data, even with a higher number of groups.

[5] It shall be mentioned that these studies are concerned with testing for inferential errors due to aggregation, but not explicitly are related to any kind of simulation modelling.

[6] Parts of this section are identical with parts of chapter 1 in Deppermann et al. (2013).

[7] The term ‘additively decomposable’ refers to the property of an inequality index, to be subgroup decomposable into exactly two terms: the between-groups inequality component which is gained by replacing all individual incomes by subgroup means and the within-group component, which is a weighted average of inequality within subgroups. As will be seen later on, the Gini coefficient e.g. is not additively decomposable in this sense (Deutsch and Silber, 1999).

However, since for a long time many official statistics only provided classified income data, some methodologies were developed to deal with the occurring bias and to approximate the real overall inequality. Two approaches can be distinguished which are sometimes commonly applied. One is based on the calculation of upper and lower bounds of the distribution. The lower bound is derived by assuming that all members of a group have the same (average) income – which basically means setting I^{within} to zero – and the upper bound is derived by the calculation of maximum possible inequality inside the single groups. Ogwang (2006) gives a recent survey on existing approaches. Nevertheless, some minimum descriptive information about the single groups is required. In general, knowledge of the income bounds (the minimum and maximum income inside one group) or other adequate information is necessary for the computation of the maximum possible inside group inequality.

A second way to deal with grouped income data is through the application of a functional form that satisfies the properties of a Lorenz curve (Ogwang, 2006). However, at least some observed points of the Lorenz curve are required for a meaningful utilization of this method. These minimum requirements are met in most classified income data, because the groups are non-overlapping and static, but usually not when grouped data are used in policy simulations.[8] Since mostly analysts are interested in (average) income effects of subpopulations defined by diverse attributes other than income (e.g. gender, area, etc.) income bounds of the subgroups are overlapping. Furthermore, bounds can only be observed in the moment of calibration, when the groups are generated on the basis of individual data. After conducting scenario simulations with the model, only average values are observable for groups.

Even if the goal is not the identification of the exact effects on overall inequality but rather the effectiveness of a certain policy (e.g. does inequality decrease at all?), it is not a priori unambiguous that measurement of sole between-groups inequality detects the direction of the change of overall inequality. To identify the change of total inequality $\Delta I^{total} = \Delta I^{within} + \Delta I^{between}$ it has to be ensured, that the change of the unobserved within-component is not overcompensating the change of the between-component. Savard (2005), Bourguignon et al. (2005) and Ahuja et al. (1997) empirically show the importance of within group inequality. It also becomes clear that the occasionally used approach to exogenously define inequality within groups and apply the distribution with a new average income after the simulation is not sufficient to capture unambiguously the effects of overall inequality changes, because there is no reason why income distribution should be unaffected by different scenario assumptions. Nevertheless, for an approximation of the effects on the absolute level of poverty this approach may be judicious (e.g. Pereira da Silva et al., 2003).

Clearly, with an increasing level of disaggregation (i.e. an increasing number of groups) and an increasing homogeneity of the individuals grouped together, an increasing part of the necessary information is expected to shift from the unobservable into the observable part of inequality (Shorrocks and Wan, 2005). A sufficient level of disaggregation, however, is a

[8] Unless subgroups consist of only one individual, of course.

priori not ascertainable. Elbers et al. (2005), for instance, empirically find that even a relatively high number of subgroups may coincide with a high within-group inequality component. Thus, the first, best level of disaggregation for inequality analysis is the individual level.

To avoid the occurrence of all kinds of aggregation biases, more disaggregated and detailed models are required. These kinds of models, on the other hand, often fail to adequately take into account interactions at the macro level. To overcome the trade-off between detailedness and generality, different stand-alone models can be coupled. In the following section, the current state of research on coupling different simulation models is introduced.

2.3 State of the art of model coupling for agricultural sectoral policy impact analysis and the assessment of income redistribution

This chapter starts with a look at the motivation to couple stand-alone models, which is mentioned in the literature. Subsequently, an overview of different attempts of model linkages is given. Due to the manifold usage of simulation models in policy analysis the focus is laid on two specific strands of literature, which are related to the present work and may be understood as a pragmatic way of summarizing relevant literature.

One strand of literature refers to the combination of stand-alone simulation models that focus on the agricultural sector (including side effects for example on the environment or land use effects) and is presented in section 2.3.2. There are only a few attempts which aim at an ex-ante analysis of redistributive effects of agricultural policy and even fewer which apply a modelling chain for that purpose. Nevertheless, some model chains estimate reactions of individual farms on sectoral policy changes. Generally, simulation model based analysis of macroeconomic impacts on income distribution has been done in numerous ways, however, mostly with regard to household income or poverty issues on the consumption side. These studies are surveyed in section 2.3.3.

For the sake of completeness it shall be mentioned that redistributive effects of agricultural policy have been analysed in manifold ways, but the bulk of the studies are ex-post studies. A few ex-ante analyses have been carried out, yet, by the application of static models. The respective literature will be reviewed extensively in section 5.2.

2.3.1 Motivation

Looking into the literature, authors give several reasons why they combine different models. Helming and Banse (2008, p. 371) state that a “chain of models gives results that are more realistic and consistent with the economic behaviour at the different levels of aggregation” and that “linking models also allows to conduct economic analysis which covers various degrees of regional and commodity coverage". For Offermann (2008, p. 361) the "increased coverage" and the "improved consistency of scenarios" are also major advantages of linking models. Britz (2008, p. 363) mentions the "combined analysis of economic and environmental consequences of policy". Helming et al. (2006) and Kuhlman et al. (2006) argue that different models possibly create diverging results for the same variable and that linking different models can counteract this issue, while creating more consistent results with economic behaviour at different aggregation levels. Böhringer and Rutherford (2006, p. 1) recognise that with an increasing level of aggregation "models may also violate fundamental physical restrictions".

Summing up, two main arguments are at the centre of linking models: besides the increased consistency and plausibility of the analyses due to better depiction of behavioural effects at different aggregation levels, the increased number of observable variables to evaluate a policy simultaneously from several different perspectives (e.g. market effects and environmental effects) is mentioned.[9]

Both of these objectives are also central to the present work. Models are coupled to broaden the scope of the analysis and observe effects of policy changes on income distribution, which requires the combined measurement of price effects at an aggregate level and income effects on the individual farm level. Second, the accuracy of supply reactions to policy changes under consideration shall be increased by the combination of different models.

2.3.2 Linking simulation models for policy impact assessment purposes in the agricultural sector

Different simulation models are coupled in different ways by using data from other models or providing data for other models (Britz, 2008). In the literature, coupling attempts are commonly distinguished by their degree of model integration (e.g. Banse and Grethe, 2008b). Britz (2008, p. 363f) divides linking approaches into three classes: 'model chain without calibration', 'one-way calibration' and 'sequential calibration'. In this chapter, his classification is used to give an overview about current attempts of coupling models. The last category, however, is referred to as 'iterative linking' instead of 'sequential calibration'.

Not considered are cases where exogenous variables like population or GDP growth estimates are simply implemented in stand-alone models. This approach is very common and virtually no simulation model would be able to run without such exogenous information. The focus of this review relies on approaches using different models to conjointly answer a specific research question by conjointly calculating a policy scenario and comparing it to a common

[9] This distinction might seem artificial, as in many cases a more detailed depiction increases the number of variables as well as the consistency of the analysis. Nevertheless, the distinction adds valuable theoretical insights to understand, why models are coupled and what kind of advantages and challenges coupling leads to.

reference scenario. This clearly distinguishes relevant model linkages from implicit linkages that utilize results of other models to create a reference scenario itself.

The first category (‘model chain without calibration’) is the oldest way of linking models. For this approach one model is used to generate data, which subsequently is used to shock another model. This approach results in an informal coupling since inconsistencies commonly arise in the conjoint outputs due to differences in underlying data, functional forms and assumptions of the stand-alone models. Nevertheless, so called soft linkages are less vulnerable in terms of model evolution compared to more integrated forms of model coupling since different models usually are run by different persons or institutions (Britz, 2008). Soft linkages often are applied to combine more than two models with each other.

One such modelling system is presented by van Tongeren (2000). In his article he presents the “LEI Modelling Funnel” which consists of models representing five different levels of aggregation, starting with a global CGE model and ending up at the farm process level represented by technical models. In between, models are applied representing the EU, the Netherlands and the farm level. These models are coupled in a top-down manner where results from a higher aggregation level are used as exogenous information in the models at the next aggregation level. The main focus of the model funnel is CAP analysis. Since the informal way of model coupling (without any calibration or iteration) is applied, the funnel is characterized as “loosely coupled”. Van Tongeren (2000) opposes the disadvantage of possible inconsistencies in results to the advantage of preciseness, which can be achieved through personal communication and as a consequence of making underlying assumptions explicit due to the discussion of specific results. An update of the model funnel is presented by Woltjer et al. (2011). However, the main coupling methodology still relies on soft linkages between the models.

In principle, the model funnel would enable the analysis of macroeconomic impacts on individual farm incomes via the Financial-Economic Simulation model (FES; see Woltjers et al., 2011), which is an FADN data based, non-behavioural accounting model on the single farm level. Price and policy changes are exogenously implemented and mapped to the single farms while taking replacement investments into consideration. However, the analysis of redistributive effects among individual farms on a supra-regional level has not been conducted so far, to the best knowledge of the author.

A similar coupling approach is applied by Manegold et al. (1998), Bertelsmeier et al. (2003) and Offermann et al. (2012) which present the “vTI Modeling Funnel” and its precursors. They use different models at different aggregation levels to analyse agricultural policy impacts from the global to the farm group level in Germany. Like van Tongeren (2000) they couple different stand-alone models in an informal way, so that the single models still are independent from each other. Bertelsmeier et al. (2003) state that due to the exchange of information and the coordination of important model assumptions, a mutual monitoring of results is achieved. This approach is also applied in Nowicki et al. (2009) for the common analysis of agricultural policy with a general and a partial equilibrium model. A comparative overview about model funnels is given by Brockmeier and Urban (2008).

Breen et al. (2005) take commodity and input price information from the partial model FAPRI-Ireland and feed them into optimization models of single farms to measure the effect of decoupling of direct payments at the farm level for cattle, tillage and dairy farms in the Irish agricultural sector. Production decisions at the farm level are modelled by linear programming models for each relevant FADN farm relying on the assumption of net margin maximization.

In the second category (one-way calibration) models are coupled in such a way that one model generates results, which in turn are used for the calibration of a second model. This procedure usually is applied in a bottom-up manner and shall ensure that a certain part of the higher aggregated model behaves in the same way like the disaggregated model does.

An example for this category is the work of Britz and Hertel (2011) who combine a partial equilibrium programming supply model of the agricultural sector with a global general equilibrium model to analyse environmental impacts of biofuel policies. Based on sensitivity experiments the highly disaggregated supply model is used to generate a set of compensated own- and cross-price supply elasticities for crop groups to represent aggregate EU supply reactions. The standard production functions in the CGE model are replaced by more flexible functions which then are calibrated so that the generated elasticities are replicated. In this way, supply behaviour of the two different models is ensured to be consistent.

A similar approach is described in Pérez Domínguez et al. (2009). They develop the EXPAMOD meta-model to econometrically parameterize a market model using simulated price reactions of bio-economic farm level models. Supply response of the farm level models is extrapolated depending on prices, farm- and environmental characteristics. Regional supply modules of a market model are then calibrated to these estimates.

Louhichi and Valin (2012) combine a CGE model and a programming model of agricultural supply of the French arable sector to estimate impacts of biofuel policies at the farm level. In the programming model behaviour of all individual arable farms of the French FADN sample is modelled. In a first step, elasticities generated by the farm level model are implemented in the CGE model. Subsequently, price changes are calculated by the CGE model for different scenarios and the farm level model is shocked with the new prices. Income effects are presented on a regional basis. Since only arable farms are modelled, redistributive effects of the whole agricultural sector cannot be estimated.

A less formalized approach is applied by Banse and Grethe (2008b) combining a CGE model with a partial agricultural sector model for the analysis of different CAP liberalization scenarios. In principle their approach is a simple mapping down of results that are endogenously calculated in the CGE model and exogenously implemented in the partial model (very much similar to the “without calibration” approach). However, additionally a detailed comparison of supply response of the two different models for the same scenario is carried out and in case of major deviations the CGE model is recalibrated to reproduce the generally more plausible results of the partial model.

The third category of model coupling (‘iterative linking’) aims at full consistency of the combined models. This is mostly achieved by an iterative procedure where results of one model are mutually used as input in another model. Jansson et al. (2009) use this approach to couple a CGE model with a PE model of the agricultural sector. The purpose of their exercise is to exploit the models specific strengths – a detailed depiction of the agricultural sector in the partial and the representation of the whole economy in the general model – and at the same time avoid conflicting results. The full link of the models is achieved by iteratively running the models. Thereby price changes are calculated by the CGE model and implemented in the PE model and the sectoral response of the PE model is mimicked via shifting the functions in the CGE model until convergence is reached.

Helming et al. (2006) couple a CGE and partial model, where the latter is a mathematical programming model for the Dutch agricultural sector. In an iterative procedure real product price changes and changes of sectoral productivity are generated by the CGE model and used as exogenous inputs in the programming model. Furthermore, the non-linear cost terms of the programming model are calibrated to CGE results. The programming model in turn generates changes of agricultural production which are exogenously implemented in the CGE model. This procedure is continued until convergence among the models is achieved. Kuhlman et al. (2006) apply the same model chain and identify that the strongest differences between model results (in the first iteration) can be observed for products where quantitative policy restrictions are in place. This is due to the fact that the CGE model does not take such bounds into account and tends to overestimate changes in production. A similar procedure for the combination of a CGE with a programming supply model is presented in Böhringer and Rutherford (2005) for the energy sector.

A global aggregate agricultural market model is consistently combined with non-linear regional programming models representing the core of the CAPRI model (Britz and Witzke, 2012). CAPRI itself is a PE model for the agricultural sector aiming at the analysis of agricultural policy changes. The linkage of the market and the supply modules is carried out via a sequential calibration procedure, whereby the market models supply functions are iteratively calibrated to the results of the programming models which in turn are driven by the prices provided by the market models (Britz, 2008). Gocht et al. (2013) use the CAPRI model to calculate effects of different scenarios of direct payment harmonization for regional farm types in Europe. They report income changes on member state and farm type level.

Grant et al. (2007) present another iterative coupling example. However, their partial model is not represented as a quadratic programming problem, but is a mixed-complementary formulation subsector model representing the dairy sector for trade analysis at the tariff line. With price changes generated by the higher aggregated CGE model and aggregate price response in the dairy sector generated by the partial model convergence is achieved “after just a few iterations" according to the authors (Grant et al., 2007, p. 274). Comparing model chain results with stand-alone results of the CGE model, they conclude that aggregate welfare changes are quite robust, but that output response and trade flow reactions to dairy market liberalization tend to be underestimated by their CGE model.

An iterative linkage between a CGE and an integrated assessment model measuring policy impacts on bio-physical processes is presented in papers of van Meijl et al. (2006) and Prins et al. (2011). Here, sectoral production growth rates, land use and productivity changes are provided by the CGE model and implemented in the bio-physical model which in turn delivers yields, land supply and feed efficiency rates to the CGE model. Due to this procedure a harmonization of land use in both models is achieved.

Deppermann et al. (2012) link an energy system model and an agricultural sector model to assess the outcomes of EU greenhouse gas emission mitigation policies. In their stand-alone versions, biomass supply is exogenous to the energy system model and biomass demand for energy production purposes is exogenous to the agricultural sector model. Through an iterative combination of the models, demand and supply of energy crops are endogenized.

An attempt at measuring impacts on the single farm taking market price effects into account is presented in Valdivia et al. (2012). Their approach doesn't exactly fit into one of the categories used before as they basically extend a farm level supply model (the Tradeoff Analysis Model, TOA) by a single demand module, which they refer to as model coupling. The TOA model consists of bio-physical process models and economic decision models representing a statistically representative sample of farms in a specific region. Based on the individual farm results an aggregate regional crop supply curve is estimated. This regional crop supply curve is augmented by a demand module, which enables the model system to also endogenously take price changes at the regional level into account. In a final step the new equilibrium price is implemented in the disaggregated module again. Valdivia et al. demonstrate their approach with a case study for the Kenyan region Machakos. The modelling system enables an ex-ante analysis of outcomes of policy reforms in terms of poverty or inequality based on single farms in the agricultural sector. However, the analysis is restricted to a regional scale, where the occurrence of price changes is assumed because of poorly integrated markets, and to the depiction of a few crops only.

Another approach for the consistent assessment of impacts at the sectoral and individual farm level is presented by Helming and Schrijver (2008). In their work they combine a partial equilibrium model for the European agricultural sector with a programming model for the Dutch agricultural sector and a bio-economic model for individual dairy farms. The two aggregate models are treated as a one-model system and are iteratively linked to the bio-economic dairy farm model. Prices of agricultural commodities and factors are calculated at the more aggregate level and passed to the bio-economic model, which in turn delivers area specific results on yield changes, animal density and unit costs per type of dairy cow to the more aggregate models.

2.3.3 Linking simulation models for policy impact assessment purposes on poverty and income distribution

Tools for the ex-ante analysis of redistributive impacts of macroeconomic or sectoral policies in the agricultural sector taking effects at the single farm level into account are rarely presented in the literature. Even though some approaches exist which account for impacts at the individual farm level, most of them only depict a share of farms like e.g. dairy farms (Helming and Schrijver, 2008) or arable farms (Louhichi and Valin, 2012). Only a few tools with a sector-wide coverage of individual farms are presented and seldom applied for the analysis of redistributive effects in the agricultural sector. Noticeable exemptions can be found in Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007) which all apply the same model chain in their studies (see below). Many more studies are concerned with impacts of macroeconomic shocks on poverty and income distribution among the overall population.

The measurement of inequality effects based on the traditional approach by the application of a few representative household groups (RHG) within a macro model turned out to be inadequate due to the unobservable changes in inner-group inequality (Savard, 2005; Bourguignon et al., 2005, see also section 2.2.2). Thus, methods were developed to commonly assess impacts of macroeconomic shocks on an aggregate and individual level by combining outputs of macro models with individual data, mostly large population or household surveys. In general, any kind of macro model can be applied for this kind of analyses. However, in most of the cases macro models are of the CGE type (Bourguignon et al., 2010).

Apart from the traditional RHG approach, one can distinguish three different approaches of macro-micro-economic modelling for the analysis of distributional effects (based on Mussard and Savard, 2010)[10]: the top-down approach, the iterative approach and the integrated approach. Similar to the approaches of model coupling for policy impact analysis in the agricultural sector, approaches are distinguished by their degree of model integration. Nevertheless, categories are differently defined since other, more integrated approaches exist in the literature of ex-ante modelling of distributional effects.

Following the *top-down approach* macroeconomic shocks are implemented in the macro model and solution variables are used as external inputs at the individual micro-level. This procedure implies that no feedback effects are accounted for in this kind of analysis. Bourguignon et al. (2008b) further differentiate the top-down approach into two sub-branches: the top-down approach with micro accounting and the top-down approach with behavioural micro simulations. In the former individuals do not adjust their consumption or production (quantities) to changing prices, which means that only first-round effects are taken

[10] For other possible classifications see e.g. Bourguignon et al. (2008a) or Agénor et al. (2004).

into account. The latter approach involves a microeconomic model that additionally accounts for behavioural responses.

Depending on the richness of information available in the applied survey data, the micro accounting procedure might vary in specificity. For the simplest alternative, individual data on total consumption or total income are required and the relative consumption or income changes provided by the macro model for the respective representative household group are used to scale all incomes of corresponding individuals (or households). This simple procedure, however, still does not account for any heterogeneity inside the groups. If the survey contains more disaggregated data on income composition (factor types or transfer sources) or even commodity specific information on individual consumption, this information can be used to account for more heterogeneity. The respective macro model results can be matched to different types of factors or transfers and individual real incomes can be adjusted by the calculation of an cost-of-living index for each individual (Lofgren et al., 2003).

According to Bourguignon et al. (2008b) the advantage of the micro accounting method is the straightforward implementation giving consideration to the largest impacts of the macroeconomic shock on individuals. They conclude that first round effects approximate total welfare effects accurately in the short to medium run and if price changes are small and markets competitive.

Such a micro accounting approach is chosen by Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007) to assess distributional impacts of WTO reforms or changes in agricultural policy in the U.S. agricultural sector. To this end, in their papers they apply a CGE model (GTAP) which is refined to distinguish between market clearing wages and capital rents for agriculture and non-agriculture. The model implies one representative household for each region. After the CGE model is shocked results are combined with a large-scale farm household survey to estimate welfare changes of individual farm households.

Keeney and Beckman (2009) assume that individual households in the U.S. behave in accordance with the representative household that depicts the U.S. in the CGE model. Labour allocation (on- versus off-farm), production and consumption response as well as price changes are identical for all households. Thus, heterogeneity is introduced by farm specific differences in initial income sources. Income changes are deflated by a consumer price index and first-round approximations of welfare changes are calculated for each household. Distributional effects are identified on the basis of decile groups.

Keeney (2009) and Hertel et al. (2007) apply the same CGE model and farm household survey, however, only superficially explain how they link CGE results to disaggregated farm households. Keeney (2009, p. 1290) draws on ”factor markets linking the macro- and micro-components of a policy simulation” and Hertel et al. (2007, p. 300) refer to “the general equilibrium changes in product and factor prices are combined with disaggregated household data to evaluate the welfare impact on different groups of farm households”. To the best knowledge of the author, these three studies are the only ones which are explicitly aimed at an ex-ante measurement of distributional effects in the agricultural sector. The following studies refer to impact assessments of macroeconomic shocks on poverty and income distribution among the overall population.

Ravallion and Lokshin (2008) also apply the top down approach with micro accounting to assess welfare impacts of different trade policy reforms for cereals in Morocco. For their analysis they commonly use a CGE model and a household sample consisting of 5,117 single households. The CGE model is applied in a first step to simulate price changes for different trade policy scenarios. In a second step, these price changes are used to calculate welfare gains for individual households in monetary terms. As prices and wages are not included in the household survey data, price changes are weighted by their corresponding expenditure and revenue shares (including earnings and household production activities) and the first order approximations of welfare changes per household are gained by the difference between revenue and expenditure changes. Subsequently, indices of vertical and horizontal inequality are calculated for the baseline and the counterfactual scenarios, respectively, to assess inequality impacts.

Another application of the top down approach with micro accounting is provided by Bussolo et al. (2008). They estimate impacts of different trade reform scenarios on poverty in Brazil, Chile, Colombia and Mexico. Again, macroeconomic effects on commodity and factor prices are calculated by a CGE model and then mapped down to the different household surveys to adjust real household incomes and to generate new counterfactual situations without allowing individual households to adjust their quantities. CGE-simulated changes in average real wages, in average real capital/land rents (differentiated by agriculture and non-agricultural) and in prices of food and non-food commodities are mapped to the endowments and consumption patterns of the individual households. Household income from pensions, public transfers, remittances and auto-consumption is assumed to be constant. Changes in household incomes are deflated with a newly calculated cost-of-living index. Finally, poverty measures are calculated based on the counterfactual individual household incomes.

Ferreira et al. (2008) provide an example for the top-down approach with behavioural micro-simulations. They assess distributional impacts of a currency crisis for Brazil. To analyse the effects of such a macroeconomic shock they econometrically estimate a model "based on a set of investment savings and liquidity preference money supply (IS-LM) equations […] using time-series national accounts and aggregated household survey data from Brazil for 1981-2000" (Ferreira et al., 2008, p. 120). Levels of employment and unemployment, wage levels and consumer price levels are generated by the macro model (distinct for different household groups and sectors) and used to recalibrate parameters in the micro-simulation model. The latter is a reduced-form model of household income determination and able to simulate individual responses to the mean changes calculated by the macro model, however, without giving any feedback to the macro level.

The *iterative approach* is applied by Bourguignon and Savard (2008) for the purpose of assessing trade reforms for the Philippines in terms of distributional effects. They combine a CGE model with a micro-simulation household model that accounts for household income structure, expenditure behaviour and labour supply decisions. In an iterative resolution process, they feed price changes calculated at the macro level into the micro-simulation model and pass back total consumption and labour supply figures from the micro to the macro level. They compare the modelling system with and without the implementation of feedback effects and find important differences in case of the existence of rigidities in the labour market. Further applications of the iterative approach are presented in e.g. Essama-Nssah et al. (2007) and Mussard and Savard (2010).

Cockburn et al. (2010) present two applications of the *integrated approach* for Nepal and the Philippines. In contrast to the iterative approach where two different models are connected via the exchange of solution variables, in the integrated approach each household from a representative household survey is depicted individually in a CGE framework. In principle, this approach can be seen as a continuation of the representative household approach. The number of household groups is expanded until it equals the number of households in the survey, i.e. each household group contains only one individual household. This approach usually requires a considerable effort to reconcile the data used by the CGE model with the household survey (Cockburn et al., 2010). For their analyses Cockburn et al. (2010) integrate 3,388 individual households for Nepal and 24,797 households for the Philippines in a CGE model. Mussard and Savard (2010) state that modelling of complex behaviour (like regime switching decisions) is difficult within the integrated approach and is therefore, often avoided.

2.3.4 Synthesis

In the preceding sections, literature regarding simulation model based policy impact analysis for the agricultural sector and regarding the simulation model based impact assessment on income distribution has been reviewed. These two branches of literature are hardly overlapping. Nevertheless, first attempts are made to ex-ante estimate policy induced distributional impacts for the agricultural sector. An example is the macro-micro framework presented by Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007). These authors combine a highly aggregated CGE model with a large farm household data survey by mapping quantity and price changes, but without the possibility for farms to adapt production patterns. Further approaches exist, in principle applicable for the consistent measurement of sectoral impacts and at the same time income changes at the individual farm level. An example is the LEI modelling funnel, among others consisting of macro and sectoral level models on the one side and farm level models on the other. A few other model chains in principle also are able to estimate income changes at the individual farm level, however, they often only depict specific farm types. Furthermore, static ex-ante approaches of measuring income effects at the individual farm level do exist (refer to section 5.2), though, to the best knowledge of the author, none of them have been linked to a sectoral or macroeconomic model to assess redistributive effects of agricultural policy at the national level. Moreover, several agricultural sector models correspond to the farm level, but they apply rather to regional farms or farm types (like the CAPRI model for example) instead of individual farms.

In contrast, manifold approaches of consistently assessing impacts of macroeconomic policies at the macro and micro level exist in the field of tax incidence or poverty analysis. Due to the high number of publications not all studies could be considered here, however, selected publications are reviewed, covering all relevant methodological branches. Virtually all studies measuring impacts on income distribution refer to household income or consumption rather than to enterprise profits. Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007) account for changes in farm production, however, under the assumption that all individual farms behave in the same way according to macro results.

For an analysis of policy induced redistributive effects in the agricultural sector, impacts have to be assessed consistently at the sectoral and at the farm level since some variables (e.g. prices) are exogenous at the farm level and others (e.g. individual income) are not observable at the sectoral level. Furthermore, due to the combination of differently aggregated models the trade-off between generality and detailedness is likely to be relaxed.

3 Modelling Chain[11]

In this chapter, a modelling system for the agricultural sector is presented, consistently taking effects of the sectoral and individual farm level into account. For this purpose, different components observed in the field of agricultural policy analysis and the field of impact assessment on income distribution are combined. Two behavioural large-scale agricultural sector models are combined in an iterative procedure (cf. section 2.3.2). As a third model, a micro accounting model is connected to the others in a top-down manner (cf. section 2.3.3). Farm groups can adjust their production relying on information from the sectoral model before results are further disaggregated by a static model, which introduces more heterogeneity in the analysis.

After a broad overview about the whole modelling chain, the single models and linking approaches are explained in more detail.

3.1 Description of the overall modelling chain

The modelling system consists of three different single models depicting three different levels of aggregation to consistently measure changes in individual incomes among western German farms resulting from agricultural policy reforms. A schematic overview of the modelling chain is presented in Figure 3.1. The model with the highest level of aggregation is an agricultural sector model depicting European agricultural markets in detail and the agricultural sector of the rest of the world in a more aggregate manner. It is a partial model in the sense that it explicitly models the agricultural sector and takes all other sectors as exogenously given. Thus, the core macroeconomic variables such as inflation rates and GDP growth rates are exogenous to the model. At the meso-level, a model which depicts the supply side of the German agricultural sector in great detail is applied to measure impacts of agricultural policy changes on 628 heterogeneous farm groups. Both simulation models are two already pre-existing large scale models, ESIM (Grethe, 2012) at the sectoral level and FARMIS (Osterburg et al., 2001; Bertelsmeier, 2005; Offermann et al., 2005) at the farm group level. They both have been used in numerous studies, alternatively as stand-alone versions (e.g. Banse and Grethe, 2008a; Bertelsmeier, 2003) or in combination with other models (e.g. Banse and Grethe, 2008b; Offermann et al., 2012). Yet, both models so far haven't been coupled in a consistent (iterative) way with other models. This iterative approach is undertaken for the study at hand to link the two models at the first stage of the overall modelling system.[12] Effects of agricultural policy at the European level are quantified by ESIM and a resulting vector of price and yield changes is exogenously implemented into FARMIS. Based on the new set of parameters, FARMIS calculates new supply quantities for

[11] This chapter served as a basis for the paper Deppermann et al. (2013) and in parts is equivalent to it.
[12] Deppermann et al. 2010 present a common interface of the two models. However, the paper is part of this dissertation project.

the German agricultural sector and a respective vector of supply changes is exogenously implemented in ESIM. This procedure is continued until both models converge in the analysis of a joint scenario. The models and the linking procedure are described in more detail in Section 3.2 below.

After convergence between ESIM and FARMIS is achieved, farm group results are passed in a top-down manner to the newly developed micro model to assess individual farm incomes for the year 2020, the final year of the simulation period. The micro model is an accounting model in the sense of Bourguignon et al. (2008b) (see section 2.3.3), which further disaggregates the results of the farm groups commonly calculated by ESIM and FARMIS. The micro model serves as an add-on for the FARMIS model, since it relies on its structure. It is based on the German farm accountancy data network (FADN). More information on the micro-accounting model is provided in section 3.3 below.

With this modelling system, different ex-ante evaluations of policy scenarios are conducted. Based on simulation results for the year 2020, income distribution indices are calculated. Results for the year 2020 are utilized in an ex-post manner for the calculation of different inequality indices to evaluate the state of income inequality in the agricultural sector and the degree of progressivity of different reform packages. To this end, inequality indices of different policy scenarios are compared to a reference scenario, the so-called *baseline.* Since the methodology of measuring inequality effects is independent from the modelling system, it is discussed in chapter 5, before the empirical discussion of the redistributive effects.

All models are coded in the The General Algebraic Modeling System (GAMS) programming language, which facilitates an automatized coupling of the models. Furthermore, the calculation of inequality indices is also done in GAMS. The ESIM-FARMIS link (the box in the upper part of Figure 3.1) is managed by a steering file (see Annex A), which was developed to run the system without manually exchanging results between the single elements. Further technical information on the coding is provided in section 3.4 below.

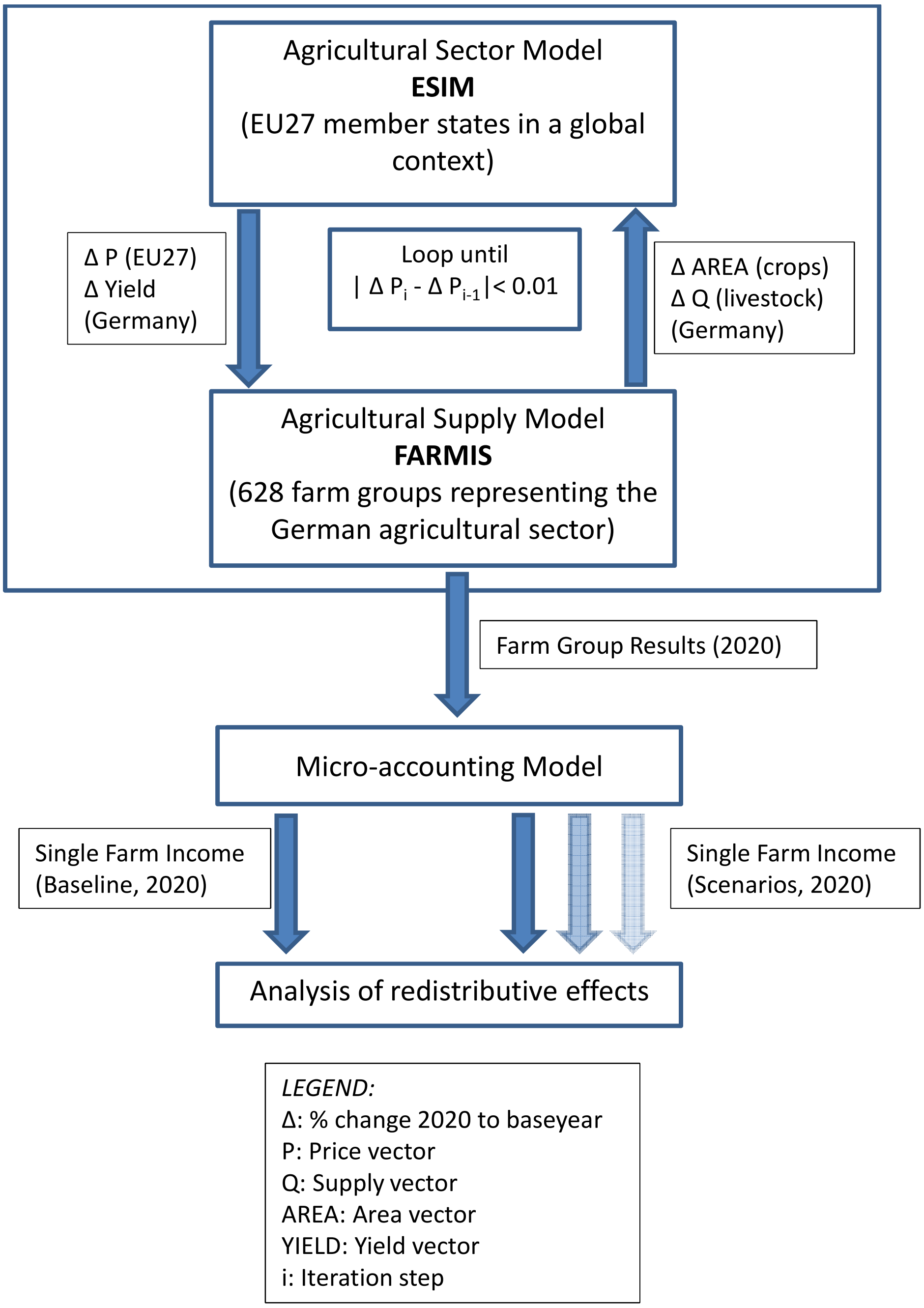

Figure 3.1: Methodological framework for an ex-ante measurement of redistributive effects of agricultural policies on farm incomes

Source: Adapted from Mussard and Savard (2010).

3.2 From the sectoral to the meso-level: an iterative approach

Before a more formal explanation of the ESIM-FARMIS coupling procedure is presented, the single models themselves are introduced in the following sections.

3.2.1 The single models

Both models are ex-ante models, however, with different theoretical foundations. The ESIM model represents agricultural demand and supply of the agricultural sector based on isoelastic functions. FARMIS is a programming model that depicts German agricultural production and is based on the income maximization assumption for several farm groups.

3.2.1.1 The agricultural sector model ESIM

ESIM is a partial equilibrium model of the agricultural sector (Grethe, 2012). It is a comparative static net trade model, which depicts the agricultural sector of the EU-27 on member state level. Furthermore, Croatia, Turkey, the Western Balkans and the USA are modelled as single areas and all other countries are subsumed in an aggregate named "rest of the world" (RoW). The first pillar of the CAP of the European Union is depicted in great detail, implying ad valorem and specific tariffs, tariff rate quotas, production quotas, export subsidies, coupled and decoupled direct payments, and set-aside regulations. Outside the EU-27 agricultural policies are not taken into consideration since the focus of the model is on the analysis of CAP reforms. All behavioural functions are isoelastic except for sugar supply and altogether 15 crops, 6 animal products, 21 processed products, pasture and voluntary set-aside are covered by the model. ESIM abstracts from regional price differences inside the EU-27 and assumes a point market mechanism for all tradable products. Prices for non-tradable products (raw milk, fresh milk, potatoes, fodder, silage maize and pasture) are determined by a market clearing mechanism at the member state level (Grethe, 2012).

Human demand functions are given for all farm and processed products except for raw milk, pasture, fodder, silage maize, set-aside, and rapeseed. Raw milk is split up into its components – fat and protein – which are further processed into several dairy products for human consumption or for direct use as animal feed. Further processing demand is defined for oilseeds, and inputs for biofuel production. The biofuel module depicts the production of bioethanol and biodiesel. Inputs for ethanol are wheat, corn, and sugar. Biodiesel is produced from rape oil, sunflower oil, soy oil and palm oil. Input ratios are endogenously determined by a CES function. Byproducts of biofuel production are accounted for and are used as additional feeding stuff in the livestock sector (Grethe, 2012; Banse and Grethe, 2008a). In the following a more detailed description of standard[13] crop and livestock production is given because these are the two components which are approximated to FARMIS results for Germany in the final model chain and thus, have to be modified in ESIM. The following explanations are based on Grethe (2012).

For EU-27 member states supply of crops is determined by a yield function and an area allocation function which are multiplicatively combined:

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[13] In ESIM some products are depicted by different supply equations. These products, however, mainly belong to the group of processed products which are not modified in the course of model coupling and thus, are not presented in this short overview of the basic model characteristics. A very detailed description can be found in Grethe (2012).

(2) $SUPPLY_{cc,cr} = YIELD_{cc,cr} * AREA_{cc,cr}$.

Yield per hectare (3) is a function of the endogenous own (producer) price of the respective crop, changes in factor costs, which are represented by exogenously implemented cost indices and an exogenous trend parameter. Five categories of factor costs (intermediates, capital, labour, energy, and fertilizer) are taken into account for the yield function. The trend parameter reflects an exogenous trend in yield changes, caused for example by technical progress in plant breeding. Furthermore, an intercept parameter is calculated for the calibration of the model, i.e. to meet a certain combination of price and yield per hectare observed in reality for the base year of the simulation period.

The yield function is specified as:

(3) $YIELD_{cc,cr} = \ yield.int_{cc,cr} * PP_{cc,cr}^{elastyd_{cc,cr}} * \prod_{fcc} f.costs_{cc,fcc}^{elast.y.fc_{cc,fcc,cr}} * tp.gr_{cc,cr}$

where

cc	= Index of countries
cr	= Index of crops
fcc	= Index of factor cost components
YIELD	= Yield per hectare
yield.int	= Intercept of the yield function
PP	= Producer price in country
f.costs	= Factor cost index
elastyd	= Own price elasticity of yield
elast.y.fc	= Elasticity of yield with respect to factor costs
tp.gr	= Trend parameter.

Area allocation is a function of own- and cross- (incentive) prices, the land price and other factor costs (4). Incentive prices in ESIM consist of the producer price for the specific product and the price-equivalent of direct payments that is assumed to have an impact on production decisions (i.e. 100% for coupled and 20% for decoupled payments). This approach takes into account that in reality farmers are only able to receive decoupled payments in combination with eligible land.[14] Product and land prices are endogenously calculated in ESIM, while all

[14] The reader may find it more logical to introduce the DPs on top of the land price instead of the producer price as payments are linked to land in reality. However, elasticities of area demand with respect to incentive prices are set proportionally to elasticities of area demand with respect to land prices, taking the share of land costs in total costs into account. Thus, impacts on area demand are similar, no matter where the subsidy is introduced.

other factor costs are exogenously determined. The obligatory intercept again is used for model calibration purposes for the base year of the model.

(4) $AREA_{cc,cr} =$

$$area.int_{cc,cr} * \prod_{cr} PI_{cc,cr}^{elastsp_{cc,cr,cr}} * LANDPRICE_{cc}^{elast.lp_{cc,cr}} * \prod_{fcc} f.costs_{cc,fcc}^{elast.a.fc_{cc,fcc,cr}}$$

where

cc	= Index of countries
cr	= Index of crops
fcc	= Index of factor cost components
AREA	= Area used for production
area.int	= Intercept of the area allocation function
PI	= Incentive price
LANDPRICE	= Hectare price for land
f.costs	= Factor cost index
elastsp	= Elasticity of area allocation with respect to own- and cross-prices
elast.lp	= Elasticity of area allocation with respect to the land price
elast.a.fc	= Elasticity of area allocation with respect to factor costs.

Supply of animal products in ESIM is a function of endogenous own- and cross- (incentive) prices of animal products, an endogenous index representing feed costs for respective animal products, exogenously determined factor costs, and an exogenous technical progress shifter representing for example progress in breeding.

(5) $SUPPLY_{cc,lv} =$

$$sup.int_{cc,lv} * \prod_{lv} PI_{cc,lv}^{elastsp_{cc,lv,lv}} * FCI_{cc,lv}^{elast.lv.f_{cc,lv}} * \prod_{fcc} f.costs_{cc,fcc}^{elast.lv.fc_{cc,fcc,lv}} * tp.gr_{cc,lv}$$

where

cc	= Index of countries
lv	= Index of animal products
fcc	= Index of factor cost components
sup.int	= Intercept of the supply function
PI	= Incentive price

FCI = Feed cost index representing changes in average feed costs

f.costs = Factor cost index

tp.gr = Trend parameter

elastsp = Elasticity of animal product supply with respect to own- and cross-prices

elast.lv.f = Elasticity of animal product supply with respect to the feed cost index

elast.lv.fc = Elasticity of animal product supply with respect to factor costs.

3.2.1.2 The programming model FARMIS

FARMIS is a comparative-static process-analytical programming model for the German agricultural sector (Osterburg et al., 2001; Bertelsmeier, 2005; Offermann et al., 2005). The model version applied for the study at hand incorporates 628 homogenous farm groups, generated by the aggregation of individual farms and stratified by region, type and size. Sectoral production covers 27 crop and 15 livestock activities. The German farm accountancy data network (FADN)[15] is used as the main data source for model specification, covering about 11,000 individual farms. Farm group specific technical coefficients are either directly taken from the data network or calculated under additional consideration of management manuals. The application of farm-specific weighting factors ensures a consistent representation of the sectors' overall production and income indicators (for a detailed description of the calculation of aggregation factors see Osterburg et al., 2001).

The core model is based on the assumption of income maximization and each farm group is represented by an objective function subject to several constraints, which determines production patterns and factor allocation. In mathematical terms the objective function of the model is represented by (6) (Bertelsmeier, 2005; Sanders, 2007)[16].

[15] It shall be noted that in the FADN, very small farms with less than 16 European Size Units are excluded for the years of our model base period. Thus, the share of rented land in the farms covered by the model is slightly higher than that for all farms since very small farms usually operate with a higher share of own land.

[16] For a more consolidated representation of the general functionality of the model, the original equation (Bertelsmeier, 2005, p. 79) is presented here in a modified version, abstracting from different levels of intensity of agricultural production and also leaving out a more detailed depiction of different subsidy and premium payments.

(6) $\quad max\ Z_n =$

$$\overbrace{\sum_j p_{nj}Y_{nj}}^{1} - \overbrace{\sum_i c_{ni}X_{ni}}^{2} + \overbrace{\sum_i dp_{ni}PX_{ni}}^{3} - \overbrace{\sum_u r_{nu}U_{nu}}^{4} - \overbrace{\sum_v r_{nv}V_{nv}}^{5}$$

$$- \overbrace{r_n^{quot}QUOT_n}^{6} - \overbrace{\sum_l r_{nl}^{land}LAND_{nl}}^{7} - \overbrace{\sum_i \kappa_{ni}X_{ni}}^{8} - \overbrace{0.5\sum_i \omega_{ni}X_{ni}^2}^{9} \quad \forall n$$

$X, PX, U, V > 0$

where

n = Index of farm groups

i = Index of production activities

j = Index of output products

l = Index of land type

u = Index of labour

v = Index of fertilisers

Z = Objective function

Y = Sales of agricultural products in tons

X = Level of activities in ha or livestock housing units (LHU)

PX = Level of activities eligible for direct payments in ha or LHU

U = Level of labour input/requirements in 1,000 hours

V = Level of fertiliser input/requirements in tons

LAND = Level of rented utilised agricultural area in ha

QUOT = Rented milk quota in tons

p = Prices for agricultural products in €

c = Net of activity-specific costs and subsidies €/ha or LHU

dp = Activity-specific direct payments in €/ha or LHU

r_{nu} = Labour costs in €/agricultural working unit

r_{nv} = Expenditures for fertilisers in €/ton

r_{nl} = Rental costs for UAA in €/ha

κ = Parameter associated with the linear PMP term

ω = Parameter associated with the non-linear PMP term.

The first term of the objective function depicts the revenues from selling agricultural production. The second term covers the specifically referable per unit costs and subsidies of production times the activity level. The third term reflects the amount of direct payments accessible by the farm group. The fourth, fifth, sixth and seventh term comprise labour costs, expenditure for fertilisers, rental costs for milk quota, and rental costs for agricultural land, respectively. Terms number eight and nine are the "so-called hidden costs", which are "used to reproduce the activity levels of the base year" (Sanders, 2007, p. 77). These two terms correspond to the application of a positive mathematical programming (PMP) procedure for model calibration and are constructed to meet externally given point elasticities in the calibration point. For this analysis an average of three subsequent years (2006-2008) is used as a model base in order to reduce the impact of the typical yearly fluctuations in the agricultural sector on model results. A more detailed description of the objective function and the model calibration procedure of FARMIS can be found in Bertelsmeier (2003) and Sanders (2007).

Model constraints refer to "the areas of feeding (energy and nutrient requirements, calibrated feed rations), intermediate use of young stock, fertiliser use (organic and mineral), labour (seasonally differentiated), crop rotations, and political instruments (e.g., set-aside, quotas)" (Offermann et al., 2005, p. 2).

For the conduction of an (ex-ante) scenario, assumptions on the continuation of agricultural policy, changes in general farm structure, and rates of technical progress have to be implemented exogenously. Furthermore, all prices except for specific agricultural production factors (milk quota, land, and young livestock) are exogenous to the model (Offermann et al., 2005).

3.2.2 A formal approach of model linking

In this section a formal approach of model linking is presented to sketch the basic ideas of the exercise before the development of the interface between ESIM and FARMIS is discussed in more detail in section 3.2.4. The approach relies on the formal explanation of coupling a CGE with a PE model, presented in Jansson et al. (2009, p. 17ff), however, adapted for purposes of this study.

In this study an iterative coupling between two partial models is achieved at the first stage of the model chain (cf. Figure 3.1). The model at the top (ESIM) is a PE model for the world agricultural sector and shall be represented by y_t indicating the vector of variables for each year of the simulation period t and by α_t indicating the respective vector of parameters of the model. With f connoting a vector of functions of the same length as y_t, an optimal solution of ESIM as a stand-alone version is represented by $f(y_t;\alpha_t) = 0$. The more disaggregated model FARMIS covers the German agricultural sector and is represented by v_t indicating the vector of variables and β_t the vector of parameters for the year t. An optimal solution is characterised by $Z_{n_0,t}(v_{n,t}, \beta_t) = \max_{v_{n_0,t}} Z_{n_0,t}(v_{n,t}, \beta_t) \;\; \forall n$ denoting that all individual farm groups n are maximizing their objective function Z in the year t.

For their base year (t = base) both models are calibrated to observed data. This is done by endogenizing sub-vectors of α_{base} and β_{base} and in turn fixing variables y_{base} and v_{base} to the observed values.[17] This procedure ensures that observed base year values are met by the model. For all t ≠ base α and β are completely exogenous parameters and variables are endogenous. Since all results presented later on in this study refer to the year 2020, time indices are omitted henceforth, and all parameters and variables are defined to correspond to 2020 unless differently stated.

The two models shall be linked by the mutual exchange of solution vectors until convergence on the exchanged variables is achieved. For that purpose, ESIM provides results for yields and prices and FARMIS provides results on area allocation and animal product supply for the German agricultural sector. The transmission of prices and yields from the higher to the lower aggregated model is straightforward, since they are endogenous to the former and exogenous to the latter. The mapping procedure can be described by the vector valued function $\boldsymbol{\Gamma}$: Y → B, with Y denoting a set of all possible solutions of ESIM and B the set of all possible parameters of FARMIS.

The aggregation function that transmits disaggregated FARMIS results into more aggregate ESIM categories is named h. Since FARMIS covers the supply side of the German agricultural sector and ESIM depicts supply and demand worldwide, the vector of all variables y shall be split up into two sub-vectors y_{EXC} (EXC referring to results that shall be exchanged) and y_{REST} where the former includes all ESIM variables which correspond to aggregated FARMIS results and the latter to all other variables $y = (y_{EXC}, y_{REST})$. Then we can write h: V → Y_{EXC}, with V indicating the set of all possible solutions of the FARMIS model. The final goal of the modelling chain is to get the same optimal solution for both models $y_{\text{EXC}} = h(v)$ with regard to the same vector of prices and yields $\beta = \boldsymbol{\Gamma}(\text{y})$.

Since area allocation and supply for animal products in Germany are variables in both models, respective functions in ESIM have to be approximated to FARMIS results while all others shall behave like before. Let f_{EXC} be a sub-vector of f for all functions that have to be shifted to mimic FARMIS results and f_{REST} a sub-vector of all other functions with $f = (f_{EXC}, f_{REST})$. Furthermore, let α_{EXC} be a sub-vector of all parameters that have to be changed in order to shift the functions f_{EXC} and α_{REST} a sub-vector of all other parameters with $\alpha = (\alpha_{EXC}, \alpha_{REST})$. To approximate y_{EXC} according to FARMIS results $h(v)$, α_{EXC} is modified to $\tilde{\alpha}_{EXC}$ such that $f_{EXC}(y_{EXC} = h(v), \tilde{\alpha}_{EXC}, \alpha_{REST}) = 0$. A formal expression for the shifting operation that transmits $y_{\text{EXC}} = h(v)$, y_{REST} and α_{REST} into $\tilde{\alpha}_{EXC}$ shall be denoted $\tilde{\alpha}_{EXC} = \Phi(y_{EXC} = h(v), y_{REST}; \alpha_{REST})$. Setting $\tilde{\alpha}_{EXC} = \alpha_{EXC}$ would create the original ESIM model. A simple method to approximate

[17] For the moment, it is abstracted from additional precalculations which are required for the PMP calibration procedure in FARMIS. The philosophy of model calibration in principle is the same: parameters are calculated based on observed data which from the next period on will be variables.

FARMIS results could be to replace f_{EXC} by a vector of constants reflecting FARMIS results. This would entail $\tilde{\alpha}_{EXC} = \Phi(h(v), y_{REST;}\ \alpha_{REST}) = h(v)$ and setting f_{EXC} to $\tilde{\alpha}_{EXC} - y_{\mathrm{EXC}} = 0$. However, this solution not necessarily leads to convergence. Different options to approximate y_{EXC} to $h(v)$ are discussed in section 3.2.3.

Based on the former definitions, the iterative linking of the two models includes the following steps:

Step 1: Set i := 0; Solve $f(y^i;\alpha) = 0$

Step 2: Compute $\beta = (y^i)$

Step 3: Solve $Z_{n_0}(v_n^i, \beta) = \max_{v_{n0}^i} Z_{n_0}(v_n^i, \beta) \quad \forall n$

Step 4: Compute $\tilde{\alpha}_{EXC}{}^i = \Phi(h(v^i), y_{\mathrm{REST}}{}^{\mathrm{i}}{}_{;}\ \alpha_{REST})$

Step 5: Set i := i + 1; Solve $f(y^i;\ \tilde{\alpha}_{EXC}{}^{i\text{-}1}, \alpha_{REST}) = 0$

Step 6: IF $(y^i - y^{i-1})$ < tolerance, THEN terminate, ELSE go to step 2.

After a first stand-alone run of the ESIM model (step 1), prices and yields are implemented into FARMIS (step 2), which is solved subsequently (step 3). In step 4 shifters for ESIM are calculated. Taking the shifters into account ESIM is solved (step 5). If ESIM results between the last two iterations differ less than a predetermined tolerance value, the procedure stops, otherwise it starts again with step 2.

After the iteration process is terminated (i.e. convergence is achieved), the parameter vectors δ and β are endogenised in the modelling system. An optimal solution to the modelling system is denoted by:

$f(y = (y_{EXC}, y_{\mathrm{REST}});\ \tilde{\alpha}_{EXC,}\ \alpha_{REST}) = 0$

$\Phi(y_{\mathrm{EXC}}, y_{\mathrm{REST};}\ \alpha_{REST}) = \tilde{\alpha}_{EXC}$

$y_{\mathrm{EXC}} = h(v)$

$Z_{n_0}(v_n, \beta) = \max_{v_{n_0}} Z_{n_0}(v_n, \beta) \quad \forall n$ and

$\beta = \boldsymbol{\Gamma}(\mathrm{y})$.

The single models rely on different conceptual frameworks and also use different data bases for their base year calibration. Thus, variations among the models' base year data are likely to occur for their common solution space, which comprises the equilibrium quantities and prices of the German agricultural sector. One way to take these differences into account is to avoid the exchange of absolute results and rather apply change rates of solution variables between the calibrated base year and the year 2020. In other words, the relative difference of quantities and prices which exists in the base year between the two models is kept constant for the simulation period. Thus, $h(\mathrm{v}_{2020})$ aggregates FARMIS results in 2020 expressed as a share in FARMIS base year values which are then multiplied by ESIM base year values to gain absolute ESIM values for 2020. The same applies for $\boldsymbol{\Gamma}$, which maps price and yield changes instead of absolute values.

3.2.3 Sequential calibration

After discussing the general approach of coupling ESIM and FARMIS, the next step is a detailed presentation of the way results are exchanged among the models. Regarding the top-down part of the linkage, ESIM results are implemented into FARMIS as parameters. This requires a simple mapping procedure of prices and yields (still, there are some possible variations of this approach which will be discussed at the end of this section). The bottom-up part of the linkage (i.e. $\Phi(h(v),y_{\mathrm{REST}};\alpha_{\mathrm{REST}})$) is less straightforward and offers several different approaches. Jansson et al. (2009, p. 20f) discuss advantages and problems of different methods of a sequential calibration procedure. Their preferred general approach described for an iterative coupling of a CGE and a PE model is applied in this study, as well. In the following lines their work is outlined and adapted to the study at hand.

As already shown in the preceding section, one simple possibility for implementing FARMIS results into ESIM would be dropping f_{EXC} and fixing y_{EXC} to $h(v)$. But, this approach is not free from shortcomings.

Figure 3.2 sketches a partial one-commodity market for Germany with S representing the sectoral supply curve provided by the FARMIS model and D depicting the demand curve of the ESIM model. Assuming for the moment that both models only depict this single commodity, convergence would be reached in the crossing point of supply and demand. The initial endogenous supply curve of ESIM is not explicitly presented in the graph, but it is very likely that the first stand-alone run of ESIM (see step 1, Section 3.2.2) creates a price which is different from the convergence-price. Thus, let the iteration procedure start with the arbitrary initial ESIM-price p^0 (point A in the graph). With p^0 FARMIS would calculate a respective quantity of supply q^1. Now, the original ESIM supply curve is replaced by a constant supply curve in accordance with FARMIS results, which is depicted by the dotted vertical line at q^1. Solving ESIM with the new (constant) supply would generate price p^1. In the next step FARMIS would respond with a supply at q^2. Following this procedure further on, it is noticeable from the graph that the point of convergence will never be reached, even though it uniquely exists. Convergence will only occur “if the slope of the supply schedule is greater than the (negative of the) slope of the demand schedule” (Jansson et al., 2009, p. 20). This, however, cannot easily be ensured for all single commodity markets in the modelling system.

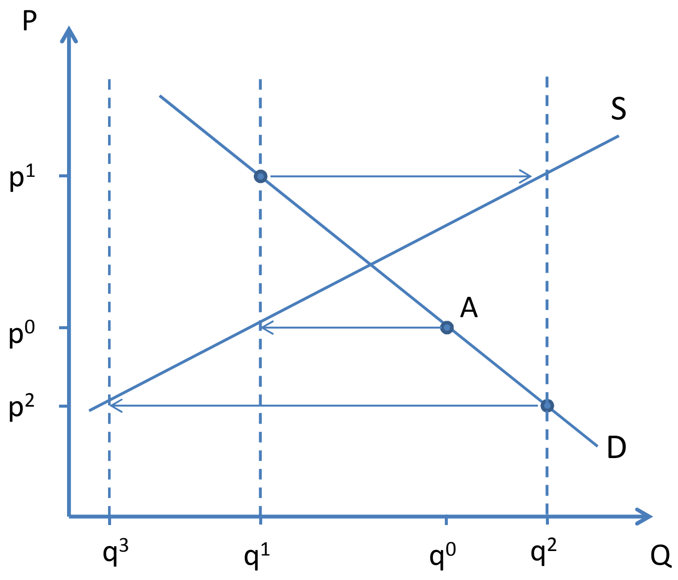

Figure 3.2: Iteration process with diversion.

Source: Adapted from Jansson et al. (2009).

Instead of fixing supply quantities in ESIM, a recalibration of the original ESIM supply curves is a better option to provide convergence. This approach is sketched in Figure 3.3 by means of linear demand and supply functions; however, the general idea also works with the non-linear functions applied in ESIM (cf. Section 3.2.1.1).

The sectoral supply curve provided by FARMIS is denoted by S_F and the ESIM demand curve by D. The original ESIM supply curve is named S_{ESIM}^0 and the stand-alone equilibrium of ESIM is indicated by point A. Like in the first approach the price is implemented into the FARMIS model, which subsequently calculates the respective supply quantity. In the next step the ESIM quantity is not fixed, but the original[18] supply curve of ESIM is recalibrated to the new price-quantity combination (p^0,q^1), indicated by S_{ESIM}^1. The resulting ESIM-endogenous equilibrium accrues at point C. The procedure restarts until the ESIM-endogenous equilibrium equals the equilibrium of the model chain. In comparison to the first approach of fixing ESIM supply, this approach is more robust and leads more likely to conversion. Furthermore, even if the first approach was leading to convergence, the second approach would be more efficient in terms of solution time since fewer steps are needed to find the equilibrium of the modelling system.[19]

[18] However, in the full ESIM model with several commodities and several cross relations among these products, the original supply function is modified (the cross relations to other commodities are cut) to facilitate a better approximation of the FAMRIS supply reactions.

[19] The recalibration approach was used for most commodities in ESIM. However, for a few commodities (especially for livestock products) supply was simply fixed to FARMIS results for the sake of convenience. This is efficient since prices for these products are determined by the world market/European market and thus, only a few iterations are necessary to reach convergence anyhow.

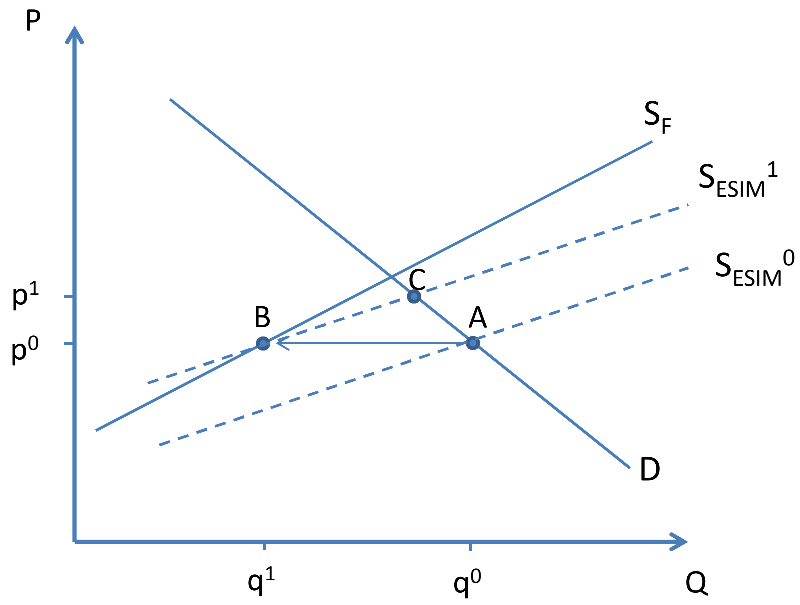

Figure 3.3: Iteration process with linear approximation.

Source: Adapted from Jansson et al. (2009).

Referring to specific ESIM equations for area allocation (4) and animal product supply (5) presented in section 3.2.1.1, *area.int* and *sup.int* respectively are the parameters to be recalibrated. With additionally cutting the cross relations to other commodities and also factor costs, equations for recalibration are:

(7) $$area.int_{"GER",cr}{}^{i} = h(X_{cr})^{i} \,/\, (PI_{"GER",cr}^{elastsp_{"GER",cr}})^{i-1}$$

where X indicates the level of activities in hectare calculated by FARMIS (cf. equation (6)), $h(\cdot)$ denotes the aggregation function from FARMIS results to ESIM categories (cf. section 3.2.2), the index "GER" denotes that only German supply is affected and index i represents the iteration step. The function for recalibration of the animal product supply curves in ESIM appears similarly:

(8) $$sup.int_{"GER",lv}{}^{i} = h(X_{lv})^{i} \,/\, (PI_{"GER",lv}^{elastsp_{"GER",lv}})^{i-1}$$

with X indicating levels of livestock housing units instead of hectare.

However, since even the recalibration method does not guarantee convergence in any case, an additional mechanism is applied to further increase the robustness of the iteration procedure. This mechanism corresponds to the top-down part of the linkage and Jansson et al. (2009, p. 21) refer to it as "partial adjustment". Prices which are transmitted to FARMIS are not simply replaced by the latest ESIM prices as suggested in the graphs above, but by an average of the last and second to last iteration. This further increases probability of convergence, however, it cannot be guaranteed in any case.

3.2.4 Development of an ESIM-FARMIS interface[20]

After the basic idea of coupling was presented in the chapters above, it is described more specifically which steps were undertaken to link ESIM and FARMIS in the following.

At first, consistent product interfaces were defined. In some cases the product aggregation level is different in ESIM and FARMIS and decisions were made about adequately mapping solution variables between both models. The detailed mapping is presented in Table B.1 in Annex B. Unlike for other commodities of agricultural production, prices for animal feed in FARMIS are not delivered by ESIM since they are endogenously determined in FARMIS, which is necessary in order to define the ratio between feed that is produced on farm and feed that is additionally purchased. Feed production in FARMIS, however, is related to animal production and required area for fodder production as determined by FARMIS is implemented into ESIM to consistently depict the price effects on other commodities in the next iteration step. Some by-products of the biofuel industry can be used as feeding stuff. For these products prices are handed over from ESIM to FARMIS since biofuel production is not depicted in FARMIS.

For a first scenario, policy assumptions as well as a wide range of parameters exogenous to both models were harmonized, including technological progress, GDP growth, inflation rates and changes of exogenous factor costs. Furthermore, FARMIS depicts the production of energy maize which is not explicitly covered in ESIM. Since demand for energy maize is assumed to increase significantly until 2020, the respective area is exogenously removed in ESIM to account for price effects on cross products. This is already done in the first stand-alone version of ESIM to facilitate a comparison of model reactions to the same vector of price and yield changes. This comparison is presented in section 4.2 and emerging differences among the models are discussed there.

3.3 From the meso to the micro-level: a top-down approach with micro accounting[21]

After ESIM and FARMIS converged in the first step of the modelling chain, detailed results regarding production patterns, factor demand and income sources for 628 farm groups are obtained representing the whole German agricultural sector. This information is necessary to further be disaggregated for an analysis of inequality effects. For this reason a micro-simulation model is developed and integrated into the modelling system (see Figure 3.1). In the following chapters the choice of the methodology will be discussed first and the income variables under consideration are explained before the model is introduced in detail.

[20] In this section, some parts are identical with Deppermann et al. (2010).
[21] This chapter served as a basis for the paper Deppermann et al. (2013) and in parts is equivalent to it.

3.3.1 Pre-information

FARMIS applies farm groups instead of individual farms due to better manageability and an increased robustness of the model. Potential data errors in individual cases in particular could result in higher solution instability. Furthermore, the application of individual data would lead to high variations among the calculated input-output coefficients between farms (Osterburg et al. 2001). Thus, the aggregation bias which occurs from aggregation over individuals is accepted in favour of stability and manageability of the model. This certainly is a justifiable choice, especially when taking into account that over- and under predictions of individual production patterns tend to cancel each other out in the aggregate level (Wu and Adams, 2002). Furthermore, the time needed to set up the model with an updated database (which would likely be longer with the implementation of individual farms) has to be taken into account. Yet, for the measurement of inequality, which so far has not been a traditional field of analysis for the FARMIS model, this choice is rather unfortunate because a certain part of inequality will be hidden inside the groups and thus, will not be observable (cf. section 2.2.2).

For this study it was decided that the two large scale models at the top of the modelling chain shall be kept exercisable as stand-alone models. This has the advantage that updated versions of the single models can easily be implemented in the modelling chain. This rather practical choice relates to the "institutional challenge" of "sustainable maintenance of linked model systems", which is a matter of "sufficient financial and/or human resources" (Offermann, 2008, p. 361). Hence, to make use of synergy effects in model development it was decided to run the FARMIS model based on farm groups and develop an add-on model that allows a further disaggregation of the grouped results instead of directly accounting for reactions of individual farms (like it was done e.g. in Louhichi and Valin (2012) for arable farms). The micro-simulation model itself can easily be switched to an updated model database.

The indicator applied for the measurement of income inequality among farms in the German agricultural sector is family farm income (FFI). FFI provides information on the return to land, labour, and capital resources owned by the farm family, as well as the remuneration of entrepreneurial risk.[22] Henceforth the terms income and FFI will be used synonymously. Later on, results are presented for FFI both without and with taking additional non-farm income (which is not incorporated in the modelling system) into account. Whenever the latter is the case it is clearly stated.

In the base period of the analysis, data for 628 homogenous farm groups are generated based on information from the German FADN set covering about 11,000 farms. Due to the dominance of corporate farms in eastern Germany all successional analyses related to the measurement of inequality in this study are restricted to 467 western German farm groups

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[22] FFI is not equal to the objective function value Z of equation (6) since for instance hidden costs of the PMP-terms do not appear in FFI and in the objective function family workers are paid by their assumed opportunity costs of time.

representing 8034 individual farms, because no comparability between different farm structures could be ensured when using FFI as an indicator.

For the base period, both individual and grouped data can be observed and thus, the information on inequality which is lost due to data grouping and working with average values instead of micro data can be calculated. For the current base data of the modelling system, a comparison of the relative Gini coefficient reveals some differences in inequality for the base period: the relative Gini coefficient of single farm income data is 0.55 and the relative Gini coefficient of farm group income data is 0.40.

3.3.2 The micro-simulation model

The objective of the micro-simulation model is the disaggregation of farm group results of the last year of the simulation period. Individual FFI data are generated by tracing back farm group results to the individual farms which were used for the generation of farm groups in the base year. The basic idea of the model is to calculate base year values of the shares each single production activity contributes to individual farm gross margin and resource requirements, and then adapt these proportionally according to the changes of respective farm group activity levels, gross margins and factor prices between the base year and 2020.

Figure 3.4 sketches the mode of operation of the micro-simulation model. The *first step* (steps are indicated by Roman numerals in dashed circles) refers to the generation of farm groups based on individual FADN data in the base period for utilization in the FARMIS model. For the study at hand, the micro-model takes 467 farm groups into account, which are generated by aggregation of 8034 western German farms that are included in the FADN data for the base year. Grouping implies the calculation of average production quantities, factor costs, gross margins and income values as well as the generation of aggregation factors to represent the respective proportion of the basic population for each farm group. These values are subsequently applied in the FARMIS model to run simulations.

Gross margins for single production activities refer to market revenues less attributable production costs for a specific activity and are not directly apparent in FADN data[23]. Since this information is crucial for running simulations with FARMIS, several assumptions and additional calculations are made to generate activity specific gross margins, when defining the farm group programming model (for details see Offermann at al., 2005 and Osterburg et al., 2001).

In *step two*, base year income of individual farms is broken down into several components which reflect the shares that single production activities contribute to the individual farm income. For that purpose activity levels from FADN data are combined with respective average gross margins which were calculated for FARMIS groups in step one. Furthermore,

[23] For example, variable input costs are not directly attributed to production activities in the German FADN.

individual costs for hired labour, capital, and rented land are as well separately calculated by utilizing average group prices and individual input quantities.

Since not all commodities, income sources, and costs indicated in the German FADN are also allocated to activities and included in FARMIS (e.g., forestry and agri-tourism are not explicitly covered in the model), a part of the original FFI is not changed by the model and is assumed to be fixed. In step two the 'variable part' of the income (the part depicted in the FARMIS model, i.e. the core agricultural production activities) is calculated for all individual farms by summing up all income components of the single production activities and all (negative) factor costs.

Step three indicates a simulation run of the ESIM-FARMIS modelling chain. In this process, farm group results for the year 2020 are generated. The generated changes of activity levels between the base year and the year 2020 are applied to individual base year levels in *step four*. That is, all individual farms covered by a specific farm group have the same percentage changes in production for all commodities. The same approach is used for capital costs. The quantity of rented land is calculated according to new farm specific crop activity levels less the farm owned share of land.

Labour requirements are calculated regarding new production quantities. With new production patterns in 2020 an individual farm may have excess capacity of family workers. In such a case it is assumed that the farm sells work to other farms at market conditions. However, work can only be 'traded' within one farm group to ensure consistency between group income and aggregated income of individual farms. Thus, in the case that the whole group as an aggregate has excess capacity of family workers, these workers are assumed to work off-farm.[24]

Then, adjusted activity levels and resource requirements are multiplied by respective gross margins and factor prices calculated by the modelling system for the year 2020. Adding up the single gross margins and cost components generates the variable part of each individual farm income for 2020.

In *step five*, the difference of the variable part of the income in the base year and the variable part of the income in 2020 (which can be positive or negative) is added to the original base year FADN values of farm income. That way, also the fixed part of the income is considered.

In a last step the generated individual data are aggregated and compared to original group results. In most cases group results are perfectly met. In case of small divergences, individual incomes are scaled to meet group results.

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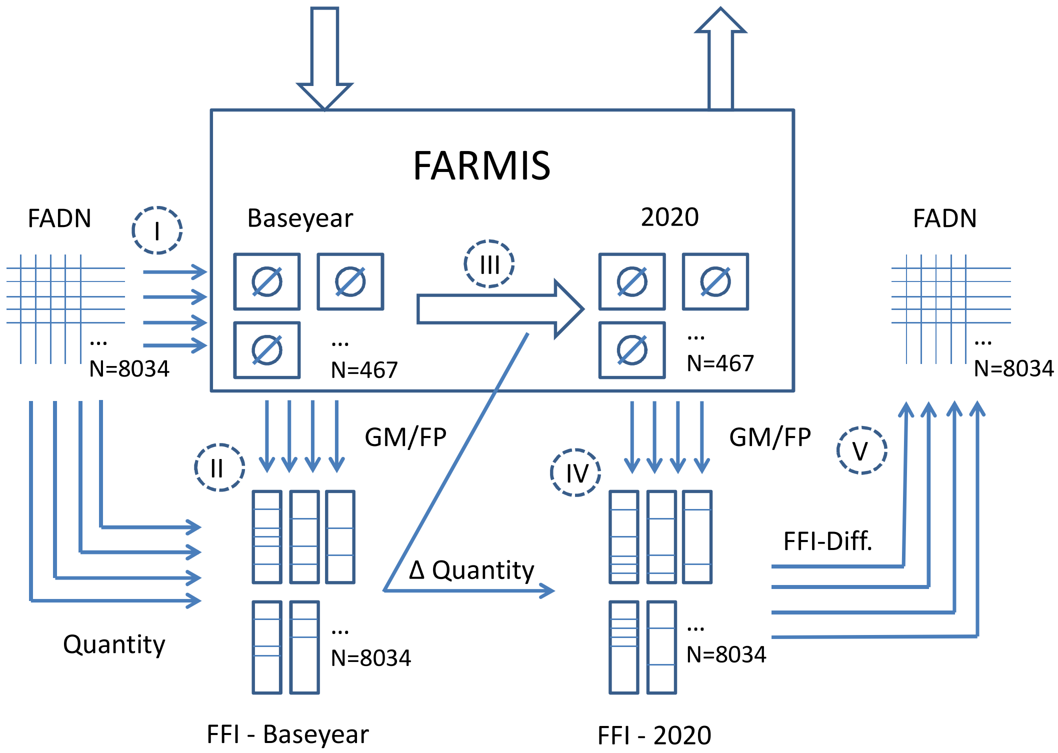
[24] Off-farm work is not included in FFI. However, the amount of income earned off the farm makes a difference when total household income is analysed instead of FFI (section 5.3.2). Thus, sensitivity of income levels of additional off-farm workers on distributional parameters was tested. To this end, a version where additional off-farm workers earn 80% of employed on-farm workers was compared to a version where additional off-farm workers are unemployed and have no income. However, the impact of this assumption on the final results is only marginal.



NB: N – Number of income units; GM – Gross Margin; FP – Factor Price; FFI – Family Farm Income.

Figure 3.4: Micro-simulation model in connection with FARMIS.

Source: own compilation.

The micro-model is of the micro accounting type in the sense of Bourguignon et al. (2008b) since the model is static which means there is no behaviour depicted in the model itself (see section 2.3.3). A similar approach for the generation of farm incomes at the micro level is used in the FES model (Woltjer et al., 2011) which applies exogenous price changes to static single farms.

The model takes adaptions of production patterns into consideration, though, only as exogenous information. In principle, it would be possible to account for behaviour of single farms (compare, for example the approach of Louhichi and Valin (2012) for arable farms). Nevertheless, due to the reasons presented in section 3.3.1 behaviour of single farms was not taken into consideration.

The same proportional reaction of all farms in one group to new price incentives is certainly a strong assumption. Still, heterogeneity among production patterns of farms in the same group is taken into consideration because different commodities might face different price changes. Furthermore, taking into account that an average group represents 17.2 FADN farms and that stratification was undertaken according to type, region, and size, an assumed similar behaviour of individual farms belonging to the same group seems acceptable. It can be argued that behavioural adaption processes are to a great extent already covered by the FARMIS model, which also makes the missing feedback effect less relevant. The application of 467 behavioural farm groups also distinguishes the modelling chain from a similar methodology presented in Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007), which, in a nutshell, map quantities and prices resulting from only one regional household of a CGE model to a disaggregated farm household survey.

One caveat, however, which appears in almost all analyses of distributional effects on the national or comparable level remains. The overall farm population of western Germany consist of more than 160,000 farms. This in turn means that 8,024 FADN farms still account for only a fraction of all farms and have to be weighted by an aggregation factor to represent their respective proportion of the overall population. Thus, an implicit assumption is that one single farm depicted in the modelling system (or in the FADN data) on average represents more than 20 farms of the overall population. This assumption is common to virtually all analyses of distributional effects since only observed units can be modelled and complete population surveys on the national level practically do not exist.

Summing up, the model is applied to account for heterogeneity of farms inside a group to allow for measuring changes in inside-group inequality. Results are disaggregated in a static, top-down manner, after the ESIM-FARMIS model chain is solved. In principle, the approach is comparable to other standard micro accounting approaches utilizing representative groups, however, this analysis refers to 467 representative farm groups from a behavioural model, which in comparison is an outstanding high number. As Lofgren et al. (2003, p. 334) argue, the distinction between the micro-simulation approach of modelling a single unit and the representative agent approach of applying only grouped data is not always sharp. This especially becomes evident, when it is taken into account that single units from large data surveys are assumed to be representative for a share of the overall population.

3.4 Technical implementation of model communication

All parts of the overall modelling system are coded in the GAMS programming language. This facilitates an automated coupling of the two large scale models ESIM and FARMIS and a successional run of the disaggregation and inequality components.

The ESIM-FARMIS coupling is managed by a steering file, presented in Appendix A. In principle, it implements the steps defined in Section 3.2.2 until convergence among the model results is ensured. To keep the structure of the models autonomous, so that they readily can be removed by an updated model version, it is necessary to run them independently from each other. Furthermore, the models have to be run several times with redefining parameters after each solve of a single model. Thus, models have to be started at execution time of the GAMS system since they are not readily available at compilation time, yet.

The basic idea to do so is to run GAMS from within the main GAMS program. This is achieved by the *'execute'* command which in general allows the implementation of external programs during execution time of GAMS (McCarl et al., 2012). This command is complemented by the use of *'execute_unload'* and *'execute_load'* to store results in a *gdx*-file and load them at execution time, respectively. The latter two commands are used to hand over results after each single-model run to the main GAMS program, convert them into commodity categories of the second model, and subsequently hand them over to a subservient GAMS program for running the adapted second model.

To save computation time, the ESIM model is split up into a component which runs the model until the year 2019 and a second component which runs the model only for 2020. This is possible due to the comparative static nature of the model. The first component is only run once at the beginning of the iteration process and intermediate results are saved for a subsequent utilization in the (adapted) 2020 component.[25]

4 Scenario description and sectoral results

In the empirical part of this study, different scenarios are analysed with the above described modelling system. These scenarios are introduced in this section. Subsequently, sectoral results of the first part of the modelling system (only ESIM-FARMIS) are presented. Inequality effects are presented afterwards in chapter 5 and 6.

4.1 Scenario description[26]

Scenarios are conducted for the year 2020 with the model base period being an average of the years 2006-2008[27]. Three different liberalization scenarios are compared with a reference scenario (the baseline) regarding their market outputs and later on regarding their income distribution. In the baseline, the *2003 Reform* and the *Health Check* of the CAP are fully implemented except for the abolishment of milk quotas. Milk quotas are assumed to increase until 2015 according to the *Agenda 2000* decision, including the additional 2% quota increase in 2008 and the fat adjustment in 2009/10. It is assumed that a (first generation) biofuel share of 8% in total EU transport fuel consumption will be reached by 2020. Furthermore, the sugar market reform decided upon in 2005 is implemented and set-aside obligations are removed in 2008. The baseline adopts constant levels of tariffs, export subsidies, tariff rate quotas (except for sugar), and the current system of intervention prices. For the international environment, ESIM is calibrated to FAPRI world market price projections (FAPRI, 2011) and no changes in external trade policies of the EU are assumed until 2020.

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[25] Actually, it is only necessary to solve the model for the base year and 2020. However, for technical reasons it is easier to run the model until 2019 and store intermediate results for subsequent utilization.

[26] This section is almost identical to Deppermann et al. (2013) and Deppermann et al. (2014).

[27] The FARMIS model applies 2006-2008 data for its base period and the baseline calibration of the modelling system for 2020 refers also to prices of 2006-2008. However, the ESIM base period refers to 2006-2007 data, which may lead to slight inconsistencies.

To account for the effects of liberalizing agricultural policy on production and income in the agricultural sector, the baseline results in 2020 are compared with results of other scenarios in 2020. The single scenario results reflect impacts of different, exogenously defined policy changes to the baseline scenario.

The strongest liberalization scenario assumes a liberalization of all first pillar agricultural policies (i.e., the abolishment of all intervention prices, tariffs, quotas, subsidies, and direct payments). Therefore, in 2020 the EU price level equals the world market price for tradable products. In another scenario isolated effects of a separate abolishment of first pillar direct payments (DP) are analysed (henceforth, No_DP scenario) and in another scenario all price policies are abolished (henceforth, No_Pricepol scenario), but direct payments are still paid to farmers to single out the effects of different policy instruments. Furthermore, a scenario with a cut of 50% of DPs is carried out (50_DP scenario) to analyse whether results are in accordance with the full abolishment of DPs, since for a 100% cut the FARMIS model clearly generates results which would be dampened in reality by structural change which is not depicted in the model.

4.2 Sectoral results[28]

In the following sections sectoral results of the described scenarios are discussed in detail. Thus, only results of the ESIM-FARMIS modelling chain are presented without application of the micro model. At first the baseline scenario, which serves as a reference later on, is described. Subsequently market impacts of the policy scenarios are presented.

To evaluate the importance of the iterative coupling procedure differences in the reaction of both stand-alone models to the same price changes will be discussed. This gives also an indication for the occurrence of aggregation biases.

4.2.1 Integrated Baseline

The overall trend of world market prices in US-dollar in the baseline is based on projections published by FAPRI for 2020 (FAPRI, 2011). The development of world market prices between the base year (2006-2008) and 2020 is characterized by a slight increase of real crop prices and a stronger increase of the real price index of animal products (see Figure 4.1). While the crop price index increases by roughly 3.5% until 2020, animal product prices rise on average by 7% in the same time period. Consequently, the real price index of all farms shows an intermediate increase of about 5%.

[28] Some parts of this chapter are identical to the paper Deppermann et al. (2010).

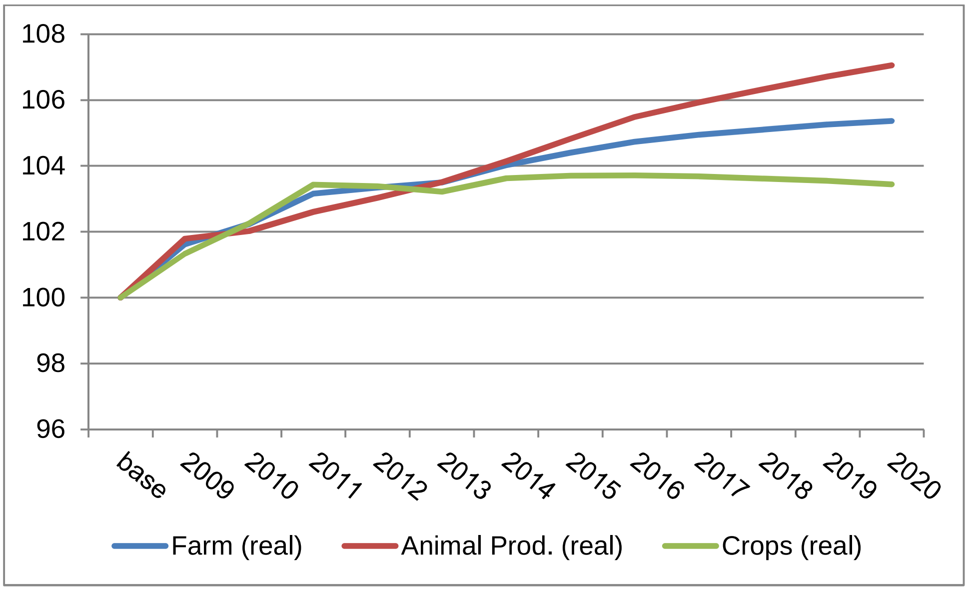

Figure 4.1: Real world market price indices for agricultural products.

Source: Own calculations.

The development of the European agricultural sector is determined by developments of the world agricultural market; however, it is additionally affected by European agricultural policy and other macroeconomic variables. In the baseline, a continuous appreciation of one percent per year of the Euro against the US-Dollar is assumed (FAPRI, 2011)[29]. This is the main reason for the decrease of agricultural prices in Europe, as presented in Figure 4.2. In accordance with the world market prices (US-Dollar based), the European price index for crops (Euro based) shows the greatest decrease. The price index of animal products declines slightly and the overall farm price index is intermediate. Additional to the exchange rate effect, the crop price index is affected by the sugar market reform which is implemented between the base year and 2010 and which substantially reduces the European price for sugar.

In spite of declining Euro-prices in the agricultural sector, supply of crops and livestock products increases until 2020. This is caused by exogenously implemented supply shifters which reflect yield increases in the agricultural sector and which are linear extrapolations of yield data of the FAO database from 1992 until 2007 (FAO, n.d.).

[29] In the original data (FAPRI, 2011) the development of the exchange rates is more volatile. For the sake of convenience the yearly development is averaged out, since the model runs more stable and our interest is only in comparative static results of the baseline and its counterfactuals in the year 2020, which are not affected by the time path a parameter follows.

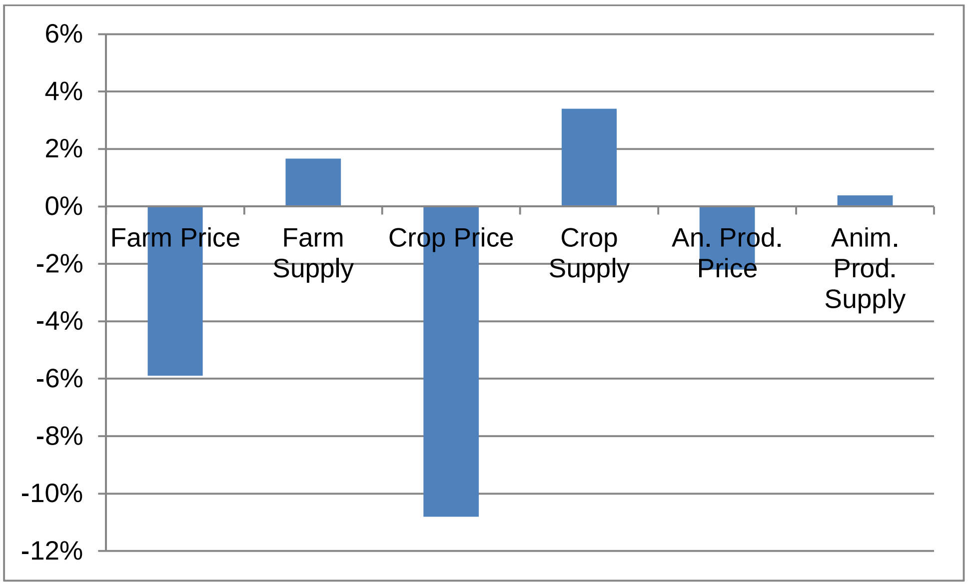

Figure 4.2: Development of EU-27 Indices of Agricultural Prices and Production (Base year – 2020).

Source: Own calculations.

In Table 4.1 price changes and responding quantity/supply changes for single products of the German agricultural sector are displayed. Columns 1-3 refer to the baseline development of ESIM and FARMIS as stand-alone models (before the iteration process), whereby ESIM prices are used to generate FARMIS results. Thus, it can be assessed how the two different models react on the same vector of price changes.

Crop prices develop in line with the overall European price index with only the wheat price slightly increasing. This is caused by the fact that the EU switches from a net export position in the base year to a net import position in 2020 and a threshold price is applied in the EU, which lies slightly above the world market price. The only commodity shown among the animal products with a decreasing price is pork. Yet, pork has a high value share among the animal products and poultry prices[30] also decline, which explains the decreasing price index of animal products in Figure 4.2 despite rising beef and milk prices.

Price drops and an increasing amount of energy maize production which is exogenously implemented in the models lead to a substantial decline in utilized agricultural area for all other crops in 2020 compared to the base year in both models. In the stand-alone version of FARMIS this effect is slightly stronger for most products than in ESIM. In general reactions of the models go into the same direction and are of similar scope. Yet, there are two main exemptions from that: beef and set-aside.

[30] Poultry is not presented in the table because only a part of the poultry production is considered in FARMIS. Namely, only poultry farming on farms with area is depicted and in western Germany production on corporate farms is excluded. In the base year, poultry production in FARMIS accounts for 42% of the production depicted in ESIM.

Differences in model reactions regarding beef production have to be discussed in combination with the milk market. Milk supply increases by 4% in both models, which is the effect of a slight expansion of the EU milk quota until 2020. The limited production of milk together with an output increase per dairy cow cause a decline in beef production in FARMIS, since with higher milk output per animal less milk cows are needed to fulfil the milk quota and calf production is reduced. In ESIM, this link is missing. Milk and beef are modelled as complementary goods, i.e. connected by a positive cross-price elasticity. Given this and a binding milk production quota, ESIM results tend to be erroneous. In the case at hand, the stable milk price doesn't affect beef production and the latter increases due to the projected price increase.

Set-aside land reported in Table 4.1 refers solely to voluntary set-aside, in the base year as well as in 2020. Obligatory set-aside is abolished already in 2008. The different reactions among the models regarding set-aside mainly go back to different modelling concepts. In ESIM the quantity of set-aside land depends on its "own-price", which in fact is the amount of direct payments linked to one hectare of eligible land, and to prices of arable crops. However, cross-price elasticities to arable crops are very small and with decreasing real values of direct payments (since nominal direct payments are assumed to be constant until 2020) the quantity decreases slightly, as well. In FARMIS the quantity of production depends on gross margins. With only slightly falling values of direct payments per hectare and at the same time heavily decreasing prices of other crops, set-aside becomes more favourable and thus, its quantity increases.

These two major differences and the minor deviations are dealt with by the iterative procedure, resulting in a convergence of model results after four iterations. Results are presented in columns four and six of Table 4.1. For the majority of products, Germany is a small country inside the European Union. This means that (EU determined) prices do not react much to relatively small changes in German supply. For these products, FARMIS determined quantity changes do not generate any relevant price feedback and after one iteration step convergence is already reached.

The model linkage is rather relevant for non-tradable goods or such goods where in Germany a big part of total EU supply is produced. An example for the latter is rye: an 8% area reduction in 2020 due to FARMIS results goes together with a decrease in prices of two percentage points. Furthermore, German beef production accounts for roughly 15% of total European production in the base year and thus, a decrease of eleven percentage points causes a two percentage point increase in beef prices compared to the ESIM stand-alone baseline.

Potatoes and raw milk are the only two goods that are modelled as non-tradable in ESIM and at the same time are more relevant for the model linkage. While in the case of potatoes a strong price effect occurs due to the less pronounced area reduction in FARMIS, there are no effects in milk supply. This is due to EU milk quota restrictions. Here, the iteration process becomes relevant in case of a non-binding quota.

In the final baseline, overall utilized agricultural area declines for most crops with the exception of wheat. Also voluntary set-aside is extended; however, the absolute area is rather small (roughly 2% of total arable land in the base year). Not depicted in the table is the exogenously driven increase of energy maize which accounts for about 7.5% of German agricultural area. Effects are clearly stronger in FARMIS, which is more price sensitive than ESIM. In case of beef supply, biophysical restrictions are crucial for the decline in quantity. Milk and sugar supply is determined by the quota.

Table 4.1: Price and area/quantity changes (in %) in the baseline (2020 compared to base year) for Germany before and after Iteration.

Products	**Before iteration**			**After iteration**			
	Change in price	**Change in area/supply in ESIM**	**Change in area/supply in FARMIS**	**Change in price**		**Change in area/supply**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	% comp. to base year	% comp. to base year	% comp. to base year	% comp. to base year	% points differ-ence with (1)	% comp. to base year	% points differ-ence with (2)
Area changes (crops)							
Wheat	2	-1	3	2	0	2	3
Barley	-6	-6	-7	-5	1	-7	1
Corn	-3	-1	-3	-2	1	-3	2
Rapeseed	-22	-21	-35	-21	1	-35	14
Rye	-9	-6	-15	-7	2	-14	8
Sugar	-22	-19	-17	-22	0	-16	-3
Other Grains [a]	-10	-7	-18	-9	1	-17	-10
Potatoes	-20	-16	-7	-30	10	-14	-2
Fodder [b]	-	0	3	-	-	3	3
Silage Maize	-	- 8	- 4	-	-	-4	4
Grass	-	0	0	-	-	0	0
Volunt. Set-aside	-	- 1	29	-	-	27	30
Supply changes (animal products)							
Pork	-2	1	8	-2	0	8	7
Beef	7	4	-7	9	2	-7	11
Milk	1	4	4	2	1	4	0

[a] Other grains: triticale and oats. [b] Fodder: other fodder except silage maize and grass.

Source: Own calculations.

4.2.2 Liberalization Scenarios

In this chapter the four different liberalization scenarios (see section 4.1) are presented and compared to the reference scenario. At first results are presented at the European level.

Figure 4.3 shows that the scenarios with a 50% and a 100% cut of DPs have similar results, whereby the effects of the full cut are clearly stronger. Results at the European level are largely determined by ESIM since FARMIS solely provides results for Germany, which in the European context have only a minor impact as seen already in the discussion of baseline results.

When DPs are cut, farm supply is decreasing because production incentives are reduced. This effect is stronger for crops since the bulk of DPs is coupled to land. Yet, for animal products some coupled DPs are still left (e.g. Article 68 payments) and additionally higher feedstock prices reduce the supply quantity in the scenario results, but to a lesser extent. Lower supply quantities subsequently result in higher prices.

It is visible from Figure 4.3 that the abolishment of price policies has much stronger effects on market development than the abolishment of DPs. This, however, is only true for the ESIM model. Diverging results regarding cuts in DPs among the models can be observed in the following tables and will be discussed in the remainder of this section in more detail.

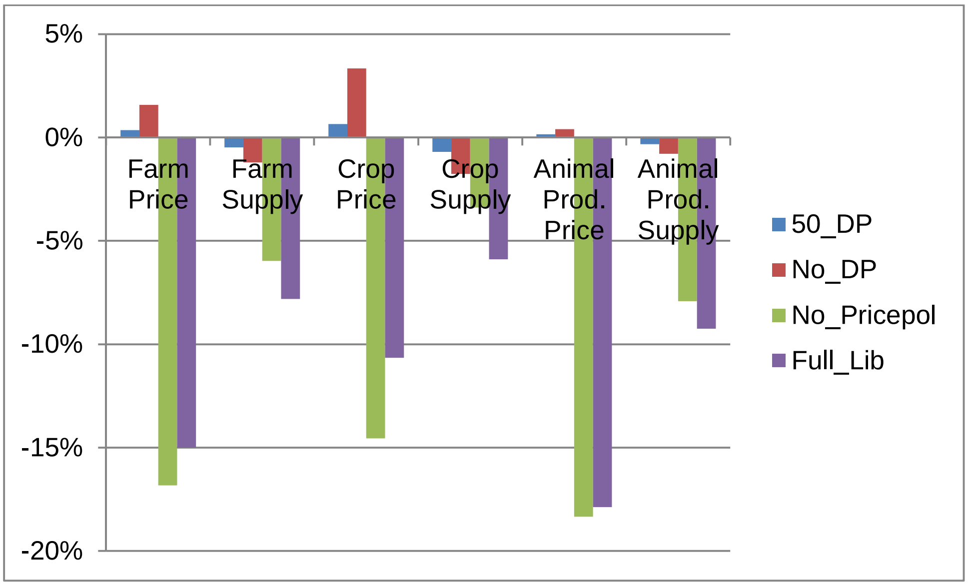

Figure 4.3: Scenario Results Relative to Baseline – EU-27 Indices of Agricultural Prices and Supply Quantities (2020).

Source: Own calculations.

The abolishment of price policies causes a different type of shock than a cut in direct payments does. The latter reduces the incentive to produce, which leads to increased market prices. The abolishment of price policies like tariffs or intervention prices directly causes lower domestic market prices, which reduce the incentive to produce (Figure 4.3).[31]

[31] Since quota restrictions are implemented together with border protection measures, the quantity effects are not *a priori* assessable.

In the Full_Lib scenario supply indices decrease more than in the No_Pricepol scenario reflecting lower production incentives due to additional cuts in DPs, which results in a higher average price level compared to the No_Pricepol scenario.

Results for the German level are presented in Table 4.2 to Table 4.5. Again, the first three columns refer to the model results when they are used as stand-alone versions without iteration procedure and the remaining columns show results of the two models commonly applied and differences to the stand-alone version results. Scenario results are presented in relation to baseline results to provide *ceteris paribus* conditions and single out the effects of policy reforms.

Table 4.2 presents results for the German agricultural sector under the scenario No_DP, which entails a full abolition of DPs. Results of the stand-alone version of ESIM show only a slight decline in utilized area for most of the crops, whereas area changes in FARMIS are significant. FARMIS reacts much more sensibly to cuts in decoupled DPs than ESIM does. The explanation is inherent to the models. In ESIM it is assumed that decoupled payments have an effect on production which is equivalent to an increase in prices by 20% of their value. Thus, only 20% of the DPs are incorporated in the model and an abolishment of DPs causes a comparatively low shock. Furthermore, structural change – in terms of an increase in average farm size as well as in terms of adoption of new production technologies – is incorporated in the supply elasticities that are utilized in ESIM. Hence, effects of strong income shocks in the agricultural sector are more moderate since it is assumed that the sector adapts not solely within given production structures but also by changing structures.

In FARMIS the land market is modelled on a regional level. DPs are assumed to fully capitalize in the land market. Hence, a reduction of DPs only affects production when gross margins without DPs become negative and subsequently production is reduced in respective regions. In many regions land rental prices are too low to absorb abolished DPs, which then leads to a strong decline in utilized area as shown in Table 4.2. In reality effects probably would be dampened by structural changes in the farming sector; however, in the current version the programming approach applied in FARMIS takes structural changes into account only exogenously between the base year and the final year of the simulation period. This means that the same rate of structural change occurs in each scenario, independently from sectoral market developments. Thus, in contrast to ESIM no structural changes occur between baseline results and scenario results. According to that, FARMIS results should be interpreted against the background that with strong reductions in average income, significant structural change such as an increase in farm size and farmers leaving the sector can be expected which is not depicted in current model specifications.

Table 4.2: Price and Area/Quantity Changes (in %) in the No_DP Scenario (2020 compared to Baseline in 2020) for Germany before and after Iteration.

Products	Before iteration			After iteration			
	Change in price	Change in area/supply in ESIM	Change in area/supply in FARMIS	Change in price		Change in area/supply	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	%	%	%	%	% points difference with (1)	%	% points difference with (2)
Area changes (crops)							
Wheat	-0.6	-0.3	-14.6	2	2.6	-12	11.7
Barley	0	-0.6	-19	1.7	1.7	-17.7	17.1
Corn	0	-0.1	-9.7	0	0	-10.1	10
Rapeseed	0.2	-1.5	-38	1.1	0.9	-35.4	33.9
Rye	1.3	-1.6	-23	8.7	7.4	-16.3	14.7
Sugar	0	0	0	0.1	0.1	0	0
Other Grains[a]	0.6	-1	-24.1	3.1	3.7	-22	21
Potatoes	-1.5	0.1	-1.6	2.7	4.2	-0.4	0.5
Volunt. Set-aside	-	-40	-60	-	-	-60.7	20.7
Fodder[b]	-	-1.3	-11	-	-	-11.1	9.8
Silage Maize	-	-1.6	-1.8	-	-	-1.9	0.3
Gras	-	-0.2	-14.2	-	-	-14	13.8
Supply changes (animal products)							
Pork	0	0.1	-0.2	0.5	0.5	-0.5	0.6
Beef	1	0.2	-3	0.7	0.3	-3.1	3.3
Milk	0	0	0	0.2	0.2	0	0

[a] Other grains: triticale and oats. [b] Fodder: other fodder except silage maize and grass.

Source: Own calculations.

ESIM results in the livestock sector might seem implausible at first glance. In Germany, beef quantities and price rise simultaneously after DPs are abolished. This, however, is a specific result for Germany since DPs are fully decoupled unlike in many other countries (e.g. France, Spain, and Austria) which kept a small share of DPs coupled, especially in the beef sector. The abolishment of coupled payments in these countries leads to a reduction of the incentive price for beef production, which in turn reduces supply and increases the market price for beef in Europe.[32] Since no coupled DPs are left in the baseline in Germany in 2020, German farmers do not suffer from abolished DPs for beef but are profiting from an increase in market prices. In ESIM this own price effect even overcompensates the increasing feedstock costs

[32] In ESIM a European point market is assumed. It is abstracted from the possibility of different regional prices that might occur due to transportation or other transaction costs.

which result from higher crop prices. Thus, at the aggregate European level beef supply is reduced but in the German sector it is slightly extended. In FARMIS the slightly increasing beef price is not sufficient to overcompensate for higher feedstock prices, hence, beef supply decreases.

After the iteration process, a significant reduction in utilized area compared to the stand-alone ESIM results (see Table 4.2, column 7) leads to rather small price changes (column 5). This again reflects that Germany is a small country within Europe (and the world) in terms of agricultural production for most commodities. For non-tradable goods (potatoes) and for crops where a substantial share of world supply is produced in Germany (rye) stronger price effects occur and the FARMIS results are dampened.

In Table 4.3 results of a 50% DP cut scenario are presented. Effects are less pronounced for this scenario compared to the full abolishment. The FARMIS stand-alone version still generates significantly stronger effects than the ESIM stand-alone version. However, area declines less than half the amount of the scenario with full abolishment of the DPs. The relation between the share of DPs that are cut and the decline of area under production is non-linear because the production decision is only affected when gross margins become negative.

The still strong area effects in FARMIS are mainly caused by low rental prices which are observed in southern German regions in the baseline in 2020. Here, even a 50% cut of DPs cannot be absorbed by the land market, whereas in the north most regions still have positive land rents after the cut. In a more aggregate version of the model these effects would have been weaker since an average land price would provide more scope for an absorption of DP cuts, since the threshold of zero rental prices would hardly be passed. This is a good example to highlight the strengths and weaknesses of the two single models: while ESIM tends to underestimate effects of DP cuts due to an aggregation error FARMIS tends to overestimate the effects in the scenario at hand due to a limited depiction of structural changes that likely would occur.

When the models are commonly used in the iterative modelling chain, these weaknesses are not fundamentally solved. Since the FARMIS model replaces only the German supply in ESIM, price effects are still determined to a great extent by the other European countries which are not disaggregated. Furthermore, the effects for Germany are likely overrated since quantity effects generated by FARMIS hardly are dampened by the small price effects at the European level.

Table 4.3: Price and Area/Quantity Changes (in %) in the 50_DP Scenario (2020 compared to Baseline in 2020) for Germany before and after Iteration.

Products	**Before iteration**			**After iteration**			
	Change in price	**Change in area/supply in ESIM**	**Change in area/supply in FARMIS**	**Change in price**		**Change in area/supply**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	%	%	%	%	% points differ-ence with (1)	%	% points differ-ence with (2)
Area changes (crops)							
Wheat	-0.1	-0.1	-5.3	0.7	0.8	-3.8	3.7
Barley	0.1	-0.5	-6.6	0.6	0.5	-5.9	5.4
Corn	0	-0.1	-2.9	0	0	-3.2	3.1
Rapeseed	0.1	-1.2	-11.4	0.4	0.3	-10.3	9.1
Rye	0.7	-1	-7.2	2.3	1.6	-5	4
Sugar	0	0	0	0	0	0	0
Other Grains[a]	0.5	-0.7	-7.5	1.1	0.6	-6.7	6
Potatoes	-0.5	0	-0.8	0.6	1.1	0	0
Volunt. Set-aside	-	-7	-18.4	-	-	-18.4	11.4
Fodder[b]	-	-0.8	-7.6	-	-	-7.5	6.7
Silage Maize	-	-0.9	-1	-	-	-0.9	0
Gras	-	0	-3.3	-	-	-3.1	3.1
Supply changes (animal products)							
Pork	0	0	0	0.1	0.1	-0.1	0.1
Beef	0.6	0.1	-0.9	0.4	0.2	-0.9	1
Milk	0	0	0	0	0	0	0

[a] Other grains: triticale and oats. [b] Fodder: other fodder except silage maize and grass.

Source: Own calculations.

Comparatively strong price changes occur in the No_Pricepol scenario (Table 4.4). For wheat and corn strong price cuts arise because of the abolishment of intervention prices which were relevant in the baseline in 2020. An even stronger reduction occurs for sugar due to the abolishment of the quota restrictions, the specific tariff, and the intervention price. In the case of beef and pork meat, high tariffs are reduced. Yet, a quality mark-up of roughly 25% of world market prices is assumed for these products in the No_Pricepol scenario to reflect the assumption that consumers care about the origin of livestock products and on average have a higher willingness to pay for domestically produced meat. Despite the mark-up, beef prices drop by 34.8% compared to the baseline in 2020. The pork meat price drops to a much lesser extent because under baseline assumptions the EU has an almost balanced net-trade (net-exports account for about 1% of EU consumption) and prices are almost at world market level in the baseline (plus the mark-up). The abolishment of the European milk quota and the simultaneous liberalization of dairy product markets (export subsidies and tariffs) lead to an 18.8% lower milk price compared to the baseline.

As has already been observed in baseline results, a biophysical link in FARMIS restricts beef production when a binding milk quota is in place. The reverse effect is now observable when the milk quota is abolished. While in ESIM beef supply is reduced by 29% due to strong price effects, FARMIS results only show a reduction of 1.8%. Due to a strong increase in milk supply additional beef meat is produced as a complementary product which compensates the price induced decline in beef production to a great extent. Pork production in ESIM is extended despite a reduced price. This effect occurs because the price drop is relatively small compared to other livestock products and the own-price effect is overcompensated by cross-price effects.

A similar case occurs for barley, rye, other grains, and rapeseed. Area in both models is extended despite reduced own-prices because of cross-price effects which are triggered by a strong decline in wheat, corn and sugar prices. The relatively small reduction of wheat and corn area in ESIM is also explained by cross-price effects.

The area utilized for feeding-stuff production is reduced in ESIM due to decreasing livestock production. The less pronounced decline in livestock production in FARMIS and the increase in milk supply lead to an increasing demand for feeding-stuff and accordingly area is expanded.

Table 4.4: Price and Area/Quantity Changes (in %) in the No_Pricepol Scenario (2020 compared to Baseline in 2020) for Germany before and after Iteration

Products	Before iteration			After iteration			
	Change in price	Change in area/supply in ESIM	Change in area/supply in FARMIS	Change in price		Change in area/supply	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	%	%	%	%	% points difference with (1)	%	% points difference with (2)
Area changes (crops)							
Wheat	-19	-5.3	-16.1	-18.6	0.4	-15.4	10.1
Barley	-3.8	4.3	2.9	-3.4	0.4	3.5	0.8
Corn	-19	-3	-18.2	-19	0	-18.2	15.2
Rapeseed	0.9	9.3	15.1	0.9	0	15.1	5.8
Rye	-3.8	4.4	4	-3.4	0.4	4.3	0.1
Sugar	-33.6	-19.8	-24.1	-33.3	0.3	-23.6	3.8
Other Grains[a]	-2.8	4.7	5.5	-3	0.2	5.3	0.6
Potatoes	-5	0.1	-1	-3.7	1.3	-0.2	0.3
Volunt. Set-aside	-	1.7	21.2	-	-	21.5	19.8
Fodder[b]	-	-9.4	4.9	-	-	3	12.4
Silage Maize	-	-12	4.7	-	-	3.6	15.6
Gras	-	-1.6	0	-	-	0	1.6
Supply changes (animal products)							
Pork	-4.3	0.5	-2	-3.9	0.4	-2.2	2.7
Beef	-34.8	-29	-1.8	-35.4	0.6	-2.6	26.4
Milk	-18.8	3.3	11.3	-21.1	2.3	9.8	6.5

[a] Other grains: triticale and oats. [b] Fodder: other fodder except silage maize and grass.

Source: Own calculations.

In the Full_Lib scenario a full market liberalization of EU agricultural policies is simulated, i.e. the abolishment of all price policies and all direct payments at once. ESIM results only marginally change compared to the No_Pricepol scenario[33]. FARMIS results conversely indicate that area for almost all crops declines heavily due to an additional abolishment of DPs. After the abolishment of price policies, average gross margins in FARMIS already are reduced so that an additional cut in DPs causes negative gross margins in many regions. Even with these enormous declines in production, world market prices are hardly affected by implementing FARMIS results into ESIM.

[33] The only exception is voluntary setaside which doesn't generate any income anymore when DPs are abolished. However, due to isoelastic functional forms production values cannot become zero.

Table 4.5: Price and Area/Quantity Changes (in %) in the Full_Lib Scenario (2020 compared to Baseline in 2020) for Germany before and after Iteration.

Products	Before iteration			After iteration			
	Change in price	Change in area/supply in ESIM	Change in area/supply in FARMIS	Change in price		Change in area/supply	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	%	%	%	%	% points difference with (1)	%	% points difference with (2)
Area changes (crops)							
Wheat	-19.6	-5.3	-35	-17.8	1.8	-33.2	27.9
Barley	-3.9	3.5	-21.4	-1.7	2.2	-19.1	22.6
Corn	-19.2	-2.9	-30.5	-18.7	0.5	-30.4	27.5
Rapeseed	1	7.7	-34.4	2.3	1.3	-30.8	38.5
Rye	-2.8	2.6	-25.2	2.2	5	-20.3	22.9
Sugar	-33.7	-23	-38	-33	0.7	-36.9	13.9
Other Grains[a]	-2.7	3.5	-25	-1.9	0.8	-23.9	27.4
Potatoes	-6.6	0.4	-3.2	-0.6	6	-0.6	1
Volunt. Set-aside	-	-39.6	-55.5	-	-	-55.2	15.6
Fodder[b]	-	-12	-13	-	-	-13.4	1.4
Silage Maize	-	-14.7	0.4	-	-	-0.5	14.2
Gras	-	-2.1	-15.7	-	-	-16.3	14.2
Supply changes (animal products)							
Pork	-4.3	0.6	-2.2	-3.5	0.8	-2.8	3.4
Beef	-34.5	-29	-6.8	-35	0.5	-7.6	21.4
Milk	-18.6	2.8	8.1	-20	1.4	7.1	4.3

[a] Other grains: triticale and oats. [b] Fodder: other fodder except silage maize and grass.

Source: Own calculations.

4.2.3 Discussion

In the baseline, for most commodities reactions of the models go in the same direction and are of similar scope. Under scenario conditions, however, quite a few differences can be observed between the stand-alone versions of the two models.

In the No_Pricepol scenario reactions for field crops are broadly in line among the models. However, FARMIS seems to be more sensitive regarding price changes than ESIM. Larger disparities occur in the livestock sector, mainly caused by different impacts of the milk quota abolishment.

Differences in scenarios with DP cuts are much more pronounced. This goes back to different theoretical concepts with regard to the modelling of direct payments and the implementation of structural change. ESIM to a certain degree considers (historically observed) structural change since it implicitly is included in its behavioural parameters. Furthermore, only 20% of the value of decoupled DPs is assumed to have an effect which is equivalent to a change in market prices. Contrarily, structural change in FARMIS is implemented exogenously. With strong reductions in average income, an increase in average farm size would be expected in reality; however, this dampening effect on supply reactions does not arise in the current model specification. Additionally, DPs are fully accounted for. When land markets are not able to absorb DP cuts via a reduction in rental prices, production becomes unprofitable in certain regions. The regional differentiation of land markets gives a more detailed picture compared to a model with a single region. In the 50_DP scenario, production declines in some regions even though the average land price of all regions would be high enough to absorb the cut in DPs almost entirely. ESIM only implicitly takes regional differences into account at the aggregate level via its elasticity approach. However, this approach implies that all farms have constant marginal reactions on a cut in DPs, no matter of the depth of the cut. Considering all these points, it can be concluded that impacts of DP cuts tend to be underestimated in ESIM and overestimated in FARMIS.

The different model reactions are dealt with in an iterative procedure. However, even significant declines in supply in FARMIS do not cause strong price feedback in ESIM. Prices are similar for many products before and after the iteration. This is due to the fact that prices in ESIM are determined at the world or European level rather than at the German level. Germany is a small country for most of the agricultural products. Only in cases where a considerable share of world production is produced in Germany or where commodities are non-tradable, are price reactions more pronounced. Thus, the iteration procedure is relevant only for few commodities depicted in the models. Another picture would emerge, when more countries depicted in ESIM would simultaneously be substituted by programming models of the FARMIS type. In such a case supply changes would be more pronounced at the aggregate level and prices would react accordingly.

From the discussion above it becomes clear that even though considerable differences among the models occur, they only partially can be traced back to the different levels of model aggregation. Nevertheless, due to the disaggregated structure, FARMIS clearly accounts for more heterogeneity of the sector, which also is reflected in aggregate results. For example, effects in the 50_DP scenario would be much lower if FARMIS was run on a higher level of aggregation. Another example is the bio-physical link between milk and beef production in FARMIS. Farmers that already fulfil their milk deliveries under quota restrictions need less dairy cows, which has an effect on calf and consequently beef production at the aggregate level.

5 Redistributive effects of agricultural policy

After the modelling system has been introduced above and it has been explained how ex-ante data are generated, in a second step these data are further analysed to draw conclusions regarding distributional effects of the different reforms of agricultural policy in the agricultural sector of western Germany.

5.1 Measuring inequality and redistributive effects – methodological aspects

In this chapter, methodological aspects of the measurement of inequality and the measurement of redistributive effects are discussed. First, it shall be clarified how inequality is measured and what in general is meant by an index of inequality. There is a broad consensus in the literature what kind of basic properties such an index is desired to satisfy. These properties are presented in the next section. Thereafter, it is explained how impacts on inequality can be assessed.

Since in the empirical analysis (presented below in section 5.3) several farms have negative incomes, the reaction of indices on the appearance of negative values in the income distribution is discussed. Negative incomes surely would be an inconceivable concept in the case of wage earners; however, for farmers negative incomes reflect losses, which at least temporarily are not unusual in the agricultural sector.

5.1.1 Definition and properties of inequality indices

Foster (1985, p. 12) gives a general definition of measures of inequality:

> "In the most general sense, a measure of inequality is a functional relationship *I* between a set *D* of social states and a set *R* of comparison points ordered by a binary relation ≥ . The measure extracts from a given social state *d* in *D* aspects that are relevant to inequality and assigns an element *I(d)* in *R* to reflect these aspects. The relation ≥ then indicates the inequality level of the state relative to other social states."

This very broad definition of an inequality measure *I* is commonly refined by several basic properties for the measurement of income inequality (see among others Foster, 1985; Chakravarty, 1999 and 2001; Bosmans and Cowell, 2010)[34]. Following these authors, the income of an individual i is a real number x_i. The income distribution for n individuals arranged in ascending order is denoted by $x = (x_1,\ldots,x_n)$ in the Euclidean n-space R^n. The set of all possible income distributions is $\cup_n^\infty R^n = X$. The dimension of an income distribution x is denoted by $n(x)$ and $\mu(x)$ is the mean income. The expression 1^n characterizes a vector of dimension n with all components being equal to 1. An inequality measure is a real valued continuous function $I{:}X \rightarrow R$. $I(x)$ is increasing with higher income inequality and shall be

[34] There exists a broad consensus about these general properties of inequality measures in the literature. For further sources refer to the references given in Chakravarty (1999).

defined for n ≥ 2 only. $I(x) = 0$ in case of an equal distribution. The following properties are defined (Bosmans and Cowell, 2010; Chakravarty, 2001)[35]:

Pigout-Dalton Transfer Principle (PD):

For all $x \in X$ and any positive real number δ, it counts that $I(x_1,\ldots,x_i,\ldots,x_j,\ldots,x_n) > I(x_1,\ldots,x_i + \delta,\ldots,x_j - \delta,\ldots,x_n)$ if $x_i < x_i + \delta < x_j - \delta < x_j$.

PD ensures that a rank preserving progressive (regressive) transfer has a decreasing (increasing) effect on the inequality index.

Symmetry: For all $x \in X$, $I(x) = I(x')$ if x' is obtained from x by rearrangement of components.

Symmetry ensures that the degree of inequality does not change when individuals switch their rankings.

Population Principle: For every $x \in X$, $I(x,x) = I(x)$.

The population principle ensures that an inequality index is the same for a given distribution and any of its replications.

A fourth criterion is differentiated for absolute and relative measures of inequality.[36] A relative index of inequality should satisfy:

Homogeneity: For every $x \in X$ and δ being any scalar > 0, $I(x) = I(\delta x)$.

Absolute measures of inequality should satisfy:

Translation invariance: For every $x \in X$ and any real number δ, $I(x) = I(x + \delta 1^n)$.

Homogeneity ensures that proportional changes in all incomes do not change inequality. Translation Invariance implies that equal absolute changes in all incomes do not cause changes in the index of inequality. A more detailed discussion of relative and absolute concepts of inequality is presented in the next section.

The presented basic properties are in general satisfied by most of the well-known and frequently used indices of inequality. Examples of relative indices are the family of generalized entropy measures (including Theils' indices), the Atkinson index, and the Gini index. Examples for absolute indices are the variance, the Kolm index, and the absolute Gini index (all these measures are discussed in more detail in Chakravarty, 1999). It is worth noting, however, that not all statistical measures of inequality satisfy all the mentioned principles; e.g. the interquartile ratio does not satisfy the PD property (Deaton, 1997).

Each of the different indices of inequality measurement has its own specific features and the "choice of a particular index will be guided by the specific objective one has in mind"

[35] The names of the properties differ among different authors. The formal expressions are taken from Bosmans and Cowell (2010) and Chakravarty (2001) in case of Homogeneity.

[36] For sake of completeness it shall be mentioned that also "intermediate" measures exist. For a detailed introduction refer to the relevant literature, e.g. Bossert and Pfingsten (1985) and Pfingsten (1986).

(Chakravarty, 2001, p. 87). For the study at hand the relative and the absolute Gini coefficient have been chosen to measure the distributional impacts of policy reforms in the agricultural sector. The rank-based formulation of the Gini coefficients is a particularly important feature since it allows the measurement of re-ranking effects. Furthermore, at least the relative Gini coefficient is a well-known and widely used measure with a straightforward geometric interpretation. However, Gini indices cannot be decomposed into only two components – the sum of inequality among subgroup means and a weighted sum of within group inequality – if subgroup income ranges overlap (Mookherjee and Shorrocks, 1982). This may make the interpretation of a decomposed Gini coefficient less straightforward, but will also in turn facilitate further insights in the composition of inequality. A detailed discussion of subgroup decomposability is presented in chapter 6. A further characteristic that is worth mentioning is that both the absolute and the relative Gini indices are most sensitive to transfers around the middle of a distribution (Chakravarty, 2001).

The relative Gini index G can (in discrete form) be specified as:[37]

(9) $$G = \frac{1}{2n^2} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| x_i - x_j \right|}{\mu}$$

where x_i is the income of individual i (i = 1,2,3,…,n) and μ represents the average income. The relative Gini coefficient is conceptually closely related to the relative Lorenz curve. The latter relates the share in overall income of the p% poorest people to the share they represent in the overall population. An arbitrary relative Lorenz curve is presented in Figure 5.1, where population is ordered from the poorest to the richest at the abscissa. The area between the 45°-line (i.e. the line of equality) and the Lorenz curve divided by the triangle under the 45°-line represents the relative Gini coefficient.

[37] See Pyatt (1976) and Stuart and Ord (1994).

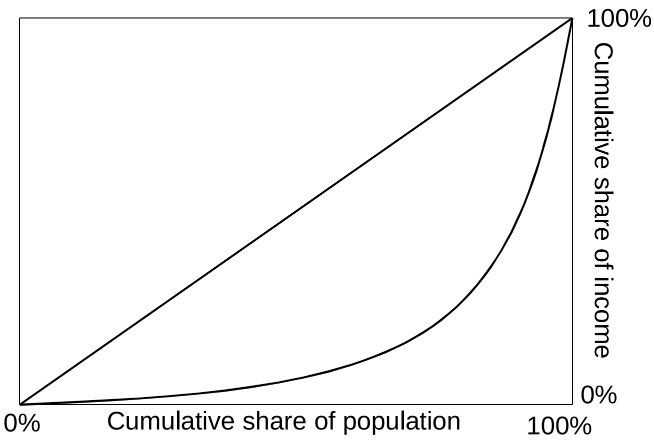

Figure 5.1: Relative Lorenz curve.

Source: Adapted from Jenkins (1991).

The absolute Gini index *AG* is equal to the relative one multiplied by mean income of the sample (Chakravarty, 1999) and thus, can be specified as:

(10) $$AG = G\mu = \frac{1}{2n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|.$$

An arbitrary absolute Lorenz curve is presented in Figure 5.2, again with the ordering of the population from the poorest to the richest. Since the concept of absolute Lorenz curves is hardly applied in the economic literature, it shall be briefly introduced in the following lines, which are taken from Jenkins, 1991, p. 4:

> "An Absolute Lorenz curve […] graphs *p*[%] times average income among the poorest *p*[%] *minus* [*p*% times] the population average income, against cumulative population share, *p*[%]. If there is complete equality, the curve coincides with the horizontal axis […], and with inequality the curve hangs below the axis like a tear-drop […]. In the extreme case where one person has all the income, the Absolute Lorenz curve is straight-edged and √ -shaped, with the length of the vertical section equal to mean income. […] The closer the Absolute Lorenz curve is to the horizontal, the more equal the distribution."

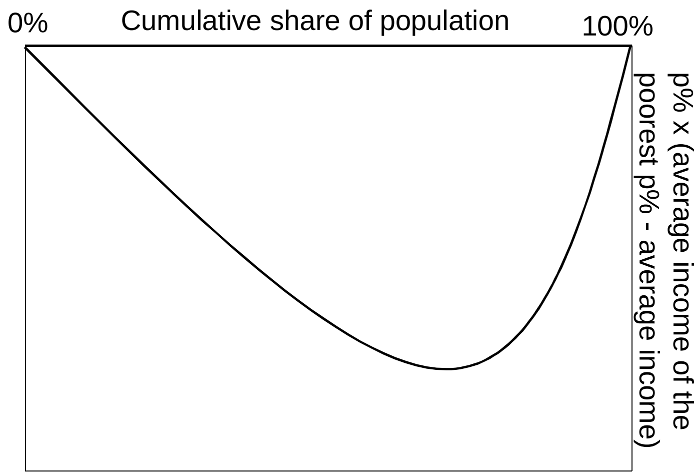

Figure 5.2: Absolute Lorenz curve.

Source: Adapted from Jenkins (1991).

Furthermore, the concept of concentration indices (e.g. Kakwani, 1980; Jenkins, 1988) shall be introduced in the following since it is extensively used in the next chapters. Starting point shall be the relative concentration *curve* because a relative concentration *index* can be derived from a concentration *curve* in a similar way as the Gini *index* can be derived from a Lorenz *curve*.

Figure 5.3 presents an artificial concentration curve. The concept is closely related to the concept of Lorenz curves; however, instead of ranking income units in ascending order with respect to the variable under consideration, income units are kept in the ordering of another distribution. For example, a concentration curve of taxes with respect to the ordering of before-tax income graphs the share in overall taxes which have to be paid by the *p*% poorest income receivers (according to before-tax income) against the share they represent in the overall population. If a tax function takes other attributes except before-tax income into account it may happen that some people with a lower rank in the before-tax ordering have to pay more taxes than people with a higher before-tax income and a higher rank. This would lead to a kinked curve as presented in Figure 5.3. In general, relative concentration curves are not restricted to lie below the 45°-line. They also can be flipped to the other side above the 45°-line. In this case the respective concentration index would take a negative value which would indicate that income units in the lower tail of the distribution (e.g. with lower before-tax incomes) have a larger share of the variable under consideration (e.g. bear a higher tax burden). The Lorenz curve is a special case of a concentration curve when the orderings of the two variables are identical.

Following Vernizzi et al. (2010), the relative concentration index can be specified as:

(11) $$C_Y = \frac{1}{2n^2} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left(y_i - y_j \right)}{\mu_y} \times \Psi \left\{ r_x \left(y_i \right) - r_x \left(y_j \right) \right\},$$

where μ_y is the mean of a variable y (e.g. taxes), $r_x(y_i)$ represents the rank of individual i in the X-ordering and $\psi\{z\}$ is an indicator function such that $\psi\{z\}=1$ if $z>0$, $\psi\{z\}=0$ if $z=0$ and $\psi\{z\}=-1$ if $z<0$. Absolute concentration indices are equal to relative ones multiplied by mean incomes of the variable under consideration, i.e. μ_y.

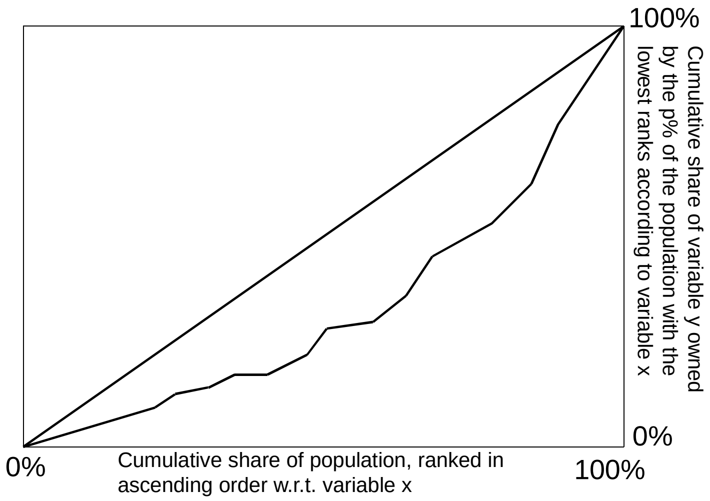

Figure 5.3: Relative concentration curve of variable *y* ranked with respect to variable *x*.

Source: Own compilation on the basis of Pyatt et al. (1980).

5.1.2 Measuring redistributive effects

After having explained how inequality is measured, in this section the measurement of redistributive effects is presented. As Lambert (2001, p. 39) points out, "redistribution is a term in the English language commonly understood to refer to *the new distribution of a given total.*" Yet, how can we talk about redistributive effects in a case where mean income is not comparable? According to Lambert (2001), this is possible because we implicitly compare the new situation with another one in which income would have been changed in a distribution neutral way. The latter is used as a natural benchmark to evaluate distributional effects.

In the following paragraphs, two different but related methodologies for the measurement of redistributive effects are introduced. The first one originally stems from the field of tax analysis. It has been applied for the analysis of redistributive effects of agricultural policy (see e.g. Allanson, 2006) and is also used in the work at hand. It distinguishes between vertical and re-ranking effects. The second methodology is also commonly utilized for the analysis of policy induced impacts on income distributions and is based on the decomposition of the Gini coefficient by income sources.

5.1.2.1 Vertical redistribution, re-ranking and progressivity [38]

In section 5.1.1 it was discussed how income distributions can be expressed by single indices. As already mentioned by Foster (1985) in the introductory quotation, to evaluate the degree of inequality of a specific distribution, it has to be compared to a reference distribution. In the study at hand different liberalization scenarios are compared with the income distribution of a reference scenario to evaluate reforms of agricultural policy in terms of (re-)distributional effects among farm incomes. Since the modeling system does not account for farm exits triggered by liberalization, negative impacts on mean farm income can be expected for the scenarios introduced in chapter 4.1.

Kakwani (1986) develops the following measure of redistribution that is based on a comparison of relative Gini coefficients and decomposes the total effect into a vertical and a re-ranking component, which Allanson (2006) applies to agricultural policy:

$$R = G_x - G_y = (G_x - C_y) + (C_y - G_y) = V + H \tag{12}$$

where R represents the overall effect of redistribution as the difference of the Gini index in the base situation (G_x) and the Gini index in the new situation (G_y), C_y is the concentration index of income in the new situation with respect to base rankings, and V and H are indices of vertical redistribution and re-ranking, respectively. Generally, the concept of vertical equity represents the idea that a monetary burden on individuals should increase with their capacity to bear that burden. A positive (negative) sign for V indicates that in case of income losses, in this work due to a reduction of government support, the burden is progressively (regressively) allocated among the total farm population. Nevertheless, V does not measure the "pure" degree of deviation from a proportional burden share but it also depends on the share of the average burden in average base income. The "pure" degree of deviation rather is indicated by the comparison of the concentration index of the burden C_B and the initial Gini coefficient G_x, which is presented by the Kakwani (1977) measure of progressivity:

$$P = C_B - G_x. \tag{13}$$

P measures the extent to which the burden is distributed more unequally or equally than income in the base situation (Aronson et al., 1994).

The connection between V and P is given as follows (Kakwani, 1986):

$$V = \frac{P \cdot s}{(1-s)} \tag{14}$$

where s represents the share of the average burden in average base income of the whole farm population.[39]

[38] Parts of this section are identical with Deppermann et al. (2011, 2013) and Deppermann et al. (2014).

Yet, the degree of deviation from a proportional share of the burden does not entirely explain the new state of distribution (Atkinson, 1980; Plotnick, 1981). The index of vertical redistribution equals the overall effect of redistribution only if no re-ranking of farms occurs. In our analysis this would be the case if farms were arranged in ascending order of income in the baseline situation and still held the same rank after liberalizing the agricultural sector. Otherwise the index of vertical equity overestimates the redistribution effect by not including rank reversal effects. To illustrate the impacts of re-ranking on inequality, let us assume an extreme case in which, due to an imaginary policy, all individuals of a population have to switch their income: The highest income is replaced with the lowest, the second highest income with the second lowest, and so on. This policy would be highly progressive since the highest income-earners would have to bear the greatest burden and the lowest income-earners would obtain the most, but there would be no change in the overall distribution of income (refer to the symmetry property of the Gini index, presented in section 5.1.1). To account for re-ranking, the index H (which is also known as the Atkinson-Plotnik-index of re-ranking) is applied in equation (12). It can be interpreted as an indicator of arbitrariness or discrimination of the examined income redistribution system. Atkinson (1980) refers to the effect as "mobility" induced by an income policy, which might be of interest in its own right. If re-ranking occurs, it always has a negative impact on the overall redistribution index (Lambert, 2001). A graphical presentation of the decomposition of the overall redistributive effect in a vertical and a re-ranking component is provided in Figure 5.4. The redistributive effect R is represented by the area between the continuous Lorenz curve which represents the initial income distribution and the dotted Lorenz curve, which present the final state of income distribution. In this artificial case, a burden (e.g. a tax) would be inequality reducing. The vertical effect V refers to the area between the initial (continuous) Lorenz curve and the kinked concentration curve. Since some re-ranking occurs in this fictive situation, the vertical effect would overstate the reduction of inequality. Thus, after (re-)ranking income units in ascending order of the new distribution the dotted Loren curve would appear and the (negative) re-ranking index H refers to the area between the kinked concentration curve and the dotted Lorenz curve.

[39] The reduction of income caused by liberalization is treated like a tax. In case one wants to measure the effects of cash benefits, the formula should be $V = (G_x\text{-}C_B)*(s/(1+s))$.

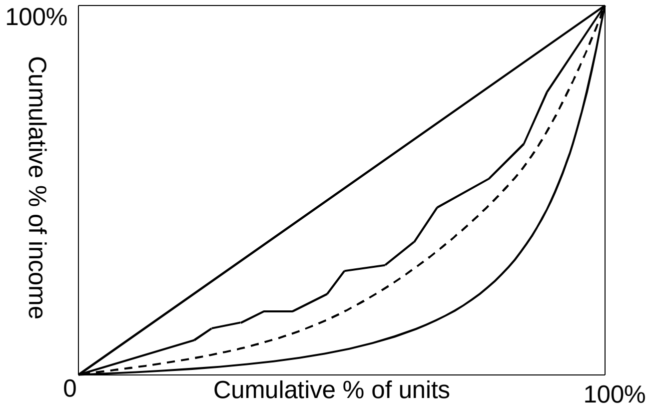

Figure 5.4: Overall redistribution, vertical effects and re-ranking.

Source: Own compilation.

The described approach has so far been based on the relative Gini coefficient. One property of relative measures of inequality is that proportional changes in all incomes do not change inequality (refer to the homogeneity property of relative inequality indices in section 5.1.1). However, it depends on subjective evaluation what kind of changes keep inequality unaffected (Chakravarty, 1990). According to different normative views on inequality equivalence, different concepts of inequality measures exist. In addition to the relative measure the absolute Gini index is applied in this work to broaden the view on inequality effects. The two concepts are closely related since the absolute Gini index is obtained by multiplying the relative one by the mean income of the sample, yet they react differently to income changes. Absolute measures of inequality are invariant to equal absolute changes in all incomes (refer to the translation invariance property of absolute inequality measures introduced in section 5.1.1).

In his seminal paper, Kolm (1976, p. 417) labels relative measures “rightist” and absolute ones “leftist” in a context of wage and salary negotiations. His view is based on the observation that social forces that traditionally could - in a political sense - be classified as leftists (e.g. trade unions) rather favor absolute equal increases of salaries than proportional ones. He explicitly states that the term “must not be taken too literally” and that it is based on a situation with “an equal increase in all incomes rather than an equal decrease” (ibid., p. 419). In our analysis we deal with decreasing income (on average) and thus, the terms might be misleading, since “leftists” probably prefer a proportional burden for everybody to an equal absolute cut in income.

Following Kolm (1976) and Pfingsten (1986), relative and absolute measures represent two extreme cases of inequality concepts because many people value an absolute equal levy as inequality extending and a proportional one as inequality reducing.[40]

Generally, the described method of decomposing the overall redistribution effect can be applied to the absolute Gini index as well (Allanson, 2008):

$$AR = AG_x - AG_y = \mu_x G_x - \mu_y G_y = (\mu_x G_x - \mu_y C_y) + (\mu_y C_y - \mu_y G_y) = AV + AH \tag{15}$$

where A indicates the absolute versions of the respective measures and μ_x and μ_y represent the average income of the base and new situation, respectively. In the absolute version, the (relative) concentration index of burden (C_B) indicates whether a burden is progressively or regressively distributed. It shows how the shares of the total burden are distributed, keeping the ranks in sequence of the base situation. Thus, a negative (positive) C_B indicates that small initial incomes have to bear a greater (smaller) part of the burden than higher incomes.[41] Comparing C_B with the relative index of progressivity (P) makes it clear that in absolute terms, a burden might be indicated as progressive (positive C_B) while in relative terms it is denoted as regressive in the case that $C_B < G_x$, since $P = C_B - G_x$. These potential discrepancies might also be found with regard to the overall effect of distribution. In the following it is clarified how the relative and absolute indices in the analysis at hand can be interpreted against this background.

Starting from an arbitrary distribution with positive average income and not all incomes being equal, five possible cases can occur with the implementation of a tax or levy (see Figure 5.5). The horizontal line indicates a constant total amount of levies that all individuals have to bear together. When moving along the line, only the distribution of the burden among individuals is changed, i.e., inequality in the new situation continuously is reduced by moving from the left to the right, keeping average levies constant. Section *a* in Figure 5.5 represents a situation in which both the relative and the absolute index of overall redistribution have a negative sign. Thus, the new situation is less equal compared to the initial one. In section *c*, both indices assess the new situation as more equal (with both showing positive values). However, in section *b* we find contradicting results with the relative index indicating increasing inequality and the absolute index indicating decreasing inequality. Here, there is decreasing absolute income spreads in the after-burden situation (absolute Gini coefficient), which are not large enough to not be overcompensated by the reduced mean in case of the relative Gini coefficient (as $G = AG/\mu$). Furthermore, with an equiproportionate reduction of all incomes, the effect of redistribution in relative terms is zero, but the redistribution effect in absolute terms is positive because absolute income spreads are reduced. With the implementation of a

[40] Therefore they suggest some "centrist" (Kolm, 1976, p. 434) or "intermediate" (Pfingsten, 1986, p. 386) concepts of inequality, which, however, are also based on normative views on inequality.

[41] However, C_B does not measure the degree of progressivity in absolute terms. It simply indicates the *relative* distribution of the respective burden. An equal absolute change of the burden for all individuals would cause a change in C_B which, in absolute terms, should be a neutral modification.

uniform levy, the absolute index of redistribution indicates no change to the prior situation and the relative index shows less equal distribution as average income is reduced.

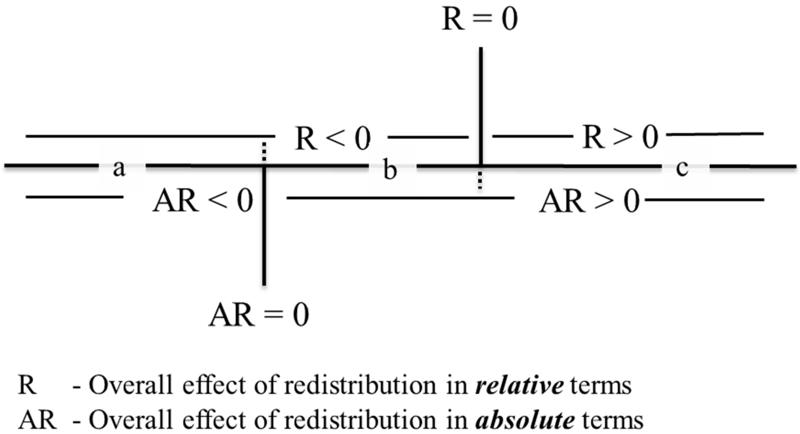

Figure 5.5: Relation of the reactions of relative and absolute redistributive indices in the context of an average income reduction.

Source: Own compilation.

To evaluate a liberalization of agricultural policy as positive in terms of redistributive effects, it is obvious that the new situation should be more equal than the previous situation. Based on the above discussion, the argumentation is that the overall redistributive effect of any reform package must be at least positive in absolute terms and preferably be positive in relative terms as well.

5.1.2.2 Distributional effects of income components

Other studies measuring inequality effects in the agricultural sector have decomposed the Gini coefficient by income sources (e.g. El Benni and Finger, 2012; Keeney, 2000). This methodology allows for the identification of impacts on overall inequality caused by marginal changes in average incomes from one specific source (e.g. direct payments). In opposition to the methodology presented in section 5.1.2.1, the source decomposition of the Gini coefficient “does not serve to provide an explicit characterisation of the redistributive properties of farm income support measures” (Allanson, 2006, p. 118). Nevertheless, the methodology shall shortly be introduced in the following to provide a better understanding of results of other studies presented in chapter 5.2. Additionally, some similarities and relations of the two methodologies shall be revealed. Typically, the relative version of the Gini coefficient is decomposed by income sources in the current literature and thus, the presentation of the methodology is limited to this case in the following.

The income source decomposition usually starts from a covariance-based formulation of the relative Gini coefficient as presented in Lerman and Yitzhaki (1984), which is numerically equivalent to the already introduced formulation in (9):

(16) $$G = \frac{2\,cov[X, F(X)]}{\mu}$$

where *F(X)* is the cumulative distribution function of the random variable *X* representing total income. With decomposing total income into different income sources such that $X = x_1 + x_2 + \ldots + x_k$ and $F(X_k)$ representing the cumulative distribution function of income source *k* equation (16) can be extended to (Lerman and Yitzhaki, 1985):

(17) $$G = \sum_{k=1}^{K} \frac{\mathrm{cov}[x_k, F(X)]}{\mathrm{cov}[x_k, F(X_k)]} \times \frac{2\,\mathrm{cov}[x_k, F(X_k)]}{\mu_k} \times \frac{\mu_k}{\mu},$$

(18) $$G = \sum_{k=1}^{K} R_k \times G_k \times S_k .$$

Following Lerman and Yitzhaki (1985), the term R_k is named Gini correlation between income source *k* and total income, G_k depicts the relative Gini coefficient of income source *k* and S_k represents the share of income from source *k* in total income.

Multiplying R_k and G_k yields the concentration index C_k which measures the distribution of income source *k* when income units are ranked according to their total income:

(19) $$C_k = \sum_{k=1}^{K} R_k \times G_k = \sum_{k=1}^{K} \frac{\mathrm{cov}[x_k, F(X)]}{\mathrm{cov}[x_k, F(X_k)]} \times \frac{2\,\mathrm{cov}[x_k, F(X_k)]}{\mu_k} .$$

The concentration index C_k sometimes also is referred to as 'Pseudo-Gini coefficient'. It is 0 if all income units get an absolute equal amount of income from source *k*, negative if income units in the lower tail of a distribution have a larger share of income from source *k*, and positive if income units in the upper tail of a distribution get the larger share of source *k* (El Benni and Finger, 2012).

Following Lerman and Yitzhaki (1985), El Benni and Finger (2012) and Keeney (2000) calculate the impact a marginal change in the mean income of source *k* would have on the overall Gini coefficient under the assumption that the internal concentration index remains undisturbed:

(20) $$\eta_k = \frac{1}{G}\left[S_k\left(C_k - G\right)\right].$$

From equation (20) it can be observed that the effect of a marginal increase of income from one specific source *k* depends on the share of income from source *k* in total income S_k, the concentration index C_k, and the relative Gini coefficient of total income *G*. As already specified in section 5.1.1, the concentration index C_k measures the distribution of income source *k* when income units are ranked according to their total income. Thus, C_k for example measures the distribution of direct payments across the farm population when farms are ranked with respect to total income. This, however, measures exactly the same as the concentration index of burden C_B (introduced in section 5.1.2.1) measures in a scenario where direct payments are abolished.

Thus, the results gained from a source decomposition of the Gini coefficient can also be calculated based on the indices introduced in section 5.1.2.1, but *vice versa* re-ranking and vertical effects are not attainable from the indices introduced in this chapter.

5.1.3 Measuring inequality and negative income

Many authors have recognized difficulties in interpretation of relative indices of inequality when negative values are allowed for in the distribution under consideration. This is observed especially in case of the relative Gini coefficient (among many others Chen et al., 1982; Ahearn et al.,1985; Boisvert and Ranney, 1990; Stich, 1996).

When negative incomes[42] appear in the distribution the relative Gini is no longer bound by the maximum value of one. Chen et al. (1982, p. 475) conclude from this "… that the [relative] Gini coefficient may overestimate the inequality of income distribution when negative incomes are included". Ahearn et al. (1985) e.g. take this into account and try to circumvent the problem by recoding all negative incomes to zero while recognizing that this will underestimate the level of inequality.

Chen et al. (1982) suggest an *adjusted* relative Gini coefficient which accounts for negative incomes as long as average income of the distribution is positive. They also present a graphical interpretation of their approach (Figure 5.6). Using their terms, the conventional relative Gini can be expressed as (A+B) / (B+C), whereas without negative values A = 0. To account for negative values, they suggest rewriting the Gini in the *adjusted* form: (A+B) / (A+B+C), since the "…conventional Gini goes wrong because it treats the indefinite size of (A + B + C) as a definite size of ½" (Chen et al., 1982, p. 477). Thus, the *adjusted* Gini is bound by the maximum value of one, even with the appearance of negative incomes. In other words, Chen et al. implicitly scale the maximum degree of inequality, which for the conventional relative Gini is equal to the denominator B+C and which implies that one member of the population owns all available income and all others have zero.[43].

[42] This discussion of course applies for any other variable as well. However, since income is the variable under consideration in this work it is used as the term of choice here.

[43] Precisely speaking, the area between the line of total equality (the 45° line) and the Lorenz curve of the distribution "one owing all and all others nothing" approximates B+C with a large number of income units.

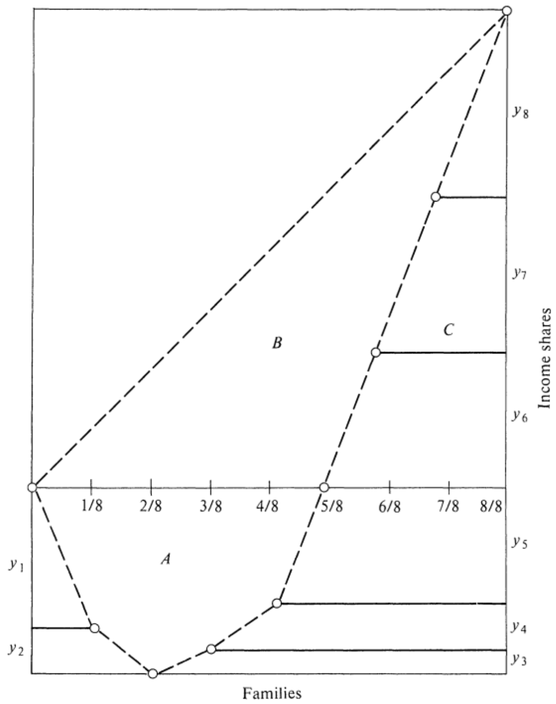

Figure 5.6: The relative Lorenz curve and negative incomes.

Source: Chen et al. (1982, p. 476).

This approach is criticised by van der Ven (2001, p. 11): "Chen et al. (1982) explicitly avoid the conceptual issues associated with the definition of perfect inequality … which complicates *any* interpretation of the coefficient that they advocate". Due to this shortcoming "comparison between two distributions are complicated … by the use of different scaling factors" (p. 11).

Another explicit criticism of the application of the relative Gini with negative values is, that transformations of the distribution under consideration might cause counterintuitive reactions. In a seldom recognized paper, Stich (1996, p. 299) defines the "Greatest Gets More axiom" (GGM), which, as he demonstrates, doesn't hold generally for the relative Gini coefficient.

GGM: $I(x) < I(x_1,\ldots,x_{n-1},x_n + k)$ *for every* $k > 0$.

The GGM axiom states that an inequality index I rises in the case that the richest individual gets more income and all others keep their incomes. The underlying mechanism for the inability of the relative Gini coefficient to fulfil the GMM axiom when negative values arise in the distribution can be explained by splitting up the simple transformation process (i.e. the richest individual gets more income) into two steps. First, assume a mean increasing but inequality preserving change. For the relative Gini i.e. all incomes are proportionally scaled by the same factor (refer to the homogeneity property). This in turn implies that negative incomes become more negative. In the second step, assume that the additional income now is collected (also the additional negative income) and given to the richest person. This step implies that all persons with positive incomes except the richest lose money and all persons with negative incomes gain by reducing their debts. With a high share of negative incomes, their gains and the losses of the positive incomes expect for the richest are weighted more than the gain of the richest person and overall inequality is announced to decrease. Stich (1996) explains the mechanism with the reaction of the Lorenz curve. Referring to Figure 5.6, an increase of the highest income would increase area B but at the same time downsize area A.

Stich (1996) concludes that relative measures of inequality should be avoided when negative incomes appear in the income distribution. He proposes the utilization of absolute or in certain cases intermediate measures of inequality.

However, absolute measures have a different normative basis than relative measures and thus, they cannot be considered as good substitutes in all cases. Also, the above proposed solutions (replacing negative values by zero; adjusting the reference base of inequality) have their shortcomings and hamper interpretation. Due to these difficulties the relative Gini and underlying data are not adjusted in the analysis at hand, even though a considerable amount of negative incomes appear in the distributions under consideration, as will be seen later on. The need to further utilize the relative Gini coefficient for the calculation of other indices would especially complicate their interpretation. The absolute Gini coefficient however, is used additionally.

Furthermore, many authors apply the conventional relative Gini coefficient even with negative values. Amiel et al. (1996, p. 65) argue that the relative Gini is a “pratical alternative” when negative values appear in the distribution since many other scale invariant measures are undefined in such a case. Allanson (2006) even develops a methodology to compare relative Gini coefficients of distributions with negative and positive average incomes.

To become more familiar with the implications of negative values on the calculation of relative Gini coefficients, a small artificial empirical experiment is provided in the following lines. This proceeding of course cannot generate any general conclusions nor is it meant to do so. However, it might help the reader to better reflect the shortcomings of the relative Gini as discussed above.

In an artificial situation, consider an income vector of three persons {15,10,5}. This initial situation is constantly changed by reducing the income of each person by one Euro (Table 5.1).

Table 5.1: Constant absolute differences with reduced mean incomes.

	Income 1	Income 2	Income 3	relative Gini
A	15	10	5	0.2222
B	14	9	4	0.2469
C	13	8	3	0.2778
D	12	7	2	0.3175
E	11	6	1	0.3704
F	10	5	0	0.4444
G	9	4	-1	0.5556
H	8	3	-2	0.7407
I	7	2	-3	1.1111
J	6	1	-4	2.2222

Source: own calculations.

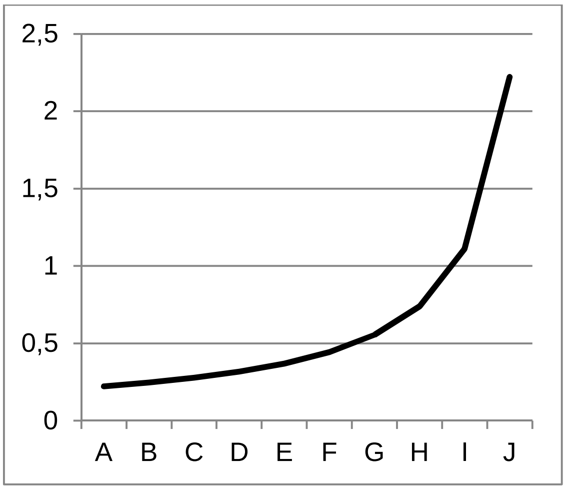

Figure 5.7: Impact of mean income reductions on the relative Gini coefficient.
Source: own calculations.

From Table 5.1 and Figure 5.7 it can be seen that the relative Gini, assumed that absolute distances between income units do not change, increases exponentially with decreasing mean income. In a more general sense this becomes clear by recalling that average distances among individuals appear in the numerator of the relative Gini and mean income in the denominator:

(9)
$$G = \frac{1}{2n^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{\mu}.$$

This reaction takes place also when negative incomes are excluded (until distribution F). However, the appearance of negative incomes tends to make this effect more pronounced because the spread between numerator and denominator in this case may increase without having a ‘natural bound’. Absolute average distances can be kept constant and at the same time mean income can become close to zero[44] and vice versa, with the allowance for negative incomes absolute average distances can increase without a ‘natural bound’ while keeping mean income constant. If this happens with an already comparatively low mean income, changes in absolute distances may seem disproportionally strong in relative terms.

Furthermore, it should be kept in mind that the relative Gini does not necessarily violate the GGM axiom as soon as one negative value in the income distribution appears: The term $2n(n-1)\mu$ is equal to the maximum possible sum of absolute distances that can occur between individual incomes when only non-negative incomes are allowed, i.e. in a situation when one

[44] Of course mean income can become negative as well, which would result in a negative value for the relative Gini. However, it is abstracted from this possibility here since the discussion of negative Ginis is beyond the scope of this work and not relevant in the empirical analysis.

person owns everything and all others own nothing. Observing that an increase of the highest income by an additional unit increases the distances among all units $\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|$ (i.e. the numerator of the relative Gini) by the same absolute amount as it increases the term $2n(n-1)\mu$ (i.e. the denominator of the relative Gini for a large n)[45], it can be concluded that for large populations only relative Ginis close to one or greater than one will not fulfill the GGM axiom. Thus, counterintuitive reactions not automatically appear when negative incomes exist; rather the ratio $\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|$ to $(2n^2\mu)$ is crucial.

It can be stated that even though the relative Gini is technically correctly specified when negative incomes are considered, it can react in a way that might not be in line with normative expectations and thus, may lead to misinterpretations. This should be kept in mind when relative inequality is discussed later in the empirical part of this work. Additionally, Lorenz curves are presented to illustrate the impact of negative values. If Lorenz curves do not intersect, no counterintuitive reactions can be expected. Yet, disproportionally strong reactions are of course still possible.

5.2 Literature review

After the discussion of methodological aspects for the measurement of inequality and redistribution, empirical results shall be presented. Before redistributive effects of the calculated scenarios are discussed in detail for the western German agricultural sector, a literature review of studies concerned with the measurement of income distribution and the redistributive effects of agricultural policy is provided below.

As already stated in the introduction, most of the studies assessing redistributive effects of agricultural policy on farm incomes are ex-post studies and static in nature.[46] Many studies only refer to separate measures of agricultural policy which are directly observable from the data without side calculations. However, other authors apply sophisticated methodologies for the quantification of support, which is not directly observable, like border protection e.g.

Within the literature regarding the measurement of redistributive effects of agricultural policy, one methodology is dominating. Several authors apply the source decomposition of the relative Gini coefficient, which was introduced in section 5.1.2.2. This method enables the assessment of impacts on overall inequality caused by marginal changes in income sources. Besides the application of a similar methodology, most of these studies have in common that they focus on agricultural support that is directly observable from official statistics, e.g. DPs of the CAP. More subtle support such as transfers from consumers to farmers often is neglected. Furthermore, most studies abstract from capitalization of support in production factors and assume that farmers are the ultimate beneficiaries of such payments. Furthermore,

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[45] For a large population n it holds that $1/2n^2\mu \approx 1/2n(n\text{-}1)\mu$.

[46] The few exemptions are already discussed in section 2.3.

incentive effects in general are not taken into account. Some studies additionally analyse inequality effects of off-farm incomes.

Keeney (2000) presents such a study for Ireland. She disaggregates family farm income into DPs and market income, where the latter includes all on-farm income sources but DPs. Based on the decomposition of the relative Gini coefficient she finds that DPs reduced relative income inequality in Ireland between 1992 and 1996 and states that an increased share of DPs has equalizing effects on farm income distribution.

In a study for Switzerland, El Benni and Finger (2012) differentiate inequality effects by region, i.e. by valley, hill and mountain area. They observe changes in farm household income inequality in relative terms between 1990 and 2009 and decompose overall income into off-farm income, DPs and a remainder market income. They find that off-farm income and DPs have equalizing effects on the distribution of household income and the opposite for market incomes. Furthermore, their results show that DPs have stronger marginal effects on inequality than off-farm incomes.

Based on the same static methodology, Severini and Tantari (2013) analyse likely redistributive impacts of different possible reforms of first pillar DPs for Italy. In their study, farm net value added is the income indicator under consideration which is decomposed into income from DPs and market based income. For the status quo they find a high concentration of income which is reduced by DPs in relative terms. Their simulation of a shift from the historical to the regional DPs model reveals only a slight reduction of inequality compared to the baseline.

Von Witzke and Noleppa (2007) decompose a relative Gini coefficient as well as a measure of absolute inequality of total farm profit into components for direct payments and market profit. The authors conclude that direct payments account for about one-third of overall inequality for family farms and for two-thirds of overall inequality for incorporated farms in Germany. However, from their numerical results it can be concluded that in relative terms DPs have an inequality reducing effect on family farms since the reported “pseudo factor Gini” is lower than the relative Gini coefficient for total income. The fact that the “pseudo factor Gini” has a positive value itself demonstrates that DPs have an inequality increasing effect in absolute terms.

Several similar studies have been carried out for U.S farm households. Ahearn et al. (1985) analyse the effects of direct government payments on income of farm operator households in 1984. They find equalizing effects of direct government payments and off-farm income at the margin in relative terms. Findeis and Reddy (1987) differentiate by regions and conclude that off-farm income has inequality reducing effects at the margin in relative terms in regions where full-time farming predominates.

Boisvert and Ranney (1990) apply the methodology to New York dairy farms. They consider net farm income, off-farm income and direct government payments and conclude that the last two have inequality reducing effects. El-Osta et al. (1995) include non-monetary[47] and monetary income in their analysis. They find equalizing effects of government payments and off-farm incomes at the margin in relative terms.

Mishra et al. (2009) investigate relative inequality effects of government payments on farm household incomes, differentiated for nine farming regions in the U.S. They conclude that a marginal increase in the off-farm and government payments components would reduce overall inequality; this is also true at the regional level for government payments and for most regions in the case of off-farm income.

As an interim conclusion it can be stated that all considered studies which apply the Gini coefficient decomposition methodology find equalizing effects of DPs or other direct government support in relative terms, no matter for which country or period the study is carried out. If off-farm incomes are included in the analyses, this component is also found to be inequality reducing in most of the cases. However, regional differences appear in some analyses. The only study explicitly taking absolute inequality into account (von Witzke and Noleppa, 2007) suggests inequality increasing effects of direct payments.

To account for different dimensions of inequality impacts, Allanson (2006, 2007, 2008) and Allanson and Rocchi (2008), through a series of papers, use the approach which was introduced in section 5.1.2.1 and which is based on a comparison of Gini indices of pre- and post-support income. They take overall agricultural (CAP) support into account. Support from market price measures is calculated on the basis of OECD producer support estimate data. Besides, DPs and other grants and subsidies are considered in the analyses. Furthermore, in contrast to the majority of the studies, they account for the fact that support only partly benefits the farmers and that a part of the payments will capitalize into prices of production factors not owned by the farm. The four studies are presented in the following in more detail.

Allanson (2006) estimates changes of relative Gini coefficients for family farm incomes in the Scottish agricultural sector. In this paper, the overall redistribution effect of agricultural policy support is split up into a vertical dimension of inequality and a re-ranking effect. The analysis suggests that support is progressive in absolute terms, which has to be interpreted against the background of a negative average income of Scottish farms in the pre-support situation. However, an unequalizing overall effect of agricultural policy is found in relative terms, which is caused by re-ranking effects overtaking the equalizing vertical effects.

In a paper explicitly taking classical horizontal inequity[48] into account, Allanson (2007) finds the same result based on three different relative inequality measures. In absolute terms his

[47] Non-monetary income refers to the value of home produced and consumed goods and the rental value of dwelling (El- Osta et al., 1995).

[48] The concept of classical horizontal inequity refers to the unequal treatment of equals. It is distinguished from other concepts of horizontal inequity like re-ranking.

results suggest a slight decrease in inequality due to agricultural support. However, negative horizontal inequity effects more or less outweigh equalizing vertical effects. Again, these rather confusing results (a more equal absolute index with a less equal relative index caused by income increasing support) appear with a negative average pre-support income which makes interpretation more difficult.

Allanson (2008) presents an analysis in absolute terms for another time period than in his afore mentioned papers. Results show for five consecutive years an unequalizing effect of agricultural policy on the distribution of farm incomes in the Scottish agricultural sector. The unequal treatment of pre-transfer equals is identified to be the main reason for the increase in overall inequality, which otherwise would have been reduced.

Allanson and Rocchi (2008) find similar results for overall inequality effects through a comparative analysis for Tuscany and Scotland. However, for Tuscany transfers are regressive in absolute terms rather than progressive as in the Scottish case. In their paper, an analysis for farm income is compared to an analysis for total household income which additionally takes off-farm income into account. In both areas – Tuscany and Scotland – inequality would decrease by additionally taking off-farm income into account when keeping ranks of the farm income distribution constant; however, since the ranks of the farms also change, pre-support income inequality effectively increases. When total household income is the indicator of choice vertical effects are less regressive/more progressive when agricultural support is introduced.

OECD (2003) measures the degree of concentration of gross farm receipts, agricultural support and net operating income by estimating relative Gini coefficients and Lorenz curves based on farm quartiles. Support consists of DPs and market price support, which is calculated based on the OECD PSE database. Based on a comparison of these measures, the authors conclude that for most OECD countries under consideration, agricultural support has relatively small effects on distribution by farm size because the distribution of agricultural support is only marginally less unequal than the distribution of gross receipts. Thus, they conclude that the distribution of support is unequal because larger farms receive a greater share. Furthermore, it is found that on average market price support is more unequally distributed than DPs.

Findings in a similar analysis by Moreddu (2011), who additionally focuses on differences among farm types and regions, are in line with these results. Using the assumption that farmers are final beneficiaries of support, it is found that market price support generally is distributed more unequally than direct payments. Yet, these differences are found to be small for Germany. It is concluded that overall support is unequally distributed but less than gross output which indicates inequality reducing effects in relative terms. Specifically for Germany, it is found that total support is as unequally distributed as gross agricultural output.

Schmid et al. (2006) compare relative Gini coefficients of direct payments per farm holding for single EU-15 member states. They show that the degree of distribution of direct payments is fundamentally different and closely related to the concentration of land inside the respective member states. In a more detailed analysis for Austria, they find that larger holdings receive the bulk of direct payments and that less favoured area payments have little equalizing effects.

Von Witzke (1979) analyses the effects of prices and price policies on income distribution in the agricultural sector. Based on a theoretical model short- and long-run effects of price changes are empirically analysed for a sample of farms located in a specific German region. He finds that increasing prices lead to a lower concentration of agricultural income in the short-run (in relative terms). In the long-run, results depend on the assumption regarding the elasticity of scale. If the elasticity of scale is assumed to be positively correlated to farm income increasing prices lead to a higher concentration of agricultural income in the long-run.

Brown (1990) applies a comparative static partial equilibrium model to identify long-run effects on producer welfare in the EU-10. In a first step, changes in producer welfare are calculated on a commodity basis for a full liberalization of the CAP. Subsequently, changes are disaggregated among representative farms. He finds that benefits of the CAP are regressively distributed.

Another methodological approach with which to analyse policy induced income effects in the agricultural sector is the spatial micro-simulation approach applied by Hynes et al. (2009a, 2009b). They statistically match different large scale datasets to generate a “synthetic population of Irish farms representing the Irish rural space” (Hynes et al., 2009a, p. 284). Hynes et al. (2009a) analyse with their spatial farm level micro-simulation model potential effects of a possible shift from the historical DP scheme to flat rate payments on the spatial distribution of family farm income in Ireland and provide their results in a GIS-based graphical form. Hynes et al. (2009b) use a similar approach to examine effects of carbon taxes in Ireland. Both analyses are static in nature even though ex-ante policy analysis is carried out.

A related branch of literature aims at the estimation of EU agricultural policy effects on regional convergence. Hansen and Teuber (2011) take direct payments as well as market price support into account by applying OECD producer support estimate figures. They calculate regional agricultural support per labour force and per hectare. Based on the coefficient of variation they calculate changes in regional inequality of farmers revenues with and without CAP support over time for an area that consist of 26 NUTS-3 regions in Hesse, Germany. They find that inequality between farmers’ revenues increases across regions over time and that the CAP has only attenuating impacts on this trend. With a similar approach Anders et al. (2004) analyse the distribution of support in the same area and find increasing variations of total support, support per farm and support per hectare among individual regions over time. However, they state that per hectare support is negatively correlated with regional per capita income. For further relevant studies in this field refer to the introduction of Hansen and Teuber (2011).

In a completely different approach, Rocchi (2009) uses a SAM-based model to analyse income distribution changes from the single payment scheme of the CAP for Italy. This approach is able to distinguish between direct and indirect impacts of agricultural policy on income distribution among agricultural as well as non-agricultural households. However, the analysis is carried out at a highly aggregated level and does not take price effects into account.

To conclude this section, it can be stated that the majority of the studies find explicitly or implicitly (e.g. "the distribution of support is unequal") that agricultural support increases inequality in absolute terms. On the other hand, agricultural support is found to be inequality reducing in relative terms. Most of the studies do not take re-ranking or classical horizontal equity effects into account, however, their importance is shown by Allanson (2006, 2008).

Virtually all of the studies which are assessing income effects at the farm level are static in nature[49]. Among them, only Allanson (2006, 2007, 2008) and Allanson and Rocchi (2008) account for the fact that farmers probably are not the final beneficiaries of the whole amount of support.

[49] It is not unambiguously clear to the author if the partial equilibrium model in Brown (1990) is a behavioural model. However, in his study production patterns at the farm level are static.

5.3 Redistributive effects of CAP reforms on western German farm incomes

In the following section, redistributive effects of policy changes assumed in the different scenarios (as introduced in section 4.1) are presented. Thereby, results of different methodological approaches are compared to each other. To ease the understanding of the methodological differences behind the analyses compared, Figure 5.8 gives an overview about the different aggregation levels, types of income, and the different styles of data generation. The left part of the figure refers to data generated by the modeling system as described above and the right part refers to a static analysis which does not take incentive effects into account. The latter serves as a reference for comparison and will be described in detail later on.

At first, aggregation biases are accounted for in inequality analysis due to the application of grouped data instead of individual data. To this end, inequality impacts calculated on the basis of 467 FARMIS groups are compared to results calculated on the basis of 8,024 individual FADN-farms. This comparison is undertaken for the income indicator FFI (second column of the left part of Figure 5.8) and for the income indicator ‘total household income’ which, in addition to family farm income, accounts for off-farm income sources (column 2 + column 3 from the left part of Figure 5.8). Off-farm income sources are not covered by the modeling system and the observed data in the base year of the analysis is assumed to be constant in real terms over time for all scenarios.

Second, an analysis for the indicator ‘FFI’ is compared to an analysis for the indicator ‘total household income’. Comparison is presented at the individual farm level. Relating to Figure 5.8, results referring to the second column in the last row of the left part are compared to results calculated on basis of the sum of the second and third column (FFI + off-farm income) in the last row of the left part of the figure.

Third, since virtually all analyses which try to assess redistributive effects of agricultural policy instruments are conducted in a static way, the importance of taking incentive effects into account is assessed. To do so, an analysis is carried out which compares statically derived income distributions with distributions generated by the modeling system. To ease the analyses of the underlying processes, this comparison is carried out on the basis of FFI values for 467 FARMIS groups (column 2, row 3, left hand side vs. column 2, row 3, right hand side).

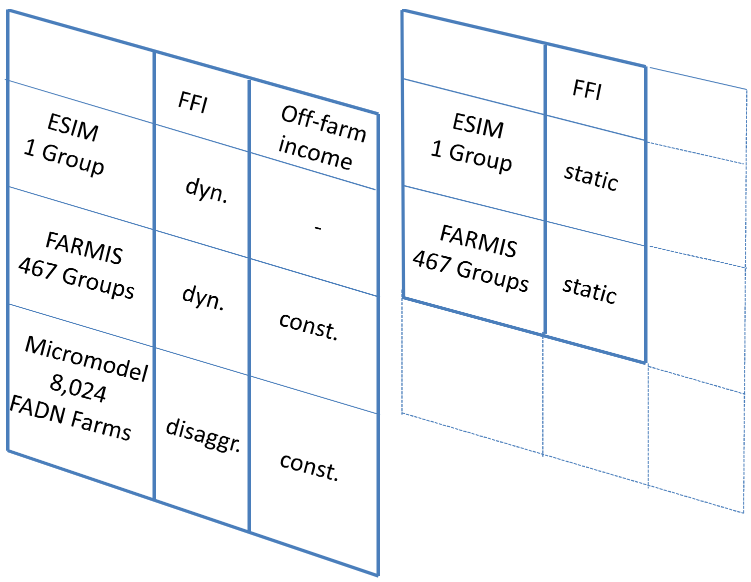

Figure 5.8: Overview of methodological approaches of inequality measurement.

Source: own compilation.

For all scenarios, baseline results with the assumed status quo of agricultural policy serve as a base situation where redistributive effects are referred to in all cases. This implies the weighting of all (marginal) income changes by baseline-rankings (Lerman and Yitzhaki, 1995).

5.3.1 Redistributive effects and aggregation error[50]

In this chapter redistributive effects of different reform scenarios are presented. Thereby, results are based on generated single farm data on the one hand and on grouped data on the other hand to evaluate the aggregation error which appears when redistributive effects are measured by the application of grouped data.

Liberalizing the agricultural sector has clear negative impacts on average farm income. In the Full_Lib scenario, the scenario with the lowest average income, 31% of all individual farms have negative incomes, whereas in the baseline there are only 10%. The impact on relative measures in this context is extensively discussed above in section 5.1.3 and will be referred to again when distributional results are discussed in detail. Furthermore, as already examined in chapter 4.2, the results should be interpreted against the background that with this strong reduction in average income, significant structural change such as an increase in farm size and farmers leaving the sector can be expected which is not depicted in the current model specification.

[50] This chapter was basis for the paper Deppermann et al. (2013) and some numerical results and paragraphs are taken unaltered.

5.3.1.1 Decile groups

Table 5.2 provides an overview of the distribution of FFI in western Germany for all scenarios based on data for individual farms. Total farm population is segmented into decile groups which are ten groups of equal size with the bottom group containing 10% of farms with the lowest incomes and the top group containing 10% of farms with the highest incomes. In the column on the left (I), the baseline income of each decile group is reported. The next columns refer to the different liberalization scenarios under the situation in which the composition of the decile groups does not change: Farms that had the lowest income under the baseline scenario are still located in the bottom decile.

Columns III, VI, IX, and XII present for each decile group its share in total income reduction for the respective scenarios. The bottom decile group under the Full_Lib scenario bears only 3% of total income reduction and the top decile bears 23%; however, for the top decile income is reduced by 48% of baseline income, which is lower than the average reduction among all farms, 69%.

On average, the effects of the 50_DP scenario are comparatively moderate. This is partly due to the high share of rented land – 68%, on average, in the baseline scenario – as well as the high rate of capitalisation of DPs in land prices which is assumed in FARMIS. As a result, land rental prices decrease significantly with a reduction of DPs, which cushions negative income effects especially for farms with a high share of rented land. The income effects more than double in the No_DP scenario compared to the 50_DP scenario because in many regions the full reduction of DPs is too high to completely be absorbed by the land market. Still, the average income reduction of a full abolishment of DPs is significantly lower (8,954 €) than the average loss of direct payments (18,331 €).

Furthermore, it becomes clear that the Full_Lib scenario is not simply a sum-up of the No_DP and the No_Pricepol scenarios. For example, on average, the top decile loses 56,670 € in the No_Pricepol scenario and loses 15,105 € in the No_DP scenario, whereas under the Full Liberalization scenario, the top decile income decreases by 73,723 €.

Table 5.2: Family farm income decile groups for western Germany based on individual farm data.

			50_DP scenario				No_DP scenario			
	Baseline income (I)		Income after 50% DP Cut (II)		Income reduction (III)	Income difference /base income (IV)	Income after 100% DP Cut (V)		Income reduction (VI)	Income difference /base income (VII)
	€/farm (av.) (Ia)	% of all (Ib)	€/farm (av.) (IIa)	% of all (IIb)	% of total reduction		€/farm (av.) (Va)	% of all (Vb)	% of total reduction	
1	-13,197	-3	-15,633	-4	7	-0.18	-18,043	-5	5	-0.37
2	1,701	0	-486	0	6	1.29	-3,294	-1	6	2.94
3	10,267	2	8,028	2	6	0.22	5,071	1	6	0.51
4	20,607	5	16,759	4	11	0.19	11,609	3	10	0.44
5	31,570	7	28,210	7	9	0.11	23,536	6	9	0.25
6	41,791	9	38,133	9	10	0.09	32,600	9	10	0.22
7	52,623	12	48,530	12	11	0.08	42,243	12	12	0.20
8	67,286	15	63,167	15	11	0.06	56,637	16	12	0.16
9	88,967	20	84,457	20	13	0.05	76,827	21	14	0.14
10	152,622	34	147,241	35	15	0.04	137,517	38	17	0.10
All	45,424	100	41,841	100	100	0.08	36,470	100	100	0.20

Source: Own calculations.

Table 5.2 (continued): FFI decile groups for western Germany based on individual farm data.

			No_Pricepol scenario				Full Liberalization scenario			
	Baseline income (I)		Income after abolition of price policies (VIII)		Income reduction (IX)	Income difference /base income (X)	Income after full liberalization (XI)		Income reduction (XII)	Income difference /base income (XIII)
	€/farm (av.) (Ia)	% of all (Ib)	€/farm (av.) (VIIIa)	% of all (VIIIb)	% of total reduction		€/farm (av.) (XIa)	% of all (XIb)	% of total reduct.	
1	-13,197	-3	-16,976	-7	2	-0.29	-21,835	-16	3	-0.65
2	1,701	0	-3,245	-1	2	2.91	-8,340	-6	3	5.90
3	10,267	2	4,127	2	3	0.60	-1,209	-1	4	1.12
4	20,607	5	9,703	4	5	0.53	710	1	6	0.97
5	31,570	7	16,396	7	7	0.48	7,136	5	8	0.77
6	41,791	9	20,920	9	10	0.50	10,821	8	10	0.74
7	52,623	12	26,888	11	12	0.49	15,672	11	12	0.70
8	67,286	15	37,223	16	14	0.45	24,986	18	13	0.63
9	88,967	20	47,241	20	19	0.47	33,615	24	18	0.62
10	152,622	34	95,952	40	26	0.37	78,899	56	23	0.48
All	45,424	100	23,823	100	100	0.48	14,046	100	100	0.69

Source: Own calculations.

When decile group values are calculated on the basis of already grouped (FARMIS) data rather than on the basis of individual data, top decile groups have a lower average income and bottom decile groups a higher one (Table 5.3). This effect is intuitive since groups are generated by criterions other than income (region, type and size). When FARMIS groups are disaggregated, higher individual incomes of middle and low-income groups move towards higher decile groups and vice versa.

Difference in the distribution of respective income reductions, however, can hardly be observed. While the top decile group has a lower income share by 25 percentage points in total income in the Full_Lib scenario, the share in total income reduction differs only by one percentage point. From this it can be concluded that though low individual incomes in high-income (FARMIS) groups tend to be smaller than high incomes in low-income (FARMIS) groups, they have similar income losses, on average, under the different scenarios.

Table 5.3: Differences in FFI decile groups when data are calculated based on grouped data compared to individual farm data (Table 5.2).

			50_DP scenario			No_DP scenario		
	Baseline income (I)		Income after 50% DP Cut (II)		Income reduction (III)	Income after 100% DP Cut (V)		Income reduction (VI)
Differences to Table 5.2 in € or %-points respectively								
	€/farm (av.) (Ia)	% of all (Ib)	€/farm (av.) (IIa)	% of all (IIb)	% of total reduction	€/farm (av.) (Va)	% of all (Vb)	% of total reduction
1	11,890	3	11,997	3	0	12,209	3	0
2	7,301	2	7,057	2	1	6,856	2	0
3	8,058	2	7,235	2	2	5,803	2	3
4	8,596	2	9,170	2	-2	10,135	3	-2
5	7,256	2	6,864	2	1	6,096	2	1
6	2,140	0	3,267	1	-3	4,638	1	-3
7	-415	0	-754	0	1	-716	0	0
8	-3,184	-1	-3,909	-1	2	-4,455	-1	1
9	-8,681	-2	-7,990	-2	-2	-7,410	-2	-1
10	-32,973	-7	-32,950	-8	0	-33,169	-9	0
All	0	0	0	0	0	0	0	0

Source: Own calculations.

Table 5.3 (continued): Differences in FFI decile groups when data are calculated based on grouped data compared to individual farm data (Table 5.2).

			No_Pricepol scenario			Full Liberalization scenario		
	Baseline income (I)		Income after abolition of price policies (VIII)		Income reduction (IX)	Income after full liberalization (XI)		Income reduc-tion (XII)
Differences to Table 5.2 in € or %-points respectively								
	€/farm (av.) (Ia)	% of all (Ib)	€/farm (av.) (VIIIa)	% of all (VIIIb)	% of total reduction	€/farm (av.) (XIa)	% of all (XIb)	% of total reduct.
1	11,890	3	11,657	5	0	12,609	9	0
2	7,301	2	7,174	3	0	6,735	5	0
3	8,058	2	6,364	3	1	4,208	3	1
4	8,596	2	6,946	3	1	8,409	6	0
5	7,256	2	3,277	1	2	2,450	2	2
6	2,140	0	6,215	3	-2	8,984	6	-2
7	-415	0	3,480	1	-2	2,938	2	-1
8	-3,184	-1	-3,953	-2	0	-5,223	-4	1
9	-8,681	-2	-5,805	-2	-1	-5,506	-4	-1
10	-32,973	-7	-35,364	-15	1	-35,615	-25	1
All	0	0	0	0	0	0	0	0

Source: Own calculations.

5.3.1.2 Lorenz curves

Before the methodology of measuring redistributive effects as described in section 5.1.2 is applied, Lorenz curves of the respective scenarios are presented. Following Jenkins (1991, p. 6) it can be stated that if two relative (absolute) Lorenz curves do not cross, the distribution with the relative (absolute) Lorenz curve closer to the diagonal (horizontal) unambiguously is more equal than the other, according to all “standard” relative (absolute) inequality measures. By “standard” Jenkins refers to all inequality measures that fulfil the properties introduced within section 5.1.1: Pigout-Dalton Transfer Principle, Symmetry, and Population Principle. The concept of absolute Lorenz domination originally was introduced into the literature by Moyes (1987).

In Figure 5.9 relative Lorenz curves of the income distributions in 2020 based on individual farm data for all scenarios are presented (Lorenz curves based on grouped data are presented in Appendix C). Since the curves do not intersect, it can be concluded that the same ranking of scenarios with regard to their degree of inequality as identified by the Gini index later on (Table 5.4) also would have been identified by all other standard inequality measures. Furthermore, it becomes apparent that the lower the average income of a scenario is, the more unequal it is ranked in relative terms. From Figure 5.10 it becomes clear that for the absolute measure exactly the opposite is true. The baseline with the highest average income unambiguously has the most unequal distribution in absolute terms while the Full_Lib scenario with the lowest average income has the lowest degree of inequality among the scenarios.

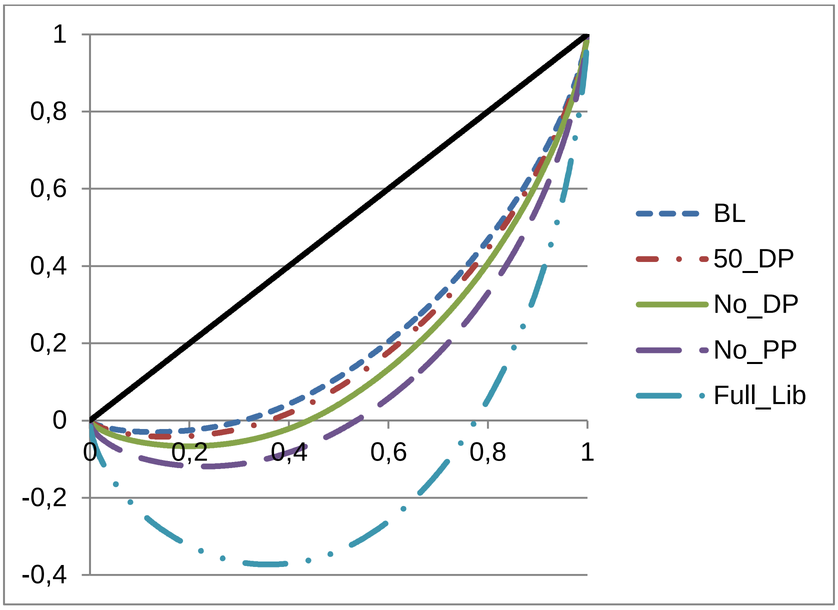

Figure 5.9: Relative Lorenz curves for baseline and all scenarios based on individual FFI data.

Source: Own calculations.

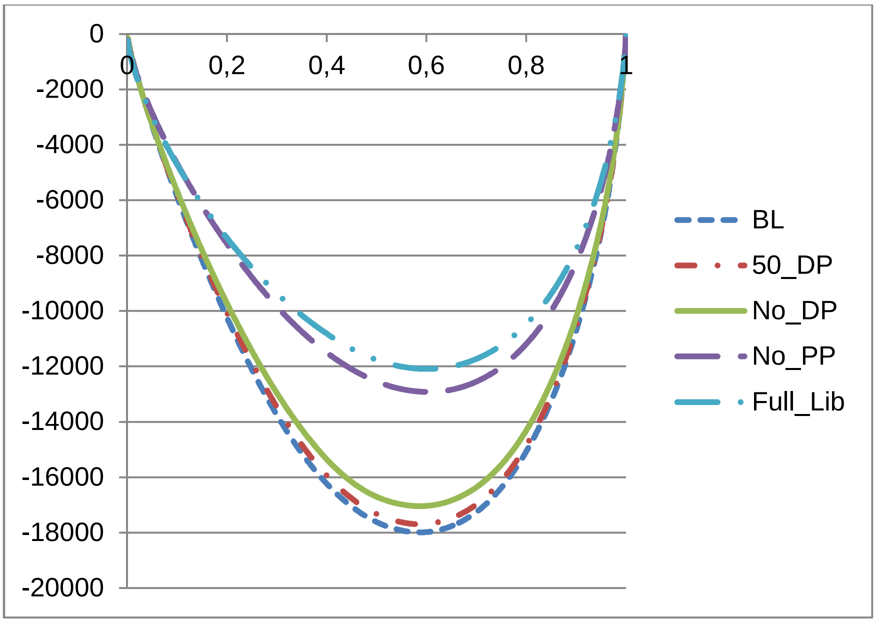

Figure 5.10: Absolute Lorenz curves for baseline and all scenarios based on individual FFI data.

Source: Own calculations.

5.3.1.3 Gini based analysis

In the following section, inequality effects of the different liberalization scenarios are analysed by decomposing the inequality changes into vertical and re-ranking effects and by measuring indices of progressivity (as described in 5.1.2). First, the results of the analysis, which is conducted on the basis of individual data, are analysed. This analysis reveals more information on inequality than the analysis based on FARMIS groups. Despite varying magnitudes of the single indicators, the direction of inequality effects is not substantially different in general. Emerging differences are discussed in more detail subsequently.

In the 50_DP scenario (Table 5.4, section II) income is reduced by 3,583€ on average, which accounts for 7.8% of income in the baseline scenario. In absolute terms the DP cut leads to a slightly more equal situation. Very small re-ranking effects occur and the overall redistributive effect is also quite small. This is due to the low value of average support reduction rather than a low level of progressivity of the reduction. The C_B measure indicates that support reduction is progressively distributed which means that higher incomes bear a higher burden of a DP cut than smaller incomes do. The results are in accordance with a priori expectations: farms with higher income have a greater acreage and get higher DPs. In relative terms we observe an opposite inequality effect. The DP cut is regressively distributed and leads to a more unequal distribution of income. The negative P value indicates that income losses are more equally distributed than initial income in the baseline scenario. Compared to other scenarios, P is even more negative if DPs are reduced by 50% representing a higher degree of regressivity of income reduction. Income losses account for a larger share in lower incomes compared to higher incomes.

Similar effects can be observed in the analysis of a full abolishment of the DPs (the No_DP scenario, Table 5.4, section III): a more equal situation in the absolute analysis and a more unequal situation in the relative analysis. A doubling of the cut in DPs (from 50% to 100%) leads to disproportionately higher effects in the inequality analysis. A 100% cut has a less negative index of progressivity which indicates that a full abolishment in relative terms is less regressive than a 50% cut. Farms with lower income tend to be less productive and tend to be located in regions with relatively low land rents. Thus, low-income farms already reduce their production area with a 50% cut while high-income farms tend to not reduce production since rental prices can absorb a great share of the DP cut and gross margins are still positive. An additional cut of the remaining DPs hits high-income farms harder because they now also reduce their production area whereas low-income farms already reduced their production area.

In the No_Pricepol scenario (Table 5.4, section IV) support cuts are pronounced in the livestock sector since tariffs and export subsidies are in place for several products in the baseline scenario and milk production is restricted due to the quota scheme. Furthermore, the sugar market is also heavily affected by relatively high border protection and the production quota that is still in place in our baseline scenario (compare sector results in section 4.2).

Compared to the No_DP scenario, much stronger income effects occur when price policies are abolished, i.e. average income is reduced by 48%.[51] The overall absolute effect of redistribution (*AR*) is positive, which also indicates a positive absolute index of vertical equity since the absolute index of re-ranking is always non-positive. Thus, farms with higher incomes tend to bear a higher absolute burden from liberalization compared to farms with lower incomes. The re-ranking effect reduces the vertical effect by about 25%.

In relative terms, income inequality increases compared to Baseline values. The redistributive effect is -0.222, which is more than double the effects in the No_DP scenario. Almost half of the overall effect, however, originates from re-ranking effects. Furthermore, due to a higher share of negative incomes compared to the No_DP scenario, comparability might be distorted in this case. The index of progressivity P is clearly negative, which indicates that low-income farms bear a larger share of the overall burden than their share of baseline income. For this indicator, comparability is given since it relies on the indicators C_B, which incorporates (positive) income losses that rarely are negative, and G_x, which is the relative Gini coefficient of the Baseline. A comparison reveals that the abolishment of market price policies clearly is less regressive than the abolishment of DPs. Despite a lower regressivity, overall effects are more negative in the No_Pricepol scenario because average income reduction is much higher and the negative vertical effect is amplified by additional re-ranking effects.

In the Full_Lib scenario (Table 5.4, section V), the liberalization policies of the No_DP and No_Pricepol scenarios are combined. Effects of both single scenarios go into the same direction, which is reflected in the results of the Full_Lib scenario. Redistributive effects of the combined scenario are stronger – i.e., they are more equalizing in absolute terms and more unequalizing in relative terms – compared to the single scenarios. Progressivity, however, is intermediate in the Full_Lib scenario. The observed increase in overall redistributive effects (more negative in relative and more positive in absolute terms) is caused by a larger scale factor s. However, the more than proportionally strong reaction of R partly goes back to a high share of negative incomes in the income distribution (see discussion in section 5.1.3).

5.3.1.4 Aggregation error

From Table 5.4 it can be observed that the analysis that is based on individual data and the one that is based on grouped FARMIS data clearly differ in terms of magnitude of the single indicators. Yet, the direction of inequality effects and the evaluation of policy reforms are similar.

It is intuitive that both absolute and relative Gini indices are larger when calculated on the basis of individual data since within-group inequality is additionally included in the analysis. For baseline results, between-groups inequality accounts for 75% of total inequality measured

[51] Income effects of this size should be interpreted in light of the modelling system not allowing for changes in farm structure.

on individual basis[52] while for the Full_Lib scenario between-groups inequality only covers 59% of total inequality.

Already, the decile group analysis revealed that some farms with comparatively low (high) incomes which were part of middle-class income groups before the disaggregation move to the lower (upper) fringe of the overall distribution after disaggregation. In return, farms with comparatively high (low) income which formerly were part of groups with low (high) average incomes ascend (descend) in the income parade. This makes clear that the ranking of incomes in the individual approach is different from the ranking which appears when individuals are ranked due to the average incomes of their groups, which is implicitly the ranking in the grouped data approach. For Baseline results average income is 3% lower in the lowest decile group and 7% higher in the top group when individual rankings are considered.

In each scenario the overall redistributive effect is more negative in case of the relative Gini and less positive in absolute terms when calculated on the basis of individual data. The vertical effect in absolute terms is higher for all scenarios, but then more than compensated by an also higher re-ranking effect. In relative terms both, V and H are more negative in all scenarios.

Redistributive effects, however, differ only slightly in the absolute analysis. The C_B indices, which also determine the absolute vertical effects, in particular are close between the approaches. For the relative analysis, differences are higher between the two approaches. This is comprehensible because after disaggregation a similar degree of distribution of losses is combined with a higher degree of inequality in Baseline incomes since $P = C_B - G_x$. Thus, similar absolute income losses are borne by higher incomes in the upper tail of the distribution and by lower incomes in the lower tail of the distribution. To conclude, it seems that after the disaggregation of groups, individual farms change their ranks to a certain extent. However, farms that change ranks, on average, lose similar absolute amounts of their incomes. This in turn, leads to more regressive income changes in relative terms.

The most remarkable difference occurs among the relative index of progressivity in the No_Pricepol scenario. It is remarkable not because of the scope of the difference but because of the qualitative interpretation. The analysis of between-groups inequality suggests an almost neutral distribution of income reductions in relative terms. Contrarily, the analysis of individual data shows a clear negative index which implies regressively distributed income losses.

However, large differences in the relative analysis, especially between the G_y values, should be interpreted with caution due to a higher share of negative incomes in the individual analysis because several individual farms with negative incomes were 'hidden' in groups with positive average income (26% of groups in Full_Lib have negative income and 36% of individuals in the same scenario; for the Baseline the ratio is 5% to 13%). Thus, with a

[52] The ratio is the same for relative and absolute indices.

constant mean income (denominator) the numerator of the relative Gini can increase heavily due to the fact that negative incomes are allowed for.

So far, analyses of redistributive effects were compared between individual and grouped data for the income indicator FFI. When instead total household income is applied as indicator (Table C.1 in Annex C) a slightly different picture appears. Conclusions are widely the same; however, due to additional off-farm income all relative Gini indices become smaller. For the analysis of grouped data in the No_Pricepol and the Full_Lib scenarios this leads to slightly positive indices of progressivity. The opposite is true for the individual data-based analysis. Here, the indices announce regressivity of liberalization burdens in relative terms. Thus, the additional disaggregation of the grouped data has a sign reversing effect on the progressivity index in these two scenarios. Yet, again, the higher share of negative incomes in the disaggregated version has to be taken into account and might relativize the differences between the approaches.

In comparison, two other studies using a similar approach to account for the impacts of grouping denote much stronger impacts on the qualitative results. Bourguignon et al. (2005) combine a standard multisector CGE model with a behavioural micro-simulation model to account for changes in real income under different real devaluation scenarios for Indonesia. They contrast results based on ten groups with constant within-group inequality with results based on disaggregated incomes of 9,800 individual households. Their results indicate substantial differences between the two methodologies. They found sign reversing effects due to the disaggregation. In a similar study Savard (2005) compared results based on seven representative household groups of a CGE model with results based on additionally disaggregated incomes for 39,520 households. For a trade liberalization scenario for the Philippines he found that the two approaches “systematically produce inverse results” (Savard, 2005, p. 326). However, the two cited studies differ from the work at hand as they apply behavioural micro-models instead of accounting models for further disaggregation of the results and also much fewer and larger representative household groups in the aggregated model. Thus, the aggregation bias in the aggregated analysis is likely much larger than in the analysis based on 467 farm groups representing 17.2 individual farms on average.

Table 5.4: Decomposition of changes in FFI inequality (individual data vs. grouped data).

		Relative analysis		Absolute analysis	
		Individual data	Grouped Data	Individual data	Grouped Data
I) Baseline Results					
Average income (in €)		45,424			
Gini index of income	(A) G_x	0.560	0.422	25,443	19,164
II) 50_DP scenario					
Average income (in €)		41,841			
Average support reduction (in €)		3,583			
Average rate of reduced support (support reduction/base income)	s	0.078			
Gini index	(A) G_y	0.598	0.448	25,028	18,743
Concentration index	(A) C_y	0.595	0.446	24,903	18,675
Total redistributive effect	(A) R	-0.038	-0.026	414	422
Index of re-ranking	(A) H	-0.003	-0.002	-125	-67
Index of vertical equity	(A) V	-0.035	-0.024	539	489
Index of progressivity of support reduction	P ; C_B	-0.410	-0.285	0.151	0.136
III) No_DP scenario					
Average income (in €)		36,470			
Average support reduction (in €)		8,953			
Average rate of reduced support (support reduction/base income)	s	0.197			
Gini index	(A) G_y	0.662	0.487	24,155	17,775
Concentration index	(A) C_y	0.649	0.480	23,662	17,496
Total redistributive effect	(A) R	-0.102	-0.065	1,288	1,389
Index of re-ranking	(A) H	-0.014	-0.008	-493	-279
Index of vertical equity	(A) V	-0.089	-0.058	1,781	1,668
Index of progressivity of support reduction	P ; C_B	-0.361	-0.236	0.199	0.186
IV) No_Pricepol scenario					
Average income (in €)		23,823			
Average support reduction (in €)		21,601			
Average rate of reduced support (support reduction/base income)	s	0.476			
Gini index	(A) Gy	0.782	0.498	18,632	11,857
Concentration index	(A) Cy	0.683	0.434	16,265	10,349
Total redistributive effect	(A) R	-0.222	-0.076	6,811	7,308
Index of re-ranking	(A) H	-0.099	-0.063	-2,367	-1,508
Index of vertical equity	(A) V	-0.123	-0.013	9,178	8,815
Index of progressivity of support reduction	P ; C_B	-0.135	-0.014	0.425	0.408

Source: Own calculations.

Table 5.4 (continued): Decomposition of changes in income inequality (individual data vs. grouped data).

		Relative analysis		Absolute analysis	
		Individual data	**Grouped Data**	**Individual data**	**Grouped Data**
Baseline Results					
Average income (in €)		45,424			
Gini index of income	(A) G_x	0.560	0.422	25,443	19,164
V) Full Liberalization scenario					
Average income (in €)		14,046			
Average support reduction (in €)		31,378			
Average rate of reduced support (support reduction/base income)	s	0.691			
Gini index	(A) G_y	1.256	0.739	17,642	10,377
Concentration index	(A) C_y	1.005	0.582	14,111	8,179
Total redistributive effect	(A) R	-0.696	-0.317	7,801	8,787
Index of re-ranking	(A) H	-0.251	-0.156	-3,531	-2,198
Index of vertical equity	(A) V	-0.445	-0.160	11,331	10,985
Index of progressivity of support reduction	P ; C_B	-0.199	-0.072	0.361	0.350

Source: Own calculations.

5.3.2 Indicator effects – family farm income versus total household income

In this section redistributive effects are analysed based on two different concepts of income – family farm income and total household income. As already stated above, family farm income provides information on return to land, labour, and capital resources owned by the farm family, as well as the remuneration of entrepreneurial risk. In contrast, total household income additionally takes all off-farm sources into account. Since off-farm income is not depicted in the modelling system, observed base year values are assumed to be constant in real terms until 2020 and for all scenarios. This assumption likely leads to an underestimation of inequality compensation effects of off-farm income sources because it can be expected that the development of off-farm income and agricultural support are negatively correlated (e.g. Vergara et al., 2004; Kwon et al., 2006).

Before going into details, it is worth emphasizing that for both income concepts only the income base is changing while losses are remaining the same for each farm. In other words, the same liberalization losses calculated in the scenarios are referred to an (on average) higher income, since off-farm income is added as an additional constant income source. Baseline rankings according to the indicator FFI differ from rankings according to total household income because off-farm income and on-farm income are negatively correlated and some farms with a lower FFI overcome other farms when total household income is considered. Nevertheless, in Baseline results inequality is lower for total household income than for FFI. Thus, inequality reducing effects of additionally taking off-farm income into account are not overcompensated by re-ranking effects when switching from FFI to total household income as it is in the case of Allanson and Rocchi (2008) for example.

The Lorenz curves for total household income as presented in Figure 5.11 and Figure 5.12 indicate that scenarios are ranked in the same way with regard to the degree of inequality as in the analysis of only FFI. A closer look at the absolute Lorenz curves, however, uncovers that the curve of the Full_Lib scenario lies outside all other curves for the first 3% of the population and inside for the remaining 97%. This denotes that absolute distances of cumulative household income to the mean income are larger for the smallest 3% of the population in the Full_Lib scenario than in all other scenarios. It also denotes that for the rest of the population, absolute distances of cumulative household income to the mean are smaller than in all other scenarios. Thus, some indices of inequality might exist which explicitly focus on the lower tail of the distribution and accordingly may rank distributions in a different way.

The relative Lorenz curves reveal that the number of negative values in the distribution of total household income is considerably lower compared to the distribution of FFI (cf. Figure 5.9) for all scenarios. For total household income 7% of the farms have negative incomes in the Baseline and 23% in the Full_Lib scenario, compared to respectively 13% and 36% of negative values for FFI.

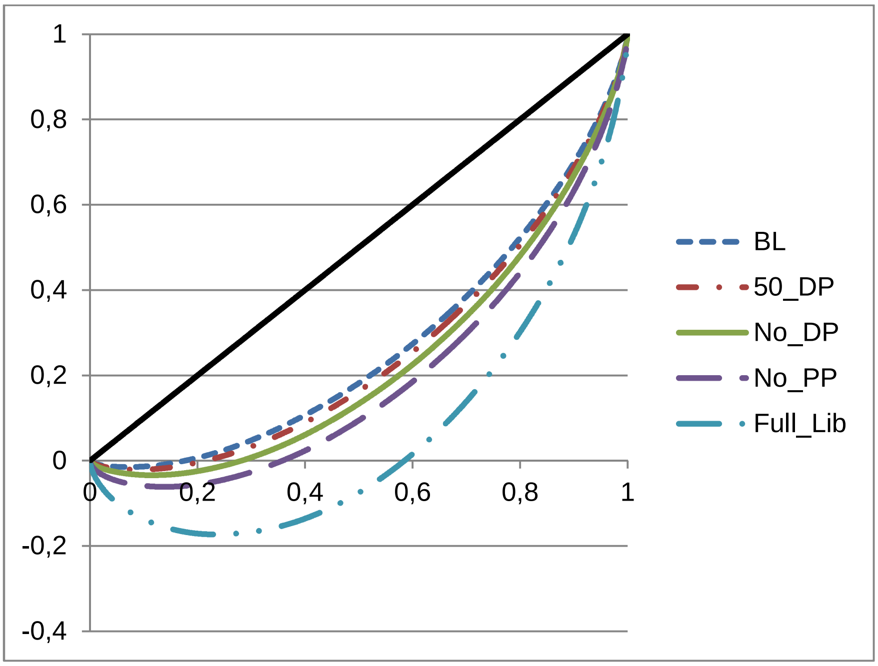

Figure 5.11: Relative Lorenz curves for baseline and all scenarios based on individual *total household income* data.

Source: Own calculations.

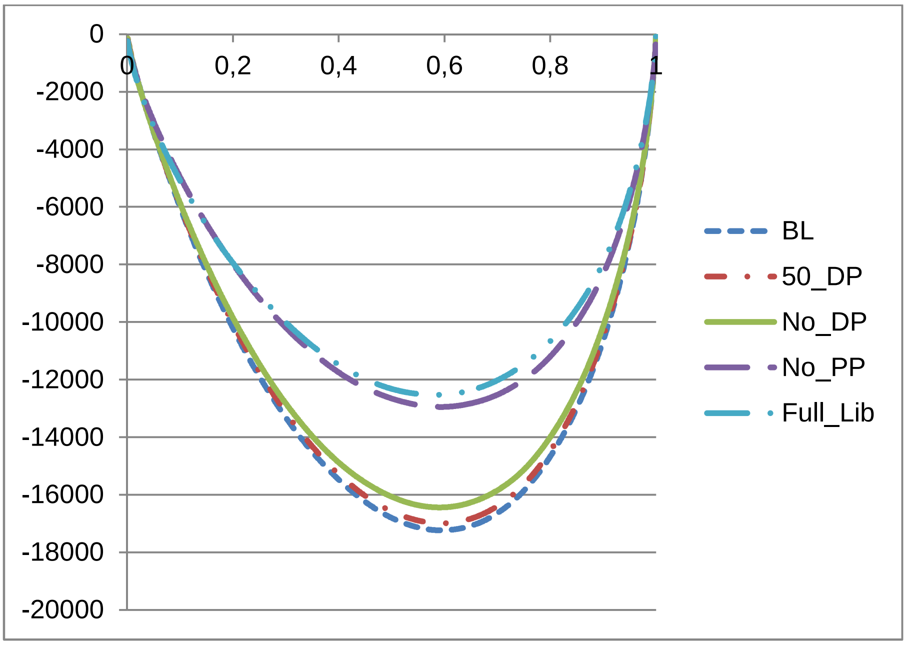

Figure 5.12: Absolute Lorenz curves for baseline and all scenarios based on individual *total household income* data.

Source: Own calculations.

In Table 5.5 it can be observed that *absolute* vertical and overall effects are smaller when total income is applied as the indicator for all scenarios. This can be explained by the fact that farms with a low FFI tend to have higher income from off-farm sources and in some cases rise in the ranking due to the additional consideration of off-farm income. Thus, since the losses are distributed progressively with regard to FFI, more farms with higher absolute losses descend in the ranking of total income and farms with lower losses ascend in the ranking. This trend is also reflected in the C_B indices which indicate that losses (which have the same average size in both analyses) are less concentrated among the high-income farms when total farm income is considered instead of FFI.

Absolute differences in vertical and overall effects are stronger for scenarios in which an abolishment of market price support measures is involved (i.e. No_Pricepol and Full_Lib) compared to the scenarios with DP cuts. Here, the level of average income losses is higher and at the same time losses are more concentrated among high-FFI farms, which leads to stronger effects when switching to total income as indicator.

In *relative* terms all indicators are closer to zero for the analysis of total household inequality. This can partly be explained by a higher average income (also leading to less negative values in the distribution). Thus, relative Gini coefficients are less sensitive with respect to changes in average income. Nevertheless, taking off-farm income sources also into account has an equalizing effect in relative terms due to the negative correlation of off-farm income and on-farm income.

Table 5.5: Decomposition of changes in income inequality based on individual data (total household income vs. FFI).

		Relative analysis		Absolute analysis	
		Total Income	**FFI**	**Total Income**	**FFI**
I) Baseline Results					
Average income (in €)		52,798	45,424	52,798	45,424
Gini index of income	(A) G_x	0.468	0.560	24,714	25,443
II) 50_DP scenario					
Average income (in €)		49,215	41,841	49,215	41,841
Average support reduction (in €)		3,583	3,583	3,583	3,583
Average rate of reduced support (support reduction/base income)	s	0.068	0.078	0.068	0.078
Gini index	(A) G_y	0.495	0.598	24,386	25,028
Concentration index	(A) C_y	0.493	0.595	24,256	24,903
Total redistributive effect	(A) R	-0.027	-0.038	329	414
Index of re-ranking	(A) H	-0.003	-0.003	-130	-125
Index of vertical equity	(A) V	-0.025	-0.035	459	539
Index of progressivity of support reduction	P ; C_B	-0.340	-0.410	0.128	0.151
III) No_DP scenario					
Average income (in €)		43,844	36,470	43,844	36,470
Average support reduction (in €)		8,953	8,953	8,953	8,953
Average rate of reduced support (support reduction/base income)	s	0.170	0.197	0.170	0.197
Gini index	(A) G_y	0.54	0.662	23,688	24,155
Concentration index	(A) C_y	0.529	0.649	23,173	23,662
Total redistributive effect	(A) R	-0.072	-0.102	1,026	1,288
Index of re-ranking	(A) H	-0.012	-0.014	-515	-493
Index of vertical equity	(A) V	-0.06	-0.089	1,541	1,781
Index of progressivity of support reduction	P ; C_B	-0.296	-0.361	0.172	0.199
IV) No_Pricepol scenario					
Average income (in €)		31,197	23,823	31,197	23,823
Average support reduction (in €)		21,601	21,601	21,601	21,601
Average rate of reduced support (support reduction/base income)	s	0.409	0.476	0.409	0.476
Gini index	(A) Gy	0.608	0.782	18,957	18,632
Concentration index	(A) Cy	0.518	0.683	16,158	16,265
Total redistributive effect	(A) R	-0.14	-0.222	5,757	6,811
Index of re-ranking	(A) H	-0.09	-0.099	-2,799	-2,367
Index of vertical equity	(A) V	-0.05	-0.123	8,556	9,178
Index of progressivity of support reduction	P ; C_B	-0.072	-0.135	0.396	0.425

Source: Own calculations.

Table 5.5 (continued): Decomposition of changes in income inequality based on individual data (total household income vs. FFI).

		Relative analysis		Absolute analysis	
		Total Income	FFI	Total Income	FFI
Baseline Results Average income (in €)		52,798	45,424	52,798	45,424
Gini index of income	(A) G_x	0.468	0.560	24,714	25,443
V) Full Liberalization scenario					
Average income (in €)		21,420	14,046	21,420	14,046
Average support reduction (in €)		31,378	31,378	31,378	31,378
Average rate of reduced support (support reduction/base income)	s	0.594	0.691	0.594	0.691
Gini index	(A) G_y	0.861	1.256	18,446	17,642
Concentration index	(A) C_y	0.667	1.005	14,278	14,111
Total redistributive effect	(A) R	-0.393	-0.696	6,268	7,801
Index of re-ranking	(A) H	-0.195	-0.251	-4,168	-3,531
Index of vertical equity	(A) V	-0.198	-0.445	10,436	11,331
Index of progressivity of support reduction	P ; C_B	-0.136	-0.199	0.333	0.361

Source: Own calculations.

5.3.3 The relevance of taking into account policy-induced production and market responses in ex-ante inequality analysis[53]

To illustrate the impact of taking into account incentive effects of agricultural policy, model-based results are compared to those of an analysis which does not allow for any adjustments to take place. To estimate income changes resulting from a liberalization of the CAP without allowing for production and market responses, it is assumed that European domestic prices equal world market prices (in principle, following the procedure adopted by Allanson (2006) and OECD (2003)) and production patterns in the FARMIS model are fixed to those of the baseline scenario. In this approach, the full amount of reduction in support is still not translated one to one into lower farm incomes since the land price is kept variable in the FARMIS model and tends to decrease with declining commodity prices and DPs. Further reductions in input prices, such as feed and seed costs, are also still taken into account. For the calculation of the No_DP scenario without adjustment effects, we rely on the assumption that DPs are essentially decoupled from production, and thus that domestic baseline prices will not change. Consequently, the No_DP scenario without adjustment effects is calculated by solely abolishing all DPs while keeping production patterns fixed.[54]

[53] This section in parts is identical with parts of the paper Deppermann et al. (2014).

[54] In the farm group model the link between payment entitlements and land is taken into account. In addition, the requirement to keep land which receives payments in good agricultural and environmental condition can have an impact on production in regions where agriculture would not be profitable without payments (Kilian et al., 2012). This causes varying results compared to the version without adjustment effects. Decoupled direct

Since this section focuses primarily on a comparison of methodologies, the analysis is conducted on the basis of grouped (FARMIS) data. By omitting the additional disaggregation step for the calculation of individual farm data, the complexity of the analysis is reduced and results are easier to compare and interpret.

In the No_DP scenario, inequality effects are generally in the same direction in both versions, i.e., with adjustment and without adjustment (Table 5.6, section II). Compared to the version without adjustment, average income losses are lower when adjustment is accounted for. This is because farms adjust their production patterns to the new support structure and specifically abstain from unprofitable activities. Compared to the version without adjustment, inequality decreases in both relative and absolute terms when adjustment is allowed. In absolute terms, however, this only occurs because of a decrease in re-ranking which offsets the lower vertical effect in the version with adjustment. If ranks of the baseline are held constant, higher-income farms tend to reduce losses marginally more by adjustment in absolute terms (AC_y increases when adjustment is allowed for), while lower-income farms gain more in relative terms (C_y decreases). Higher C_B values in the version with adjustment indicate that lower-income farms can reduce their share in the overall income losses accruing from the abolishment of DPs because of adjustment.

Many individual farm characteristics explain adjustment reactions of a farm and thus the ability to reduce income losses from a DP cut. Factors that determine the reaction of a farm are: regional land prices, shares of farm owned land, individual production patterns, and gross margins per hectare. In the analysis at hand, there is one key factor among these attributes which explains why low-income farms tend to reduce their share in the overall income losses of all farms when adjustment is accounted for compared to the version without adjustment: in the sample, lower-income farms have a lower gross margin, on average, for most of the important products. As a consequence, due to the DP cut, lower-income farms have a higher share of production activities with negative gross margins, on average, compared to farms with a higher income. Thus, when adjustments are allowed, lower-income farms are able to reduce their income losses by reducing or stopping the respective production activities. Higher-income farms, in contrast, tend to have a higher share of production with positive gross margins even after the abolishment of DPs. Hence, even though adjustment is accounted for, higher-income farms cannot reduce their losses by simply abandoning these activities. Resources may be shifted to other farming activities, yet other activities are in most cases affected by reduced support payments as well. Thus, it can be observed that low-income farms tend to reduce their production to a larger extent when adjustment is allowed, compared to farms with higher income.

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payments may also affect production via wealth and insurance effects (Bhaskar and Beghin, 2009), however, these effects are not taken into account in the analysis.

Table 5.6: Decomposition of changes in income inequality based on (FARMIS) groups results (dynamically vs. statically derived FFI).

		Relative analysis		Absolute analysis	
		with adjustment	no adjustment	with adjustment	no adjustment
I) Baseline Results					
Average income (in €)		45,369			
Gini index of income	(A) G_x	0.422		19,149	
II) No_DP scenario					
Average income (in €)		36,376	33,864	36,376	33,864
Average support reduction (in €)		8,993	11,505	8,993	11,505
Average rate of reduced support (support reduction/base income)	s	0.20	0.25	0.20	0.25
Gini index	(A) G_y	0.49	0.53	17,748	17,815
Concentration index	(A) C_y	0.48	0.51	17,467	17,427
Total redistributive effect	(A) R	-0.07	-0.1	1,401	1,335
Index of re-ranking	(A) H	-0.01	-0.01	-281	-388
Index of vertical equity	(A) V	-0.06	-0.09	1,682	1,722
Index of progressivity of support reduction	P ; C_B	-0.23	-0.27	0.19	0.15
III) No_Pricepol scenario					
Average income (in €)		23,899	22,918	23,899	22,918
Average support reduction (in €)		21,470	22,450	21,470	22,450
Average rate of reduced support (support reduction/base income)	s	0.47	0.49	0.47	0.49
Gini index	(A) G_y	0.5	0.53	11,893	12,118
Concentration index	(A) C_y	0.44	0.47	10,396	10,695
Total redistributive effect	(A) R	-0.08	-0.11	7,256	7,032
Index of re-ranking	(A) H	-0.06	-0.06	-1,497	-1,423
Index of vertical equity	(A) V	-0.02	-0.04	8,753	8,454
Index of progressivity of support reduction	P ; C_B	-0.01	-0.05	0.41	0.38
IV) Full Liberalization scenario					
Average income (in €)		14,191	10,510	14,191	10,510
Average support reduction (in €)		31,178	34,859	31,178	34,859
Average rate of reduced support (support reduction/base income)	s	0.69	0.77	0.69	0.77
Gini index	(A) G_y	0.74	1.09	10,455	11,498
Concentration index	(A) C_y	0.58	0.84	8,273	8,878
Total redistributive effect	(A) R	-0.31	-0.67	8,695	7,652
Index of re-ranking	(A) H	-0.15	-0.25	-2,181	-2,620
Index of vertical equity	(A) V	-0.16	-0.42	10,876	10,271
Index of progressivity of support reduction	P ; C_B	-0.07	-0.13	0.35	0.29

Source: Own calculations.

Note: Numerical results of the analysis with adjustment minimally differ from the figures presented above for the comparison between different levels of aggregation. These differences occur due to slight changes in the model code. However, results and conclusions are not affected.

A comparison of the No_Pricepol scenarios (Table 5.6, section III) with and without adjustment reveals similar differences found in the comparison between the No_DP scenarios. In the No_Pricepol scenarios, inequality decreases in comparison to the static version when adjustments are allowed. Lower-income farms are able to reduce income losses to a larger extent, on average, than higher-income farms – not only in relative terms, but also in absolute terms. This is indicated by a lower absolute concentration index (AC_y) and a higher absolute vertical effect of liberalization (AV) in the version with adjustment compared to the version without adjustment.

Again, adjustment reactions of farms depend on individual characteristics such as production patterns and factor endowments. In the No_Pricepol scenario, production patterns are even more relevant because product price reactions vary with commodity specific adjustment effects (world market prices increase, on average, when adjustment is allowed, dampening price cuts that accrue in the static scenario). Furthermore, due to the abolition of production quotas, the farm specific magnitudes of quota rents also impact adaption abilities.

One reason for the higher reduction of losses in absolute terms in lower-income farms in the No_Pricepol scenario with adjustment compared to the scenario without adjustment, is an effect triggered by the abolishment of the milk quota. Without being restricted by the quota scheme, dairy production, on average, increases when adjustment is allowed.[55] As a by-product of increased dairy production, the supply of calves increases. At the same time, the abolishment of price policies leads to a decrease in beef prices and thus a decrease in the profitability of beef fattening activities. When production patterns are adjusted, this leads to a decrease in the demand for calves. The resulting negative price effect for calves negatively affect dairy farms, on average, in the scenario with adjustment compared to the scenario without adjustment. In our baseline scenario, prices for dairy products are high and most dairy farms are in the upper two income terciles. Thus, the negative income effect resulting from these specific market price adjustments counteracts the reduction of income losses from adjustments in farm production, mainly for higher-income farms. The negative income effect of falling calf prices also explains the lower reduction of average losses of all farms due to adjustment in the No_Pricepol scenario compared to the No_DP scenario.

Nevertheless, dairy farms do not show homogenous adjustment behaviour. Some farms decrease dairy production because of low baseline quota rents, while others expand milk production because of initially high quota rents. As a consequence, some dairy farms have even greater losses from liberalization when production and market adjustments are allowed, compared to when adjustments are not allowed, given the combination of lower calf prices and decreased milk production due to low quota rents. Other dairy farms, however, can partly compensate their losses by increasing milk production.

[55] In the version without adjustment quantities are fixed to baseline values.

Another reason for the comparatively high reduction of income losses of lower-income farms due to adjustments in the No_Pricepol scenario is the fact that many of the farms which specialized in beef production are in the lowest income tercile in the baseline scenario. Since beef is a highly protected product in the Baseline scenario, liberalization entails a higher demand and a lower supply in Europe. These market adjustment effects have considerable positive impacts on the world market price of beef. Thus, taking market adjustment effects into account, price cuts for beef are lower compared to the version without adjustment effects.

Due to these additional adjustment processes in the No_Pricepol scenario, the general pattern of adaption observed in the No_DP scenario – i.e., it being easier for lower-income farms to avoid income losses from liberalization by abandoning production activities which have negative margins under scenario conditions – is less important in the No_Pricepol scenario.

In the Full_Lib scenario (Table 5.6, Section IV), differences between the version with and without adjustment are more distinct, both in relative and absolute terms. Similar to the No_Pricepol scenario, lower-income farms can reduce their losses to a greater extent due to adjustment processes, even in absolute terms. This is indicated by a higher index of vertical equity (AV) in the version with adjustment, compared to the version without adjustment.

The more profound differences between the analysis with and without adjustment can be explained mainly by two effects. First, with higher average support cuts, a larger share of production activities obtain negative marginal incomes, which is mainly the case for less profitable farms with lower incomes. These losses are more readily avoided by abandoning unprofitable farming activities than losses caused by support cuts for products that still have positive marginal income effects. Second, profitable farms with a high share of quota products, particularly dairy farms, tend to have opposing adjustment strategies in the No_DP and No_Pricepol scenarios: In the former, production activities tend to be reduced because unprofitable land is taken out of production. In the latter, production, on average, is extended due to the abolishment of quota restrictions. The combination of these two opposing strategies leads to a lower ability of farms to reduce losses due to adjustment in the Full_Lib scenario, mainly for farms with a higher income.

When adjustment effects are allowed, in all three scenarios, lower-income farms tend to reduce their share in overall income losses compared to the version without adjustment. In general, the adjustment mechanisms of factor markets might counteract this effect. This is particularly with an abolition of production quotas since more profitable farms tend to extend their production, resulting in additional costs for less profitable farms due to a demand-driven increase in factor prices. In our analysis, however, this effect is less distinct and other effects dominate the results.

In the No_Pricepol and the Full_Lib scenarios, lower-income farms, on average, are able to avoid liberalization losses to a greater extent due to adjustment processes compared to higher-income farms – even in absolute terms. This effect is a rather specific feature of the empirical analysis for western Germany and is mainly caused by the dampening market price effect, particularly for farms that specialize in beef production and that tend to have low Baseline incomes, and the negative effect of lower calf prices for dairy farms which tend to have middle or high incomes in the Baseline scenario.

Furthermore, farm specific production patterns, regional factor markets, and individual factor endowments determine the ability of farms to adapt to new market structures and to avoid income losses. For these factors, however, no general distinction between low and high income farms can be made based on our model results.

From the empirical analysis, it can be concluded that taking adjustment effects into account clearly has an impact on the dimension of inequality indicators. When comparing analyses that ignore adjustment effects to ones that do not, the largest differences are found in the Full_Lib scenario. Nevertheless, in all of the scenarios, distributional effects have the same directional impact both in the static analysis and in the analysis with adjustment effects. In general, the evaluation and ranking of the different reform scenarios with respect to their impact on income equality is similar regardless of adjustment effects.

5.3.4 Discussion

To conclude, it can be said that the results of the calculated scenarios are robust with regard to the tested aggregation levels, income indicators and the inclusion of behavioural effects, at least with regard to the direction of redistributive effects. Only when total household income is applied does a further disaggregation of grouped results lead to sign reversing effects for vertical effects of two scenarios. Still, results differ substantially in magnitude, mostly when different levels of aggregation are compared with each other.

Results are in line with most of the existing literature. An abolishment of market price support and/or direct payments would decrease absolute income differences in the agricultural sector because high-income farms lose higher amounts of money. On the other hand, low-income farms would have to bear a higher share of the burden in relative terms. With regard to the different policy instruments, it turns out that the abolishment of market price support is more progressive in absolute terms and less regressive in relative terms than the abolishment of DPs.

A caveat of the analysis is clearly the static way in which the micro-model disaggregates the grouped results. Due to this approach, individual income changes are to a certain extent determined by changes in production patterns of the respective farm groups at the meso-level. Furthermore, no structural change is implemented in the modelling system. This likely has an effect on the analysis of income distribution since farms with large negative incomes would probably leave the sector and average farm size would increase. Moreover, the adaption of new production technologies is not considered in the analysis.

In addition, several assumptions regarding the development of agricultural markets until the final year of the analysis have to be made for the generation of the Baseline scenario. It is well-known that redistributive effects are influenced by the distribution of income in the base situation (Lerman and Yitzhaki, 1995). Thus, it should be kept in mind that any ex-ante analysis implies a certain extent of uncertainty.

6 Subgroup decomposition of inequality effects in the western German agricultural sector

In section 2.2.2 the terms between-groups inequality and within-group inequality were introduced to substantiate the claim that inequality is systematically underestimated when it is measured on the basis of grouped data. After the detailed explanation of how individual farm income data are generated in this work and after an extensive analysis of redistributive effects of CAP liberalization, now a subgroup decomposition of inequality indices is undertaken. To give a more detailed picture of the underlying processes of inequality changes, individual farms are grouped according to different farm characteristics to reveal the contribution of inequality within the groups and between the groups to overall inequality. Total farm population is decomposed into subgroups according to farm types and in a second analysis, according to regional criteria.

6.1 Methodology

The literature generally distinguishes between inequality measures which are additively decomposable into only two components and measures which yield three components. Generalized Entropy indices, among others, belong to the first group. They can be decomposed into one component containing inequality within groups and another one containing inequality between groups. Inequality between groups in this context is accounted for by substituting all individual incomes within a given group by the groups mean income. In summary, both components yield the overall inequality level (for an overview and axiomatic derivations see Deutsch and Silber, 1999). Such a measure can be represented by equation (1) in section 2.2.2: $I^{total} = I^{within} + I^{between}$.

The Gini coefficient, both in absolute and in relative terms, is decomposable into a measure of inequality within groups and a measure of inequality between group means only if subgroup populations do not overlap. Two subgroups do not overlap if all members of the group with the lower mean income are poorer than the poorest member of the richer group. Such a situation is depicted in Figure 6.1b.

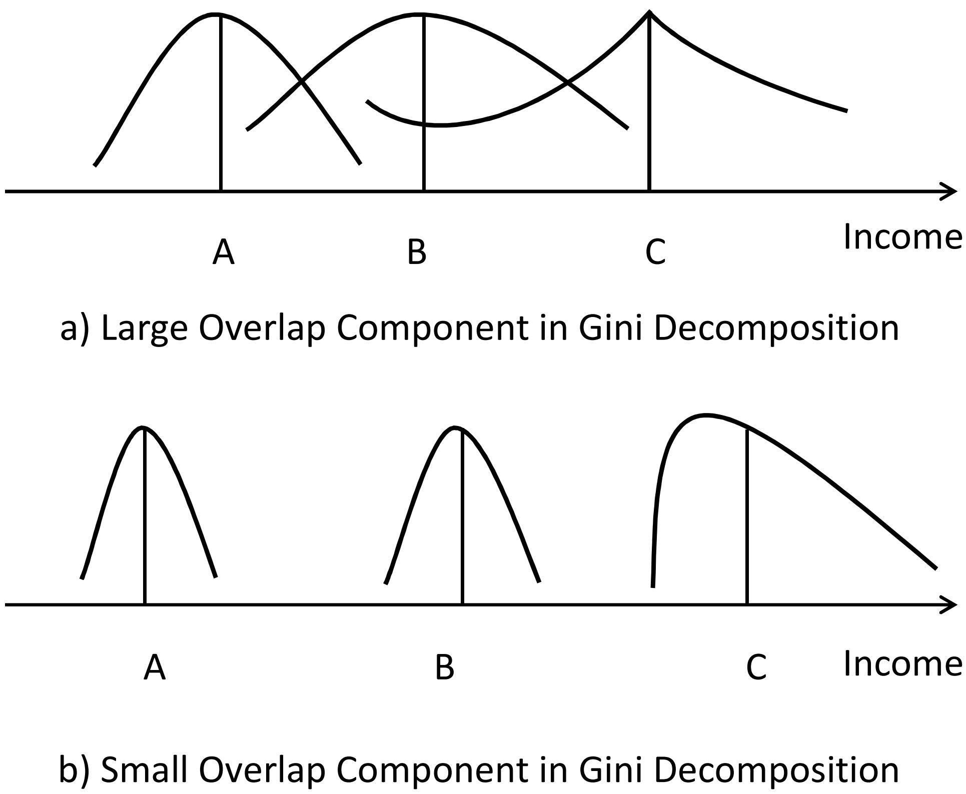

Figure 6.1: Overlapping of Distributions.

NB: Vertical lines depict mean incomes of subgroups.
Source: Milanovic (2002).

In the case of overlapping group distributions (represented in Figure 6.1a) a third term appears when the Gini coefficient is decomposed. With G depicting the Gini coefficient, G_W the within-group inequality component, G_B the between-group inequality component, and OV the overlapping term it counts:

(21) $$G = G_W + G_B + OV \, .$$

Bhattacharya and Mahalanobis (1967) were among the first authors using the Gini decomposition by subgroups in their analysis of household consumption in India. Other authors followed suit, with each proposing a new technical decomposition methodology or interpretation (see Deutsch and Silber (1998), Monti (2007), and Radaelli (2010) for historical outlines of the development of decomposing the Gini coefficient by subgroups). For a long time the methodology was discussed controversially, especially because of the overlapping term which was seen as a rather disturbing term not containing any valuable information. Often, two-term decomposable indices were considered as superior. Mookherjee and Shorrocks (1982, p. 889) for instance write about the overlapping term: “However, there still remains […] the ‘interaction effect’ […], which is impossible to interpret with any precision, except to say that it is the residual necessary to maintain the identity. Furthermore, the way in which it reacts […] is so obscure that it can cause the overall Gini value to respond perversely". Lambert and Aronson (1993) provide a geometrical analysis of the overlapping term within the Lorenz diagram. They interpret *OV* as a term which accounts for the re-ranking which is "necessary to form the true income parade, from the poorest to the overall richest" (p. 1222) when in the initial situation individuals are ranked in ascending order within subgroups and subgroups in ascending order with regard to their mean income. However, they did not see the Gini coefficient "rehabilitated" and suggest Generalized Entropy measures for the analysis of inequality sources (p. 1225).

In other papers, however, the overlapping term is appreciated as a source of additional information (e.g. Dagum, 1997; Lambert and Decoster, 2005). Dagum (1997, p. 519) suggests that between groups inequality is more accurately depicted when overlapping is explicitly taken into consideration. To "take the income means of the subpopulation as their representative values to estimate inequality between subpopulations […] is inappropriate for the income distributions of the subpopulations often differ in variance and asymmetry". Yitzhaki and Lerman (1991) and Yitzhaki (1994) explore the link between income distribution and income stratification. Yitzhaki (1994) develops an index of stratification based on the overlapping of subgroup distributions. However, the stratification index and the between-groups component in this literature differ from the 'traditional' approach in the sense of Bhattacharya and Mahalanobis (1967) and others. Gradín (1999, 2000) develops an indicator which is very similar to Yitzhaki's (1994) indicator, but which is rooted in the 'traditional' approach.

Monti (2007) shows that results of the decomposition approaches proposed by Mookherjee and Shorrocks (1982), Lambert and Aronson (1993), and Dagum (1997) are numerically equivalent. Radaelli (2010, p. 82) refers to this (specifically, to Dagum's) approach as the "most widespread Gini index decomposition currently applied in a subgroups framework". This approach is also applied in the work at hand and is presented in detail below. Equations are taken from Monti (2007)[56] who shows that the overlapping term can be further decomposed as a weighted sum of overlapping between each pair of groups. Equations are adopted where it seemed appropriate to the style of Radaelli (2010) to increase intelligibility.

Using the same notations as before with x_i representing the income of individual i (i = 1,2,3,…,n) and μ the average income, the relative Gini coefficient can be expressed as:

(22) $$G = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right| = \frac{\Delta}{2\mu}$$

with Δ indicating Gini's mean difference, which represents the average distance between all possible pairs of income in the distribution. Now, let us consider a segmentation of the total population n into k mutually exclusive subgroups with n_k members, an average income of μ_k,

[56] Monti (2007) in turn builds on the equations presented in Dagum (1997).

and the total number of groups K. The mean difference among all members of group k is denoted Δ_{kk}. Then, the relative Gini index for each group k is represented by:

$$G_{kk} = \frac{1}{2n_k^{\ 2}\mu_k} \sum_{i=1}^{n_k} \sum_{j=1}^{n_k} \left| x_{ki} - x_{kj} \right| = \frac{\Delta_{kk}}{2\mu_k} \tag{23}$$

and total within-group inequality is subsumed in G_W, which is defined as

$$G_W = \sum_k G_{kk} p_k s_k \tag{24}$$

with p_k representing the population share of group k in overall population and s_k its share in overall income. Accounting for the fact that all individuals within one group build pairs (and thus cause inequality) not only with members of the same group but also with all other members of the total population, a Gini ratio is presented which accounts for inequality between members of group k and group h, but not within the subgroups:

$$G_{kh} = \frac{1}{n_k n_h (\mu_k + \mu_h)} \sum_{i=1}^{n_k} \sum_{j=1}^{n_h} \left| x_{ki} - x_{hj} \right| = \frac{\Delta_{kh}}{\mu_k + \mu_h} = G_{hk} \,. \tag{25}$$

Based on equation (25) the gross Gini component G_{GB} is defined, subsuming inequality that occurs between groups and excluding the inequality within the groups:

$$G_{GB} = \sum_k \sum_{h \neq k} G_{kh} p_k s_h \tag{26}$$

Gross inequality between groups G_{GB} is further decomposable. The component G_B represents net inequality between groups and is obtained by substituting all individual incomes within a given group by the respective groups' mean income. The second term OV is a component that reflects the degree of overlapping of distributions. Thus:

$$G_{GB} = G_B + OV \tag{27}$$

with

$$G_B = \frac{1}{2\mu} \sum_k \sum_h \left| \mu_k - \mu_h \right| p_k p_h \tag{28}$$

and

$$OV = \sum_k \sum_{h \neq k} \frac{1}{\mu_k + \mu_h} (\Delta_{kh} - \left| \mu_k - \mu_h \right|) p_k s_h \,. \tag{29}$$

Above, the decomposition methodology was introduced for the relative Gini coefficient. In the work at hand the absolute Gini coefficient is additionally used. Thus, absolute versions of the inequality components are derived in the following. We know that the relative Gini coefficient is equal to the absolute Gini divided by mean income. Thus, we easily can see that:

$$AG = G\mu = G_W \mu + G_B \mu + OV \mu = AG_W + AG_B + AOV \tag{30}$$

and thus, from equations (23) and (24)

(31) $$AG_W = \sum_k \mu G_{kk} p_k s_k = \sum_k AG_{kk}(p_k)^2 \text{ ,with } AG_{kk} = \frac{\Delta_{kk}}{2} \text{ and } s_k = \frac{n_k \mu_k}{n\mu}.$$

Furthermore, multiplying (28) and (29) by mean income yields:

(32) $$AG_B = \frac{1}{2}\sum_k \sum_h |\mu_k - \mu_h| p_k p_h$$

and

(33) $$AOV = \mu \sum_k \sum_{h \neq k} \frac{1}{\mu_k + \mu_h}(\Delta_{kh} - |\mu_k - \mu_h|) p_k s_h$$

$$= \mu \sum_{k=2}^{K} \sum_{h=1}^{k-1} \frac{(\Delta_{kh} - |\mu_k - \mu_h|)}{\mu_k + \mu_h} p_k s_h + \frac{(\Delta_{hk} - |\mu_h - \mu_k|)}{\mu_h + \mu_k} p_h s_k$$

$$= \mu \sum_{k=2}^{K} \sum_{h=1}^{k-1} \frac{(\Delta_{kh} - |\mu_k - \mu_h|)}{\mu_k + \mu_h} (p_k s_h + p_h s_k)$$

$$= \sum_{k=2}^{K} \sum_{h=1}^{k-1} \frac{n_k n_h}{n^2} (\Delta_{kh} - |\mu_k - \mu_h|).$$ [57]

The three presented Gini components so far, $(A)G_W$, $(A)G_B$ and $(A)OV$ sum up to the total (absolute) Gini coefficient and thus, represent the shares of inequality which are caused by the respective types when divided by the overall coefficient. $(A)G_W$ itself is a weighted sum of Gini ratios representing inequality within the single groups. $(A)G_B$ and $(A)OV$ are, respectively, weighted sums of Gini ratios representing inequality between each single pair of groups when individual incomes are replaced by group means, and overlapping that occurs between each pair of groups (as was shown by Monti, 2007). These (unweighted) single ratios henceforth shall be denoted as 'fractional Ginis' to highlight the fact that a Gini coefficient is calculated by only taking a fraction of the overall population into consideration.

Relative 'fractional Ginis' are defined as [G_{kk}] for within group inequality, as [$|\mu_k - \mu_h| / (\mu_k + \mu_h)$] for the between group inequality and as [$(\Delta_{kh} - |\mu_k - \mu_h|)/(\mu_k + \mu_h)$] for the overlapping term. The absolute versions are defined as [AG_{kk}], [$|\mu_k - \mu_h|/2$], and [$(\Delta_{kh} - |\mu_k - \mu_h|)/2$] in respective order. By weighting a Gini equivalent with its respective weight and dividing it by the overall Gini coefficient one calculates the share in overall inequality that is respectively caused by inequality within a group, inequality between the means of two specific groups or overlapping of two specific groups with each other (Monti, 2007; Mussard, 2004). As an example, I show for the share of overall inequality which is caused by overlapping between group *k* and group *h*, that it depends only on the distances between the considered incomes and has the same numerical value in the relative (term 1) and the absolute version (term 2):

[57] By observing that: $p_k s_h + p_h s_k = \left[n_k n_h (\mu_k + \mu_h)\right] / n^2 \mu$ (Monti, 2007, p. 7).

By observing that $\Delta_{kh} - |\mu_k - \mu_h| = \dfrac{\sum_{i=1}^{n_k}\sum_{j=1}^{n_h}(|x_{ki} - x_{hj}| - |\mu_k - \mu_h|)}{n_k n_h}$,

$$(34)\quad share\_OV_{kh} = \underbrace{\frac{\frac{n_k n_h}{n^2\mu}\left(\frac{\Delta_{kh} - |\mu_k - \mu_h|}{2}\right)}{\frac{\Delta}{2\mu}}}_{1} = \underbrace{\frac{\frac{n_k n_h}{n^2}\left(\Delta_{kh} - |\mu_k - \mu_h|\right)}{\Delta}}_{2} = \frac{\sum_{i=1}^{n_k}\sum_{j=1}^{n_h}(|x_{ki} - x_{hj}| - |\mu_k - \mu_h|)}{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}.$$

Regarding the interpretation of the overlapping term, Lambert and Aronson (1993) recognize that it would be higher the closer the means of the subpopulations. They state that the term *OV* is "at once a between groups and a within groups effect [which] measures a between groups phenomenon, overlapping, that is generated by inequality within groups" and which is "a phenomenon with intrinsic economic interest". (p. 1224). Shorroks and Wan (2005) conclude that a reduced overlapping component is likely to translate into increasing between group inequality, but that this relation is not an unambiguous one since distances between subgroup means do not necessarily have to increase when overlapping is reduced.

A link between the overlapping term and the concepts of stratification and segmentation is established by Yitzhaki and Lerman (1991) and Yitzhaki (1994). In their works, overlapping is interpreted as non-stratification. Based on this insight, Yitzhaki (1994) develops a clearly defined index of overlapping that is consistently integrated in the framework of a Gini decomposition. Thereby, the Gini is decomposed into three terms. However, only the within-groups inequality component is numerically equal to the one presented by Dagum (1997) and others. Yitzhaki (1994) emphasises the importance of the measurement of stratification in connection with income inequality by linking it to the inequality tolerance of a society. He points out with reference to Runciman (1966) that inequality tolerance is higher in stratified societies. Furthermore, he suggests the application of his index in the field of market segmentation or to measure the "segmentation of the students' population by school … [which] is an important factor which determines the ability to predict students' performance from knowing their school" (p. 149).

The between-groups and the overlapping components are differently defined. Still, the two different ways of Gini decomposition are closely related, which is demonstrated by Milanovic and Yitzhaki (2002) and by Monti and Santoro (2009, 2011).

Gradin (1999, 2000) develops an overlapping index which is close to the index of Yitzhaki (1994) but is rooted in the 'traditional' approach of Gini decomposition proposed by Bhattacharya and Mahalanobis (1967), Dagum (1997), and others. In his work he utilizes overlapping within his framework to estimate polarization by subgroup characteristics in Spain. His index is based on the decomposition approach presented above. It is presented in the following section and is later on applied in the empirical analysis of the work at hand.

Milanovic (2002) utilizes the Gini decomposition methodology to analyse composition of world income. He connects the overlapping component to the stratification literature of Yitzhaki and Lerman (1991) and Yitzhaki (1994) and interprets it as 'homogeneity' of population. He concludes that "…[t]he more important the 'overlapping' component compared to the other two, the more homogeneous the population – or differently put, the less one's income depends on where she lives" (p. 70).

Pyatt (1976) and Mussard and Savard (2012) go one step further and recognize a link between overlapping and incentives. Pyatt connects overlapping to the decision of an individual to migrate from one group to another group. Mussard and Savard refer to overlapping as 'good inequality'. They argue that "For instance, in the case of wage inequalities, we have some close interrelations with incentives. Hence, if some individuals of the poorest groups feel deprived compared to other groups, they may increase their effort to earn more than the members of the richest groups" (p. 1239). Even though their argument may not be straightforward because considering the exact opposite effect (e.g. resignation in the poorest group) is also possible, it stresses the impact that overlapping might have on incentives.

In the work at hand, different scenarios of agricultural policy reforms are analysed regarding their impacts on individual farm incomes. One interesting analysis regarding subgroup decomposition is now to decompose farms by type of their specialization and analyse the impacts on inequality within subgroups. Furthermore, it is of interest, how the subgroups relate to each other.

A certain degree of overlapping between the different farm type groups can be expected a priori; however, the extent of overlapping between the subgroups and especially the impact of different reforms cannot be anticipated. The relation between the groups might on its own be of interest to a policy maker to anticipate unintended policy effects. Moreover, based on the links between incentives and overlapping as presented before, an interesting interpretation might be with regard to structural change in the agricultural sector. As stated earlier, structural change is not implemented in the modelling system, but due to an inequality decomposition analysis of model results some developments might be anticipated. In general, two types of structural changes can be identified: structural change in terms of farm exits and increasing average farms size and structural change in terms of farm specialization (as described for instance in Gocht et al., 2012). When a subgroup characterised by a specific farm type has a comparatively low average income and is also segmented at the lower part of the income scale with no or little overlapping to other subgroups, disproportionally many farm exits (or downgrades to part time farms) might accrue among farmers of this specific farm type. Moreover, the incentives to change the specialization of the farm might be higher if the farmer observes that most of the farms with the same specialization have lower incomes then farms with other specializations (i.e. the overlapping component is small). Of course, the individual decision of a farm exit or change in farm specialization depends on many factors and clearly more research is needed to test the link between overlapping and structural change.

Another possibility to group farms is by region. Below, both a farm type and a regional decomposition analysis for scenario results are carried out. Before the presentation of empirical results, the overlapping index of Gradin (1999, 2000) is presented in more detail in the following lines.

Gradin (2000, p. 464) introduces an overlapping index O_{kh} for the k-th group with respect to the h-th group as:

$$(35) \qquad O_{kh} = \frac{\int_0^\infty \int_0^\infty |x-y|\, dF_h(y) dF_k(x) - |\mu_k - \mu_h|}{\int_0^\infty \int_0^\infty |x-y|\, dF_k(y) dF_k(x)}$$

with F_k denoting the cumulative distribution of group k. Gradìn (2000) notes that the denominator is equal to the absolute Gini coefficient of the k-th group and that the index is group-symmetric only if both subgroups share the same absolute Gini. The term in the numerator is numerically equal to the absolute version of the overlapping index as expressed (in discrete form) in equation (33). Gradín's formulation of the index is only defined for non-negative values. Since in the work at hand incomes can be negative, the index is calculated as AOV_{kh} / AG_{kk}, where the numerator refers to the absolute overlapping between the groups k and h and the denominator is the absolute Gini coefficient of group k.

Thus, the overlapping between two subpopulations is expressed in relation to the absolute Gini of one of the subpopulations. Properties of the index are described by Gradìn (2000, p. 464), given that $\mu_h \geq \mu_k$: "(1) O_{kh} and O_{hk} are non-negative and unbounded. They are equal to 0 if, and only if, there is no overlap between both groups, and by definition O_{kk} = 1. (2) The larger the share of people in h with incomes below the richest person in k, the higher the O_{kh}. The larger the share of people in group k with incomes above the poorest person in h, the higher the O_{hk}. […] (4) Given the distribution of k, O_{kh} reaches its maximum if all income in the group h is concentrated on one individual".[58]

The overlapping index of group k with all the other groups is defined as:

$$(36) \qquad O_k = \sum_{h=1}^{K} O_{kh} p_h .$$

This index indicates the overlapping of group k with the overall distribution, including group k itself. Thus, its minimum value is the population share of group k, since O_{kk} = 1 per definition.

The aggregated overlapping index for all subpopulations is a weighted average of O_k:

$$(37) \qquad O = \sum_{k=1}^{K} O_k p_k .$$

[58] In the original version, Gradín (2000) uses I_{ij} instead of O_{kh}.

As shown by Gradìn (1999), the index of overlapping can consistently be integrated in the Gini decomposition:

(38) $$G = G_B + \sum_k s_k G_{kk} O_k \ .$$

With equations (30) and (31) we can verify that the absolute Gini can be decomposed equivalently, without changing the formulation of the overlapping index O:

(39) $$AG = AG_B + \sum_k p_k AG_{kk} O_k \ .$$

The fact that the minimum value of O_k is the population share of the group k, as described above, hampers comparability between the different groups regarding their degree of stratification. Thus, for comparison of the overlapping between group k and the rest of the population simply an index $O_{k,rest}$ in the sense of equation (33) is computed where group k is compared with one other group in which the rest of the population is subsumed.

6.2 Empirical analysis

In the following, an empirical analysis of scenario results using the Gini decomposition is presented. Total farm population is decomposed into subgroups according to farm types which are defined by the predominant commodity specialization of a farm. Farms are classified according to standard gross margins in the base year of the modelling exercise and cannot switch their status during the simulation period. Farms are mutually exclusively assigned to one of the following groups (acronyms in parenthesis):

- Dairy farms (DF)
- Pig and poultry farms (PP)
- Arable farms (AF)
- Other grazing livestock farms (GL)
- Permanent crops farms (PC)
- Mixed farms (MF).

In Table 6.1 aggregated results of an analysis of decomposed inequality effects by farm types are presented. Since the same scenarios are considered as presented in the chapters before, we already know that relative inequality increases and absolute inequality decreases with increasing average income losses.

Within groups, inequality strongly correlates with overall inequality: increasing relative and decreasing absolute inequality can on average be found within the subgroups. The within-groups inequality component constantly amounts to circa one fifth of overall inequality for all scenarios. Cuts in DPs slightly increase the relative and absolute between-groups Ginis and also the share of between-groups inequality in overall inequality. The share and the value of the absolute overlapping component decrease slightly while in relative terms the value of the overlapping component is increased. In absolute terms, this indicates that average distances within subgroups are reduced but distances between group means are increased. This combination leads to a reduction of overlapping. Since the relative Gini is equal to the absolute Gini divided by mean income, we can conclude that absolute changes are overcompensated by a reduced mean income in relative terms for the within-groups inequality and the overlapping components while the increase of the between-groups Gini is amplified.

Unlike for within-groups inequality, the shares of between-groups inequality and overlapping are not constant for all scenarios. Strongest differences to baseline shares can be observed in the No_Pricepol scenario. Here, the share of between-groups inequality decreases to 23% and overlapping rises to 57% starting from 39% and 41% in the baseline, respectively. Disparities between group means are significantly reduced, especially in absolute terms. Together with an almost constant share of inequality within the groups this drives the share of overlapping in overall inequality. Following the argumentation of Milanovic (2002), the farm population is more homogenous after the abolishment of market price policies and farm income depends less on the specialization of the farm. Regarding the share of inequality components, the Full_Lib scenario shows intermediate result between the No_DP and the No_Pricepol scenarios.

Table 6.1: Aggregate results of farm type decomposition (based on FFI).

	BL	50_DP	No_DP	No_PP	Full_Lib
Average income (€)	45,424	41,841	36,470	23,823	14,046
	RELATIV				
Gini	0.56	0.598	0.662	0.782	1.256
	100%	*100%*	*100%*	*100%*	*100%*
Gini-Within	0.109	0.115	0.126	0.156	0.244
	19%	*19%*	*19%*	*20%*	*19%*
Gini-Between	0.22	0.248	0.283	0.178	0.375
	39%	*41%*	*43%*	*23%*	*30%*
Overlapping	0.231	0.235	0.254	0.449	0.636
	41%	*39%*	*38%*	*57%*	*51%*
	ABSOLUT				
Abs. Gini	25,443	25,028	24,155	18,632	17,642
	100%	*100%*	*100%*	*100%*	*100%*
Abs. Gini-Within	4,934	4,808	4,595	3,711	3,433
	19%	*19%*	*19%*	*20%*	*19%*
Abs. Gini-Between	10,003	10,376	10,314	4,232	5,269
	39%	*41%*	*43%*	*23%*	*30%*
Abs. Overlapping	10,505	9,845	9,246	10,687	8,940
	41%	*39%*	*38%*	*57%*	*51%*
$O_{\_Gradin}$	0.678	0.662	0.653	0.812	0.753

Source: own calculations.

Due to the high deviations of results of the No_Pricepol scenario in comparison to the Baseline, this scenario is discussed in greater detail in the following paragraphs. Detailed results for all other scenarios are presented in Table D.1 to Table D.7 in Annex D. Disaggregated results are only presented for absolute inequality because of the prevalence of negative incomes in some subgroups. In the Full_Lib scenario, for example, average income for other grazing livestock farms is negative in 2020. These effects are difficult to interpret. Furthermore, the share of inequality that is caused by different inequality components is independent from the concept of inequality measurement (cf. equation (34)) and basic conclusions can be drawn either way.

At first, detailed results for the Baseline are presented in Table 6.2. Subsequently, Table 6.3 shows results for the No_Pricepol scenario and in Table 6.4 changes between Baseline and No_Pricepol results are presented. The reason for the significant decrease in between-groups inequality can be easily discerned by looking at changes in average group income in Table

6.4. The group with the former highest income – dairy farms – lose 60% of their income when market price policies are abolished, which is due in great part to the removal of the milk production quota. The group with the former second highest income – pig and poultry farms – lose only 25% on average, however, this group only accounts for 6% of the farm population while dairy farms account for 32%. On the other side of the income spectrum, the group with the lowest income (grazing livestock farms) loses 68% of income on average but accounts only for 11% of overall population while the second lowest income group (arable farms) have to bear only losses of 39% on average and represent 20% of the population. Thus, on average income disparities between group means are reduced. Furthermore, permanent crop farms hardly lose income because the bulk of their produced commodities is not affected by agricultural policy or not depicted as variable in the modelling system, e.g. wine or fruit production.

Table 6.2: Detailed results of farm type decomposition in 2020 for the Baseline scenario.

BASELINE	**AF**	**DF**	**GL**	**MF**	**PP**	**PC**
Average Income (€)	28,787	68,825	19,514	42,982	54,175	31,421
Income share	0.12	0.48	0.05	0.21	0.07	0.07
Farm population	31,762	51,376	17,135	36,376	9,445	15,979
Population share	0.20	0.32	0.11	0.22	0.06	0.10

% Contribution to Gini and Absolute Gini

		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		3.4%	9.2%	0.8%	4.9%	0.4%	0.8%	19.5%
Between $_{k,h}$	**AF**							7.2%
	DF	4.9%						14.5%
	GL	0.4%	3.2%					5.3%
	MF	1.2%	3.6%	1.1%				6.7%
	PP	0.6%	0.5%	0.4%	0.3%			2.1%
	PC	0.1%	2.3%	0.2%	0.5%	0.3%		3.4%
Overlapping $_{k,h}$	**AF**							8.8%
	DF	2.4%						9.5%
	GL	1.3%	0.7%					3.8%
	MF	3.0%	3.9%	1.1%				10.6%
	PP	0.6%	1.4%	0.2%	1.1%			3.6%
	PC	1.5%	1.1%	0.5%	1.5%	0.3%		4.9%
								100%

Absolute fractional Ginis

		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		22,753	23,241	17,293	24,699	26,800	20,204	
Between $_{k,h}$	**AF**							11,565
	DF	20,019						17,131
	GL	4,636	24,656					14,486
	MF	7,098	12,922	11,734				9,830
	PP	12,694	7,325	17,331	5,597			9,578
	PC	1,317	18,702	5,954	5,780	11,377		9,736
Overlapping $_{k,h}$	**AF**							14,293
	DF	9,652						11,080
	GL	15,717	5,425					10,302
	MF	17,486	13,831	11,427				15,382
	PP	14,469	18,872	9,086	20,557			16,765
	PC	20,314	9,118	13,378	17,370	14,155		14,432

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms
Source: own calculations.

Table 6.3: Detailed results of farm type decomposition in 2020 for the No_Pricepol scenario.

No_Pricepol		**AF**	**DF**	**GL**	**MF**	**PP**	**PC**	
Average Income (€)		17,542	27,339	6,309	25,047	40,832	30,943	
Income share		0.14	0.36	0.03	0.24	0.10	0.13	
Farm population		31,762	51,376	17,135	36,376	9,445	15,979	
Population share		0.20	0.32	0.11	0.22	0.06	0.10	
		% Contribution to Gini and Absolute Gini						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		4.0%	8.2%	0.8%	5.5%	0.4%	1.0%	19.9%
Between $_{k,h}$	**AF**							4.5%
	DF	1.6%						4.9%
	GL	0.6%	1.9%					5.0%
	MF	0.9%	0.4%	1.2%				3.5%
	PP	0.7%	0.7%	0.6%	0.6%			2.8%
	PC	0.7%	0.3%	0.7%	0.4%	0.2%		2.3%
Overlapping $_{k,h}$	**AF**							11.7%
	DF	4.4%						16.0%
	GL	1.2%	1.1%					4.0%
	MF	3.9%	6.4%	1.1%				14.6%
	PP	0.8%	1.4%	0.2%	1.1%			4.0%
	PC	1.4%	2.7%	0.4%	2.1%	0.5%		7.1%
								100%
		Absolute fractional Ginis						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		19,339	15,151	12,736	20,394	23,864	20,029	
Between $_{k,h}$	**AF**							5,383
	DF	4,898						4,246
	GL	5,617	10,515					9,792
	MF	3,752	1,146	9,369				3,662
	PP	11,645	6,746	17,262	7,893			9,031
	PC	6,701	1,802	12,317	2,948	4,944		4,589
Overlapping $_{k,h}$	**AF**							13,892
	DF	13,326						13,765
	GL	10,890	5,985					7,856
	MF	16,517	16,879	8,887				15,639
	PP	12,448	13,751	6,099	15,201			13,383
	PC	13,812	15,895	6,528	17,402	17,727		14,837

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms
Source: own calculations.

Table 6.4: Results of farm type decomposition in 2020 for the No_Pricepol scenario in comparison to Baseline results in 2020.

No_Pricepol / BASELINE		**AF**	**DF**	**GL**	**MF**	**PP**	**PC**	
Average Income (€)		0.61	0.40	0.32	0.58	0.75	0.98	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		1.18	0.89	1.00	1.12	1.00	1.25	1.02
Between $_{k,h}$	**AF**							0.63
	DF	0.33						0.34
	GL	1.50	0.59					0.94
	MF	0.75	0.11	1.09				0.52
	PP	1.17	1.40	1.50	2.00			1.33
	PC	7.00	0.13	3.50	0.80	0.67		0.68
Overlapping $_{k,h}$	**AF**							1.33
	DF	1.83						1.68
	GL	0.92	1.57					1.05
	MF	1.30	1.64	1.00				1.38
	PP	1.33	1.00	1.00	1.00			1.11
	PC	0.93	2.45	0.80	1.40	1.67		1.45
		Relative to Baseline (Absolute fractional Ginis)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		0.85	0.65	0.74	0.83	0.89	0.99	
Between $_{k,h}$	**AF**							0.47
	DF	0.24						0.25
	GL	1.21	0.43					0.68
	MF	0.53	0.09	0.80				0.37
	PP	0.92	0.92	1.00	1.41			0.94
	PC	5.09	0.10	2.07	0.51	0.43		0.47
Overlapping $_{k,h}$	**AF**							0.97
	DF	1.38						1.24
	GL	0.69	1.10					0.76
	MF	0.94	1.22	0.78				1.02
	PP	0.86	0.73	0.67	0.74			0.80
	PC	0.68	1.74	0.49	1.00	1.25		1.03

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms
Source: own calculations.

In the aggregate results it was observed that changes in within-group inequality are proportional to the overall development of inequality. By looking at disaggregated results we can observe that the average numbers conceal some information. Table 6.4 shows that within-group inequality prominently decreases for the group of dairy farms when price policies are abolished while for some other groups like permanent crop farms, a changed inequality within the group can hardly be detected. In the Baseline the group of dairy farms accounts for 9.2% of overall inequality due to within-group inequality (Table 6.2). By replacing individual incomes of dairy farmers by the mean income of all dairy farmers, overall inequality would be reduced by at least 9.2% (further reductions in overlapping are expected but cannot be exactly quantified). This conclusion can be drawn since "overlap cannot rise as the result of a within-group rich-to-poor money transfer" (Lambert and Decoster, 2005, p. 8), between-groups inequality would be constant, and within-group inequality would vanish.

The group of dairy farms has the largest share of within-group and between-group inequality and the second largest share of inequality caused by overlapping with other groups. However, when looking at absolute fractional Ginis, we can observe that within-group and overlapping values are not among the highest and thus, high shares in overall inequality are mainly caused by the high population share of the group. The fractional Gini for between-groups inequality in contrast is the highest among the groups which reflects the comparatively high average income of dairy farms. After the abolishment of price policies we can see from Table 6.3 and Table 6.4 that for inequality caused by dairy farms, a reduction in within-group inequality and between-groups inequality is partly compensated by an increased overlapping term.

Table 6.5 reveals that dairy farms have the smallest overlap with the group of grazing livestock farms, which have the smallest average subgroup income. The last column of Table 6.5 shows the overlapping index $O_{k,rest}$ when a group is compared with an aggregate of all other groups but the group itself. The group of dairy farms has the smallest value among all farms in the Baseline. Thus, we can conclude that in the Baseline this is the most clearly stratified group in the agricultural sector. The index of overlapping relates the overlapping component between two groups to the within-group inequality of one of the groups; thus, *ceteris paribus*, the smaller the amount of inequality within the group, the higher the index. This may reflect the perception of overlapping of the group members. The same amount of overlapping may be more strongly perceived by all members of a group with small within-group inequality than by members of a group with high inequality. The former group is more homogenous and thus relations to other members may be perceived to be stronger than in the latter group where members may recognize links to other members more loosely since distances within the group are large.

Table 6.5: Disaggregate results of the overlapping index of farm type decomposition for the Baseline and the No_Pricepol scenario.

	$O\_{Gradin\ k,h}$						$O\_{Gradin,k} = \sum_i O\_{Gradin,k,h} * p_h$	$O\_{Gradín\ k,rest}$
Baseline								
	AF	**DF**	**GL**	**MF**	**PP**	**PC**		
AF		0.424	0.691	0.769	0.636	0.893	0.70	0.63
DF	0.415		0.233	0.595	0.812	0.392	0.64	0.48
GL	0.909	0.314		0.661	0.525	0.774	0.64	0.60
MF	0.708	0.560	0.463		0.832	0.703	0.71	0.62
PP	0.540	0.704	0.339	0.767		0.528	0.65	0.63
PC	1.005	0.451	0.662	0.860	0.701		0.74	0.71
No_Pricepol								
AF		0.689	0.563	0.854	0.644	0.714	0.77	0.72
DF	0.880		0.395	1.114	0.908	1.049	0.94	0.91
GL	0.855	0.470		0.698	0.479	0.513	0.66	0.62
MF	0.810	0.828	0.436		0.745	0.853	0.82	0.77
PP	0.522	0.576	0.256	0.637		0.743	0.59	0.56
PC	0.690	0.794	0.326	0.869	0.885		0.77	0.74

NB: DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

In the second-to-last column of Table 6.5, the weighted average of all single comparisons is presented. Here, the value for the index of dairy farms is very close to the groups of other grazing livestock farms, and pig and poultry producers. This is the case because in the weighted average the overlapping of each group with itself is included. The overlapping of one group with itself by definition is one and thus, the group contributes its full weight (the population share) to the index. Thus, the high share of dairy farms in the sample cushions the degree of segregation of their group.

It should be noted that even though the group of dairy farms seems to be the most separated, a considerable amount of overlapping still appears between this group and the other groups. For a better understanding of this concept, histograms of two distributions are presented in Figure 6.2. One histogram refers to the frequency of dairy farms in different income intervals in the Baseline and the other refers to all other farms in the Baseline.

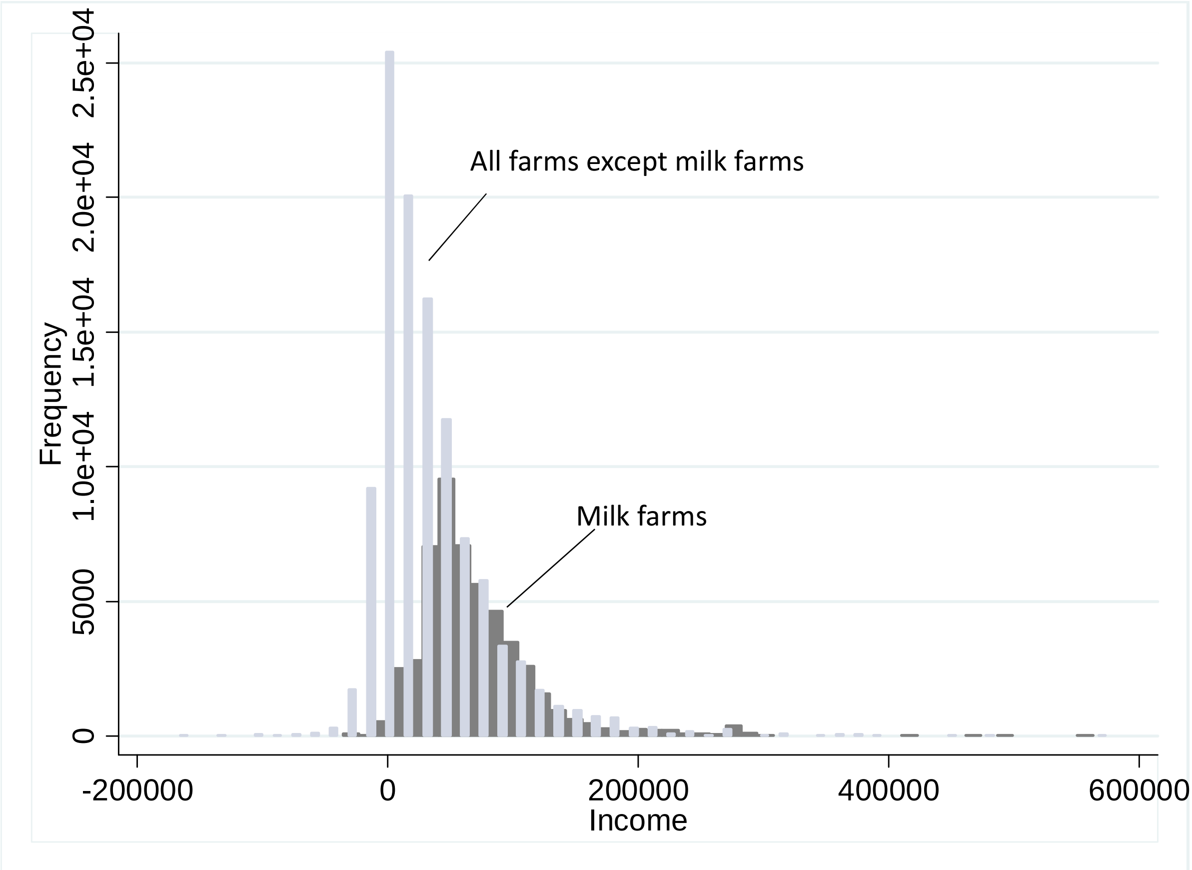

Figure 6.2: Histogram of incomes of milk farmers in the Baseline in 2020 in comparison to all other farms.

Source: own calculations.

Compared to the distribution of all other farms, the distribution of dairy farms is shifted to the right. The area of overlapping, however, is high and it can be seen that the between-groups inequality, which is measured by replacing all incomes by their respective group income means, would clearly understate the inequality between all members of the two groups.

After price policies are abolished, the distribution of dairy farms lies almost in the center of the distribution of all other farms, which is depicted in Figure 6.3. This is also reflected by the overlapping term in Table 6.5, which increases from the lowest value in the Baseline to the highest in the No_Pricepol scenario.

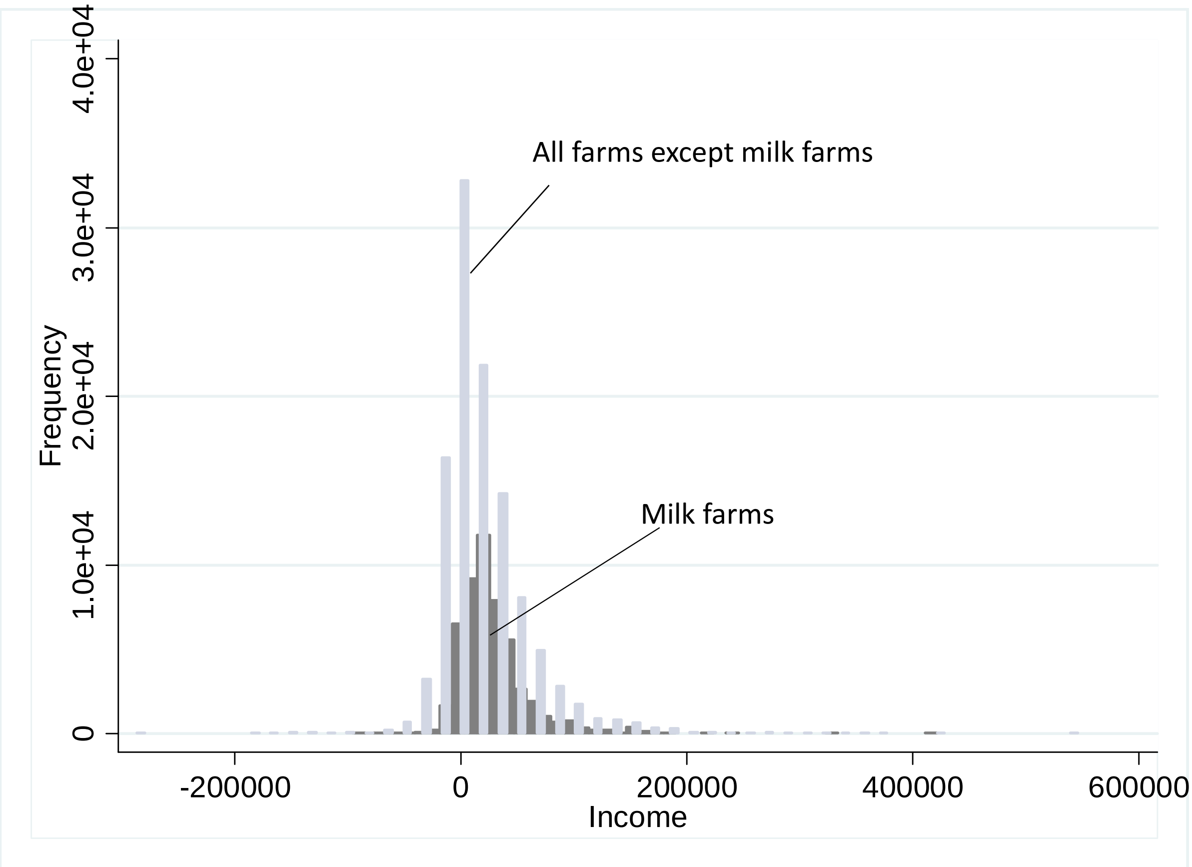

Figure 6.3: Histogram of incomes of milk farmers in the No_Pricepol scenario in 2020 in comparison to all other farms.

Source: own calculations.

The only group whose overlapping term decreases when market price policies are abolished is the class of pig and poultry farms. In the Baseline, pig and poultry farmers are the group with the second highest average income. Due to relatively moderate losses (Table 6.4) they become the group with the highest average income after price policies are abolished. Thus, comparatively high values of between-group inequality and comparatively low overlapping values occur. The relatively moderate losses emerge because pig production in this group is predominant and pig meat prices only decrease slightly compared to other products when price policies are abolished. From Table 6.4 and Table 6.5 we can observe that overlapping with all other groups except for the group of permanent crops farms is reduced in the No_Pricepol scenario. Particularly with dairy farmers, overlapping is reduced since the two groups had a high overlapping component in the Baseline but develop differently with regard to average income under scenario conditions.

The only exceptional group for which increasing overlapping with the group of pig and poultry producers is reported, is the group of permanent crops farms. Permanent crops farms are able to almost keep their average Baseline incomes under scenario conditions. Since mean incomes of the two groups are closer to each other after the abolishment of price policies and at the same time within-group inequality is only slightly reduced, between-groups inequality is reduced and overlapping is increased.

Nevertheless, in general, the group of pig and poultry farms tends to be more separated from the majority of the other groups in the No_Pricepol scenario. However, given its population share of 6% this effect is overcompensated by the narrowing effects of the other groups in the aggregate results.

A decomposition analysis for regional subgroups is also carried out. Groups are constructed according to eight[59] western German *Federal Laender*, namely *Nordrhein-Westfalen (NR)*, *Niedersachsen (NS)*, *Schleswig-Holstein (SH)*, *Bayern (BA)*, *Baden-Württemberg (BW)*, *Hessen (HE)*, *Saarland (SL)* and *Rheinland-Pfalz (RP)*.

Compared to the farm type decomposition, the regional decomposition clearly reveals higher overlapping components already in the Baseline. Thus, farm specialization matters more for the expected income of a farm than the region where a farm is located. Nevertheless, regions with a higher frequency of large dairy farms (*Niedersachsen* and *Schleswig-Holstein*) tend to have a higher average income and slightly lower overlapping with other regions in the Baseline. Effects of liberalization scenarios on the composition of overall inequality are less pronounced in the regional analysis. Detailed results for the regional subgroup decomposition are presented in Annex D (Table D.8 until Table D.18).

Furthermore, aggregated results of farm type and regional decomposition analyses are presented for total household income rather than FFI in Annex D in Table D.19 and Table D.20, respectively. Farm type groups with lower average FFI tend to have a higher additional non-farm income. It follows that the share of the between-groups income component decreases and the share of overlapping increases when total household income is taken into account, especially in the No_Pricepol and the Full_Lib scenarios.

The regional decomposition of total household income inequality reveals very similar aggregate patterns like the analysis based on the indicator FFI. Overlapping, however, is slightly more important for total household income in the No_Pricepol and the Full_Lib scenarios.

[59] The cities of *Hamburg* and *Bremen* have the status of a *Federal Land*. However, due to their small size, *Hamburg* is added to the larger *Federal Land* of *Schleswig-Holstein* and *Bremen* is added to *Niedersachsen*.

7 Summary and conclusions

In this last chapter, the presented work shall be summarized and conclusions shall be drawn. Furthermore, some weaknesses and caveats are addressed and future research areas are proposed.

7.1 Background and achievement

In recent decades agricultural support in Europe has increasingly shifted from market price support measures to budgetary payments. This development has made support more visible and it has raised public attention to the distribution of support, which in turn increased political awareness of the topic. Thus, the redistributive effects of agricultural policy and further reforms of agricultural policy have become more important in political terms. Furthermore, the analysis of effects of agricultural policy on the income distribution among farmers is also of intrinsic economic interest.

While in many other policy fields it is a common practice to analyse redistributive effects before a reform is implemented, the bulk of the literature regarding policy induced redistributive effects in the agricultural sector is carried out ex post.

Since the aggregation of data may create a significant bias when redistributive effects are analysed (Bourguignon et al., 2005; Savard, 2005), many standard tools that are developed for policy analysis in the agricultural sector are not suitable for distribution analyses. Furthermore, the CAP is a sector wide policy which may influence (world market) prices of agricultural products. A pure microanalysis would thus not be able to take these effects into account properly.

In agricultural economics, however, some approaches do exist to model redistributive effects in an ex-ante way. For example, Keeney and Beckman (2009), Keeney (2009), and Hertel et al. (2007) combine CGE model results with a large farm household data survey for the U.S.; however, they map results from one representative regional household to disaggregated farm households, resulting in equal behavioural adjustments of all individual farms. Furthermore, in principle, it is possible to model income changes at the single farm level which are induced by sectoral policies with the LEI model funnel presented by van Tongeren (2000) and Woltjers et al. (2011). Moreover, several model chains have been developed which account for behaviour at the single farm level (e.g. Louhichi and Valin, 2012, Helming and Schrijver, 2008). These attempts, however, are mostly restricted to certain farm types and to the best knowledge of the author no analysis of redistributive effects[60] has been undertaken by the application of these tools so far.

Against this background, in the work at hand a tool is developed which enables the consistent assessment of CAP reform induced impacts on individual farm incomes while simultaneously taking sectoral adjustments into account and thus, facilitates an ex-ante analysis of redistributive effects in the western German agricultural sector. To this end, two pre-existing large-scale simulation models are linked and extended by a newly developed micro model. The model chain is then applied to different CAP liberalization scenarios.

The additional implementation of a meso-model which allows for individual adjustment of production patterns of different farm groups, introduces a high degree of heterogeneity in the analysis and distinguishes the work from previous research on ex-ante measurement of redistributive impacts of agricultural policy (Keeney and Beckman, 2009; Keeney, 2009; Hertel et al., 2007). Moreover, the application of agricultural sector models allows for a more detailed depiction of farm production processes. Nevertheless, the approach applied in previous research allows for the adjustment of non-farm incomes which are assumed to be constant in the work at hand.

After changes in individual incomes are calculated in a first step by the modelling system for different scenarios, model results are analysed in a second step by the application of a methodology for the measurement of redistributive effects which was originally developed for the analysis of tax reforms and has also been used to assess redistributive effects of agricultural policy (e.g. Allanson, 2006, 2008). This methodology is applied for the first time in an ex-ante analysis of redistributive effects in the agricultural sector. For the analysis of redistributive effects, scenario results are evaluated relative to the income distribution of the Baseline scenario where the CAP is still in place.

To account for different conceptual impacts of inequality analysis on results, the analysis is carried out at different aggregation levels, for different income classifications, and for income data generated in a static way in comparison to data generated by the modelling system.

Additionally, the Gini inequality index is decomposed by subgroups to conduct a more detailed inequality analysis and to detect underlying developments which are not visible through the analysis of overall inequality effects. The methodology facilitates the analysis of the degree of separation between subgroups and the importance of the grouping attribute for the expected income of a farm.

[60] As already specified above, the term ‘redistributive effects‘ in this case explicitly refers to the evaluation of a new income distribution with regard to another income distribution and the assessment of progressivity or related concepts. It does not refer to the pure calculation of income changes in different regions or for different farm types, as for example presented in Louhichi and Valin (2012).

7.2 Major results

It can be stated that inequality effects are robust with regard to the conceptual differences tested for, at least in terms of the direction of inequality changes. All calculated liberalization scenarios lead to decreasing absolute income differences among western German farms in 2020 because high-income farms lose higher absolute amounts of money than small-income farms. However, relative to their Baseline incomes low-income farms tend to lose a higher share compared to high-income farms which leads to increasing relative inequality due to liberalization. Only one exemption from this pattern of results exists, namely, if grouped results are disaggregated and total household income is considered instead of FFI.

In general, when inequality is considered with regard to FFI, inequality indices are significantly higher after the disaggregation of the grouped data, already in the Baseline. This is intuitive since within-group inequality is additionally included in the analysis. Redistributive indicators show less equalizing effects of the same reform in absolute terms and stronger unequalizing effects in relative terms when data are disaggregated. However, differences in absolute redistributive effects are small. For the relative analysis, differences are more pronounced because after disaggregation a similar degree of distribution of absolute losses is compared to a higher degree of inequality in Baseline incomes. Thus, similar absolute income losses have to be borne by higher incomes in the upper tail of the distribution and by lower incomes in the lower tail of the distribution. Large differences in relative terms, however, should be interpreted with caution due to a higher share of negative incomes in the disaggregated distribution.

Despite these differences, total effects head in the same direction in both the analyses, based on grouped and disaggregated data, when FFI is the variable under consideration. When instead total household income is applied, conclusions are widely the same, but for two exceptions. For the analysis of grouped data in the No_Pricepol and the Full_Lib scenarios, slightly positive indices of progressivity are presented while for the individual data-based analysis the opposite is true, i.e. indices of progressivity are negative. This is because the adding of off-farm incomes to FFI as a constant positive income variable has an inequality decreasing effect on all relative Gini coefficients, for grouped as well as disaggregated data. For the analysis based on grouped data, initial total household income is more equally distributed than absolute income losses. In comparison, the analysis of disaggregated data reveals that absolute income losses are similarly distributed but initial income inequality increases after disaggregation so that losses are regressively distributed in relative terms. Thus, different directions of relative redistributive effects between the group-based and the disaggregated data-based analyses are triggered by the increase of initial inequality of household incomes rather than by a change of the distribution of income losses.

A comparison explicitly undertaken to examine the differences between an inequality analysis of the variable FFI and an analysis of the variable total household income reveals comparatively small differences between inequality indices in absolute terms and stronger differences in relative terms. In absolute terms, losses are slightly less concentrated among the high-income farms when total farm income is considered instead of FFI. This can be explained by the fact that farms with a low FFI tend to have higher income from off-farm sources and tend to rise in the ranking due to the additional consideration of off-farm income. Thus, since losses are distributed progressively with regard to FFI, more farms with higher absolute losses descend in the ranking of total income and vice versa, i.e. farms with lower absolute losses ascend in the ranking.

In *relative* terms all inequality indicators are less pronounced for the analysis of the variable total household income. This can partly be explained by less negative values in the distribution. Consequently, relative Gini coefficients are less sensitive with respect to changes in average income. Nevertheless, taking off-farm income sources additionally into account has an equalizing effect in relative terms due to the negative correlation of off-farm income and on-farm income.

Moreover, the relevance of taking into account policy-induced production and market responses in ex-ante inequality analysis was assessed in this work. Since most of the existing literature regarding distributional effects of agricultural policy is static in nature, it has been attempted to quantify the bias that occurs when behavioural effects are neglected. From the empirical analysis, it can be concluded that taking adjustment effects into account clearly has an impact on the magnitude of the inequality indices. Overall inequality is lower in absolute as well as relative terms and losses are distributed more progressively/less regressively in the different scenarios when adjustment is taken into consideration. When comparing the static analysis to the model based analysis, the largest differences can be observed for the Full_Lib scenario which also causes the strongest reductions in average incomes. Nevertheless, in all of the scenarios, distributional effects have the same directional impact both in the static analysis and in the analysis with adjustment effects. In general, the evaluation and ranking of the different reform scenarios with respect to their impact on income equality is similar regardless of adjustment effects. In all scenarios with adjustment effects, some evidence is found that lower-income farms have a lower share in total income losses compared to the static analysis. Among other scenario-specific reasons, this is because it is easier for lower-income farms to reduce income losses from liberalization by abandoning production activities that have negative margins under scenario conditions compared to higher-income farms that often have still positive marginal incomes for great parts of their production activities.

Again, the comparison of relative inequality analyses has to be undertaken with caution since negative incomes appear in all of the distributions under consideration and the relative Gini coefficient reacts more sensitively in this case, which might relativize the differences between the approaches in relative terms.

With regard to the different policy instruments, it turns out that the abolishment of market price support is more progressive in absolute terms and less regressive in relative terms than the abolishment of DPs. This is because income reductions caused by the abolishment of market price support is more unequally distributed (a higher share of losses in the upper tail of the distribution and a lower share in the lower tail) than losses caused by the abolishment of DPs.

Even though the defined minimum requirement of a CAP reform, i.e. a positive redistributive effect in absolute terms, is fulfilled in all conducted scenarios, it is difficult to give policy recommendations based solely on this analyses since redistributive effects are only one concern of agricultural policy. The developed modelling tool is mainly suited to observe (unintended) distributional effects of CAP reforms, which are intended rather, to complement other policy analyses than being the sole decision criterion. In general, it can be stated that DPs are better suited to shape redistributive policy effects than market price support instruments since eligibility can more easily be coupled to specific farm features. Nevertheless, each reform proposal needs to be evaluated individually.

From a methodological point of view further contributions could be made to the existing literature. The iterative coupling procedure applied in this work can be found in several other publications, as well. Nevertheless, only few examples exist (e.g. Britz and Witzke, 2012) where a partial equilibrium model of the agricultural sector (ESIM) is linked to a more disaggregated programming model (FARMIS). The specificity of this work is that agricultural production of only one out of several countries depicted in the partial equilibrium model is substituted by another, more detailed model. Due to this approach, even significant changes in production in FARMIS cause only minor price reactions in ESIM since prices are determined by worldwide or European-wide supply quantities. Germany is a small country in economic terms for most of the depicted commodities. For only a few products where a considerable share of world supply is produced in Germany, price effects can be observed. Additionally, the iteration procedure matters for non-tradable products. Another picture probably would emerge if more or all countries were substituted by more disaggregated programming models.

Additionally, a decomposition of inequality effects of CAP liberalization by subgroups is carried out in this work, which to the best knowledge of the author is done for the first time with regard to the agricultural sector. When the Gini coefficient is decomposed, three inequality components can be defined: inequality within subgroups, inequality between subgroup means and a term that arises when distributions of subgroups are overlapping. From the overlapping term the state of segregation of the farm population with regard to subgroups can be derived. Furthermore, a more detailed picture of the underlying processes of inequality changes can be revealed with this methodology.

In a first analysis subgroups refer to farm types and in a second analysis subgroups refer to the region a farm is located in. Based on this analysis, for example, the importance of the group of dairy farmers for inequality effects is discovered. Furthermore, there is some evidence that farm specialization matters more for the expected income of a farm than the region where a farm is located.

7.3 Limitations and outlook

Finally, some limitations of the work at hand and resulting future research options shall be addressed. In the modelling system only one small country of the worldwide agricultural sector, which is depicted in the partial equilibrium model, is substituted by a more disaggregated programming model. Thus, quantity changes of the programming model cause only small price changes for most tradable commodities in the partial equilibrium model and for these commodities the iterative coupling mostly is of limited value. The substitution of additional countries by more disaggregated models would increase feedback effects emerging at the micro level and thus increase the detailedness of the analysis.

Generally, incentive effects are accounted for in the analysis due to the application of the introduced modelling chain. In reality, however, additional adjustment processes are likely to occur which are not depicted in the current version of the models. Structural change, for example, is implemented only exogenously in the programming model. This has an effect on the analysis of income distribution since farms with large negative incomes would likely leave the sector in reality and average farm size would increase. In addition, the adaption of new production technologies is not considered in the analysis. This drawback of the current modelling tool could be addressed by the endogenizing of structural changes in the programming model.

Another limitation of the analysis is clearly the static nature of the micro-model. Due to this approach individual income changes are affected by changes in production patterns of the respective farm groups at the meso-level.

A related caveat is almost inevitable and common in all similar analyses because only observed units can be modelled and complete population surveys hardly exist on the national level. Even though the analysis is conducted for an already high number of farms, one simulated farm still represents more than 20 farms of the overall farm population. To account for this fact, simulated farms are weighted by an aggregation factor and it is implicitly assumed that one simulated farm reacts representatively for many others. Thus, representative agent and micro-simulation approaches cannot always be sharply distinguished (Lofgren et al., 2003).

In addition, several assumptions regarding the development of agricultural markets until the final year of the analysis have to be made for the generation of the Baseline scenario. It is well-known that redistributive effects are influenced by the distribution of income in the base situation (Lerman and Yitzhaki, 1995). Thus, it should be kept in mind that any ex-ante analysis implies a certain extent of uncertainty and that results are affected by the choice of behavioural parameters and by base year conditions.

Moreover, interactions with other sectors of the economy are neglected by the applied modelling system which consists solely of agricultural sector models. This limitation could be overcome by the additional integration of a CGE model into the modelling system. However, given the relatively small share of agriculture in overall GDP and workforce in Europe and especially Germany, impacts on factor prices (except for land, which is taken into consideration by the presented modelling chain) should be limited.

Furthermore, off-farm income is not adapted, but assumed to be constant in the analysis. This assumption has rather strong impacts at the micro level and likely leads to an underestimation of inequality compensation effects of off-farm income sources because it can be expected that the development of off-farm income and agricultural support are negatively correlated (e.g. Vergara et al., 2004; Kwon et al., 2006). To overcome this weakness, a micro-simulation model depicting the labour allocation decision of farm households could additionally be applied in the analysis of redistributive effects of CAP liberalization.

Summing up, this work provides an innovative combination and extension of different simulation models which enables the ex-ante measurement of income changes for individual farms. This information in turn facilitates the measurement of redistributive effects in the agricultural sector taking behavioural effects into account. The new modelling system is able to answer questions which might become more relevant for coming reforms of the CAP. In combination with advanced methodologies for the measurement of redistributive effects and for the decomposition of inequality indices, the tool can provide valuable contributions to the development and design of agricultural policy.

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Appendix A – Steering file

```
*Baselinename
$setglobal BASELINENAME "fap_new"
*scenario name
*$setglobal scenario "baseline"
*$setglobal scenari "baseline"
$setglobal scenario "full_lib"

*full scenario name in Farmis result files
$setglobal scenarioname "%Baselinename%_%scenario%"

*$setglobal Lice "D:\Lizenz\gamslice.txt"
$setglobal Inequality_path "E:\Agrarpolitik\KOPPLUNG\GESAMTMODELL\INEQUALITY"

**********************for FARMIS*****************************************************
$setglobal Farmis_Path "E:\Agrarpolitik\KOPPLUNG\GESAMTMODELL\FARMIS"
$setglobal scenario_file "scenario_DE_test.xls"
*DE_test auf BL Ebene

$setglobal report_file "Project_files\DE_test\_report_data\report_DE_DE"
$setglobal report_file_groups "Project_files\DE_DFG_0608\_report_data\report_DE_DE"
* DE_DFG_0608 - Gruppenebene
***********************************************************************************

***********************for ESIM****************************************************
$setglobal ESIM         "E:\Agrarpolitik\KOPPLUNG\GESAMTMODELL\ESIM"
$setglobal ESIM_path    "E:\Agrarpolitik\KOPPLUNG\GESAMTMODELL"
$setglobal save_file    "E:\Agrarpolitik\KOPPLUNG\GESAMTMODELL\ESIM_2019"
$setglobal ESIM_FOLDER  "./ESIM/"

*$setglobal version      "esim_fix"
$setglobal version      "esim_calib"
***********************************************************************************

$set gamsparm "ide=%gams.ide% lo=%gams.lo% errorlog=%gams.errorlog% errmsg=1"

$include map_price_yield.inc
$include map_quantities.inc

set time /base, 2020 /;
set results /r_pd, r_area, r_supp /;
set results_comm /r_hdem, r_sdem, r_fdem, r_tuse, r_pd, r_pdem, r_supp, r_area, r_yiel /;
set results_cc / landpr1 /;

Parameter
farmis_quant(IND)
esim_quant(esim_pr)
esim_prices(esim_pr)
esim_inc(esim_pr)
FARMIS_Price(FARMIS_pr)
esim_yield(esim_pr)
farmis_yield(farmis_pr)
chk_diff(*,*,*)
sum_chk_diff
counter
intercept_ge(esim_pr)
first_quant(esim_pr)
farmis_first_quant
esim_vgl(time,esim_pr,results)
vgl_ohne_iter
```

```
;

farmis_quant(IND)       = 0;
esim_quant(esim_pr)     = 0;
esim_prices(esim_pr)    = 0;
FARMIS_Price(FARMIS_pr) = 0;
esim_yield(esim_pr)     = 0;
farmis_yield(farmis_pr) = 0;

Parameter
r_comm(*,*,*,*)
r_cc(*,*,*)
;

set cc /GE /;

Set iter
/0*100/
;

Scalar turn;
turn = 0;
Scalar el;
Scalar infl_rate;

Parameter
iter_results(iter,*,*);

chk_diff(iter,"esim_quant",esim_pr) = 0;

PARAMETER REPORT_SECTOR(*,*);
REPORT_SECTOR("BAS","dummy")=0;
REPORT_SECTOR("%scenarioname%","dummy")=0;
PARAMETER REPORT_SECTOR_FARM(*,*);

Parameter
CH_PRICE(*,*,*,*,*)
CH_YIELD(*,*,*,FARMIS_pr);

Parameter
exog_area;

* Introduction of area used for growing Energy Maize in FARMIS in 2020
execute_load '%Farmis_Path%\%report_file%', REPORT_SECTOR;
exog_area = REPORT_SECTOR("%scenarioname%","L_EMAIZE") -
REPORT_SECTOR("BAS","L_EMAIZE");

execute_unload '.\ESIM\Exog_area.gdx' exog_area;

*1) First stand-alone run of ESIM to generate a price/yield vector
execute 'gams.exe esim.gms Wdir=%ESIM% %gamsparm% user1="%scenario%"
user2="%BASELINENAME%" user3="%ESIM_FOLDER%" s=%save_file%';
*license=%Lice%
el = errorlevel;
display "errorlevel", el;
if (el<>0, abort "ERROR" );

*1a) execute only for 2020:
execute 'gams.exe simulation_2020.gms Wdir=%ESIM% %gamsparm%  r=%save_file% '  ;
*license=%Lice%
el = errorlevel;
```

```
display "errorlevel", el;
if (el<>0, abort "ERROR" );

* Price and Yield changes as well as conversion into nominal terms already done in ESIM!!!
execute_LOAD '.\esim\esim_p_y.gdx', esim_prices, esim_yield, esim_vgl, infl_rate, esim_inc;

execute_load '.\esim\results.gdx', r_comm, r_cc;

iter_results("0","r_hdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_hdem") ;
iter_results("0","r_supp",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_supp") ;
iter_results("0","r_sdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_sdem") ;
iter_results("0","r_fdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_fdem") ;
iter_results("0","r_pdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_pdem") ;
iter_results("0","r_pd",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_pd") ;
iter_results("0","r_tuse",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_tuse") ;
iter_results("0","r_area",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_area") ;
iter_results("0","r_yiel",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_yiel") ;
iter_results("0","r_landpr1",esim_pr) =  r_cc("GE","2020","r_landpr1");

iter_results("0","esim_prices",esim_pr) =  esim_prices(esim_pr);
iter_results("0","av_esim_pr",esim_pr)  =  esim_prices(esim_pr);
iter_results("0","esim_inc",esim_pr)    =  esim_inc(esim_pr);
iter_results("0","av_esim_inc",esim_pr) =  esim_inc(esim_pr);

iter_results("0","real_esim_prices",esim_pr) =  esim_prices(esim_pr) / infl_rate ;
iter_results("0","real_av_esim_pr",esim_pr)  =  esim_prices(esim_pr) / infl_rate ;
iter_results("0","real_esim_inc",esim_pr)    =  esim_inc(esim_pr)    / infl_rate ;
iter_results("0","real_av_esim_inc",esim_pr) =  esim_inc(esim_pr)    / infl_rate ;

display iter_results;

*Prices for Calibration in the first run
execute_unload '.\%version%\av_price.gdx' esim_prices, infl_rate, esim_inc;

***************************************************
****      START ITERATION LOOP      *****
***************************************************

Repeat(

turn = turn+1;

* Mapping of prices and yield from ESIM results to FARMIS categories
FARMIS_Price(FARMIS_pr) $ SUM(map_farmis_esim(farmis_pr,esim_pr),1)
   =
100*SUM(map_farmis_esim(farmis_pr,esim_pr),esim_prices(esim_pr))/SUM(map_farmis_esim(farmis_pr,esim
_pr),1)-100;
display   FARMIS_Price;

FARMIS_YIELD(FARMIS_y) $ SUM(map_farmis_esim(farmis_y,ESIM_Y),1)
    =
100*SUM(map_farmis_esim(farmis_y,ESIM_Y),ESIM_Yield(ESIM_Y))/SUM(map_farmis_esim(farmis_y,ESI
M_Y),1)-100;
display   FARMIS_YIELD;

CH_PRICE("DE","GROWTHRATE","CON","%scenarioname%",FARMIS_pr) =
FARMIS_Price(FARMIS_pr);
execute_unload 'temp_price.gdx',CH_PRICE;
EXECUTE 'GDXXRW temp_price.gdx o=%Farmis_Path%\_scenario_data\%scenario_file% par=CH_PRICE
rng=price_sce!a4 merge'
;
```

```
CH_YIELD("DE","GROWTHRATE","%scenarioname%",FARMIS_pr) = FARMIS_YIELD(FARMIS_pr);
execute_unload 'temp_yield.gdx',CH_YIELD;
EXECUTE 'GDXXRW temp_yield.gdx o=%Farmis_Path%\_scenario_data\%scenario_file% par=CH_YIELD
rng=yield_sce!b3 merge'
;

*3a) Run FARMIS on laender level with ESIM prices and yields to determin young livestock prices
execute 'copy %Farmis_Path%\4_project_DE_test.gms %Farmis_Path%\4_project.gms'
execute 'copy %Farmis_Path%\Project_files\DE_test\4_Farmis_steering_KopplungESIM.gms
%Farmis_Path%\Project_files\DE_test\4_Farmis_steering.gms'
execute 'gams.exe 3_farmis_main.gms Wdir=%Farmis_Path% Cdir=%Farmis_Path% %gamsparm% --
Xscenario %Scenario% --XBaselinename %Baselinename%';
el = errorlevel;
display "errorlevel", el;
if (el<>0, abort "ERROR" );

*get young livestock prices
execute_load '%Farmis_Path%\%report_file%', REPORT_SECTOR_FARM,REPORT_SECTOR;

*****************************************************************************************
*---from here comment out in case of not using the group specific version of FARMIS ----*
*****************************************************************************************
*$ontext
CH_PRICE("DE","GROWTHRATE","CON","%scenarioname%",youngani2) $
sum(map_yani_prices(youngani2,yaniprices),REPORT_SECTOR_FARM("BAS",yaniprices))
                        = sum(map_yani_prices(youngani2,yaniprices),
                          (REPORT_SECTOR_FARM("%scenarioname%",yaniprices)-
REPORT_SECTOR_FARM("BAS",yaniprices))/REPORT_SECTOR_FARM("BAS",yaniprices)*100);
execute_unload 'temp_price.gdx',CH_PRICE;
EXECUTE 'GDXXRW temp_price.gdx o=%Farmis_Path%\_scenario_data\%scenario_file% par=CH_PRICE
rng=price_sce!a4 merge'

*3b) Run FARMIS owith ESIM prices and yields and equilibrium young livestock prices
execute 'copy %Farmis_Path%\4_project_DE_DFG0608.gms %Farmis_Path%\4_project.gms'
execute 'copy %Farmis_Path%\Project_files\DE_DFG_0608\4_Farmis_steering_KopplungESIM.gms
%Farmis_Path%\Project_files\DE_DFG_0608\4_Farmis_steering.gms'
execute 'gams.exe 3_farmis_main.gms Wdir=%Farmis_Path% Cdir=%Farmis_Path% --Xscenario %Scenario% -
-XBaselinename %Baselinename%'

* Mapping of FARMIS results to ESIM products
execute_load '%Farmis_Path%\%report_file_groups%', REPORT_SECTOR;

*$offtext
*************************************
* ----- comment out until here -----*
*************************************

farmis_quant(IND) $ REPORT_SECTOR("BAS",IND) =
REPORT_SECTOR("%scenarioname%",IND)/REPORT_SECTOR("BAS",IND);
display farmis_quant;

exog_area = REPORT_SECTOR("%scenarioname%","L_EMAIZE") -
REPORT_SECTOR("BAS","L_EMAIZE");
execute_unload '.\%version%\Exog_area.gdx' exog_area;

esim_quant(esim_pr)$ SUM(map_quantities(esim_pr,IND),1) =
SUM(map_quantities(esim_pr,IND),farmis_quant(IND));
display esim_quant;

execute_unload '.\%version%\esim_change.gdx' esim_quant;
```

```
*4) Run ESIM with fixed supply side
execute 'gams.exe simulation_2020_%version%.gms Wdir=%ESIM_path%\%version%  %gamsparm%
r=%save_file%  ';
*license=%Lice%
el = errorlevel;
display "errorlevel", el;
if (el<>0, abort "ERROR" );

execute_LOAD '.\%version%\esim_p_y.gdx', esim_prices, esim_yield, intercept_ge, infl_rate, esim_inc;

execute_load '.\%version%\results.gdx', r_comm, r_cc;

* Storage of intermediate iteration results
loop(iter$((ord(iter)-1) = turn),
iter_results(iter,"farmis_quant",IND)$farmis_quant(IND)            =  farmis_quant(IND)       ;
iter_results(iter,"esim_quant",esim_pr)$esim_quant(esim_pr)        =  esim_quant(esim_pr)     ;
iter_results(iter,"esim_prices",esim_pr)$esim_prices(esim_pr)      =  esim_prices(esim_pr)    ;
iter_results(iter,"FARMIS_Price",farmis_pr)$FARMIS_Price(FARMIS_pr) =  FARMIS_Price(FARMIS_pr) ;
iter_results(iter,"esim_yield",esim_pr)$esim_yield(esim_pr)        =  esim_yield(esim_pr)     ;
iter_results(iter,"farmis_yield",farmis_pr)$farmis_yield(farmis_pr) =  farmis_yield(farmis_pr) ;
iter_results(iter,"intercept_ge",esim_pr)$intercept_ge(esim_pr)    =  intercept_ge(esim_pr)   ;

iter_results(iter,"esim_inc",esim_pr)$esim_inc(esim_pr)    =  esim_inc(esim_pr)   ;

iter_results(iter,"r_hdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_hdem") ;
iter_results(iter,"r_supp",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_supp") ;
iter_results(iter,"r_sdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_sdem") ;
iter_results(iter,"r_fdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_fdem") ;
iter_results(iter,"r_pdem",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_pdem") ;
iter_results(iter,"r_pd",esim_pr)    =  r_comm("GE","2020",esim_pr,"r_pd") ;
iter_results(iter,"r_tuse",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_tuse") ;
iter_results(iter,"r_area",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_area") ;
iter_results(iter,"r_yiel",esim_pr)  =  r_comm("GE","2020",esim_pr,"r_yiel") ;
iter_results(iter,"r_landpr1",esim_pr) =  r_cc("GE","2020","r_landpr1");

iter_results(iter,"real_esim_prices",esim_pr) =  esim_prices(esim_pr) / infl_rate ;
iter_results(iter,"real_av_esim_pr",esim_pr)  =  esim_prices(esim_pr) / infl_rate ;
iter_results(iter,"real_esim_inc",esim_pr)    =  esim_inc(esim_pr)    / infl_rate ;
iter_results(iter,"real_av_esim_inc",esim_pr) =  esim_inc(esim_pr)    / infl_rate ;

chk_diff(iter,"esim_prices",esim_pr) = 0;
chk_diff(iter,"esim_prices",esim_pr)$(iter_results(iter-1,"esim_prices",esim_pr) gt 0)
        = round( (iter_results(iter,"esim_prices",esim_pr) -  iter_results(iter-1,"esim_prices",esim_pr)) ,3);

counter(esim_pr) = 0;
counter(esim_pr)$(abs(chk_diff(iter,"esim_prices",esim_pr)) le 0.01) = 1;
display chk_diff;

*for the use in FARMIS to anticipate convergence

esim_prices(esim_pr) =  0.5 * esim_prices(esim_pr) + 0.5 * iter_results(iter-1,"av_esim_pr",esim_pr);

esim_inc(esim_pr) =  0.5 * esim_inc(esim_pr) + 0.5 * iter_results(iter-1,"av_esim_inc",esim_pr);

iter_results(iter,"av_esim_pr",esim_pr)$esim_prices(esim_pr)      =  esim_prices(esim_pr)    ;
iter_results(iter,"av_esim_inc",esim_pr)$esim_inc(esim_pr)      =  esim_inc(esim_pr)    ;

*loop iter end
);

execute_unload '.\%version%\av_price.gdx' esim_prices, infl_rate, esim_inc;
```

```
display counter;
until(  ((sum(esim_pr,counter(esim_pr)) eq card(esim_pr)) or (turn = 15))
*Until end
)

*Repeat end
);
********
execute_unload "res_%version%_%BASELINENAME%_%scenario%.gdx", iter_results;
execute_unload '.\INEQUALITY\inflation.gdx' infl_rate;
```

Appendix B – Mapping of commodities between FARMIS and ESIM

Table B.1: Mapping of commodities between ESIM and FARMIS.

ESIM	FARMIS
Poultry	Broiler meat; Other poultry meat; Poultry meat from laying hens
Pork	Pork meat; Sows meat
Potatoes	Potatoes
Beef	Beef from a bull; Beef from a heifer Meat from slaughtered cows (dairy cull suckler) Veal from fattening calves
Corn	Grain maize
Milk	Milk
Wheat	Soft wheat; Summer wheat; Winter wheat
Rye	Rye
Durum	Durum wheat
Eggs	Eggs from laying hens
Rapeseed	Rapeseed; Oilseeds for energy; Non Food (Oilseeds)
Barley	Summer barley; Winter barley; Feeding cereals
Rap meal	Feeding stuffs (by-products) energy-rich
Sun meal; Gluten feed	Feeding stuffs (by-products) other
SMP	Milk replacer
Soymeal	Feeding stuffs (by-products) protein-rich
Other Grains	Oats; Other cereals; Triticale
Sunseed	Sunseed; Other oils
Sheep	Meat from sheep and goat for fattening Wool from sheep
Sugar	Sugar beet

Source: Own Compilation.

Appendix C – Additional results of analysing redistributive effects

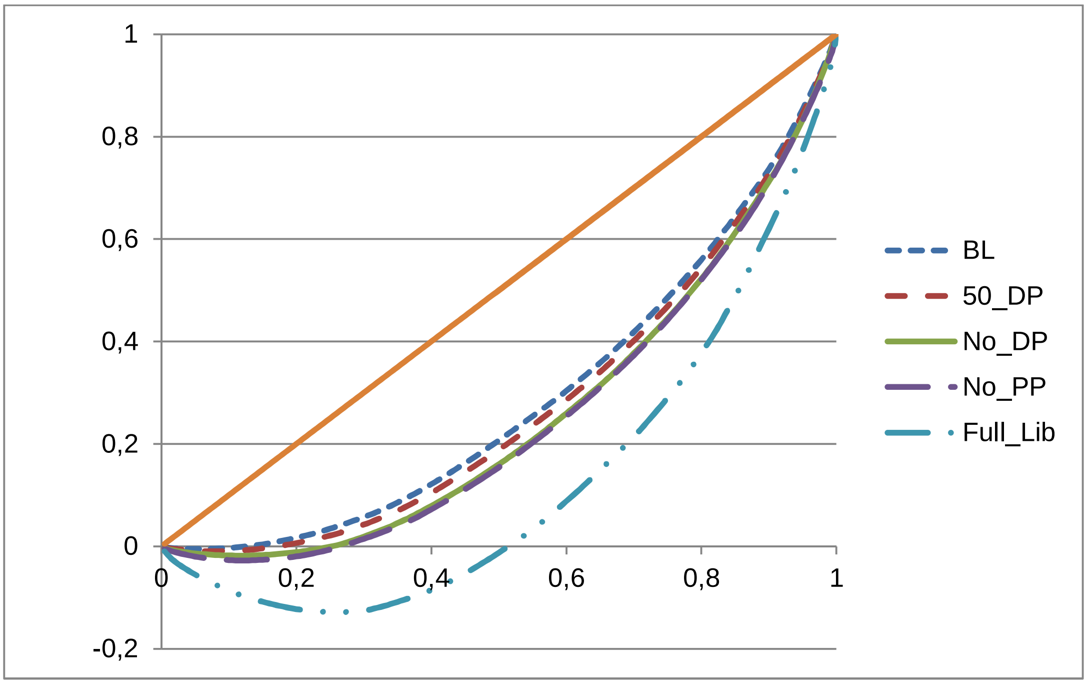

Figure C. 1: Relative Lorenz curves for baseline and all scenarios based on *grouped data*.

Source: Own compilation.

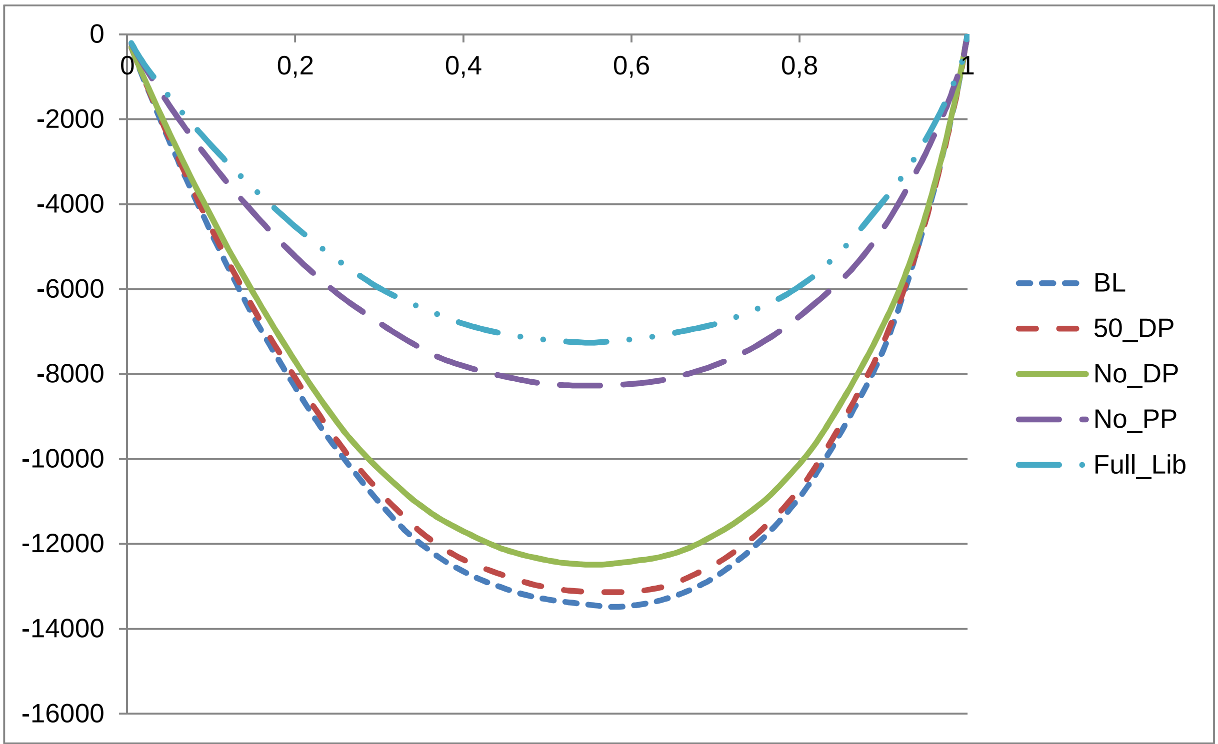

Figure C.2: Absolute Lorenz curves for baseline and all scenarios based on grouped data.

Source: Own compilation.

Table C.1: Decomposition of changes in *total household income* inequality (individual data vs. grouped data).

		Relative analysis		Absolute analysis	
		Individual data	Grouped Data	Individual data	Grouped Data
VI) Baseline Results					
Average income (in €)		52,798			
Gini index of income	(A) G_x	0.468	0.32	24,714	17,128
VII) 50_DP scenario					
Average income (in €)		49,215			
Average support reduction (in €)		3,583			
Average rate of reduced support (support reduction/base income)	s	0.068			
Gini index	(A) G_y	0.495	0.34	24,386	16,758
Concentration index	(A) C_y	0.493	0.34	24,256	16,670
Total redistributive effect	(A) R	-0.027	-0.02	329	370
Index of re-ranking	(A) H	-0.003	0.00	-130	-88
Index of vertical equity	(A) V	-0.025	-0.01	459	458
Index of progressivity of support reduction	P ; C_B	-0.34	-0.20	0.128	0.13
VIII) No_DP scenario					
Average income (in €)		43,844			
Average support reduction (in €)		8,953			
Average rate of reduced support (support reduction/base income)	s	0.17			
Gini index	(A) G_y	0.54	0.36	23,688	15,894
Concentration index	(A) C_y	0.529	0.35	23,173	15,551
Total redistributive effect	(A) R	-0.072	-0.04	1,026	1,234
Index of re-ranking	(A) H	-0.012	-0.01	-515	-343
Index of vertical equity	(A) V	-0.06	-0.03	1,541	1,577
Index of progressivity of support reduction	P ; C_B	-0.296	-0.148	0.172	0.176
IX) No_Pricepol scenario					
Average income (in €)		31,197			
Average support reduction (in €)		21,601			
Average rate of reduced support (support reduction/base income)	s	0.409			
Gini index	(A) Gy	0.608	0.33	18,957	10,165
Concentration index	(A) Cy	0.518	0.27	16,158	8,367
Total redistributive effect	(A) R	-0.14	0.00	5,757	6,964
Index of re-ranking	(A) H	-0.09	-0.06	-2,799	-1,798
Index of vertical equity	(A) V	-0.05	0.06	8,556	8,761
Index of progressivity of support reduction	P ; C_B	-0.072	0.081	0.396	0.406

Source: own calculations.

Table C.1 continued: Decomposition of changes in *total household income* inequality (individual data vs. grouped data).

		Relative analysis		Absolute analysis	
		Individual data	**Grouped Data**	**Individual data**	**Grouped Data**
Baseline Results					
Average income (in €)		52,798			
Gini index of income	(A) G_x	0.468	0.32	24,714	17,128
X) Full Liberalization scenario					
Average income (in €)		21,420			
Average support reduction (in €)		31,378			
Average rate of reduced support (support reduction/base income)	s	0.594			
Gini index	(A) G_y	0.861	0.43	18,446	9,145
Concentration index	(A) C_y	0.667	0.29	14,278	6,303
Total redistributive effect	(A) R	-0.393	-0.10	6,268	7,983
Index of re-ranking	(A) H	-0.195	-0.13	-4,168	-2,841
Index of vertical equity	(A) V	-0.198	0.03	10,436	10,825
Index of progressivity of support reduction	P ; C_B	-0.136	0.021	0.333	0.34

Source: own calculations.

Appendix D – Subgroup decomposition results

Table D.1: Disaggregate results of the overlapping index of farm type decomposition for the Baseline and the scenarios 50_DP, No_DP and Full_Lib.

	$O_{\_Gradin\ k,h}$						$O_{\_Gradin,k}= \sum_j O_{\_Gradin,k,h} * p_h$	$O_{\_Gradin\ k,rest}$
Baseline								
	AF	**DF**	**GL**	**MF**	**PP**	**PC**		
AF		0.424	0.691	0.769	0.636	0.893	0.70	0.63
DF	0.415		0.233	0.595	0.812	0.392	0.64	0.48
GL	0.909	0.314		0.661	0.525	0.774	0.64	0.60
MF	0.708	0.560	0.463		0.832	0.703	0.71	0.62
PP	0.540	0.704	0.339	0.767		0.528	0.65	0.63
PC	1.005	0.451	0.662	0.860	0.701		0.74	0.71
50_DP								
	AF	**DF**	**GL**	**MF**	**PP**	**PC**		
AF		0.392	0.733	0.750	0.602	0.821	0.68	0.60
DF	0.363		0.224	0.555	0.796	0.398	0.62	0.45
GL	0.919	0.304		0.657	0.509	0.714	0.63	0.59
MF	0.670	0.535	0.468		0.81	0.761	0.70	0.61
PP	0.488	0.696	0.329	0.735		0.548	0.63	0.61
PC	0.880	0.461	0.611	0.914	0.725		0.73	0.70
No_DP								
	AF	**DF**	**GL**	**MF**	**PP**	**PC**		
AF		0.374	0.738	0.741	0.577	0.738	0.67	0.58
DF	0.334		0.225	0.531	0.809	0.441	0.62	0.44
GL	0.870	0.296		0.624	0.476	0.609	0.60	0.55
MF	0.649	0.520	0.464		0.787	0.865	0.70	0.61
PP	0.448	0.703	0.314	0.699		0.595	0.62	0.59
PC	0.747	0.499	0.523	1.001	0.775		0.73	0.70
Full_Lib								
	AF	**DF**	**GL**	**MF**	**PP**	**PC**		
AF		0.627	0.621	0.813	0.575	0.529	0.73	0.66
DF	0.762		0.384	1.053	0.864	0.817	0.87	0.82
GL	0.866	0.441		0.670	0.438	0.355	0.63	0.58
MF	0.753	0.802	0.445		0.696	0.671	0.78	0.72
PP	0.427	0.528	0.233	0.559		0.845	0.54	0.51
PC	0.470	0.596	0.226	0.643	1.009		0.61	0.56

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D. 2: Detailed results of farm type decomposition in 2020 for the 50_DP scenario.

50_DP		**AF**	**DF**	**GL**	**MF**	**PP**	**PC**	
Average Income (€)		23,346	66,219	15,810	38,527	51,089	30,212	
Income share		0.11	0.5	0.04	0.21	0.07	0.07	
Farm population		31,762	51,376	17,135	36,376	9,445	15,979	
Population share		0.20	0.32	0.11	0.22	0.06	0.10	

		% Contribution to Gini and Absolute Gini						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		3.3%	9.2%	0.8%	4.8%	0.4%	0.8%	19.3%
Between $_{k,h}$	**AF**							7.8%
	DF	5.3%						15.4%
	GL	0.3%	3.4%					5.5%
	MF	1.3%	3.9%	1.1%				7.0%
	PP	0.6%	0.6%	0.4%	0.3%			2.1%
	PC	0.3%	2.2%	0.3%	0.4%	0.2%		3.4%
Overlapping $_{k,h}$	**AF**							8.2%
	DF	2.1%						8.9%
	GL	1.3%	0.7%					3.8%
	MF	2.8%	3.6%	1.1%				10.1%
	PP	0.6%	1.4%	0.2%	1.0%			3.5%
	PC	1.4%	1.1%	0.5%	1.6%	0.3%		4.9%
								100%

		Absolute fractional Ginis						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		21,325	23,009	17,015	23,893	26,325	19,887	
Between $_{k,h}$	**AF**							12,492
	DF	21,436						17,846
	GL	3,768	25,204					14,554
	MF	7,591	13,846	11,359				10,126
	PP	13,872	7,565	17,639	6,281			10,003
	PC	3,433	18,003	7,201	4,158	10,439		9,632
Overlapping $_{k,h}$	**AF**							12,893
	DF	8,352						10,281
	GL	15,635	5,165					9,969
	MF	15,999	12,776	11,183				14,555
	PP	12,845	18,325	8,661	19,355			15,938
	PC	17,508	9,164	12,156	18,184	14,428		13,915

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D.3: Results of farm type decomposition in 2020 for the 50_DP scenario in comparison to Baseline results in 2020.

50_DP / BASELINE		**AF**	**DF**	**GL**	**MF**	**PP**	**PC**	
Average Income (€)		0.81	0.96	0.81	0.90	0.94	0.96	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		0.97	1.00	1.00	0.98	1.00	1.00	0.99
Between $_{k,h}$	**AF**							1.08
	DF	1.08						1.06
	GL	0.75	1.06					1.04
	MF	1.08	1.08	1.00				1.04
	PP	1.00	1.20	1.00	1.00			1.00
	PC	3.00	0.96	1.50	0.80	0.67		1.00
Overlapping $_{k,h}$	**AF**							0.93
	DF	0.88						0.94
	GL	1.00	1.00					1.00
	MF	0.93	0.92	1.00				0.95
	PP	1.00	1.00	1.00	0.91			0.97
	PC	0.93	1.00	1.00	1.07	1.00		1.00
		Relative to Baseline (Absolute fractional Ginis)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		0.94	0.99	0.98	0.97	0.98	0.98	
Between $_{k,h}$	**AF**							1.08
	DF	1.07						1.04
	GL	0.81	1.02					1.00
	MF	1.07	1.07	0.97				1.03
	PP	1.09	1.03	1.02	1.12			1.04
	PC	2.61	0.96	1.21	0.72	0.92		0.99
Overlapping $_{k,h}$	**AF**							0.90
	DF	0.87						0.93
	GL	0.99	0.95					0.97
	MF	0.91	0.92	0.98				0.95
	PP	0.89	0.97	0.95	0.94			0.95
	PC	0.86	1.01	0.91	1.05	1.02		0.96

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D.4: Detailed results of farm type decomposition in 2020 for the No_DP scenario.

No_DP	**AF**	**DF**	**GL**	**MF**	**PP**	**PC**
Average Income (€)	17,469	60,447	9,578	32,544	46,406	29,054
Income share	0.09	0.53	0.03	0.2	0.07	0.08
Farm population	31,762	51,376	17,135	36,376	9,445	15,979
Population share	0.20	0.32	0.11	0.22	0.06	0.10

% Contribution to Gini and Absolute Gini

		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		3.2%	9.2%	0.8%	4.7%	0.4%	0.8%	19.1%
Between $_{k,h}$	**AF**							8.4%
	DF	5.5%						15.6%
	GL	0.3%	3.5%					5.8%
	MF	1.4%	4.1%	1.1%				7.2%
	PP	0.7%	0.5%	0.5%	0.4%			2.3%
	PC	0.5%	2.0%	0.4%	0.2%	0.2%		3.3%
Overlapping $_{k,h}$	**AF**							7.6%
	DF	1.9%						8.8%
	GL	1.3%	0.7%					3.6%
	MF	2.7%	3.5%	1.0%				10.0%
	PP	0.5%	1.4%	0.2%	1.0%			3.5%
	PC	1.2%	1.3%	0.4%	1.8%	0.4%		5.1%
								100%

Absolute fractional Ginis

		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		19,813	22,176	16,810	22,640	25,502	19,576	
Between $_{k,h}$	**AF**							12,854
	DF	21,489						17,552
	GL	3,946	25,435					15,036
	MF	7,538	13,951	11,483				9,915
	PP	14,469	7,021	18,414	6,931			10,002
	PC	5,793	15,697	9,738	1,745	8,676		8,917
Overlapping $_{k,h}$	**AF**							11,567
	DF	7,407						9,707
	GL	14,631	4,981					9,256
	MF	14,689	11,773	10,496				13,783
	PP	11,431	17,939	8,000	17,814			15,150
	PC	14,631	9,777	10,241	19,589	15,176		13,679

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D.5: Results of farm type decomposition in 2020 for the No_DP scenario in comparison to Baseline results in 2020.

No_DP / BASELINE		**AF**	**DF**	**GL**	**MF**	**PP**	**PC**	
Average Income (€)		0.61	0.88	0.49	0.76	0.86	0.92	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		0.94	1.00	1.00	0.96	1.00	1.00	0.98
Between $_{k,h}$	**AF**							1.17
	DF	1.12						1.08
	GL	0.75	1.09					1.09
	MF	1.17	1.14	1.00				1.07
	PP	1.17	1.00	1.25	1.33			1.10
	PC	5.00	0.87	2.00	0.40	0.67		0.97
Overlapping $_{k,h}$	**AF**							0.86
	DF	0.79						0.93
	GL	1.00	1.00					0.95
	MF	0.90	0.90	0.91				0.94
	PP	0.83	1.00	1.00	0.91			0.97
	PC	0.80	1.18	0.80	1.20	1.33		1.04
		Relative to Baseline (Absolute fractional Ginis)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		0.87	0.95	0.97	0.92	0.95	0.97	
Between $_{k,h}$	**AF**							1.11
	DF	1.07						1.02
	GL	0.85	1.03					1.04
	MF	1.06	1.08	0.98				1.01
	PP	1.14	0.96	1.06	1.24			1.04
	PC	4.40	0.84	1.64	0.30	0.76		0.92
Overlapping $_{k,h}$	**AF**							0.81
	DF	0.77						0.88
	GL	0.93	0.92					0.90
	MF	0.84	0.85	0.92				0.90
	PP	0.79	0.95	0.88	0.87			0.90
	PC	0.72	1.07	0.77	1.13	1.07		0.95

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D.6: Detailed results of farm type decomposition in 2020 for the Full_Lib scenario.

Full_Lib	**AF**	**DF**	**GL**	**MF**	**PP**	**PC**
Average Income (€)	5,167	17,430	-3,696	14,058	32,840	28,700
Income share	0.07	0.39	-0.03	0.22	0.14	0.20
Farm population	31,762	51,376	17,135	36,376	9,445	15,979
Population share	0.20	0.32	0.11	0.22	0.06	0.10

		% Contribution to Gini and Absolut Gini						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		3.8%	8.1%	0.8%	5.3%	0.4%	1.1%	19.5%
Between $_{k,h}$	**AF**							6.0%
	DF	2.2%						6.7%
	GL	0.5%	2.0%					5.3%
	MF	1.1%	0.7%	1.2%				4.6%
	PP	0.9%	0.8%	0.6%	0.7%			3.1%
	PC	1.3%	1.0%	1.0%	0.9%	0.1%		4.3%
Overlapping $_{k,h}$	**AF**							10.2%
	DF	3.8%						14.2%
	GL	1.3%	1.0%					3.9%
	MF	3.5%	6.0%	1.1%				13.2%
	PP	0.6%	1.3%	0.2%	1.0%			3.7%
	PC	1.0%	2.1%	0.3%	1.6%	0.6%		5.6%
								100%

		Absolute fractional Ginis						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		17,248	14,194	12,362	18,628	23,204	19,442	
Between $_{k,h}$	**AF**							6,687
	DF	6,131						5,419
	GL	4,431	10,563					9,919
	MF	4,446	1,686	8,877				4,659
	PP	13,836	7,705	18,268	9,391			9,979
	PC	11,766	5,635	16,198	7,321	2,070		8,396
Overlapping $_{k,h}$	**AF**							11,426
	DF	10,818						11,579
	GL	10,705	5,450					7,194
	MF	14,025	14,948	8,287				13,346
	PP	9,913	12,260	5,415	12,967			11,941
	PC	9,129	11,591	4,386	12,497	19,611		10,955

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D.7: Results of farm type decomposition in 2020 for the Full_Lib scenario in comparison to Baseline results in 2020.

Full_Lib / BASELINE		**AF**	**DF**	**GL**	**MF**	**PP**	**PC**	
Average Income (€)		0.18	0.25	-0.19	0.33	0.61	0.91	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**SUM**
Within $_{k,k}$		1.12	0.88	1.00	1.08	1.00	1.38	1.00
Between $_{k,h}$	**AF**							0.83
	DF	0.45						0.46
	GL	1.25	0.63					1.00
	MF	0.92	0.19	1.09				0.69
	PP	1.50	1.60	1.50	2.33			1.48
	PC	13.00	0.43	5.00	1.80	0.33		1.26
Overlapping $_{k,h}$	**AF**							1.16
	DF	1.58						1.49
	GL	1.00	1.43					1.03
	MF	1.17	1.54	1.00				1.25
	PP	1.00	0.93	1.00	0.91			1.03
	PC	0.67	1.91	0.60	1.07	2.00		1.14
		Relative to Baseline (Absolute fractional Ginis)						
		AF	**DF**	**GL**	**MF**	**PP**	**PC**	**Average**
Within $_{k,k}$		0.76	0.61	0.71	0.75	0.87	0.96	
Between $_{k,h}$	**AF**							0.58
	DF	0.31						0.32
	GL	0.96	0.43					0.68
	MF	0.63	0.13	0.76				0.47
	PP	1.09	1.05	1.05	1.68			1.04
	PC	8.93	0.30	2.72	1.27	0.18		0.86
Overlapping $_{k,h}$	**AF**							0.80
	DF	1.12						1.05
	GL	0.68	1.00					0.70
	MF	0.80	1.08	0.73				0.87
	PP	0.69	0.65	0.60	0.63			0.71
	PC	0.45	1.27	0.33	0.72	1.39		0.76

NB: Values of between-groups inequality and overlapping for the same groups are symmetric. For reasons of clearness only half of the table is filled.
DF – Dairy farms; MF – Mixed farms; PP – Pig and poultry farms; AF – Arable farms; GL – Grazing livestock farms; PC – Permanent crop farms.
Source: own calculations.

Table D.8: Aggregate results of regional subgroup decomposition (based on FFI).

	BL	**50_DP**	**No_DP**	**No_PP**	**Full_Lib**
Average income (€)	45,424	41,841	36,470	23,823	14,046
			RELATIV		
Gini	0.56	0.598	0.662	0.782	1.256
	100%	*100%*	*100%*	*100%*	*100%*
Gini-Within	0.105	0.112	0.124	0.146	0.232
	19%	*19%*	*19%*	*19%*	*18%*
Gini-Between	0.116	0.128	0.141	0.121	0.197
	21%	*21%*	*21%*	*15%*	*16%*
Overlapping	0.339	0.358	0.397	0.514	0.827
	61%	*60%*	*60%*	*66%*	*66%*
			ABSOLUT		
Abs. Gini	25,443	25,028	24,155	18,632	17,642
	100%	*100%*	*100%*	*100%*	*100%*
Abs. Gini-Within	4,767	4,690	4,529	3,488	3,259
	19%	*19%*	*19%*	*19%*	*18%*
Abs. Gini-Between	5,288	5,373	5,137	2,893	2,768
	21%	*21%*	*21%*	*16%*	*16%*
Abs. Overlapping	15,388	14,965	14,489	12,251	11,614
	60%	*60%*	*60%*	*66%*	*66%*
$O_{\_Gradin}$	0.839	0.833	0.836	0.884	0.887

Source: own calculations.

Table D.9: Disaggregate results of the overlapping index of regional subgroup decomposition.

	$O_{Gradin\ k,h}$								$O_{Gradin,k} = \sum_j O_{Gradin,k,h} * p_h$	$O_{Gradín\ k,rest}$
Baseline										
	NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**		
NR		0.88	0.81	0.72	0.7	0.73	0.66	0.66	0.78	0.75
NS	0.79		0.92	0.55	0.54	0.57	0.51	0.51	0.67	0.61
SH	0.64	0.81		0.45	0.45	0.47	0.42	0.42	0.56	0.54
BA	0.99	0.84	0.78		0.97	1.02	0.91	0.92	0.95	0.92
BW	0.82	0.72	0.67	0.84		0.95	0.9	0.89	0.84	0.82
HE	0.86	0.75	0.7	0.88	0.96		0.92	0.93	0.87	0.86
SL	0.92	0.79	0.74	0.93	1.06	1.08		0.99	0.93	0.93
RP	0.93	0.80	0.75	0.94	1.05	1.09	1.00		0.94	0.93
50_DP										
	NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**		
NR		0.89	0.83	0.71	0.67	0.67	0.58	0.65	0.77	0.74
NS	0.8		0.93	0.55	0.53	0.53	0.46	0.51	0.67	0.61
SH	0.66	0.82		0.46	0.44	0.44	0.38	0.43	0.57	0.54
BA	0.97	0.85	0.8		0.94	0.95	0.82	0.92	0.94	0.91
BW	0.81	0.72	0.68	0.83		0.98	0.89	0.88	0.84	0.81
HE	0.83	0.73	0.7	0.86	0.99		0.89	0.91	0.86	0.85
SL	0.83	0.73	0.7	0.86	1.05	1.02		0.91	0.87	0.87
RP	0.92	0.81	0.76	0.94	1.02	1.02	0.89		0.93	0.92
No_DP										
	NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**		
NR		0.91	0.84	0.7	0.65	0.63	0.51	0.68	0.77	0.73
NS	0.81		0.92	0.55	0.53	0.51	0.41	0.54	0.67	0.61
SH	0.67	0.83		0.46	0.44	0.43	0.35	0.45	0.57	0.55
BA	0.96	0.87	0.8		0.94	0.91	0.73	0.97	0.95	0.92
BW	0.81	0.74	0.69	0.84		0.97	0.79	0.87	0.85	0.82
HE	0.81	0.74	0.69	0.85	1.01		0.82	0.88	0.85	0.84
SL	0.77	0.71	0.66	0.8	0.97	0.96		0.82	0.81	0.81
RP	0.93	0.84	0.78	0.96	0.97	0.94	0.75		0.93	0.92
No_Pricepol										
	NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**		
NR		1.02	0.92	0.68	0.73	0.64	0.55	0.91	0.82	0.79
NS	0.85		0.92	0.6	0.64	0.57	0.5	0.8	0.74	0.68
SH	0.83	0.98		0.56	0.61	0.53	0.46	0.77	0.71	0.70
BA	0.99	1.04	0.9		1.09	0.95	0.8	0.84	0.99	0.99
BW	0.88	0.93	0.82	0.91		0.88	0.77	0.78	0.90	0.89
HE	0.89	0.94	0.82	0.9	1.01		0.86	0.77	0.91	0.91
SL	0.91	0.98	0.84	0.91	1.04	1.03		0.76	0.93	0.93
RP	1.09	1.15	1.03	0.69	0.77	0.66	0.55		0.87	0.86
Full_Lib										
	NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**		
NR		1.08	0.99	0.65	0.74	0.58	0.43	0.88	0.81	0.78
NS	0.87		0.93	0.6	0.67	0.54	0.43	0.84	0.75	0.70
SH	0.92	1.07		0.59	0.68	0.53	0.4	0.9	0.77	0.76
BA	0.98	1.13	0.97		1.09	0.89	0.63	0.8	1.01	1.01
BW	0.91	1.02	0.9	0.88		0.78	0.58	0.77	0.91	0.89
HE	0.88	1.03	0.88	0.89	0.97		0.73	0.72	0.92	0.91
SL	0.77	0.95	0.77	0.75	0.84	0.86		0.6	0.80	0.79
RP	0.97	1.15	1.07	0.58	0.69	0.52	0.37		0.80	0.78

Source: own calculations.

Table D.10: Detailed results of regional subgroup decomposition in 2020 for the Baseline.

Baseline		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		49,524	60,307	70,290	40,643	35,400	37,651	36,902	37,340	
Income share		0.15	0.22	0.08	0.32	0.12	0.05	0.004	0.07	
Farm population		22,029	26,723	8,572	57,355	23,957	9,255	713	13,469	
Population share		0.14	0.16	0.05	0.35	0.15	0.06	0.004	0.08	
		% Contribution to Gini and Absolute Gini								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		2.0%	3.3%	0.4%	10.1%	2.0%	0.3%	0.0%	0.5%	18.6%
Between $_{k,h}$	**NR**									2.7%
	NS	0.5%								5.2%
	SH	0.3%	0.2%							2.6%
	BA	0.8%	2.3%	1.1%						5.0%
	BW	0.6%	1.2%	0.5%	0.5%					2.8%
	HE	0.2%	0.4%	0.2%	0.1%	0.0%				0.9%
	SL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%			0.0%
	RP	0.3%	0.6%	0.3%	0.2%	0.0%	0.0%	0.0%		1.4%
Overlapping $_{k,h}$	**NR**									9.5%
	NS	2.2%								10.4%
	SH	0.6%	1.0%							3.8%
	BA	3.8%	4.0%	1.2%						17.1%
	BW	1.5%	1.6%	0.5%	4.1%					9.5%
	HE	0.6%	0.7%	0.2%	1.7%	0.7%				4.3%
	SL	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%			0.2%
	RP	0.8%	0.9%	0.3%	2.2%	1.0%	0.4%	0.0%		5.6%
										100%
		Absolute fractional Ginis								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		27,982	31,284	35,312	20,499	23,689	23,638	20,062	20,027	
Between $_{k,h}$	**NR**									5,701
	NS	5,392								9,543
	SH	10,383	4,991							13,128
	BA	4,440	9,832	14,824						5,614
	BW	7,062	12,454	17,445	2,621					5,881
	HE	5,936	11,328	16,319	1,496	1,126				4,505
	SL	6,311	11,703	16,694	1,871	751	375			4,503
	RP	6,092	11,483	16,475	1,651	970	156	219		4,723
Overlapping $_{k,h}$	**NR**									20,905
	NS	24,584								19,052
	SH	22,613	28,700							19,056
	BA	20,196	17,300	15,937						18,907
	BW	19,493	17,022	15,925	19,889					19,334
	HE	20,357	17,720	16,455	20,871	22,580				20,359
	SL	18,400	15,870	14,768	18,714	21,361	21,666			18,656
	RP	18,562	16,014	14,972	18,793	21,124	21,890	19,955		18,613

Source: own calculations.

Table D.11: Detailed results of regional subgroup decomposition in 2020 for the 50_DP scen.

50_DP		NR	NS	SH	BA	BW	HE	SL	RP	
Average Income (€)		46,750	56,611	65,890	37,289	31,507	32,207	29,820	34,221	
Income share		0.15	0.22	0.08	0.32	0.11	0.04	0.003	0.07	
Farm population		22,029	26,723	8,572	57,355	23,957	9,255	713	13,469	
Population share		0.14	0.16	0.05	0.35	0.15	0.06	0.004	0.08	
		% Contribution to Gini and Absolute Gini								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		2.0%	3.4%	0.4%	10.1%	2.0%	0.3%	0.0%	0.5%	18.7%
Between $_{k,h}$	**NR**									0.0%
	NS	0.4%								5.2%
	SH	0.3%	0.2%							2.6%
	BA	0.9%	2.3%	1.1%						5.3%
	BW	0.6%	1.2%	0.5%	0.6%					3.0%
	HE	0.2%	0.5%	0.2%	0.2%	0.0%				1.1%
	SL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%			0.0%
	RP	0.3%	0.6%	0.3%	0.2%	0.1%	0.0%	0.0%		1.5%
Overlapping $_{k,h}$	**NR**								0.8%	9.6%
	NS	2.2%							0.9%	10.3%
	SH	0.7%	1.0%						0.3%	3.9%
	BA	3.8%	4.0%	1.2%					2.2%	16.8%
	BW	1.5%	1.6%	0.5%	4.0%				1.0%	9.5%
	HE	0.6%	0.6%	0.2%	1.5%	0.8%			0.4%	4.1%
	SL	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%		0.0%	0.2%
	RP	0.8%	0.9%	0.3%	2.2%	1.0%	0.4%	0.0%		5.6%
										100%
		Absolute fractional Ginis								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		27,728	31,073	35,207	20,170	22,800	22,376	19,373	19,821	
Between $_{k,h}$	**NR**									5,894
	NS	4,931								9,431
	SH	9,570	4,639							12,696
	BA	4,731	9,661	14,301						5,740
	BW	7,622	12,552	17,191	2,891					6,072
	HE	7,272	12,202	16,841	2,541	350				5,230
	SL	8,465	13,396	18,035	3,734	843	1,193			6,037
	RP	6,264	11,195	15,834	1,534	1,357	1,007	2,201		4,739
Overlapping $_{k,h}$	**NR**									20,386
	NS	24,763								18,826
	SH	23,073	28,846							19,090
	BA	19,634	17,176	16,052						18,380
	BW	18,446	16,390	15,566	19,024					18,543
	HE	18,523	16,430	15,554	19,142	22,255				18,972
	SL	16,142	14,223	13,520	16,569	20,381	19,815			16,801
	RP	18,153	15,986	15,151	18,622	20,167	20,315	17,625		18,228

Source: own calculations.

Table D.12: Results of regional subgroup decomposition in 2020 for the 50_DP scenario in comparison to Baseline results in 2020.

50_DP / Baseline		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		0.94	0.94	0.94	0.92	0.89	0.86	0.81	0.92	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		1.00	1.03	1.00	1.00	1.00	1.00	-	1.00	1.01
Between $_{k,h}$	**NR**									-
	NS	0.80								1.00
	SH	1.00	1.00							1.00
	BA	1.13	1.00	1.00						1.06
	BW	1.00	1.00	1.00	1.20					1.07
	HE	1.00	1.25	1.00	2.00	-				1.22
	SL	-	-	-	-	-	-			-
	RP	1.00	1.00	1.00	1.00	-	-	-		1.07
Overlapping $_{k,h}$	**NR**									1.01
	NS	1.00								0.99
	SH	1.17	1.00							1.03
	BA	1.00	1.00	1.00						0.98
	BW	1.00	1.00	1.00	0.98					1.00
	HE	1.00	0.86	1.00	0.88	1.14				0.95
	SL	-	-	-	1.00	1.00	-			1.00
	RP	1.00	1.00	1.00	1.00	1.00	1.00	-		1.00
		Relative to Baseline (Absolute fractional Ginis)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		0.99	0.99	1.00	0.98	0.96	0.95	0.97	0.99	
Between $_{k,h}$	**NR**									1.03
	NS	0.91								0.99
	SH	0.92	0.93							0.97
	BA	1.07	0.98	0.96						1.02
	BW	1.08	1.01	0.99	1.10					1.03
	HE	1.23	1.08	1.03	1.70	0.31				1.16
	SL	1.34	1.14	1.08	2.00	1.12	3.18			1.34
	RP	1.03	0.97	0.96	0.93	1.40	6.46	10.05		1.00
Overlapping $_{k,h}$	**NR**									0.98
	NS	1.01								0.99
	SH	1.02	1.01							1.00
	BA	0.97	0.99	1.01						0.97
	BW	0.95	0.96	0.98	0.96					0.96
	HE	0.91	0.93	0.95	0.92	0.99				0.93
	SL	0.88	0.90	0.92	0.89	0.95	0.91			0.90
	RP	0.98	1.00	1.01	0.99	0.95	0.93	0.88		0.98

Source: own calculations.

Table D.13: Detailed results of regional subgroup decomposition for the No_DP scenario.

No_DP		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		41,733	50,433	59,015	31,932	26,679	26,075	21,263	30,501	
Income share		0.16	0.23	0.09	0.31	0.11	0.04	0.003	0.07	
Farm population		22,029	26,723	8,572	57,355	23,957	9,255	713	13,469	
Population share		0.14	0.16	0.05	0.35	0.15	0.06	0.004	0.08	
		% Contribution to Gini and Absolute Gini								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		2.1%	3.4%	0.4%	10.1%	2.0%	0.3%	0.0%	0.6%	18.9%
Between $_{k,h}$	**NR**									2.9%
	NS	0.4%								5.1%
	SH	0.3%	0.2%							2.5%
	BA	1.0%	2.2%	1.0%						5.1%
	BW	0.6%	1.2%	0.5%	0.6%					3.0%
	HE	0.3%	0.5%	0.2%	0.2%	0.0%		0.0%	0.0%	1.2%
	SL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%		0.0%	0.0%
	RP	0.3%	0.6%	0.3%	0.1%	0.1%	0.0%	0.0%		1.4%
Overlapping $_{k,h}$	**NR**									9.5%
	NS	2.3%								10.5%
	SH	0.7%	1.0%							3.9%
	BA	3.7%	4.1%	1.2%						16.9%
	BW	1.5%	1.6%	0.5%	4.0%					9.3%
	HE	0.5%	0.6%	0.2%	1.5%	0.7%				3.9%
	SL	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%			0.1%
	RP	0.8%	0.9%	0.3%	2.3%	1.0%	0.4%	0.0%		5.7%
										100%
		Absolute fractional Ginis								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		26,827	30,426	33,825	19,430	21,733	20,886	17,742	19,586	
Between $_{k,h}$	**NR**									5,763
	NS	4,350								8,903
	SH	8,641	4,291							11,902
	BA	4,901	9,250	13,541						5,488
	BW	7,527	11,877	16,168	2,627					5,813
	HE	7,829	12,179	16,470	2,929	302				5,535
	SL	10,235	14,585	18,876	5,335	2,708	2,406			7,637
	RP	5,616	9,966	14,257	716	1,911	2,213	4,619		4,191
Overlapping $_{k,h}$	**NR**									19,643
	NS	24,527								18,533
	SH	22,666	28,113							18,552
	BA	18,648	16,851	15,485						17,779
	BW	17,555	16,092	15,026	18,349					17,816
	HE	16,957	15,547	14,505	17,717	21,029				17,621
	SL	13,642	12,519	11,772	14,129	17,223	17,089			14,341
	RP	18,139	16,502	15,327	18,882	18,989	18,363	14,625		18,103

Source: own calculations.

Table D.14: Results of regional subgroup decomposition in 2020 for the No_DP scenario in comparison to Baseline results in 2020.

No_DP / Baseline		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		0.84	0.84	0.84	0.79	0.75	0.69	0.58	0.82	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		1.05	1.03	1.00	1.00	1.00	1.00	-	1.20	1.02
Between $_{k,h}$	**NR**									1.07
	NS	0.80								0.98
	SH	1.00	1.00							0.96
	BA	1.25	0.96	0.91						1.02
	BW	1.00	1.00	1.00	1.20					1.07
	HE	1.50	1.25	1.00	2.00	-				1.33
	SL	-	-	-	-	-	-			-
	RP	1.00	1.00	1.00	0.50	-	-	-		1.00
Overlapping $_{k,h}$	**NR**									1.00
	NS	1.05								1.01
	SH	1.17	1.00							1.03
	BA	0.97	1.03	1.00						0.99
	BW	1.00	1.00	1.00	0.98					0.98
	HE	0.83	0.86	1.00	0.88	1.00				0.91
	SL	-	-	-	1.00	0.00	-			0.50
	RP	1.00	1.00	1.00	1.05	1.00	1.00	-		1.02
		Relative to Baseline (Absolute fractional Ginis)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		0.96	0.97	0.96	0.95	0.92	0.88	0.88	0.98	
Between $_{k,h}$	**NR**									1.01
	NS	0.81								0.93
	SH	0.83	0.86							0.91
	BA	1.10	0.94	0.91						0.98
	BW	1.07	0.95	0.93	1.00					0.99
	HE	1.32	1.08	1.01	1.96	0.27				1.23
	SL	1.62	1.25	1.13	2.85	3.61	6.42			1.70
	RP	0.92	0.87	0.87	0.43	1.97	14.19	21.09		0.89
Overlapping $_{k,h}$	**NR**									0.94
	NS	1.00								0.97
	SH	1.00	0.98							0.97
	BA	0.92	0.97	0.97						0.94
	BW	0.90	0.95	0.94	0.92					0.92
	HE	0.83	0.88	0.88	0.85	0.93				0.87
	SL	0.74	0.79	0.80	0.75	0.81	0.79			0.77
	RP	0.98	1.03	1.02	1.00	0.90	0.84	0.73		0.97

Source: own calculations.

Table D.15: Detailed results of regional subgroup decomposition for the No_Pricepol scenario in 2020.

No_Pricepol		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		27,549	31,049	33,592	19,715	19,084	17,216	15,306	28,086	
Income share		0.16	0.22	0.08	0.29	0.12	0.04	0.003	0.10	
Farm population		22,029	26,723	8,572	57,355	23,957	9,255	713	13,469	
Population share		0.14	0.16	0.05	0.35	0.15	0.06	0.004	0.08	
		% Contribution to Gini and Absolute Gini								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		2.1%	3.7%	0.4%	9.7%	2.0%	0.3%	0.0%	0.6%	18.8%
Between $_{k,h}$	**NR**									2.0%
	NS	0.2%								3.3%
	SH	0.1%	0.1%							1.4%
	BA	1.0%	1.8%	0.7%						4.4%
	BW	0.5%	0.8%	0.3%	0.1%					2.0%
	HE	0.2%	0.3%	0.1%	0.1%	0.0%				0.8%
	SL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%			0.0%
	RP	0.0%	0.1%	0.1%	0.7%	0.3%	0.1%	0.0%		1.3%
Overlapping $_{k,h}$	**NR**									10.4%
	NS	2.6%								12.7%
	SH	0.7%	1.1%							4.3%
	BA	3.7%	4.7%	1.3%						17.6%
	BW	1.6%	2.1%	0.6%	4.4%					10.3%
	HE	0.6%	0.7%	0.2%	1.5%	0.7%				4.0%
	SL	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%			0.1%
	RP	1.2%	1.5%	0.4%	1.9%	0.9%	0.3%	0.0%		6.2%
										100%
		Absolute fractional Ginis								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		20,891	25,051	23,341	14,438	17,276	15,084	12,686	17,521	
Between $_{k,h}$	**NR**									3,245
	NS	1,750								4,487
	SH	3,022	1,272							5,157
	BA	3,917	5,667	6,938						3,574
	BW	4,232	5,982	7,254	316					2,925
	HE	5,166	6,916	8,188	1,249	934				3,512
	SL	6,121	7,871	9,143	2,205	1,889	955			4,277
	RP	269	1,481	2,753	4,185	4,501	5,435	6,390		3,175
Overlapping $_{k,h}$	**NR**									16,475
	NS	21,303								17,134
	SH	19,276	22,985							16,226
	BA	14,245	14,976	13,053						14,318
	BW	15,285	15,988	14,145	15,670					15,319
	HE	13,407	14,186	12,367	13,645	15,277				13,701
	SL	11,590	12,450	10,634	11,529	13,256	13,047			11,825
	RP	19,096	20,089	17,992	12,144	13,441	11,540	9,600		15,100

Source: own calculations.

Table D.16: Results of regional subgroup decomposition in 2020 for the No_Pricepol scenario in comparison to Baseline results in 2020.

No_Pricepol / Baseline		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		0.56	0.51	0.48	0.49	0.54	0.46	0.41	0.75	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		1.05	1.12	1.00	0.96	1.00	1.00	-	1.20	1.01
Between $_{k,h}$	**NR**									0.74
	NS	0.40								0.63
	SH	0.33	0.50							0.54
	BA	1.25	0.78	0.64						0.88
	BW	0.83	0.67	0.60	0.20					0.71
	HE	1.00	0.75	0.50	1.00	-				0.89
	SL	-	-	-	-	-	-			-
	RP	0.00	0.17	0.33	3.50	-	-	-		0.93
Overlapping $_{k,h}$	**NR**									1.09
	NS	1.18								1.22
	SH	1.17	1.10							1.13
	BA	0.97	1.18	1.08						1.03
	BW	1.07	1.31	1.20	1.07					1.08
	HE	1.00	1.00	1.00	0.88	1.00				0.93
	SL	-	-	-	1.00	0.00	-			0.50
	RP	1.50	1.67	1.33	0.86	0.90	0.75	-		1.11
		Relative to Baseline (Absolute fractional Ginis)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		0.75	0.80	0.66	0.70	0.73	0.64	0.63	0.87	
Between $_{k,h}$	**NR**									0.57
	NS	0.32								0.47
	SH	0.29	0.25							0.39
	BA	0.88	0.58	0.47						0.64
	BW	0.60	0.48	0.42	0.12					0.50
	HE	0.87	0.61	0.50	0.83	0.83				0.78
	SL	0.97	0.67	0.55	1.18	2.52	2.55			0.95
	RP	0.04	0.13	0.17	2.53	4.64	34.84	29.18		0.67
Overlapping $_{k,h}$	**NR**									0.79
	NS	0.87								0.90
	SH	0.85	0.80							0.85
	BA	0.71	0.87	0.82						0.76
	BW	0.78	0.94	0.89	0.79					0.79
	HE	0.66	0.80	0.75	0.65	0.68				0.67
	SL	0.63	0.78	0.72	0.62	0.62	0.60			0.63
	RP	1.03	1.25	1.20	0.65	0.64	0.53	0.48		0.81

Source: own calculations.

Table D.17: Detailed results of regional subgroup decomposition for the Full_Lib scenario.

Full_Lib		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		18,245	19,888	20,340	9,808	10,683	6,537	1,119	21,448	
Income share		0.18	0.23	0.08	0.25	0.11	0.03	0.0004	0.13	
Farm population		22,029	26,723	8,572	57,355	23,957	9,255	713	13,469	
Population share		0.14	0.16	0.05	0.35	0.15	0.06	0.004	0.08	
		% Contribution to Gini and Absolute Gini								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		2.1%	3.8%	0.3%	9.3%	2.0%	0.2%	0.0%	0.7%	18.4%
Between $_{k,h}$	**NR**									2.1%
	NS	0.1%								2.9%
	SH	0.0%	0.0%							0.9%
	BA	1.2%	1.7%	0.6%						4.8%
	BW	0.4%	0.6%	0.2%	0.1%					1.8%
	HE	0.3%	0.4%	0.1%	0.2%	0.1%				1.3%
	SL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%			0.0%
	RP	0.1%	0.1%	0.0%	1.0%	0.4%	0.2%	0.0%		1.8%
Overlapping $_{k,h}$	**NR**									10.3%
	NS	2.7%								13.3%
	SH	0.8%	1.1%							4.6%
	BA	3.5%	4.9%	1.4%						17.2%
	BW	1.7%	2.3%	0.6%	4.2%					10.3%
	HE	0.5%	0.7%	0.2%	1.3%	0.6%				3.6%
	SL	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%			0.1%
	RP	1.1%	1.6%	0.5%	1.8%	0.9%	0.3%	0.0%		6.2%
										100%
		Absolute fractional Ginis								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		19,924	24,688	21,436	13,081	16,223	13,002	11,103	18,070	
Between $_{k,h}$	**NR**									3,180
	NS	822								3,682
	SH	1,048	226							3,420
	BA	4,218	5,040	5,266						3,627
	BW	3,781	4,603	4,828	437					2,663
	HE	5,854	6,675	6,901	1,636	2,073				4,007
	SL	8,563	9,385	9,611	4,345	4,782	2,709			6,492
	RP	1,602	780	554	5,820	5,383	7,456	10,165		4,037
Overlapping $_{k,h}$	**NR**									15,586
	NS	21,551								17,175
	SH	19,675	22,879							16,267
	BA	12,859	14,758	12,743						13,221
	BW	14,697	16,499	14,565	14,313					14,500
	HE	11,480	13,398	11,419	11,587	12,651				11,844
	SL	8,583	10,561	8,577	8,306	9,355	9,520			8,822
	RP	17,537	20,826	19,344	10,508	12,505	9,402	6,693		14,150

Source: own calculations.

Table D.18: Results of regional subgroup decomposition in 2020 for the Full_Lib scenario in comparison to Baseline results in 2020.

Full_Lib / Baseline		**NR**	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	
Average Income (€)		0.37	0.33	0.29	0.24	0.30	0.17	0.03	0.57	
		Relative to Baseline (% Contribution to Gini and Absolute Gini)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**SUM**
Within $_{k,k}$		1.05	1.15	0.75	0.92	1.00	0.67	-	1.40	0.99
Between $_{k,h}$	**NR**									0.78
	NS	0.20								0.56
	SH	0.00	0.00							0.35
	BA	1.50	0.74	0.55						0.96
	BW	0.67	0.50	0.40	0.20					0.64
	HE	1.50	1.00	0.50	2.00	-				1.44
	SL	-	-	-	-	-	-			-
	RP	0.33	0.17	0.00	5.00	-	-	-		1.29
Overlapping $_{k,h}$	**NR**									1.08
	NS	1.23								1.28
	SH	1.33	1.10							1.21
	BA	0.92	1.23	1.17						1.01
	BW	1.13	1.44	1.20	1.02					1.08
	HE	0.83	1.00	1.00	0.76	0.86				0.84
	SL	-	-	-	1.00	0.00	-			0.50
	RP	1.38	1.78	1.67	0.82	0.90	0.75	-		1.11
		Relative to Baseline (Absolute fractional Ginis)								
		NR	**NS**	**SH**	**BA**	**BW**	**HE**	**SL**	**RP**	**Average**
Within $_{k,k}$		0.71	0.79	0.61	0.64	0.68	0.55	0.55	0.90	
Between $_{k,h}$	**NR**									0.56
	NS	0.15								0.39
	SH	0.10	0.05							0.26
	BA	0.95	0.51	0.36						0.65
	BW	0.54	0.37	0.28	0.17					0.45
	HE	0.99	0.59	0.42	1.09	1.84				0.89
	SL	1.36	0.80	0.58	2.32	6.37	7.22			1.44
	RP	0.26	0.07	0.03	3.53	5.55	47.79	46.42		0.85
Overlapping $_{k,h}$	**NR**									0.75
	NS	0.88								0.90
	SH	0.87	0.80							0.85
	BA	0.64	0.85	0.80						0.70
	BW	0.75	0.97	0.91	0.72					0.75
	HE	0.56	0.76	0.69	0.56	0.56				0.58
	SL	0.47	0.67	0.58	0.44	0.44	0.44			0.47
	RP	0.94	1.30	1.29	0.56	0.59	0.43	0.34		0.76

Source: own calculations.

Table D.19: Aggregate results of **farm type** decomposition (based on **total household income**).

	BL	50_DP	No_DP	No_PP	Full_Lib
Average income (€)	52,798	49,215	43,844	31,197	21,420
			RELATIV		
Gini	0.47 *100%*	0.496 *100%*	0.54 *100%*	0.608 *100%*	0.861 *100%*
Gini-Within	0.093 *20%*	0.097 *20%*	0.106 *20%*	0.123 *20%*	0.172 *20%*
Gini-Between	0.16 *34%*	0.18 *36%*	0.196 *36%*	0.077 *13%*	0.16 *19%*
Overlapping	0.21 *45%*	0.22 *45%*	0.239 *44%*	0.408 *67%*	0.529 *61%*
			ABSOLUT		
Abs. Gini	24,714 *100%*	24,368 *100%*	23,688 *100%*	18,957 *100%*	18,446 *100%*
Abs. Gini-Within	4,890 *20%*	4,795 *20%*	4,632 *20%*	3,832 *20%*	3,677 *20%*
Abs. Gini-Between	8,520 *34%*	8,730 *36%*	8,574 *36%*	2,396 *13%*	3,429 *19%*
Abs. Overlapping	11,304 *45%*	10,861 *45%*	10,482 *44%*	12,729 *67%*	11,341 *61%*
$O_{\_Gradin}$	0.711	0.702	0.699	0.901	0.849

Source: own calculations.

Table D.20: Aggregate results of **regional subgroup** decomposition (based on **total household income**).

	BL	50_DP	No_DP	No_PP	Full_Lib
Average income (€)	52,798	49,215	43,844	31,197	21,420
	RELATIV				
Gini	0.468 *100%*	0.495 *100%*	0.54 *100%*	0.608 *100%*	0.861 *100%*
Gini-Within	0.087 *19%*	0.092 *19%*	0.101 *19%*	0.115 *19%*	0.163 *19%*
Gini-Between	0.102 *22%*	0.109 *22%*	0.116 *21%*	0.08 *13%*	0.098 *11%*
Overlapping	0.279 *60%*	0.294 *59%*	0.323 *60%*	0.413 *68%*	0.601 *70%*
	ABSOLUT				
Abs. Gini	24,714 *100%*	24,386 *100%*	23,688 *100%*	18,957 *100%*	18,446 *100%*
Abs. Gini-Within	4,607 *19%*	4,549 *19%*	4,431 *19%*	3,594 *19%*	3,488 *19%*
Abs. Gini-Between	5,369 *22%*	5,371 *22%*	5,074 *21%*	2,488 *13%*	2,090 *11%*
Abs. Overlapping	14,738 *60%*	14,465 *59%*	14,183 *60%*	12,875 *68%*	12,868 *70%*
$O_{\_Gradin}$	0.83	0.827	0.832	0.903	0.918

Source: own calculations.

Author’s Declaration

I hereby declare that I have completed the dissertation independently and on my own. I have not been supported by a commercial agent in writing this dissertation. Additionally, no aids other than the indicated sources and resources have been used. Furthermore, I assure that all quotations and statements that have been inferred literally or in a general manner from published or unpublished writings are marked as such. This work has not been previously used neither completely nor in parts to achieve any other academic degree.

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