

# On the economics of climate change: The distribution and redistribution of farmers' income

*Essais sur l'économie du changement climatique : distribution et  
redistribution du revenu des agriculteurs*

## Thèse de doctorat de l'université Paris-Saclay

École doctorale n°581, agriculture, alimentation, biologie, environnement et santé  
(ABIES)

Spécialité de doctorat : Sciences économiques  
Graduate School : Biosphera. Référent : AgroParisTech

Thèse préparée dans l'unité de recherche Paris-Saclay Applied Economics (Université  
Paris-Saclay, INRAE, AgroParisTech), sous la direction de **Pierre-Alain Jayet**, Directeur  
de Recherche

Thèse soutenue à Paris-Saclay, le 16 septembre 2022, par

**Maxime OLLIER**

## Composition du Jury

|                                                                                      |                        |
|--------------------------------------------------------------------------------------|------------------------|
| <b>Lionel RAGOT</b><br>Professeur (Université Paris-Nanterre)                        | Président              |
| <b>Marc FLEURBAEY</b><br>Directeur de Recherche, CNRS (Université Panthéon-Sorbonne) | Rapporteur & Examineur |
| <b>Philippe QUIRION</b><br>Directeur de Recherche, CNRS (Université-PSL)             | Rapporteur & Examineur |
| <b>Cloé GARNACHE</b><br>Associate Professor, Oslo Metropolitan University            | Examinatrice           |
| <b>Pierre-Alain JAYET</b><br>Directeur de recherche, INRAE (Université Paris-Saclay) | Directeur de thèse     |

**Titre :** Essai sur l'économie du changement climatique : distribution et redistribution du revenu des agriculteurs

**Mots clés :** Changement climatique, politiques climatiques, impacts, adaptation, inégalités de revenu, agriculture européenne

**Résumé :** L'objectif de cette thèse de doctorat est d'étudier l'effet de différents aspects du changement climatique (atténuation, impacts, adaptation) sur les inégalités de revenu des agriculteurs.

Le premier chapitre explore les effets distributifs de diverses politiques climatiques. Après avoir analytiquement examiné la question, nous montrons qu'une taxe sur les émissions accroît les inégalités de revenu parmi les agriculteurs, mais qu'une remise peut rendre la politique progressive.

Dans le deuxième chapitre, nous évaluons l'effet distributif des températures extrêmes sur le revenu des céréaliers français. Nos résultats suggèrent que les extrêmes froids augmentent les inégalités de revenu, tandis que les extrêmes chauds les diminuent.

Le troisième chapitre s'intéresse à l'adaptation au changement climatique. Nous constatons que le changement climatique peut conduire à une situation pire que la situation actuelle à court terme, mais à une meilleure situation à long terme.

**Title :** On the economics of climate change: The distribution and redistribution of farmers' income

**Keywords :** Climate change, climate policies, impacts, adaptation, income inequality, European agriculture

**Abstract :** The broad objective of this PhD thesis is to investigate the effect of different aspects of climate change (i.e. mitigation, impacts, adaptation) on farmers' income inequality.

The first chapter explores the distributional consequences of various climate policies with an application to the European agricultural sector. After examining the question from an analytical approach, we find that an emission tax increases income inequality among farmers, but a well-chosen rebate of the collected tax turns the policy progressive.

In the second chapter, we econometrically assess the distributional effect of extreme temperatures on French crop producers' income. Our results suggest that cold extremes may increase income inequality, while hot extremes may decrease inequality.

The third chapter is interested in adaptation to climate change. We find that climate change may lead to a worse situation than the present one in the short-term horizon but to a better situation in the long-term horizon.





# *Remerciements*

Mes remerciements s'adressent en premier lieu à mon directeur de thèse, Pierre-Alain Jayet. Je lui suis infiniment reconnaissant pour la confiance qu'il m'a accordée, pour sa disponibilité et pour ses pertinents conseils toujours prodigués avec bienveillance.

Merci à l'INRAE et à la Chaire Economie du Climat de m'avoir soutenu financièrement. En particulier, merci au métaprogramme ACCAF, et à Anna Creti et Philippe Delacote pour avoir cru en ce projet.

Je remercie profondément Marc Fleurbaey, Philippe Quirion, Cloé Garnache et Lionel Ragot pour leur participation à ce jury. C'est un honneur qu'ils aient accepté d'évaluer cette thèse, et j'espère qu'elle les intéressera.

Je remercie vivement mes co-auteurs. Ce travail doit énormément à Stéphane De Cara, dont la rigueur n'a d'égal que la sympathie, et auprès de qui j'ai beaucoup appris. Merci à Clément Nedoncelle pour cette collaboration économétriquement dynamique et à Pierre Humblot de faire en sorte que le couplage de modèles fonctionne. Merci aussi à Aurélie Méjean, Jean-Sauveur Ay et Philippe Delacote pour leur implication dans le comité de suivi de cette thèse.

Mes remerciements vont aussi aux relecteurs qui ont permis d'améliorer la lisibilité de ce manuscrit. Merci à Loïc, qui en plus d'être un excellent joueur de futsal, a été un chouette partenaire de bureau. Merci à Quentin et Etienne pour leurs conseils et leurs critiques, et pour avoir adouci la solitude de la thèse en temps de confinement en faisant de leurs appartements des espaces de co-workings. Je leur souhaite beaucoup de réussite dans leurs universités respectives.

Ces presque quatre années de thèse n'auraient pas été les mêmes sans les excellentes conditions de travail fournies par les labos qui m'ont accueillis. Merci aux grignonnais·e·s d'Economie Publique Maïa, Stéphane, Laure, Pierre-Alain, Estelle, Poly, Jean-Christophe, Vincent, Stéphan, Régis et Olivier de contribuer activement à faire du labo un lieu agréable. Je suis sûr que la convivialité des pauses café de Grignon perdurera à Palaiseau. Je remercie aussi Anna, François et Raja pour l'aide qu'ils m'ont apporté à divers moments de cette thèse. J'ai également une pensée pour

les doctorant·e·s/docteur·e·s de PSAE, en particulier merci à Maïmouna, Stello, Roxanne, Ines, Julie, Maxence, Liza, Lucille, Edouard, Loïc, Ondine, Valentin et Léa pour tous les bons moments. Du côté de la Chaire Economie du Climat, je remercie Philippe, Richard, Etienne, Léa, Jessica, Giulia, Edouard pour l'agréable ambiance de travail au sein du pôle 2. Je salue également Simon, Côme, Valentin, Raph, Mohamed, Esther, Edouard, Marie, Adrien, Aliénor qui ne rechignent jamais à aller boire une bière. Je souhaite plein de force aux doctorant·e·s pour la poursuite de leurs travaux.

La rédaction de ce manuscrit m'a bien évidemment laissé un peu de temps libre. Merci aux ami·e·s parisien·e·s Cassandre, Marie, Daniela, Tanguy qui va devoir trouver une alternative à son running-gag sur cette interminable thèse de 3 ans et 8 mois, Tanguy de fait bien plus sympa que l'autre Tanguy, Iris, Damien, Nico et à celles et ceux de Sainté Anne-So, Evo, Manon, Mathou, Yannis pour ne citer qu'elles-eux pour nos vacances, week-ends et autres soirées endiablées. Mes sincères salutations à Joules, mollo expatrié, à qui la figure 3.5 remémorera la douceur du mistral Domazanais, et à Gautier, mollo expatrié, à qui la figure 3.5 ne remémorera absolument rien. C'est également toujours un plaisir de partager un ramen avec Franck-Neil. Merci à Pauline, pour les petites attentions qui touchent, mais aussi à Timothée et Claire-Lise pour les soirées à la butte.

Je remercie mes oncles, tantes, cousin·e·s ainsi que ma belle-famille que je suis content d'avoir près de moi. Merci à mes grands-parents pour leur soutien financier durant mes études. J'ai aussi une pensée émue pour ceux qui m'ont aidé à grandir mais qui ont quitté ce monde bien trop tôt. Merci à mon frère Quentin, dont la rigueur intellectuelle force mon admiration, pour sa complicité et pour l'intérêt qu'il porte à mes recherches. Merci à mes parents Geneviève et Franck de m'avoir soutenu dans l'entreprise de ces longues études, et de m'avoir transmis la curiosité et la persévérance, des qualités que je crois essentielles à l'écriture d'une thèse. Enfin, merci à mon Alice, pour sa présence douce et son soutien sans faille, pour sa joie de vivre, et pour son amour.







\* \* \*

*Il faut des centaines, des milliers,  
des millions, des milliards,  
des virées, des histoires,  
à raconter à nos progénitures.*

Guizmo - *C'est tout*

\* \* \*



# *Résumé*

L'objectif général de cette thèse est d'étudier les conséquences distributives de différents aspects du changement climatique dans le secteur agricole. Nous examinons successivement l'effet (i) des politiques d'atténuation des émissions de gaz à effet de serre (GES), (ii) des impacts du changement climatique, et (iii) de l'adaptation au changement climatique sur la distribution du revenu des agriculteurs.

Le premier chapitre étudie les conséquences distributives de diverses politiques climatiques dans le secteur agricole européen. Les impacts d'une politique sur les inégalités dépendent de la distribution des émissions initiales et des coûts de réduction entre les agents, ainsi que de la conception de la politique. Nous développons un modèle analytique pour démêler ces effets. Nous proposons des conditions pour qu'un système de taxe sur les émissions avec remise réduise les inégalités, et nous examinons comment ces conditions varient en fonction du niveau de la taxe. Nous examinons également différentes remises (seuil absolu d'émission constant, seuil relatif de réduction d'émission constant) avec des implications différentes pour le budget du régulateur. Ce cadre est ensuite appliqué au cas des émissions de gaz à effet de serre (GES) de l'agriculture européenne. Les résultats indiquent qu'une taxe sur les émissions sans remise permet une réduction substantielle des émissions du secteur mais augmente les inégalités de revenu. Une remise basée sur un seuil d'émission bien choisi peut réduire les inégalités de revenu tout en maintenant la politique environnementale coût-efficace. Nous quantifions également la contribution de la région et du type d'agriculture aux inégalités de revenu.

Le deuxième chapitre se concentre sur les impacts des températures extrêmes. Le changement climatique devrait modifier la fréquence d'occurrence des événements de température extrême. A l'aide de données françaises sur la période 2002-2017, nous évaluons économétriquement l'effet marginal des températures extrêmes sur le revenu des producteurs céréaliers français. Les résultats indiquent que les températures extrêmes, qu'elles soient chaudes ou froides, pendant la saison de croissance peuvent réduire de manière significative le revenu moyen des agriculteurs. L'analyse des effets distributifs suggère des effets opposés des extrêmes froids et chauds. Alors que les

extrêmes froids affectent plus fortement les agriculteurs pauvres, les extrêmes chauds sont plus dommageables pour les riches. Nous discutons de deux explications possibles de cet effet distributif opposé. Il pourrait y avoir un effet de culture ; la proportion de maïs diminue avec le revenu, tandis que celle de colza augmente. Il pourrait aussi y avoir un effet de localisation ; la probabilité d'être situé dans le Nord augmente avec le revenu.

Le troisième chapitre s'intéresse à l'adaptation au changement climatique. Les agriculteurs confrontés à un changement durable des conditions climatiques peuvent s'adapter de manière autonome par la marge intensive, la marge extensive ou par l'adoption de nouvelles pratiques. En s'appuyant sur un couplage entre un modèle micro-économique de l'agriculture européenne (AROPAj) et un modèle de culture (STICS), ce chapitre étudie les impacts distributifs potentiels de l'adaptation autonome des exploitations au changement climatique au sein de l'Union européenne (UE). Nous modélisons deux niveaux d'adaptation autonome pour les agriculteurs, et deux horizons temporels. Toutes choses égales par ailleurs, les résultats indiquent que le changement climatique peut conduire à une situation pire que la situation actuelle, en termes de bien-être social, à court terme, mais à une meilleure situation à long terme en raison (i) d'une part de revenu stable pour les bas revenus et (ii) d'une augmentation du revenu total. En décomposant les inégalités de revenu des agriculteurs, nous montrons que ces dernières s'expliquent largement par la région des agriculteurs et le type d'agriculture.

# *Summary*

The broad objective of this PhD thesis is to investigate the distributional consequences of different aspects of climate change within the agricultural sector. We successively examine the effect of (i) greenhouse gas (GHG) emissions mitigation policies, (ii) climate change impacts, and (iii) adaptation to climate change on the distribution of farmers' income.

The first chapter investigates the distributional consequences of various emission tax-and-rebate schemes, with an application to GHG emissions from the European agricultural sector. The impacts on income distribution depend on the distribution of initial emissions and abatement costs among agents, as well as on the design of the rebate. We develop an analytical model to disentangle these effects. We propose conditions for an emission tax-and-rebate scheme to be inequality-reducing, and examine how these conditions vary with respect to the level of the tax. We also examine various possible rebate designs (constant absolute emission threshold, constant relative abatement threshold) with contrasted implications for the regulator's budget. This framework is then applied to the regulation of GHG emission from European agriculture. The findings indicate that an emission tax with no rebate tends to increase income inequality within the sector. A rebate based on a well-chosen emission threshold may reduce income inequality while preserving the cost-effectiveness of the environmental policy. In an annex, we decompose income inequality and quantify the marginal contribution of two main farms' characteristics, i.e., region and type of farming to overall income inequality.

The second chapter focuses on extreme temperatures impacts. Climate change is expected to change the frequency of occurrence of extreme temperature events. Based on pooled cross sectioned data from France over the period 2002-2017, we econometrically assess the marginal effect of extreme temperatures on French crop producers' income. Findings indicate that both hot and cold extreme temperatures during the growing season may significantly reduce on average farmers' income. Leveraging on a quantile regression approach, we estimate the distributional effects of extreme weather events on farmers' income. Our results suggest opposite effects of cold and hot ex-

tremes. While cold extremes may more strongly affect poor farmers, hot extremes may be more damaging for farmers in the top of the distribution of income. We discuss two potential explanations for this opposite effect. First, there could be a crop effect; the proportion of corn in the crop mix decreases with income while the proportion of rapeseed increases. Second, there could be a location effect; the probability of being located in the North increases with income.

The third chapter is interested in adaptation to climate change. Farmers facing a durable change in climate conditions may autonomously adapt through the intensive margin, the extensive margin, or through the adoption of new practices. Relying on a soft-coupling between a micro-economic model of European agriculture (AROPAj) and a crop model (STICS), this chapter investigates the potential distributional impacts of farm-level autonomous adaptation to climate change within European Union (EU). We implement two levels of autonomous adaptation for farmers, and two time horizons. Findings indicate that, *ceteris paribus*, climate change may lead to a worse situation than the present one, in terms of social welfare, in the short-term horizon but to a better situation in the long-term horizon due to (i) a stable income share for bottom quantiles and (ii) an increase in total income. Decomposing farmers' income inequality, we show that income inequality is largely explained by farmers region and type of farming. We explore how adaptation to climate change affect the marginal contribution of these two individual characteristics to overall income inequality.

# Contents

|                                                                                                            |            |
|------------------------------------------------------------------------------------------------------------|------------|
| <b>Contents</b>                                                                                            | <b>i</b>   |
| <b>List of Figures</b>                                                                                     | <b>iii</b> |
| <b>List of Tables</b>                                                                                      | <b>vii</b> |
| <b>Lists of Acronyms</b>                                                                                   | <b>ix</b>  |
| <b>1 General Introduction</b>                                                                              | <b>1</b>   |
| 1 The Economics of Climate Change . . . . .                                                                | 2          |
| 2 Social Justice . . . . .                                                                                 | 8          |
| 3 Contributions of the dissertation . . . . .                                                              | 12         |
| <b>2 Distributional consequences of climate policies: An application to European agriculture</b>           | <b>19</b>  |
| 1 Introduction . . . . .                                                                                   | 22         |
| 2 Analytical framework . . . . .                                                                           | 25         |
| 3 Impacts of tax-and-rebate schemes on income inequality . . . . .                                         | 30         |
| 4 Simulation data: Abatement costs of GHG emissions from EU agriculture                                    | 36         |
| 5 Distributional impacts of a tax-and-rebate scheme applied to GHG emissions from EU agriculture . . . . . | 42         |
| 6 Concluding remarks . . . . .                                                                             | 50         |
| 2.A Proofs . . . . .                                                                                       | 53         |
| 2.B EU-FADN types of farming covered by the model . . . . .                                                | 56         |
| 2.C Robustness checks . . . . .                                                                            | 57         |

|          |                                                                                                        |            |
|----------|--------------------------------------------------------------------------------------------------------|------------|
| 2.D      | Income inequality decomposition . . . . .                                                              | 61         |
| <b>3</b> | <b>Extreme temperatures and inequality: Evidence from French agri-<br/>culture</b>                     | <b>69</b>  |
| 1        | Introduction . . . . .                                                                                 | 72         |
| 2        | Related Literature . . . . .                                                                           | 74         |
| 3        | Data sources and main variables . . . . .                                                              | 77         |
| 4        | Empirical Strategy . . . . .                                                                           | 82         |
| 5        | Results . . . . .                                                                                      | 83         |
| 6        | Discussion . . . . .                                                                                   | 89         |
| 7        | Conclusion . . . . .                                                                                   | 92         |
| 3.A      | French extreme degree days. . . . .                                                                    | 93         |
| 3.B      | Robustness checks: OLS estimation results. . . . .                                                     | 94         |
| 3.C      | Robustness checks: Quantile regression estimation results. . . . .                                     | 97         |
| <b>4</b> | <b>Distributional impacts of autonomous adaptation to climate change<br/>from European agriculture</b> | <b>101</b> |
| 1        | Introduction . . . . .                                                                                 | 104        |
| 2        | Modeling strategy . . . . .                                                                            | 107        |
| 3        | Results . . . . .                                                                                      | 112        |
| 4        | Discussion . . . . .                                                                                   | 121        |
| 5        | Conclusion . . . . .                                                                                   | 123        |
| 4.A      | Modeling strategy . . . . .                                                                            | 125        |
| 4.B      | Classification of types of farming . . . . .                                                           | 127        |
| 4.C      | Gini index . . . . .                                                                                   | 127        |
|          | <b>General Conclusion</b>                                                                              | <b>131</b> |
|          | Summary of contributions . . . . .                                                                     | 132        |
|          | Future research . . . . .                                                                              | 134        |
|          | <b>Résumé long</b>                                                                                     | <b>139</b> |



# List of Figures

|     |                                                                                                                                                                                                                                                                                                                          |    |
|-----|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| 2.1 | Situation of an individual agent with pre-policy income $y$ under a tax-and-rebate scheme defined by a tax rate $t$ and a relative abatement threshold $\tilde{\alpha}^S(t, y)$ . . . . .                                                                                                                                | 27 |
| 2.2 | Gini index of the distribution of income (per unpaid AWU) under an emission tax from 0 to 100 €/tCO <sub>2</sub> eq and five rebate schemes. . . . .                                                                                                                                                                     | 44 |
| 2.3 | Lorenz curves of post-policy income (left) and delta Lorenz curves relative to the pre-policy situation (right) of income under the no-rebate scheme and for various emission tax rates. . . . .                                                                                                                         | 45 |
| 2.4 | Individual initial emissions (left, in tCO <sub>2</sub> eq per unpaid AWU) and net loss in income per unit of initial emissions (right, in €/tCO <sub>2</sub> eq per unpaid AWU) with respect to initial income (in € per unpaid AWU) for an emission tax rate of 100 €/tCO <sub>2</sub> eq with no rebate (NR). . . . . | 46 |
| 2.5 | Lorenz curves of post-policy income (left) and delta Lorenz curves relative to the pre-policy situation (right) of income under the five rebate designs and for an emission tax rate of 100 €/tCO <sub>2</sub> eq. . . . .                                                                                               | 46 |
| 2.6 | Net loss or gain in income per unit of initial emissions for an emission tax rate of 100 €/tCO <sub>2</sub> eq (in €/tCO <sub>2</sub> eq per unpaid AWU), with respect to initial income (in € per unpaid AWU). . . . .                                                                                                  | 49 |

|      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            |    |
|------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| 2.7  | Gini index under an emission tax from 0 to 100 €/tCO <sub>2</sub> eq and five rebate schemes for two normalizations (per farm or per unpaid AWU) and four sets of farms: Only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq, only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq and excluding the top and bottom 0.5% of income, full set of farms (Generalized Gini Index, Raffinetti et al. (2014)), full set of farms with negative income set to 0. . . . .            | 57 |
| 2.8  | Delta Lorenz curves relative to the pre-policy situation of income under the no-rebate scheme and for various emission tax rates for two normalizations (per farm or per unpaid AWU) and four sets of farms: Only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq, only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq and excluding the top and bottom 0.5% of income, full set of farms, full set of farms with negative income set to 0. . . . .                           | 58 |
| 2.9  | Individual initial emissions (in tCO <sub>2</sub> eq per farm or per unpaid AWU) for two sets of farms: Only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq, only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq and excluding the top and bottom 0.5% of income. . . . .                                                                                                                                                                                                    | 59 |
| 2.10 | Delta Lorenz curves relative to the pre-policy situation of income under the five rebate schemes and for an emission tax rate of 100 €/tCO <sub>2</sub> eq for two normalizations (per farm or per unpaid AWU) and four sets of farms: Only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq, only farms with positive income at $t = 100$ €/tCO <sub>2</sub> eq and excluding the top and bottom 0.5% of income, full set of farms, full set of farms with negative income set to 0. . . . . | 60 |
| 2.11 | Average regional per unpaid AWU income (k€) in the initial situation and for five rebate schemes under an emission tax rate of 100€/tCO <sub>2</sub> eq. . . . .                                                                                                                                                                                                                                                                                                                                           | 61 |
| 3.1  | Average annual extreme degree days experienced by farmers, left: hot extremes ( $H_t^{90}$ ), right: cold extremes ( $C_t^{10}$ ). . . . .                                                                                                                                                                                                                                                                                                                                                                 | 80 |
| 3.2  | Quantile regression estimates for hot extreme degree days ( $H_{it}^{90}$ ). . . . .                                                                                                                                                                                                                                                                                                                                                                                                                       | 87 |

|     |                                                                                                                                                                                                                                                                                                                                                                                                                       |     |
|-----|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| 3.3 | Quantile regression estimates for cold extreme degree days ( $C_{it}^{10}$ ). . . .                                                                                                                                                                                                                                                                                                                                   | 87  |
| 3.4 | Quantile regression estimates for liquid precipitations. . . . .                                                                                                                                                                                                                                                                                                                                                      | 88  |
| 3.5 | Proportion of area allocated to four major crops by income deciles (left),<br>and regional proportion by income deciles (right). . . . .                                                                                                                                                                                                                                                                              | 90  |
| 3.6 | French average annual extreme degree days, left: hot extremes ( $H_t^{90}$ ),<br>right: cold extremes ( $C_t^{10}$ ). . . . .                                                                                                                                                                                                                                                                                         | 93  |
| 3.7 | Quantile regression estimates for hot extreme degree days ( $H_{it}^{90}$ ), cold<br>extreme degree days ( $C_{it}^{10}$ ), and liquid precipitation on farms gross pro-<br>duction. . . . .                                                                                                                                                                                                                          | 97  |
| 3.8 | Quantile regression estimates for hot extreme degree days ( $H_{it}^{90}$ ), cold<br>extreme degree days ( $C_{it}^{10}$ ), and liquid precipitation on per unpaid AWU<br>farmers income. . . . .                                                                                                                                                                                                                     | 98  |
| 4.1 | Overview of the modeling framework. . . . .                                                                                                                                                                                                                                                                                                                                                                           | 107 |
| 4.2 | Distribution of farmers' income for <i>weak adaptation</i> level. Left: Lorenz<br>curves. Right: Delta Lorenz curves with respect to present time horizon.                                                                                                                                                                                                                                                            | 114 |
| 4.3 | Distribution of farmers' income for <i>strong adaptation</i> level. Left: Lorenz<br>curves. Right: Delta Lorenz curves with respect to present time horizon.                                                                                                                                                                                                                                                          | 115 |
| 4.4 | Generalized Lorenz curves of farmers' income. Left: Weak adaptation.<br>Right: Strong adaptation. . . . .                                                                                                                                                                                                                                                                                                             | 115 |
| 4.5 | Future income with respect to present income (in logs). Top left: Short-<br>term horizon and weak adaptation, Top right: Short-term horizon and<br>strong adaptation, Bottom left: Long-term horizon and weak adapta-<br>tion, Bottom right: Long-term horizon and strong adaptation. . . . .                                                                                                                         | 117 |
| 4.6 | Average regional per unpaid AWU farmers' income ( $10^3\text{€}$ ). Top left:<br>Present horizon and weak adaptation, Top right: Present horizon and<br>strong adaptation, Middle left: Short-term horizon and weak adapta-<br>tion, Middle right: Short-term horizon and strong adaptation, Bottom<br>left: Long-term horizon and weak adaptation, Bottom right: Long-term<br>horizon and strong adaptation. . . . . | 118 |

|     |                                                                                                                           |     |
|-----|---------------------------------------------------------------------------------------------------------------------------|-----|
| 4.7 | Normalized distance between year observations and average values for periods 2006-2035, 2041-2070, and 2071-2100. . . . . | 126 |
|-----|---------------------------------------------------------------------------------------------------------------------------|-----|

# List of Tables

|     |                                                                                                                                                                                                                              |    |
|-----|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| 2.1 | Five rebate designs and their impacts on the regulator's budget and total post-policy income. . . . .                                                                                                                        | 29 |
| 2.2 | Descriptive statistics of the main variables of interest for two normalizations and two sets of farms. . . . .                                                                                                               | 39 |
| 2.3 | EU-aggregated results for the full (3.766 M farms, 4.967 M unpaid AWU) and restricted (3.503 M farms, 4.611 M unpaid AWU) sets of farms. . . . .                                                                             | 39 |
| 2.4 | Aggregate farm income and impacts on the regulator's budget of the five tax-and-rebate schemes. . . . .                                                                                                                      | 43 |
| 2.5 | Classification of main types of farming from the EU-FADN. . . . .                                                                                                                                                            | 56 |
| 2.6 | Average per unpaid AWU income (k€) by type of farming in the initial situation (IS) and for five rebate schemes under an emission tax rate of 100€/tCO <sub>2</sub> eq. . . . .                                              | 62 |
| 2.7 | Marginal contributions of region ( $\omega$ ) and type of farming ( $\sigma$ ) to overall income inequality in the initial situation and for five rebate schemes under a 100€/tCO <sub>2</sub> eq emission tax rate. . . . . | 64 |
| 3.1 | French class of soil texture. . . . .                                                                                                                                                                                        | 80 |
| 3.2 | Descriptive statistics of income for two normalizations and two sets of farms. . . . .                                                                                                                                       | 81 |
| 3.3 | Regional repartition of restricted sample. . . . .                                                                                                                                                                           | 82 |
| 3.4 | Estimation results. . . . .                                                                                                                                                                                                  | 86 |
| 3.5 | Estimation results. . . . .                                                                                                                                                                                                  | 94 |
| 3.6 | Estimation results. . . . .                                                                                                                                                                                                  | 95 |

|     |                                                                                                                                                                                                                                                                                          |     |
|-----|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| 3.7 | Estimation results. . . . .                                                                                                                                                                                                                                                              | 96  |
| 4.1 | Aggregate results for studied sample (4.702 million unpaid AWU for <i>weak adaptation</i> vs. 4.731 million unpaid AWU for <i>strong adaptation</i> ) for crop production (corn & wheat), input consumption (mineral fertilizers & irrigation water), GHG emissions, and income. . . . . | 113 |
| 4.2 | Average per unpaid AWU farmers' income by type of farming for weak and strong adaptation and for three time horizons. . . . .                                                                                                                                                            | 119 |
| 4.3 | Shapley decompositions of per unpaid AWU farmers' income Gini index for three time horizons. . . . .                                                                                                                                                                                     | 120 |
| 4.4 | Types of farming modeled . . . . .                                                                                                                                                                                                                                                       | 127 |
| 4.5 | Gini index for per unpaid AWU and per farm income, for <i>weak</i> and <i>strong adaptation</i> levels, and for three time horizons. . . . .                                                                                                                                             | 127 |

# Lists of Acronyms

- AS: abatement subsidy
- AWU: annual workforce unit
- BC: budget costly
- BN: budget neutral
- CAET: constant absolute emission threshold
- CAP: Common Agricultural Policy
- CNRM: centre national de recherches météorologiques
- CRAT: constant relative abatement threshold
- CH<sub>4</sub>: methane
- CO<sub>2</sub>: carbon dioxide
- EU: European Union
- ESDB: European soil database
- FADN: farm accountancy data network
- GHG: greenhouse gas
- IAMs: integrated assessment models
- IS: initial situation
- LSCE: laboratoire des sciences du climat et de l'environnement
- MRV: monitoring, reporting, and verification
- NR: no rebate
- N<sub>2</sub>O: nitrous oxide
- RCP: representative concentration pathway
- SRES AR5: second report on emission scenario, assessment report 5
- UNFCCC: united nations framework convention on climate change
- US: United-States









# Chapter 1

## General Introduction

Climate change is arguably one of the most important challenge humanity has to overcome in the 21<sup>st</sup> century. The accumulation in the atmosphere of greenhouse gases (GHG) such as carbon dioxide or methane due to anthropogenic activity, is altering Earth climate. Around the world, average temperatures are increasing, the level and intensity of precipitations are changing, and the occurrence of extreme weather events is more and more frequent (IPCC, 2022). Climate change, by impacting both natural ecosystems and human societies, will potentially have strong implications in the long-run.

In the face of climate change, agriculture occupies a special place. First, agriculture is a significant contributor to greenhouse gas emissions. Agriculture, forestry and other land use contribute to 23% of global anthropogenic emissions (IPCC, 2019), 10% of European emissions (European Environment Agency, 2020), and 18% of French emissions (Citepa, 2021). Second, agriculture substantially hinges on climate. Temperatures, precipitations, extreme weather events are all influencing agricultural outcomes. Important economic damage from climate change expected in agriculture, where for instance water availability is projected to be reduced, are likely to encourage ambitious adaptation strategies in the sector (IPCC, 2022).

This introductory chapter aims at providing an overview of the economics of climate change, and its potential links to social justice. A particular attention is paid to agriculture.

# 1 The Economics of Climate Change

This section gives a broad overview of the economics of climate change. First, we introduce the economics of mitigating greenhouse gas emissions. Second, we tackle the issue of impacts of climate change on the economy. Third, we detail the potential adaptation to climate change. In each part, we discuss some distributional issues and provide a focus on the agricultural sector.

## 1.1 Greenhouse gas emissions mitigation

Greenhouse gas emissions are a typical example of an economic externality (Pigou, 1920). Agents, by emitting greenhouse gas, are deteriorating the welfare of other agents. This net welfare loss is the consequence of a market failure, where the resource allocation is not Pareto optimal. A central question in environmental economics is how to internalize this externality (and so, how to overcome the market failure) in a cost-effective way. Among the policy instruments available to tackle this issue, market-based instruments are in general favored by economists. By pricing the pollution, they incentivize agents to adopt a more desirable behavior.

A vast literature in economic theory emphasizes the cost-effectiveness of carbon taxes (Pearce, 1991; Stiglitz, 2019). In a stylized framework, where carbon emissions are perfectly observable, the regulator is able to directly put a price on it. The optimal situation can be reached when the tax is Pigovian (i.e., the price level is set to the social cost of carbon), so that the externality is internalized. Despite a large consensus among economists on the importance of pricing emissions for a cost-effective mitigation, the majority of emissions remain untaxed (World Bank, 2020). Among OECD countries, approximately 60% of emissions are currently not subject to any carbon price (OCDE, 2021).

Several reasons may contribute to explain this lack of emission taxes around the world. For instance, there is a time dissociation between costs and benefits of these policies due to the inertia of the climate system (Tebaldi and Friedlingstein, 2013). The burden of reducing GHG emissions rests on the generation that implements such policies, but the benefits in terms of climate preservation will be enjoyed by

future generations. Hence, most people will not see neither the benefit of an effort of mitigating emissions nor the dramatic consequences of a continuous increase in GHG emissions. Another reason may be the negative distributional consequences of such policies within a given generation. For instance, this may occur when low-income agents spend a larger share of their income in carbon intensive goods than high-income agents. Consequently, the tax burdens more low-income than high-income individuals and increases income inequality. In developed countries, carbon taxes in the energy consumption sector are generally found to be regressive (see e.g. [Ohlendorf et al. \(2020\)](#) for a review). Some examples include [Araar et al. \(2011\)](#) studying the incidence on households of pollution control policies and identifying inequality-increasing effects of payroll tax, or [Bento et al. \(2009\)](#) indicating that an increase in US gasoline taxes is likely to be regressive. Thus, the absence of perceptibility of future climate damages, or the potential regressive impact of GHG emission taxes can contribute to the lack of political acceptability of such policies ([Tiezzi, 2005](#)), and finally compromising their implementation ([Parry, 2015](#)).

Agriculture does not constitute an exception to the rule. Despite the fact that similar marginal abatement costs to the industry, or the energy consumption sector have been identified in the agricultural sector ([Vermont and De Cara, 2010](#); [Pellerin et al., 2017](#)), it is still to a large extent excluded from the scope of climate policies. The causes mentioned above for the energy sector also operate in agriculture. In addition one may add other reasons, specific to the agricultural sector.

The vast majority of agricultural GHG emissions comes from two non-CO<sub>2</sub> gas (more than 85% of net European agricultural emissions according to [Grosjean et al. \(2016\)](#)): methane (CH<sub>4</sub>) and nitrous oxide (N<sub>2</sub>O). These two gases are characterized by particularly high global warming potentials (i.e. 27 to 30 CO<sub>2eq</sub> and 273 CO<sub>2eq</sub> for respectively CH<sub>4</sub> and N<sub>2</sub>O over a 100-year period). In Europe CH<sub>4</sub> emanates from livestock (mainly due to ruminants enteric fermentation and manure management) and N<sub>2</sub>O from fertilizer applications to soils. [Grosjean et al. \(2016\)](#) report that, for year 2012, 44% (respectively 42%) of EU agricultural emissions originate from enteric fermentation (respectively manure management). The sector also has the singular capacity of storing carbon in soils and biomass through notably the adoption

of practices relative to soil tillage, cover crops, temporary or permanent pastures and grassland, hedges, agro-forestry (Pellerin et al., 2017). Hence, the important diversity of (positive and negative) emission sources makes it difficult to price agricultural GHG emissions. Exploring the costs of various policies targeting agricultural GHG emissions in California, Garnache et al. (2017) show that implementing second-best policies may be less costly than implementing first-best policies to mitigate emissions originating from an important number of diversified sources.

Another complication lies in the measurement of emissions. GHG emissions from the agricultural sector are not easily measurable as they depend on local factors.  $N_2O$  emissions from mineral fertilizers strongly depend on the type of soil where fertilizers are applied on.  $CH_4$  emissions from enteric fermentation significantly vary according to animal feeding (Vermont and De Cara, 2010). Emissions are *de facto* not easily traceable as in the case of fossil fuel combustion, and may require monitoring, reporting, and verification (MRV) procedures. On this topic, De Cara et al. (2018) provide a thorough investigation on the optimal coverage of an agricultural GHG emission tax in the presence of MRV costs.

All of these barriers to the establishment of serious climate policies prevent human societies to curb GHG emissions growth and make the earliest climate change damages already visible.

## 1.2 Climate change impacts

Since the seminal articles from Nordhaus (1977, 1982, 1991), the economic literature has covered an important number of studies trying to quantify climate change impacts on the economy. The large majority of integrated assessment models (IAMs) estimating climate change impacts on total welfare reports negative impacts. According to Tol (2018), they roughly evaluate that a  $2.5^\circ C$  increase in global average temperature may lead to a 1.3% decrease in total welfare. However, these works are sometimes under criticism for their lack of accuracy (Heal, 2017; Pindyck, 2017).

Another approach, based on historical observations, consists in regressing a set of variables including climate variables, on economic output. As an example, Dell et al. (2012) using country-aggregated data for the period 1950-2003, find for poorer

countries that a 1°C increase in average temperature may reduce economic growth by 1.3%. Econometric methods are also not exempted from objections, particularly cross-section analysis from which it can be difficult to isolate a direct effect of climate or weather (Dell et al., 2014).

As climate change impacts is more pronounced on specific regions or economic sectors, one may prefer delimited rather than aggregate analysis. The hypothesis that weather may impact health and mortality has received particular attention in recent years. Authors generally highlight the harmful effects of an increase in exposure to extreme temperatures. In the United States (US), Deschênes and Greenstone (2011) find that each extra day above 32°C may increase mortality by 0.11% with respect to an average 10-15°C day. Note that they also find that mortality is also increased by extreme cold. Barreca (2012) similarly identifies that three additional days above 90°F increases deaths by 0.54 per 100,000 inhabitants. In developing countries, the impact of growing temperatures could be even more substantial, as revealed by Burgess et al. (2011) for India. A growing body of evidence suggests that climate variables may have important consequences on conflict and political stability. The three main mechanisms at stake are that weather events may negatively affect economic output and in turn (i) reduce the opportunity cost of protesting against the government, (ii) decrease government revenues and the ability to maintain order and, (iii) provoke riots through an increase in food prices. For instance, Couttenier and Soubeyran (2013) document a positive link between drought and civil war in sub-Saharan Africa over the period 1957-2005.

The corpus of literature assessing weather and climate effect also addresses other economic sectors. The reader may refer to Connolly (2008); Zivin and Neidell (2014) for weather influence on labor productivity, to Jacob et al. (2007) for weather impact on crime, or to Jones and Olken (2010) for weather shocks on trade.

Most of works assessing differentiated effects of climate change pay a particular attention to between-countries (or between-regions) studies. Poor countries or regions seem to be more vulnerable than rich ones. As stated by Tol (2018), this may be explained first, by the fact that poorer regions are often hotter ones, where a marginal increase in temperature could be more detrimental. Second, poor countries generally

bear an important share of their economic production to weather-exposed sectors (e.g. agriculture) whereas rich countries are essentially relying on industries and services.

Agriculture is probably the most scrutinized sector by the climate impacts literature. Due to its natural link to weather conditions (temperature or precipitations are inputs for crop production) agriculture is particularly threatened by climate change.

The first works that have attempted to quantify the impacts of climate on agriculture have relied on a *production function approach*, linking explicitly agricultural output and climate variables. Then the relation is used to assess the effect of a change in climate (Adams et al., 1998). The method has been criticized for under-estimating farmers' adaptive capacities. For instance, these studies rarely allow the adoption of new crops which may be better adapted to a different climate.

The *Ricardian approach* initiated by Mendelsohn et al. (1994) explicitly takes into account adaptation through changes in area allocation to different crops. The extensively used method (approximately fifty studies reviewed by Mendelsohn and Massetti (2017)) mostly estimates beneficial effects for cold places, neutral effects for warmer places, and detrimental effects for hot places of climate change (Van Passel et al., 2016). Results are globally consistent with the *production function approach*, but of lower magnitude (certainly due to a better inclusion of adaptation). Several authors express doubts about the reliability of the estimates provided by *Ricardian* analysis because of omitted variables. For example, Schlenker et al. (2006) reproaches the difficulty of accounting for irrigation.

Deschênes and Greenstone (2007) suggest to use panel data with individual fixed effects and year-to-year weather fluctuations to sharpen the estimation of potential climate impacts on agriculture. Authors estimate that climate change will increase annual profits by 4%. These *panel* and *Ricardian* approaches, even if they fully include adaptation, do not allow to isolate it.

Hence, it appears crucial to have a better understanding of climate change adaptation to put in place the right public policies.



### 1.3 Adaptation to climate change

A change in climate implies that agents have to modify their decisions. How individuals adapt by changing decisions when their production environment is changing has been extensively studied in economics at least since (Samuelson, 1947). By specifying a relationship between economic production and weather variables, one can predict how a change in climate shifts private optimum and affects production (Hsiang, 2016). Economists disentangle adaptation actions that occur at the intensive margin, where behavioral changes adjust to a continuous choice variable, and at the extensive margin where discrete changes are made. Assessing adaptation to climate change within the California timber industry, Guo and Costello (2013) find that extensive margin adaptations may be more crucial than intensive margin adaptations for alleviating climate change effects.

Some studies attempt to quantify differential adaptive capabilities among populations. Due to a difficult access to modern technology, poor countries are found to have more limited capacities of adaptation than rich countries (Adger, 2006). These countries are found to be less equipped in terms of technologies (e.g., air conditioning, irrigation infrastructure) but also institutions (e.g., medicine, crop insurance) that may provide assistance against climate change impacts. For example, in a case study on the Bangladesh coast, Brouwer et al. (2007) show that households facing higher exposure to flood risk are both the poorest and the least well prepared.

For agriculture, several authors quantify the potential for adaptation to climate change using the *production function* approach. In a meta-analysis based on more than 1,700 published simulations, Challinor et al. (2014) indicate that crop-level adaptation is expected to increase yields by an average of 7 to 15%, with adaptation strategies particularly efficient for wheat and rice. Adaptation strategies differ according to regions; Mediterranean regions have less options than Northern Europe regions for lessening climate change impacts (Iglesias et al., 2011). Other studies, based on econometric analysis provide evidence on farmers' adaptive behavior concerning consumption and savings. See for example Di Falco et al. (2011) studying Ethiopian rural households. A very recent stream of literature aims at quantifying farmers' short-term adaptations to

weather changes. Examples include Aragón et al. (2021) indicating that extreme heat can increase the planted area, and change crop mix among Peruvian rural households. Jagnani et al. (2020) show that in Kenya, higher temperatures that occur early in the growing season reduce fertilizer applications but increase pesticides consumption. Concerning developed countries, Bareille and Chakir (2021) find that climate change may increase fertilizer but decrease pesticide applications in Meuse, France.

Agriculture is a relevant sector for climate economics. However, very few studies address inequality issues in agriculture in the light of climate change.

## 2 Social Justice

This section provides a broad overview of social justice with regard to climate change. We first present the main social justice theories, without being completely exhaustive. Second, we concentrate on climate justice.

### 2.1 Theories of social justice

As long as assets and resources are limited, the question of their distribution naturally arises. Economists and philosophers have paid a considerable attention in seeking a theory defining what is *fair*.

#### Marxism

Marxian theory (Marx, 1867) focuses on consumption. The latter has to be in proportion of provided labour. Consequently, the theory defines two distinct class: exploiters, i.e., when the ratio consumption/labour is in excess, and exploited, i.e., when the ratio consumption/labour is too low. As this theory favours agents with the strongest labour abilities, Marx added a principle, *to each according his needs*, that may be interpreted as a way to reach welfare equality. Among criticism that importantly challenged the Marxian exploitation theory, the most crucial one perhaps concerns the impossible conversion of value in price. Despite recent development of the Marxian exploitation

theory, see among others Roemer (1982)<sup>1</sup>, its concepts are today deserted.

### Libertarianism

Libertarian thought, importantly developed by Nozick (1974) and Rothbard (1973), is interested in individual rights. In this theory, all resources must be subject to individual property rights. Then, once property rights are equally allocated, there is no need for a distribution in terms of results (for example, consumption or utility). This approach also suggests to abolish the so-called *oppressive* state. This theory faces important objections. For instance, the state allows the proper functioning of a market economy by providing a legal framework for contracts. It is hard to imagine that individuals may freely construct this framework and peacefully interact, rather than making clans and/or entering in conflicts. Another criticism lies in the appropriation of property rights. Libertarians based the property rights on an original appropriation. This may be a problem as the appropriation of some rights could have happened contrary to Libertarian justice principles and may require reparation. Other criticisms are exposed in Fleurbaey (1996).

### Utilitarianism

Utilitarianism is arguably one of the most popular theories of justice. Its most famous contributors are Bentham, Mill, or Harsanyi. It considers as *fair* the situation that maximizes total utility (or welfare). As it is focused on an aggregate measure of welfare, this approach allows for important distributional implications. Several critics came from libertarians, as for instance Nozick (1974) with his "*utility monster*". An utilitarian society should spend all its resources for satisfying a person who is extremely more efficient than the others for transforming resources in utility (i.e., a *utility monster*). The theory also struggles to defend fundamental rights. In a racist or a theocratic state, discriminatory laws could contribute to maximize aggregate welfare. A strong objection to the theory that emanates from Rawls (1971) concerns the neglect of differences between individuals, and particularly of a plausible positive social

---

<sup>1</sup>The reader may also refer to Elster (1985); Roemer (1986) for analytical development of Marxian exploitation

aversion for utilities inequality (Sen, 1973). It should be noted that utilitarianism can be egalitarian. Due to decreasing properties of the marginal utility of money, it may recommend to redistribute money to the poorest people for maximizing total welfare.

### Liberal-egalitarianism

Liberal-egalitarianism has been built in opposition to utilitarianism. Rawls (1971) wonders how to identify justice principles to govern the society. In a famous thought experiment, he placed individuals under a "*veil of ignorance*". He derived three major principles from imagining what agents not knowing about their particular circumstances (i.e., social position, natural skills, and conception of life) would choose as a principle. First, individuals may agree on an *equal liberty* principle, to guarantee certain fundamental rights (e.g., freedom of conscience and expression, freedom of association). Second, they may consent on an *equal opportunity* principle, according to which individuals identically skills could have the same access opportunity to various social positions. Third, they could approve a *difference* principle that justifies social or economic inequality if and only if it benefits to worse-off individuals. The probable risk-averse behavior of individuals under *the veil of ignorance* is responsible for this egalitarian principle. Harsanyi, a fervent supporter of utilitarianism, criticized this approach arguing for instance that it does not permit any sacrifices of the poor, whatever the gain of the rich, or that it is irrational to base individual choice on unfavourable alternatives, as it is the case with the *veil of ignorance* (Harsanyi, 1975).

## 2.2 Climate justice

Social justice is at the heart of the climate problem. Inequality is present, relatively to both causes and consequences of climate change, but also at various scales (e.g., national, international, or inter-generational). On the one hand, GHG emissions are highly heterogeneous across countries: rich countries are the biggest emitters (actually, but also historically). In 2020, China, US and Europe were responsible for 58.4% of total GHG emissions.<sup>2</sup> On the other hand, climate change impacts are also importantly

---

<sup>2</sup>Source: <https://ourworldindata.org>

heterogeneous. Poorest individuals and future generations are likely to be the most touched. The question of sharing the costs of fighting against climate change therefore naturally arises.

The *polluter pays* principle lies on a simple intuition: moral responsibility derives from causal responsibility (Pigou, 1920). The person causing the damage must repair it. This principle is particularly consensual among economists as it also encourages to reduce pollution and internalizes the externality due to GHG emissions. Caney (2005) addresses several limits to this principle. First, as a significant share of GHG emissions are due to earlier generations, and thus already dead individual polluters, we cannot make the polluter pay. Second, there is a *pardonable ignorance* as we only undoubtedly know that GHG emissions are causing climate change since the early nineties. Agents cannot be morally responsible for their actions if they ignore the consequences. The third objection concerns poverty: what about individuals producing GHG emissions who cannot afford to pay?

According to the *beneficiary pays* principle (Page, 2012), agents (or countries) who benefit from past or actual emissions (whatever they originate from them or no) are responsible for the implementation of climate policies. Gosseries (2004) defines trans-generational free-riding to describe individuals benefiting from past and present emissions without bearing the costs. This principle remedies several limitations of the *polluter pays* principle. First, even if past polluters are dead, it is possible to make present generations contribute, as they benefit from past emissions. Second, present generations are not guilty for past emissions, they just have a duty to address, so the past ignorance on GHG emissions consequences does not matter. However, this principle is complicated to implement in practice because of the difficulty of measuring the actual benefit from past GHG emissions.

Rather than focusing on past emissions, the *ability to pay* principle (Caney, 2005) is interested in future impacts of climate change. It appeals to the moral responsibility of those who have the financial means to pay. The ones with the most important capacity to tackle climate change have to bear the largest share of the effort.

International climate negotiations illustrate the challenge for countries to agree on justice principles. While developed countries may prefer the *polluter pays* principle,

developing countries may opt for *beneficiary pays* or *ability to pay* principles.

## 3 Contributions of the dissertation

### 3.1 Research questions and scope

This dissertation studies different aspects of climate change in agriculture, in the light of income distribution. It contains three chapters that are completely independent. Chapter two deals with the regulation of GHG emissions, chapter three with extreme temperatures, and chapter four with autonomous adaptation to climate change. Obviously, this thesis does not pretend to capture all channels through which climate change impacts and mitigation can affect agriculture.

### 3.2 Description of the chapters

#### **Distributional consequences of climate policies: An application to European agriculture**

The main objective of this chapter is to assess the distributional impacts of various tax-and-rebate schemes from both an analytical and an empirical approach.

Consequently to the work of [Kolm \(1969\)](#) and [Atkinson \(1970\)](#) defining the Lorenz-dominance criterion<sup>3</sup>, a theoretical literature emerged from [Jakobsson \(1976\)](#) and [Kakwani \(1977\)](#) to link the progressivity of a tax schedule to Lorenz-dominance properties. [Jakobsson \(1976\)](#) demonstrates that a tax is inequality-reducing in the Lorenz sense if and only if it is progressive everywhere. This model has then been refined in terms of hypothesis by [Eichhorn et al. \(1984\)](#), adding a condition on the rank-preservation of income, or extended to composite taxation by [Le Breton et al. \(1996\)](#). This literature is particularly well synthesized in [Lambert \(1993\)](#). We build on this literature to address the issue of an emission tax, possibly accompanied by a rebate of the collected tax. Our framework allows us to disentangle the importance of (i) the distribution of initial emissions with respect to initial income, and (ii) the

---

<sup>3</sup>Comparing two distributions, a situation may be preferred to another in terms of aggregate welfare if and only if the Lorenz curve of its distribution entirely lies above the other one.

distribution of marginal abatement costs with respect to income for the tax to be inequality-reducing in the sense of Lorenz. We explicit two types of rebates of the collected tax: rebates based on a constant absolute emission threshold, equivalent to lump-sum transfers to agents, and rebates based on a constant relative abatement threshold, proportional to individual initial emissions. For both types of rebates, the regulator can redistribute the total amount of the collected tax, or more. We compare the different tax-and-rebate schemes in terms of inequality-reducing properties and we also examine how the latter are affected by an increase in the tax rate.

We then apply this framework to the issue of European regulation of GHG emission in agriculture. Exploring the distributional consequences of climate policies within European agriculture is relevant for several reasons. First, despite the fact that European agriculture contributes to approximately 10% of total European GHG emissions, it is not subject to any constraining climate policy. Second, the Common Agricultural Policy (CAP) presents equity goals for European farmers. Third, farms have been shown to be highly heterogeneous in terms of both GHG emissions and marginal abatement costs. Our assessment relies on a set of simulations (Isbasoiu, 2019) obtained from a micro-economic model of European agriculture. In this model, representative farmers, calibrated on real farms data, maximize their gross margin, subject to various constraints. We thus construct an income, subtracting wages paid from the gross margin, and normalizing by the number of unpaid workers on the farm. It should be noted the presence of negative income, not rare in agriculture, that we remove for the distributional analysis, in line with the literature. Our results indicate that an emission tax with no rebate would increase farmers' income inequality. This is mainly due to an elasticity of GHG emissions with respect to income lower than one. However, we show that rebates based on a well-chosen threshold may bring income inequality to a lower level than the initial (i.e., pre-tax) level.

In an annex, we suggest an extension of this work. Applying a framework based on the Shapley value (Chantreuil et al., 2019), we decompose farmers' income inequality. We quantify the marginal contribution of two main characteristics, i.e., region and type of farming, to overall income inequality. We also examine how these contributions vary, according to the type of climate policy implemented.

**Extreme temperatures and inequality: Evidence from French agriculture**

The goal of this chapter is to estimate the distributional effects of extreme temperatures on French crop producers' income.

Recent studies from DePaula (2020) and Malikov et al. (2020) investigate the potential impact of climate variables on inequality between farmers. DePaula (2020) who studies Brazilian commercial farms, finds that a 1°C of warming may be more detrimental to farms with warm climates, and with high quality land. Malikov et al. (2020), working on US Corn and soybean production, indicate that future climate change impacts may be more detrimental to lower yield quantiles. Building on these studies, this chapter focuses on the distributional impacts of extreme temperatures within crop producers, in France. To that purpose, we combine three databases. First, we use individual information from the French Farm Accountancy Data Network (FADN). It provides farms accounting data (e.g., operating surplus, production, input costs), but also information on the crop mix, for 18,546 farms on the period 2002-2017. Second, we take advantage of a *MétéoFrance* database. It delivers daily weather information at the SAFRAN grid (8km × 8km) that we disaggregate at a city-level. We then construct variables for capturing the effect of extreme temperatures during the growing season. A period of twelve years, from 1988 to 1999, is taken as a (local) reference distribution. Then, days when the temperature is in the bottom (respectively top) 10% of the distribution are considered as cold (resp. hot) extremes. We consider their cumulative sum as our variable capturing extreme temperatures. Note that our empirical framework also controls for the effect of average temperatures and precipitations. Third, we leverage on the European Soil Database. It gives us soil quality information at a city-level in five classes of texture.

We then estimate the effect of hot and cold extreme temperatures on farms income (i.e. operating surplus), controlling for weather variables (i.e., average temperatures, precipitations), land quality, farm characteristics (e.g., land surface, irrigation) and accounting information (e.g., input expenditure, subventions perceived). Results indicate that both hot and cold extreme temperatures are particularly costly for farmers. We estimate an elasticity of -0.131 (resp. -0.048) for hot (resp. cold)



extreme degree days with respect to farms' income. Leveraging on a quantile regression framework (Koenker and Basset, 1978; Machado and Silva, 2019), we go deeper in the distribution. Our analysis reveals antagonistic effects of extremely cold and hot temperatures. While cold extreme temperatures impacts are found to be more harmful for bottom incomes, and thus increasing inequality, extreme heat is found to be more damaging for top incomes, and thus decreasing inequality. We explore two potential explanations for these opposite distributional effects. First, there could be a crop effect: the proportion of corn in the crop mix reduces with income, while the one of rapeseed increases with income. Second, there could be a region effect: the probability of being located in the North of France increases with income.

### **Distributional impacts of autonomous adaptation to climate change from European agriculture**

The objective of this chapter is to quantify the effect on the distribution of income of farms autonomous adaptation to climate change within Europe.

Facing a durable change in their climate environment, farmers may autonomously adapt, at their scale. This private adaptation may come from the intensive margin, the extensive margin, or even from the adoption of new practices. Our modeling strategy relies on a soft-coupling between a micro-economic model of European agriculture (AROPAj) and a crop model (STICS). AROPAj depicts the annual economic behaviour of a set of European representative farmers in terms of farmland allocation (crops, pastures and grasslands) and livestock management (animal numbers and feeding). The model includes various agricultural productions in terms of crops (i.e. 24 major European crops, permanent and temporary grassland) and animal husbandry (i.e. dairy and non-dairy cattle, sheep, goats, swine, poultry). Each farmer maximizes its gross margin subject to technical (e.g. required crop rotations) and political (e.g. CAP payments, environmental policies) constraints. To overcome the lack of exhaustivity of the EU-FADN, AROPAj is sharpened by substituting a function extracting from STICS linking inputs and yields at the plot scale. STICS simulates the soil-atmosphere-crop system applied to a wide range of crops and pedo-climatic conditions (Brisson et al., 2003), and then requires climate parameters, soil

information, and data on agricultural management practices.

We consider the representative concentration pathway (RCP) 4.5 from the second report on emission scenario, assessment report 5 (SRES AR5). We compute three time horizons: a present horizon (period 2006-2035), a short-term horizon (period 2041-2070), and a long-term horizon (period 2071-2100). We simulate two levels of autonomous adaptation for farmers. First, a *weak adaptation* level, where farmers may adapt to a change in weather conditions through both the extensive and the intensive margins, but only through crops initially present in their farm type. Second, a *strong adaptation* level, where farmers can in addition, adopt new crop varieties or change the sowing date. Findings indicate that, ceteris paribus, climate change may lead to a worse situation than the present one, in terms of social welfare, in the short-term horizon, because of (i) a decreasing income share for lower quantiles and (ii) a decrease in total income. However, the situation may be better in the long-term horizon due to (i) a stable income share for bottom quantiles and (ii) an increase in total income. We then apply an inequality decomposition framework from [Chantreuil et al. \(2019\)](#) and assess marginal contributions of region and type of farming to income inequality. Then, we examine how farms' autonomous adaptation to climate change affect these contributions.





## Chapter 2

# Distributional consequences of climate policies: An application to European agriculture



\* \* \*

The potential regressivity of an emission tax is a major obstacle to the implementation of this otherwise cost-effective instrument; rebate schemes may help overcome this difficulty. The consequences of such schemes on the distribution of income depend on their design and the distribution of initial emissions and abatement costs among agents. We develop a stylized analytical framework to disentangle these effects, derive general conditions under which a tax-and-rebate scheme is inequality-reducing, and compare various possible designs with contrasting impacts on aggregate income and the regulator's budget. This framework is subsequently applied to the regulation of greenhouse gas emissions from European agriculture. An emission tax with no rebate is found to deliver substantial mitigation, but also to have regressive impacts. If combined with a rebate based on a constant emission threshold, aggregate income would be less negatively impacted (or even increase relative to the initial situation) and income inequality would decrease well below pre-policy levels. For the same impact on the regulator's budget and aggregate income, a threshold proportional to each farmer's initial emissions has a very small impact on income inequality. These findings show that a well-designed rebate can be pivotal for the political acceptability of climate policy instruments.

\* \* \*

## 1 Introduction<sup>1</sup>

Emission taxes have been proposed for decades as a cost-effective instrument to incentivize greenhouse gas (GHG) mitigation (Goulder and Parry, 2008; Stiglitz et al., 2017). However, their potentially regressive impacts are increasingly scrutinized (Metcalfe, 2009; Ohlendorf et al., 2020). A major concern is that the consequences on income inequality undercut the political support to such instruments and jeopardize the implementation of ambitious climate policies (Tiezzi, 2005; Parry, 2015). Transfers, for instance in the form of a rebate, may be used to lessen the adverse distributional impacts of the policy (Bento et al., 2009). However, given the heterogeneity in individual initial emissions, mitigation costs, and behavioral responses to the tax, the design of such transfers raises issues with regard to post-policy income inequality and budget implications.

The first objective of this study is to clarify how the design of an emission tax-and-rebate scheme affects income inequality. The second objective is to empirically assess the distributional implications of tax-and-rebate schemes aimed at mitigating agricultural GHG emissions in the European Union (EU).

This study contributes to a growing body of literature on distributional effects of emission taxes. The focus of this literature is mainly on carbon or energy taxes that target households. The results with respect to the distributional impacts of such policies have been ambiguous (Ohlendorf et al., 2020). Although a few studies have reported progressive effects (Dissou and Siddiqui, 2014; Labandeira et al., 2009; Landis et al., 2021; Feindt et al., 2021), carbon taxes have been found to increase income inequality in many contexts (Mathur and Morris, 2014; Araar et al., 2011; Grainger and Kolstad, 2010; Ravigné et al., 2022). Several authors have investigated how this effect could be compensated by a simple flat-recycling rebate (Bento et al., 2009; Klenert and Mattauch, 2016; Goulder et al., 2019; Douenne, 2020; Cronin et al., 2019) or by a modification of the tax system (Chiroleu-Assouline and Fodha, 2006, 2014).

The agricultural sector provides an interesting application case for several rea-

---

<sup>1</sup>This chapter comes from a collaboration with Stéphane De Cara.



sons. First, although agriculture is a substantial contributor to GHG emissions (about 10% of total EU GHG emissions, mostly due to direct emissions of methane and nitrous oxide, [European Environment Agency, 2020](#)), it is still largely absent from the scope of the main climate policy instruments currently in place at both the member states and EU levels ([Grosjean et al., 2016](#)). The contribution of this sector is critical to the fulfillment of the EU’s objectives of reducing GHG emissions by 40% by 2030 relative to 2005 in the sectors covered by the Effort Sharing Regulation ([European Parliament, 2018](#); [European Commission, 2021b](#)). Second, “*ensuring a fair standard of living for the agricultural community*” was historically one of the founding objectives of the Common Agricultural Policy (CAP) and “*generating fairer economic returns*” has remained an important goal in the subsequent CAP reforms ([European Commission, 2020](#)). Third, the European agricultural sector is characterized by large income inequality ([European Commission, 2021a](#)) and large heterogeneities across farms in terms of both GHG emissions and marginal abatement costs ([De Cara et al., 2018](#); [Fellmann et al., 2021](#)).

The regulation of agricultural GHG emissions has attracted increasing attention in environmental economics, with contributions quantifying the mitigation potential and costs in the agricultural sector at various spatial scales and resolutions ([Vermont and De Cara, 2010](#); [Frank et al., 2018](#); [Fellmann et al., 2021](#)), or simulating the consequences of various second-best policy designs ([Garnache et al., 2017](#); [De Cara et al., 2018](#)). This literature focuses on cost-effectiveness and to a large extent, is disconnected from the distributional consequences of the policies. In parallel, the issue of income inequality within the agricultural sector has given rise to a substantial body of literature, mostly in low- and middle-income countries, but also in more developed regions ([Finger and El Benni, 2014](#)). In Europe, this issue has been often examined in relation to the role of the CAP ([Hanson, 2021](#); [Piet and Desjeux, 2021](#)).

Our contribution is twofold. First, we analytically investigate and compare various tax-and-rebate schemes and derive general conditions under which they reduce income inequality. We compare rebates based on a constant emission threshold and on a constant relative abatement threshold. The former are akin to lump-sum transfers; the latter are equivalent to transfers proportional to initial emissions. Depending on

the chosen threshold level, the policy can be budget neutral or entail a net cost for the regulator. Combining these two dimensions, we can compare the performances of schemes that are based on a similar design but have contrasting impacts on the regulator's budget, and schemes that have the same consequences on the regulator's budget but differ in their design. This analysis builds on the abundant literature on Lorenz-dominance and the measurement of inequality (Atkinson, 1970; Jakobsson, 1976; Fellman, 1976). See for instance Aaberge (2001) for an axiomatic approach. Our findings confirm the key role played by the elasticity of initial emissions with respect to initial income, a feature often at the center of attention in analyses of income inequality and the environment (Chancel, 2021). They also reveal the importance of how individual mitigation costs and potential vary with respect to initial income, a feature that has drawn less attention in the literature. The analytical framework sheds new light on how various rebate designs compare in terms of income inequality, and how their distributional impacts vary with respect to the emission tax rate.

Our second contribution is empirical. We quantify the distributional impacts of an emission tax on GHG emissions from European agriculture, and explore various rebate scheme designs with contrasting impacts on the regulator's budget and aggregate income. To the best of our knowledge, this study is the first to examine the distributional impacts of climate-policy instruments in the agricultural sector. In the absence of GHG emission regulation, the distributional consequences of the policy cannot be estimated directly. The analysis builds on a simulations produced by Isbasoiu (2019), which rely on a micro-economic, supply-side model of EU agriculture that operates at the farm level and covers a wide diversity of contexts across the EU. As the model accounts for heterogeneities across farms in terms of GHG emissions, supply response to an emission tax, and marginal abatement costs, the simulations enable to discuss the implications of various tax-and-rebate schemes on income at both the farm and aggregate levels. Our findings indicate that an emission tax with no rebate tends to increase income inequality among European farmers. They also show that a rebate based on a well-chosen emission threshold may offset these regressive impacts and even substantially reduce pre-existing income inequality, while preserving cost-effectiveness.

The remainder of this chapter is organized as follows. Section presents the an-

alytical framework developed in the study. The conditions under which an emission tax-and-rebate scheme is inequality-reducing are examined in Section 3, along with an analysis of how these conditions vary with the design of the rebate and tax rate. Section 4 presents the simulations used, the model they are based on, and the adjustments made for the analysis of income inequality. The impacts on aggregate income and the regulator's budget, and the distributional implications of an emission tax combined with various designs of the rebate scheme are analyzed in Section 5. Section 6 concludes.

## 2 Analytical framework

Consider a continuum of heterogeneous agents whose population is normalized to 1. Agents are characterized by their (positive) initial income  $y$ . The distribution of initial income is denoted by  $\mathcal{Y}$ , and is defined by the cumulative distribution function  $F(y)$ .

The activity of each agent causes emissions. We assume that initial emissions can be mapped with initial income, so that agent with initial income  $y$  initially emits  $e_0(y) > 0$ , with  $e_0(y)$  differentiable for all  $y$ .<sup>2</sup> Agents may reduce their emissions at a cost  $c(\alpha, y)$ , where  $\alpha$  denotes the rate of reduction in emissions relative to initial emissions.  $c(\alpha, y)$  is defined for all  $y$  and for all  $\alpha$  such that  $0 \leq \alpha \leq 1$ , and is assumed to be twice differentiable with respect to both arguments. The following standard assumptions are made for all  $y$  (subscripts indicate partial derivatives):  $c(0, y) = 0$ ,  $c_\alpha(0, y) = 0$ , and  $c_\alpha(\alpha, y) > 0$ ,  $c_{\alpha\alpha}(\alpha, y) > 0$  for all  $\alpha$  such that  $0 < \alpha \leq 1$ .

The regulator considers a policy scheme  $S$  that combines an emission tax and a rebate. Each unit of emission is taxed at a constant rate  $t$ . The rebate is defined by a (pre-determined) non-negative quantity of emissions  $\tilde{e}^S(t, y)$  that is deducted from the tax bill. Note that  $\tilde{e}^S(t, y)$  depends on  $y$  to accommodate the fact that the regulator may opt for an individualized rebate. It also takes  $t$  as an argument as the rebate may be determined by the total tax revenues collected by the regulator, as will be seen

---

<sup>2</sup>Pre-policy income  $y$  is assumed to be a pre-determined characteristic of the agent. The notation  $e_0(y)$  should thus be interpreted as the initial emissions of agent with initial income  $y$ , rather than as a structural relationship between emissions and income. The same remark applies to mitigation costs  $c(\alpha, y)$ .

later. Under scheme S, the net amount paid by an agent with income  $y$  who reduces emissions by  $\alpha$  is:

$$g^S(t, y) = t \cdot \left( (1 - \alpha)e_0(y) - \tilde{e}^S(t, y) \right) = te_0(y) \left( \tilde{\alpha}^S(t, y) - \alpha \right), \text{ where } \tilde{\alpha}^S(t, y) = 1 - \frac{\tilde{e}^S(t, y)}{e_0(y)}. \quad (2.1)$$

All agents emitting more than  $\tilde{e}^S(t, y)$  (i.e., reducing their emissions by less than  $\tilde{\alpha}^S(t, y)$ ) are liable for a positive net payment ( $g^S(t, y) > 0$ ). All agents emitting less than  $\tilde{e}^S(t, y)$  (i.e., reducing their emissions by more than  $\tilde{\alpha}^S(t, y)$ ) receive a positive net transfer ( $g^S(t, y) < 0$ ).

The case where  $\tilde{\alpha}^S(t, y) = 1$  for all  $y$  corresponds to a standard emission tax without any rebate (no rebate, or NR). The case where  $\tilde{\alpha}^S(t, y) = 0$  for all  $y$  corresponds to a subsidy to each unit of abatement at constant rate  $t$  (abatement subsidy, or AS).

The post-policy income of an agent with initial income  $y$  who reduces emissions by  $\alpha$  is:

$$x^S(t, y) = y - c(\alpha, y) - g^S(t, y). \quad (2.2)$$

As long as individual agents cannot influence  $\tilde{e}(t, y)$ , the rebate does not interfere with their abatement decisions. It is easy to see that the abatement maximizing  $x^S(t, y)$  is such that:

$$c_\alpha(\alpha, y) = t \text{ for all } y. \quad (2.3)$$

Eq. (2.3) implicitly defines the optimal individual abatement supply  $\alpha(t, y)$ . As a direct consequence of the assumptions regarding abatement costs, the abatement supply for any agent is equal to zero if the emission tax is zero, and is positive and monotone increasing with respect to  $t$  for all positive emission tax rates. Thus, for all  $y$ , we have that  $\alpha(0, y) = 0$ . In addition, for all  $y$  and all  $t > 0$ ,  $0 < \alpha(t, y) \leq 1$  and  $\alpha_t(t, y) > 0$ .

It will be useful to normalize the impact of the policy on agents' income. Using Eqs. (2.1), (2.2), and (2.3), the net loss in income per unit of initial emissions can be expressed as

$$\ell^S(t, y) = \frac{y - x^S(t, y)}{e_0(y)} = t\tilde{\alpha}^S(t, y) - \int_0^t \alpha(u, y) du. \quad (2.4)$$

Figure 2.1 depicts the situation for an agent with initial income  $y$ , facing an emis-

sion tax  $t$  and a rebate defined by a relative abatement threshold  $\tilde{\alpha}^S(t, y)$ . If  $\tilde{\alpha}^S(t, y) = 1$  for all  $y$  (NR), then  $\ell^{\text{NR}}(t, y)$  is unambiguously non-negative ( $0 \leq \ell^{\text{NR}}(t, y) \leq t$ ). Conversely, if  $\tilde{\alpha}^S(t, y) = 0$  for all  $y$  (AS), then  $-t \leq \ell^{\text{AS}}(t, y) \leq 0$ . More generally, if the rebate scheme leads to a net positive payment from the agent to the regulator (i.e. if  $\alpha(t, y) \leq \tilde{\alpha}^S(t, y)$ ), then the corresponding agent's income is negatively affected by the policy, that is  $\ell^S(t, y) \leq 0$ . If, as is the case in the situation illustrated in Figure 2.1,  $\alpha(t, y) > \tilde{\alpha}^S(t, y)$ , then  $\ell^S(t, y)$  can be either positive (net loss for the agent) or negative (net gain).

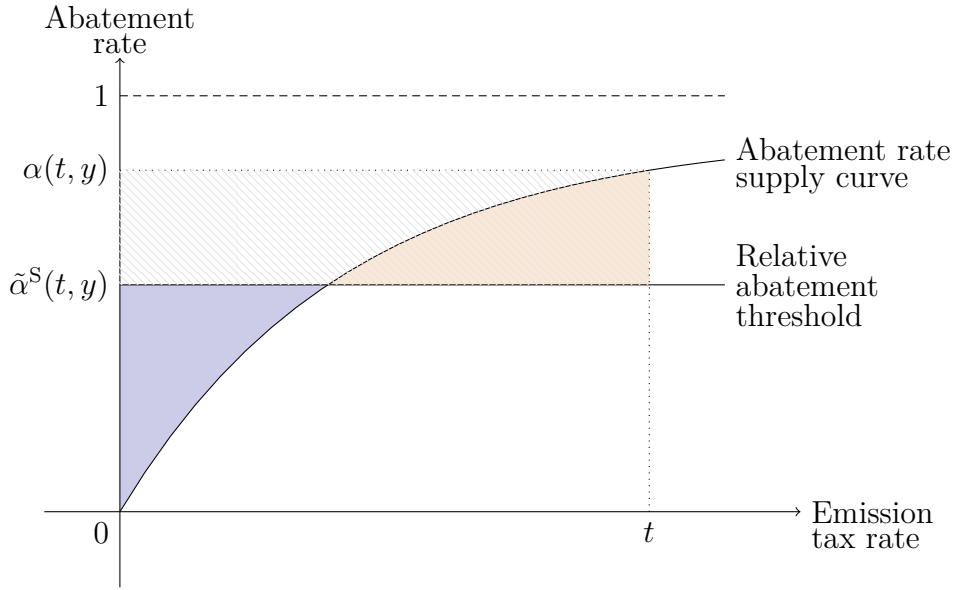


Figure 2.1: Situation of an individual agent with pre-policy income  $y$  under a tax-and-rebate scheme defined by a tax rate  $t$  and a relative abatement threshold  $\tilde{\alpha}^S(t, y)$ .

*Note:* The net loss in income per unit of initial emissions,  $\ell^S(t, y)$ , is given by the difference between the blue area and the orange area; the grey hatched area represents the net payment per unit of initial emissions ( $g^S(t, y)/e_0(y)$ ), which is negative in this case (net transfer to the agent).

As the focus is on the distributional effects of environmental policy rather than on its optimality at the aggregate level, its impacts will be examined for any emission tax rate, regardless of the actual value of the marginal damage caused by emissions. Nevertheless, it is useful to consider the aggregate impact of the policy on the regulator's budget. Integrating  $g^S(t, y)$  over the entire population yields the total net amount of tax collected by the regulator:

$$G^S(t) = t \int_{\mathcal{Y}} e_0(y) \left( \tilde{\alpha}^S(t, y) - \alpha(t, y) \right) dF(y). \quad (2.5)$$

The net tax revenue for the regulator under an emission tax with no rebate amounts to  $G^{\text{NR}}(t) = t(E_0 - A(t))$ , where  $E_0$  and  $A(t)$  are the aggregate initial emissions and abatement, respectively. An abatement subsidy entails a net budget cost for the regulator ( $G^{\text{AS}}(t) = -tA(t)$ ).

Budget-neutral (BN) schemes—such that  $G^{\text{S}}(t) = 0$ —are of particular interest. If based on a constant absolute emission threshold (CAET), one such scheme is defined by:

$$\tilde{e}^{\text{BN-CAET}}(t, y) = E_0 - A(t) \text{ for all } y. \quad (2.6)$$

If the rebate is based on Eq. (2.6), agents with higher-than-average<sup>3</sup> post-policy emissions are liable for a positive net payment to the regulator, whereas agents with lower-than-average post-policy emissions receive a net transfer from the regulator.

A budget-neutral scheme may also be based on a constant relative abatement threshold (CRAT):

$$\tilde{\alpha}^{\text{BN-CRAT}}(t, y) = \frac{A(t)}{E_0} \text{ for all } y. \quad (2.7)$$

In this case, any agent who reduces emissions by a greater (lower) rate than the average abatement rate receives (pays) a net positive amount from (to) the regulator.

Specifications (2.6) and (2.7) assume that the regulator can predict the overall abatement  $A(t)$  when setting the rebate. If this information is not available, one can imagine a rebate based on a constant absolute emission threshold equal to the average initial emissions:

$$\tilde{e}^{\text{BC-CAET}}(t, y) = E_0 \text{ for all } y. \quad (2.8)$$

Specification (2.8) imposes the same net budget cost (BC) to the regulator as in the case of an abatement subsidy ( $G^{\text{BN-CAET}}(t) = -tA(t)$ ), but involves a different distribution of post-policy income.

The five rebate designs discussed above are presented in Table 2.1. By construction, for a given tax rate, they are all equivalent in terms of total emissions and abatement costs. The sum of the total post-policy income and net tax revenue is also constant across schemes ( $X^{\text{S}}(t) + G^{\text{S}}(t) = Y - C(t)$ ). Note that the total post-

---

<sup>3</sup>Remember that, as the population mass is normalized to 1, aggregate emissions are equal to average emissions.

CHAPTER 2. DISTRIBUTIONAL CONSEQUENCES OF CLIMATE POLICIES:  
AN APPLICATION TO EUROPEAN AGRICULTURE

policy income  $X^S(t)$  is smaller than the pre-policy income  $Y$  under the first three schemes (NR, BN-CAET, BN-CRAT), and larger than  $Y$  under BC-CAET and AS (as  $tA(t) > C(t)$ ).

Table 2.1: Five rebate designs and their impacts on the regulator's budget and total post-policy income.

| Rebate  | Absolute emis-<br>sion threshold           | Relative abate-<br>ment threshold | Net tax revenue | Post-policy<br>income      |
|---------|--------------------------------------------|-----------------------------------|-----------------|----------------------------|
| $S$     | $\tilde{e}^S(t, y)$                        | $\tilde{\alpha}^S(t, y)$          | $G^S(t)$        | $X^S(t)$                   |
| NR      | 0                                          | 1                                 | $t(E_0 - A(t))$ | $Y - C(t) - t(E_0 - A(t))$ |
| BN-CAET | $E_0 - A(t)$                               | $1 - \frac{E_0 - A(t)}{e_0(y)}$   | 0               | $Y - C(t)$                 |
| BN-CRAT | $e_0(y) \left(1 - \frac{A(t)}{E_0}\right)$ | $\frac{A(t)}{E_0}$                | 0               | $Y - C(t)$                 |
| BC-CAET | $E_0$                                      | $1 - \frac{E_0}{e_0(y)}$          | $-tA(t)$        | $Y - C(t) + tA(t)$         |
| AS      | $e_0(y)$                                   | 0                                 | $-tA(t)$        | $Y - C(t) + tA(t)$         |

*Note: Variables in uppercase are the aggregate counterparts of the individual variables (in lowercase) defined in the text, and can be interpreted indifferently as total or population average. NR: No rebate; AS: Abatement subsidy; BN: Budget-neutral; BC: Budget-costly; CAET: Constant absolute emission threshold; CRAT: Constant relative abatement threshold.*

The rebate design impacts not only post-policy income, but also how it varies with respect to the tax rate. Differentiating the net loss in income per unit of initial emissions with respect to  $t$  yields (see Eq. (2.4)):

$$\ell_t^S(t, y) = \tilde{\alpha}^S(t, y) + t\tilde{\alpha}_t^S(t, y) - \alpha(t, y) \quad (2.9)$$

The term  $t\tilde{\alpha}_t^S(t, y)$  in Eq. (2.9) is relevant only for budget-neutral schemes (BN-CAET, BN-CRAT), and is equal to zero under the three other rebate designs (NR, BC-CAET, and AS, see Table 2.1). This term captures the fact that, as total abatement rises in response to the tax increase, the threshold needs to be adjusted accordingly to ensure budget-neutrality.

A marginal increase in  $t$  decreases the income for all agents under the no-rebate scheme (NR), and increases it under an abatement subsidy (AS). For the other three schemes, the change in income is negative (positive) for agents reducing their emissions by a rate smaller (larger) than  $\tilde{\alpha}^S(t, y) + t\tilde{\alpha}_t^S(t, y)$ .

To describe how the various components of the model vary with respect to  $y$ , we introduce the following notations:

$$\varepsilon(y) = \frac{ye'_0(y)}{e_0(y)}, \quad \lambda^S(t, y) = \frac{y\ell_y^S(t, y)}{\ell^S(t, y)}, \quad \nu^S(t, y) = \frac{y\ell_{ty}^S(t, y)}{\ell_t^S(t, y)}, \quad (2.10)$$

that represent the (local) elasticity of initial emissions, net loss in income per unit of initial emissions, and change in net loss in income per unit of initial emissions due to a marginal change in  $t$ , respectively, with respect to initial income.

### 3 Impacts of tax-and-rebate schemes on income inequality

We now examine how the design of an emission tax-and-rebate scheme affects income inequality. The comparison of income distributions is based on the Lorenz-dominance criterion. In particular, we use that the post-policy income distribution  $\mathcal{X}^S$  Lorenz-dominates the pre-policy income distribution  $\mathcal{Y}$ —that is,  $\mathcal{Y} \preceq_L \mathcal{X}^S$ —if and only if the policy is (i) progressive everywhere (i.e.  $x^S(t, y)/y$  is non-increasing with respect to  $y$  for all  $y$  in  $\mathcal{Y}$ ) and (ii) rank-preserving everywhere (i.e.  $x^S(t, y)$  is non-decreasing with respect to  $y$  for all  $y$  in  $\mathcal{Y}$ ) (Eichhorn et al., 1984).

For any given value of  $t$ , and assuming that  $y > 0$  and  $x^S(t, y) > 0$  for all  $y$ , these conditions can be summarized as follows:

$$0 \leq \xi^S(t, y) \leq 1 \text{ for all } y, \text{ with } \xi^S(t, y) = \frac{yx_y^S(t, y)}{x(t, y)}, \quad (2.11)$$

where  $\xi^S(t, y)$  is the elasticity of post-policy income with respect to  $y$ .

Conditions (2.11) can be rearranged and expressed in terms of the net loss in income ( $e_0(y)\ell^S(t, y)$ , see Eq. (2.4)) and how it varies with respect to initial income.

**Proposition 1** *Consider a tax-and-rebate scheme  $S$  with an emission tax rate  $t > 0$  such that post-policy income is positive for all  $y$ .  $S$  is inequality-reducing ( $\mathcal{Y} \preceq_L \mathcal{X}^S$ )*



if and only if:

$$1 \leq \varepsilon(y) + \lambda^S(t, y) \leq \frac{y}{e_0(y)\ell^S(t, y)} \text{ for all } y \text{ such that } \ell^S(t, y) > 0 \quad (2.12)$$

$$\text{and } \frac{y}{e_0(y)\ell^S(t, y)} \leq \varepsilon(y) + \lambda^S(t, y) \leq 1 \text{ for all } y \text{ such that } \ell^S(t, y) < 0 \quad (2.13)$$

*Proof.* See Appendix.

The tax-and-rebate scheme is progressive if the net loss in income varies more than linearly with respect to initial income for agents who loose from the policy, and less than linearly with respect to  $y$  for those who gain from the policy. Conditions (2.12) and (2.13) also ensure that the policy is rank-preserving. These conditions permit to distinguish the respective roles of the distribution of initial emissions with respect to pre-policy income (through  $\varepsilon(y)$ ) from that of the loss in income per unit of initial emissions (through  $\lambda^S(t, y)$ ). Additionally, they underscore the importance of how the chosen threshold partitions the population into agents who incur a net loss due to the policy (2.12) and those who benefit from it (2.13).

To clarify the interpretation of Proposition 1, first consider a policy involving a positive emission tax but no rebate. In this case (NR), it is clear that all agents face a net loss and, hence, that conditions (2.12) apply for all  $y$ . For illustrative purposes, further assume that agents cannot reduce their emissions, for example because abatement is prohibitively expensive or simply because there are no feasible abatement options. In this case, conditions (2.12) simplify to:

$$1 \leq \varepsilon(y) \leq \frac{y}{te_0(y)} \text{ for all } y. \quad (2.14)$$

In such a situation, for the policy to be inequality-reducing, the elasticity of initial emissions with respect to  $y$  must be neither too large nor too small for all agents. If it is too large, the policy is not rank-preserving. If, on the contrary,  $\varepsilon(y)$  is smaller than 1 for all  $y$ , lower-income agents have proportionally larger emissions than higher-income agents, which makes them proportionally more affected by the emission tax. When initial emissions increase less than linearly with initial income, the emission tax tends to be regressive.

However, agents generally have the ability to reduce their emissions in response to the tax. The extent to which this can compensate for the potentially regressive impacts of the emission tax depends on how abatement and the associated costs vary with respect to initial income  $y$ . This is encapsulated in  $\lambda^S(t, y)$ , which is the elasticity of the net loss in income per unit of initial emissions with respect to  $y$  ( $\ell^S(t, y)$ , see Eq. (2.4)). For clarity, still assume that there is no rebate but now consider that agents can reduce their emissions. Conditions (2.12) indicate that, in this case (NR), even if  $\varepsilon(y) < 1$  for some values of  $y$ , the policy can still be progressive provided that  $\lambda^{NR}(t, y)$  is sufficiently large for the respective agents.

Now, consider the polar case of an abatement subsidy (AS). In this case ( $\tilde{\alpha}^{AS}(t, y) = 0$  for all  $y$ ), all agents unambiguously gain from the policy and conditions (2.13) apply. A comparison of the conditions for NR and AS shows that the effect of the distribution of initial emissions on inequality depends on the rebate design. Other things held constant, an increase in  $\varepsilon(y)$  makes the no-rebate scheme more progressive, whereas it makes the abatement subsidy more regressive.

The three other rebate designs (BN-CAET, BN-CRAT, and BC-CAET) split the population into two categories: those who face a net loss and those who enjoy a net gain from the policy. Whether each scheme reduces or increases income inequality partly depends on whether the agents in the former category are also those with higher or lower initial income.

As seen in the previous section, the various rebate designs differ only in the total level and distribution of post-policy income, as well as in their impacts on the regulator's budget. The following proposition examines how they compare in terms of income inequality.

**Proposition 2** *For a given emission tax rate  $t > 0$ , assume that post-policy income is positive under the no-rebate scheme for all agents, i.e.  $x^{NR}(t, y) > 0$  for all  $y$ . The following results hold:*

$$(i) \mathcal{X}^{NR} \preceq_L \mathcal{X}^{BN-CAET} \preceq_L \mathcal{X}^{BC-CAET};$$

$$(ii) \text{ If } 0 < \varepsilon(y) \leq \xi^{NR}(t, y) \text{ for all } y, \text{ then } \mathcal{X}^{NR} \preceq_L \mathcal{X}^{BN-CRAT} \preceq_L \mathcal{X}^{AS};$$

$$\text{ If } 0 < \xi^{NR}(t, y) \leq \varepsilon(y) \text{ for all } y, \text{ then } \mathcal{X}^{AS} \preceq_L \mathcal{X}^{BN-CRAT} \preceq_L \mathcal{X}^{NR};$$

(iii) If  $\varepsilon(y) > 0$ ,  $\xi^{BN-CAET}(t, y) > 0$ , and  $\varepsilon(y) \geq \frac{e_0(y) - E_0}{e_0(y)} \xi^{BN-CAET}(t, y)$  for all  $y$ , then

$$\mathcal{X}^{BN-CRAT} \preceq_L \mathcal{X}^{BN-CAET};$$

(iv) If  $\varepsilon(y) > 0$ ,  $\xi^{BC-CAET}(t, y) > 0$ , and  $\varepsilon(y) \geq \frac{e_0(y) - E_0}{e_0(y)} \xi^{BC-CAET}(t, y)$  for all  $y$ , then

$$\mathcal{X}^{AS} \preceq_L \mathcal{X}^{BC-CAET}.$$

*Proof.* See Appendix.

The first message of Proposition 2 is that it is always possible to design a rebate that reduces income inequality relative to an emission tax. In particular, a rebate based on a constant absolute emission threshold (CAET) unambiguously reduces inequality compared with an emission tax with no rebate (part (i) of the proposition). This result is not surprising because CAET-based rebates are akin to lump-sum transfers. However, they entail a cost for the regulator relative to the situation with no rebate. The larger the emission threshold, the lower the inequality, but also the larger the net budget cost.

Part (ii) of the proposition indicates that inequality can also be reduced through a rebate based on a constant relative abatement threshold (CRAT). However, this requires that  $\varepsilon(y)$  not be too large. In particular, if, for all  $y$ ,  $0 < \varepsilon(y) < 1$  and the no-rebate scheme is regressive (i.e.,  $\xi^{NR}(t, y) > 1$ , or equivalently,  $\varepsilon(y) + \lambda^{NR}(t, y) < 1$ , see (2.12)), then the first conditions in (ii) are readily verified. By contrast, if  $\varepsilon(y)$  is sufficiently large, such schemes may perform worse than an emission tax with no rebate in terms of income inequality. This occurs notably if  $\varepsilon(y) > 1$  for all  $y$  and the no-rebate scheme is inequality-reducing compared with the pre-policy situation. Interestingly in that case, the greater the rebate, the greater the budget cost, but the greater the post-policy income inequality.

Parts (iii) and (iv) compare the tax-and-rebate schemes that have the same impact on the regulator's budget. Note that the conditions in (iii) and (iv) are readily verified for agents with smaller-than-average emissions, who also have lower initial income as soon as  $\varepsilon(y) > 0$ . These agents are better off if the rebate is based on a constant absolute emission threshold (CAET) than on a constant relative abatement threshold (CRAT). For agents with greater-than-average emissions,  $\varepsilon(y)$  must be sufficiently large for the CAET rebate to reduce income inequality compared with the

CRAT rebate. If the conditions in (iii) are fulfilled, the conditions in (iv) are also verified because (i) implies that  $\xi^{\text{BN-CAET}}(t, y) \geq \xi^{\text{BC-CAET}}(t, y)$  for all  $y$  and any given  $t > 0$ .

How does a change in the emission tax rate affect inequality for a given rebate scheme?

**Proposition 3** *Consider a tax-and-rebate scheme  $S$  defined by a tax rate  $t$  and a relative abatement threshold  $\tilde{\alpha}^S(t, y)$  such that post-policy income is positive and rank-preserving for all agents ( $x^S(t, y) > 0$  and  $x_y^S(t, y) > 0$  for all  $y$ ). A marginal increase in the tax rate  $t$  reduces income inequality if and only if:*

$$\varepsilon(y) + \nu^S(t, y) \geq \xi^S(t, y) \text{ for all } y \text{ such that } \alpha(t, y) < \tilde{\alpha}^S(t, y) + t\tilde{\alpha}_t^S(t, y), \quad (2.15)$$

$$\text{and } \varepsilon(y) + \nu^S(t, y) \leq \xi^S(t, y) \text{ for all } y \text{ such that } \alpha(t, y) > \tilde{\alpha}^S(t, y) + t\tilde{\alpha}_t^S(t, y). \quad (2.16)$$

*Proof.* See Appendix.

The left-hand side of inequalities (2.15) and (2.16) corresponds to the elasticity of the net change in income due to a marginal increase in  $t$ . Income inequality is reduced when the net change in income increases more (less) rapidly than post-policy income with respect to  $y$  for agents reducing their emissions by a small (large) rate.

Consider the case of an emission tax with no rebate (NR). In this situation, condition (2.15) applies for all  $y$ , and reduces to:

$$\varepsilon(y) - \frac{y\alpha_y(t, y)}{1 - \alpha(t, y)} \geq \xi^{\text{NR}}(t, y) \quad \text{for all } y. \quad (2.17)$$

The left-hand side of inequality (2.17) corresponds to the elasticity of post-policy emissions with respect to  $y$ . Notice that, by construction,  $\xi^S(0, y) = 1$  for all  $y$ . Moreover, as  $\alpha(0, y) = 0$  for all  $y$ , we have that  $\alpha_y(0, y) = 0$  for all  $y$ . Therefore, starting from  $t = 0$ , a marginal increase in the emission tax rate decreases income inequality under a no-rebate scheme if and only if  $\varepsilon(y) \geq 1$  for all  $y$ . The intuition is similar to that behind condition (2.14). In the neighborhood of  $t = 0$ , the direction

of the change in income inequality due to a marginal increase in  $t$  is predominantly determined by the distribution of initial emissions. If  $\varepsilon(y) < 1$ , the emission tax with no rebate tends to be regressive, and a marginal increase in  $t$  reinforces its regressivity. That is only when starting from a sufficiently large tax rate that the distribution of  $\alpha_y(t, y)$  might counteract this tendency at the condition that lower-income agents are able to cut their emissions by a larger rate than higher-income agents (i.e.  $\alpha_y(t, y) < 0$ ).

Under an abatement subsidy (AS) with  $t > 0$ , condition (2.16) applies as  $\alpha(t, y) > 0$  for all  $y$ . Therefore, in this context, a marginal increase in  $t$  decreases inequality if and only if:

$$\varepsilon(y) + \frac{y\alpha_y(t, y)}{\alpha(t, y)} \leq \xi^{\text{AS}}(t, y) \quad \text{for all } y. \quad (2.18)$$

The left-hand side of inequality (2.18) corresponds to the elasticity of individual abatement with respect to  $y$ . A comparison of conditions (2.17) and (2.18) highlights the contrasting roles played by  $\varepsilon(y)$  and  $\alpha_y(t, y)$  under NR and AS.

Under the other three rebate designs (BC-CAET, BN-CAET, and BN-CRAT), some agents—those reducing their emissions by a rate lower than  $\tilde{\alpha}(t, y) + t\tilde{\alpha}_t(t, y)$ —see their net loss in income increase, whereas the other agents see their net loss decrease (or their net gain increase).

Using Eqs. (2.8) and (2.10), it can be shown that under BC-CAET, conditions (2.15) and (2.16) are equivalent to:

$$\varepsilon(y) - \frac{y\alpha_y(t, y)}{1 - \alpha(t, y)} \geq \left(1 - \frac{E_0}{e_0(y)(1 - \alpha(t, y))}\right) \xi^{\text{BC-CAET}} \quad \text{for all } y. \quad (2.19)$$

A slightly more involved but similar condition can be found under BN-CAET:

$$\varepsilon(y) - \frac{y\alpha_y(t, y)}{1 - \alpha(t, y)} \geq \left(1 - \frac{E_0 - A(t) \left(1 + \frac{tA'(t)}{A(t)}\right)}{e_0(y)(1 - \alpha(t, y))}\right) \xi^{\text{BN-CAET}} \quad \text{for all } y. \quad (2.20)$$

Note the presence in (2.20) of the elasticity of sector-wide abatement with respect to  $t$  ( $\frac{tA'(t)}{A(t)}$ ), which determines the adjustment needed to maintain budget neutrality. This parameter can be determined by sector-wide simulations of the abatement response to an emission tax. As an illustration, based on a meta-analysis of such approaches in the context of the mitigation of non-CO<sub>2</sub> greenhouse gases in the agricultural sector,

Vermont and De Cara (2010) estimated the value of this elasticity at approximately 0.6. Note also that if (2.20) holds true, then (2.19) also holds true, as  $\xi^{\text{BC-CAET}} \leq \xi^{\text{BN-CAET}}$  (part (i) of Proposition 2) and  $A'(t) > 0$ .

Propositions 1 to 3 confirm the importance of the elasticity of initial emissions with respect to  $y$  when assessing the distributional consequences of any tax-and-rebate scheme. However, whether initial emissions vary less or more than linearly with initial income is not sufficient on its own to compare various candidate schemes with contrasting consequences on the regulator's budget and/or income distribution. This should be examined jointly with the distribution of agents' ability to reduce emissions. Therefore, the ranking of various rebate schemes also depends on the heterogeneity of agents in terms of abatement potential and costs, which, to a large extent, is an empirical question.

## 4 Simulation data: Abatement costs of GHG emissions from EU agriculture

We now turn to the empirical application to the mitigation of GHG emissions from EU agriculture. In addition to comprehensive sectoral coverage, the framework presented above requires a representation of individual heterogeneity not only in terms of initial income and emissions, but also in terms of abatement potential and costs. The set of simulations produced by Isbasoiu (2019), which examines the impacts of the implementation of an emission tax on EU agricultural GHG emissions and covers the period 2007-12, is one of the rare empirical modeling exercises providing such information both at the farm and EU levels. For ease of presentation, only the results for the most recent year covered by the simulations (2012) are used in the analysis.

The model underlying these simulations is a micro-economic model of the EU agricultural supply, AROPAj (Jayet et al., 2021). It describes the optimal annual economic behavior of a set of representative farmers in terms of farmland allocation (food and feed crops, temporary and permanent pastures, and grasslands) and livestock management (animal numbers, animal feeding). The model integrates the relevant

CAP provisions and a rich technical content in terms of crop and livestock production. The relationships between agricultural activities and environmental outcomes (GHG emissions, nitrogen compounds, and water usage) make it possible to assess the environmental impacts of policies affecting the EU agricultural sector (De Cara and Jayet, 2011; Lungarska and Jayet, 2018; De Cara et al., 2018; Isbasoiu, 2019).

The behavior of each representative farmer is modeled using a static, mixed integer linear-programming model. Farmers are assumed to be price-takers and act independently of one another. In a given economic and policy context (input and output prices, taxes and subsidies, CAP provisions), each farmer chooses crop area allocation, animal feeding, and animal numbers to maximize the farm's gross margin, subject to technical (e.g., crop rotations, animal-specific feeding requirement), resource availability (e.g., available farmland area, herd size), and CAP-related constraints.

Most parameters and initial values of the model variables are taken from or estimated based on the EU Farm Accountancy Data Network (EU-FADN), which provides accounting and structural data (revenues, variable costs, prices, yields, crop area, animal numbers, support received, and type of farming) for more than 70,000 surveyed professional farms across the EU. The surveyed farms are representative of the diversity of farming production contexts at the regional level. The EU-FADN provides a weight attached to each surveyed farm that enables the aggregation of farm results at regional, country, or EU scales. The EU-FADN surveyed farms included in the model are representative of a total population of 3.766 million farms for 2012.

The model covers the 24 main annual crops currently grown in Europe as well as temporary and permanent pastures and grasslands. Perennial crops (orchards and vineyards) and specialty crops are excluded. Animal categories represented in the model are sheep, goats, swine, poultry, dairy, and non-dairy cattle. Cattle are further disaggregated into age and sex categories. The possible interactions between vegetal and animal production activities occurring at the farm level are explicitly modeled, notably through the on-farm consumption of feed crops. This is particularly important for mixed-farming systems that represent a substantial share of European agriculture.

Representative farms are constructed as clusters of the farms surveyed by the EU-FADN. This classification groups farms that operate in the same region and are

similar in terms of main type of farming (14 modalities, see Table 2.5; a representative farm may combine several types of farming), economic size, and altitude (0-300 m, 300-600 m, and over 600 m). This typology resulted in 1,993 representative farms across 133 regions in 2012.

The main agricultural sources of GHG emissions are endogenously determined at the representative farm level: nitrous oxide ( $\text{N}_2\text{O}$ ) emissions due to agricultural soils and manure management and methane ( $\text{CH}_4$ ) emissions due to enteric fermentation, manure management, and rice cultivation. Smaller sources (such as  $\text{CO}_2$  emissions due to the use of fossil fuels and carbon-containing fertilizers in the sector) are not covered by the model. Note that carbon sinks/sources in soils and biomass, which would require a dynamic approach, are not included. The calculation of emissions relies on country-specific emission factors taken from member states' GHG inventory reports to the UNFCCC. These factors link the level of the relevant activity for any representative farm to that of the corresponding sources of emissions.  $\text{N}_2\text{O}$  and  $\text{CH}_4$  emissions are converted into  $\text{CO}_2\text{eq}$  based on the respective 100-year global warming potential:  $\text{GWP}_{\text{N}_2\text{O}} = 298$  and  $\text{GWP}_{\text{CH}_4} = 25$ .

Over the full set of farms represented in Isbasoiu (2019), initial emissions average about 97  $\text{tCO}_2\text{eq}$  per farm (see Table 2.2), with a wide range of variation in per-farm emissions from 0.2 to more than 8,500  $\text{tCO}_2\text{eq}$ . The resulting distribution of initial emissions is right-skewed, with a median almost four times lower than the mean and a coefficient of variation slightly above 2.

The main purpose of these simulations was to evaluate the response of each representative farm to an emission tax. We focus on tax rates ranging from 0 to 100 €/t $\text{CO}_2\text{eq}$  (by steps of 1 € up to 60 €/t $\text{CO}_2\text{eq}$ , and of 2.5 € from 60 to 100 €/t $\text{CO}_2\text{eq}$ ). The highest value of this range is slightly larger than the maximum price observed on the EU Emissions Trading System to date and also larger than the carbon tax rates currently implemented in most European countries (World Bank, 2022). Farmers respond to the tax by adjusting their input use and output through changes in their crop area allocation, animal numbers, and/or animal feeding (e.g., on-farm produced vs. marketed feed, forage vs. concentrates) within the feasible set defined by the model constraints. For each simulated tax rate  $t$ , one obtains a point evaluation of



## CHAPTER 2. DISTRIBUTIONAL CONSEQUENCES OF CLIMATE POLICIES: AN APPLICATION TO EUROPEAN AGRICULTURE

Table 2.2: Descriptive statistics of the main variables of interest for two normalizations and two sets of farms.

|                                                                                    | Per farm |      |        |      |       | Per unpaid AWU |      |        |      |       |
|------------------------------------------------------------------------------------|----------|------|--------|------|-------|----------------|------|--------|------|-------|
|                                                                                    | mean     | s.d. | min    | med. | max   | mean           | s.d. | min    | med. | max   |
| <i>Full set of farms</i>                                                           |          |      |        |      |       |                |      |        |      |       |
| Emissions (tCO <sub>2</sub> eq)                                                    | 96.8     | 206  | 0.2    | 26.1 | 8,570 | 73.4           | 162  | 0.1    | 21.9 | 8,570 |
| Gross margin (k€)                                                                  | 45.8     | 111  | -312.4 | 14.6 | 4,589 | 34.7           | 90   | -242.4 | 11.0 | 4,589 |
| Income (k€)                                                                        | 41.0     | 99   | -447.0 | 13.0 | 3,311 | 31.1           | 79   | -398.4 | 10.0 | 3,531 |
| <i>Only farms with positive income at <math>t = 100</math> €/tCO<sub>2</sub>eq</i> |          |      |        |      |       |                |      |        |      |       |
| Emissions (tCO <sub>2</sub> eq)                                                    | 97.2     | 209  | 0.2    | 26.2 | 8,570 | 73.9           | 164  | 0.1    | 21.9 | 8,570 |
| Gross margin (k€)                                                                  | 49.7     | 113  | 0.0    | 16.1 | 4,589 | 37.7           | 91   | 0.0    | 12.4 | 4,589 |
| Income (k€)                                                                        | 46.5     | 98   | 0.0    | 15.1 | 3,311 | 35.4           | 77   | 0.0    | 11.7 | 3,531 |

*Note: Income is proxied by operational surplus (see text). AWU: Annual Workforce Unit; Full set of farms: 3.766 million farms and 4.967 million unpaid AWU; Only farms with positive income at  $t = 100$  €/tCO<sub>2</sub>eq: 3.503 million farms and 4.611 million unpaid AWU.*

the abatement supply (difference between initial emissions and emissions at price  $t$ ) and abatement costs (initial gross margin minus gross margin at price  $t$  excluding the total amount of tax paid).

Table 2.3 reports the EU-wide results for three emission tax rates. Emissions (365 MtCO<sub>2</sub>eq with no tax) are reduced by approximately 6, 9, and 15% for tax rates of 30, 50, and 100 €/tCO<sub>2</sub>eq, respectively. The total abatement costs reach up to 2.1 billion € for the highest explored tax rate.

Table 2.3: EU-aggregated results for the full (3.766 M farms, 4.967 M unpaid AWU) and restricted (3.503 M farms, 4.611 M unpaid AWU) sets of farms.

|                                                                   | Emission tax ( $t$ , in €/tCO <sub>2</sub> eq) |     |     |       |
|-------------------------------------------------------------------|------------------------------------------------|-----|-----|-------|
|                                                                   | 0                                              | 30  | 50  | 100   |
| <i>Full set of farms</i>                                          |                                                |     |     |       |
| Emissions ( $E(t)$ , in MtCO <sub>2</sub> eq)                     | 365                                            | 343 | 332 | 312   |
| Abatement ( $A(t)$ , in MtCO <sub>2</sub> eq)                     | .                                              | 21  | 33  | 53    |
| Abatement costs ( $C(t)$ , in M€)                                 | .                                              | 238 | 698 | 2,148 |
| <i>Only farms with positive income at 100 €/tCO<sub>2</sub>eq</i> |                                                |     |     |       |
| Emissions ( $E(t)$ , in MtCO <sub>2</sub> eq)                     | 341                                            | 320 | 309 | 290   |
| Abatement ( $A(t)$ , in MtCO <sub>2</sub> eq)                     | .                                              | 21  | 32  | 50    |
| Abatement costs ( $C(t)$ , in M€)                                 | .                                              | 231 | 677 | 2,038 |

In line with the purpose of eliciting mitigation costs at the farm level, the main variable of interest in [Isbasoiu \(2019\)](#) was the gross margin per representative farm.

This raises three main issues. First, the gross margin may not perfectly align with farm income. In particular, the gross margin provided in the simulations (sales value minus variable costs) does not account for wages paid, depreciation of capital, land, opportunity cost of own capital, or possible off-farm income sources. Second, a farm may support more or less than one farmer. This raises the question of whether income inequality should be measured per individual or per farm. Third, a recurring issue with farm accounting data is that a non-negligible share of farms reports a negative value of income (Piet and Desjeux, 2021; European Commission, 2021a). Although this is not an issue *per se* for profit maximization, it is clearly problematic when applying the analytical framework presented in Sections 2 and 3, which requires that both pre- and post-policy incomes be positive. The presence of negative income values blurs the interpretation of Lorenz curves, hinders their use in comparing income distributions (Atkinson, 1970), and impedes to relate scheme progressivity and inequality-reducing properties (Le Breton et al., 1996).

These difficulties lead us to make three changes to the simulation data. First, following Piet and Desjeux (2021), we use the operating surplus as a proxy for income. For each representative farm, we retrieved from the EU-FADN the wages paid to workers external to the farm for each representative farm and subtracted them from the gross margin. Total wages amount to approximately 18.1 billion €, or an average of approximately 4,800 € per farm. Annual per-farm income averages about 41,000 € and is characterized by a large coefficient of variation (approximately 2.4), and a median more than three times lower than the mean (see Table 2.2).

Second, we analyze the income distribution on a per-individual basis rather than on a per-farm basis. Thus, we retrieved the number of unpaid workers from the FADN database to account for the number of individuals supported by the respective farm's income. These numbers are expressed in full-time equivalent annual workforce units (AWU). The farms represented in the simulations occupy 4.967 million unpaid AWU. This corresponds to an average of 1.32 unpaid AWU per farm, with values ranging from 0.04 to 6 AWU. All variables at the farm level are normalized using the respective number of unpaid AWU (see the right part of Table 2.2). This normalization slightly increases the coefficient of variation and median-to-mean ratio for both emissions and

income.

Third, we exclude farms with negative income, as is done for example in [Piet and Desjeux \(2021\)](#). Approximately 3.6% of the farms represented in the model (approximately 136,300 farms) fall in this category even in the absence of an emission tax. This share is consistent with that reported by the [European Commission \(2021a, Figure 1.20, p. 24\)](#). As post-policy income must also be positive, we further restrict the analysis to farms with a positive operating surplus for the maximum emission tax rate (100 €/tCO<sub>2</sub>eq). This leads us to exclude 7% of the represented farms (approximately 263,500 farms), corresponding to 7.2% of the total unpaid AWU (approximately 356,100 AWU). As the initial emissions of the excluded farms are, on average, slightly lower than that of the total population, the average initial emissions among the remaining farms are slightly larger than those of the full set of farms (See Table 2.2). Over the retained set of farms, the total initial emissions are almost 7% (ca. 24 MtCO<sub>2</sub>eq) lower than over the full set of farms (see Table 2.3). Nevertheless, the overall relative changes in emissions remain very close to those obtained with the full set of farms for the range of emission tax rates presented in Table 2.3.

These modeling choices call for some discussion. First, as labor is not endogenously modeled, the number of unpaid AWU per farm and the amount of wages paid are assumed to not vary with the tax rate. Second, there are alternatives to operating surplus as a measure of farm income ([Finger and El Benni, 2021](#)). Unfortunately, the simulation data set did not contain the information necessary to compute the corresponding variables. Third, using per-farm (instead of per-individual) income and emissions may make sense from the policymaker's standpoint. Fourth, alternative treatments of farms with negative income might be envisaged, for example by including all farms and arbitrarily setting income to 0 for those with negative income or restricting the analysis to that of a synthetic inequality index that can accommodate negative values such as the generalized Gini index ([Raffinetti et al., 2014](#)). Fifth, farms with extreme income values might be considered too influential and excluded as outliers, as is done for example in [Piet and Desjeux \(2021\)](#). Various combinations of normalizations and alternative treatments for farms with negative and/or extreme income values are explored as robustness checks in Appendix C.

## 5 Distributional impacts of a tax-and-rebate scheme applied to GHG emissions from EU agriculture

We now examine the consequences of the schemes introduced in Section 2 and applied to the simulation data presented in Section 4, starting with their effects at the aggregate level.

The results reported in Table 2.4 underscore the contrasting impacts of the various rebate schemes on total farm income and the regulator's budget. When no rebate accompanies the emission tax (NR), the aggregate farm income is substantially affected. It decreases by 6, 10, and 19% for emission tax rates of 30, 50, and 100 €/tCO<sub>2</sub>eq, respectively. The abatement costs represent only a small fraction of this decrease. The loss in income is predominantly due to the tax burden on unabated emissions, which represents more than 93% of the aggregate loss of income across the range of tax rates. By construction, the tax burden is fully redistributed to farmers under budget-neutral schemes (BN-CAET and BN-CRAT). As a result, the decrease in aggregate farm income relative to initial income remains limited in that case, reaching at most 1.3% of initial income for a 100 €/tCO<sub>2</sub>eq emission tax. Under the two remaining rebate schemes (BC-CAET and AS), farmers see their income increase by up to 3 billion € (1.8% of the total initial income) for a 100 €/tCO<sub>2</sub>eq emission tax. The corresponding cost for the regulator's budget reaches more than 5 billion €.

The Gini index is computed for the five rebate schemes and the full range of emission tax rates. Although it is well known that the Gini index alone does not provide clear-cut conclusions with regard to the ordering of income distributions (Lorenz curves may intersect), it gives a synthetic overview of the consequences in terms of income inequality.

The results are shown in Figure 2.2. The initial situation is characterized by substantial income inequality, with a Gini index value of 0.673. This value is very close to that reported by the European Commission (2021a, Tab. 1.1, p. 24) for the year 2012 (0.67). Figure 2.2 suggests that the design of the rebate has a larger impact on the value of the Gini index than its overall level.

Under an emission tax with no rebate (NR), the Gini index increases with the

## CHAPTER 2. DISTRIBUTIONAL CONSEQUENCES OF CLIMATE POLICIES: AN APPLICATION TO EUROPEAN AGRICULTURE

Table 2.4: Aggregate farm income and impacts on the regulator’s budget of the five tax-and-rebate schemes.

|                                     | Emission tax ( $t$ , in €/tCO <sub>2</sub> eq) |         |         |         |
|-------------------------------------|------------------------------------------------|---------|---------|---------|
|                                     | 0                                              | 30      | 50      | 100     |
| Income ( $X^S(t)$ , in M€)          |                                                |         |         |         |
| NR                                  | 163,034                                        | 153,205 | 146,914 | 131,982 |
| BN-CAET / BN-CRAT                   | 163,034                                        | 162,803 | 162,357 | 160,996 |
| BC-CAET / AS                        | 163,034                                        | 163,421 | 163,941 | 166,035 |
| Net tax revenue ( $G^S(t)$ , in M€) |                                                |         |         |         |
| NR                                  | .                                              | 9,598   | 15,442  | 29,014  |
| BN-CAET / BN-CRAT                   | .                                              | .       | .       | .       |
| BC-CAET / AS                        | .                                              | -618    | -1,584  | -5,039  |

*Note: Income is proxied by operational surplus (see text). The scope is restricted to farms with positive income at  $t = 100$  €/tCO<sub>2</sub>eq (3.503 million farms and 4.611 million unpaid AWU across the EU-27).*

emission tax rate, and reaches a maximum value of 0.690 for a tax rate of 100 €/tCO<sub>2</sub>eq. This finding suggests an increase in income inequality relative to the initial situation.

If the rebate is based on a constant relative abatement threshold (BN-CRAT and AS), the Gini index remains very close to its initial value, increasing by at most 0.15% under BN-CRAT and decreasing by at most 0.08% under AS. By contrast, if the rebate is based on a constant absolute emission threshold (CAET), the Gini index decreases markedly with the emission tax rate. At its minimum (for  $t = 100$  €/tCO<sub>2</sub>eq), it reaches 0.566 and 0.549 under BN-CAET and BC-CAET, respectively, that is, more than 10 percentage points below its initial value, and almost 15 percentage points below that with the same tax rate but no rebate. This suggests a strong decrease in income inequality. These findings are robust to various alternative combinations of assumptions regarding the measure of income (per farm or per unpaid AWU), treatment of farms with negative income, and exclusion of potential outliers with extreme income values (see Figure 2.7 in Appendix C).

As a synthetic measure, the Gini index does not fully describe the policy impact on income distribution across all income quantiles. To refine the analysis of the distributional impacts of the tax, we examine these impacts along the full distribution of initial income, first focusing on the case of an emission tax with no rebate (NR).

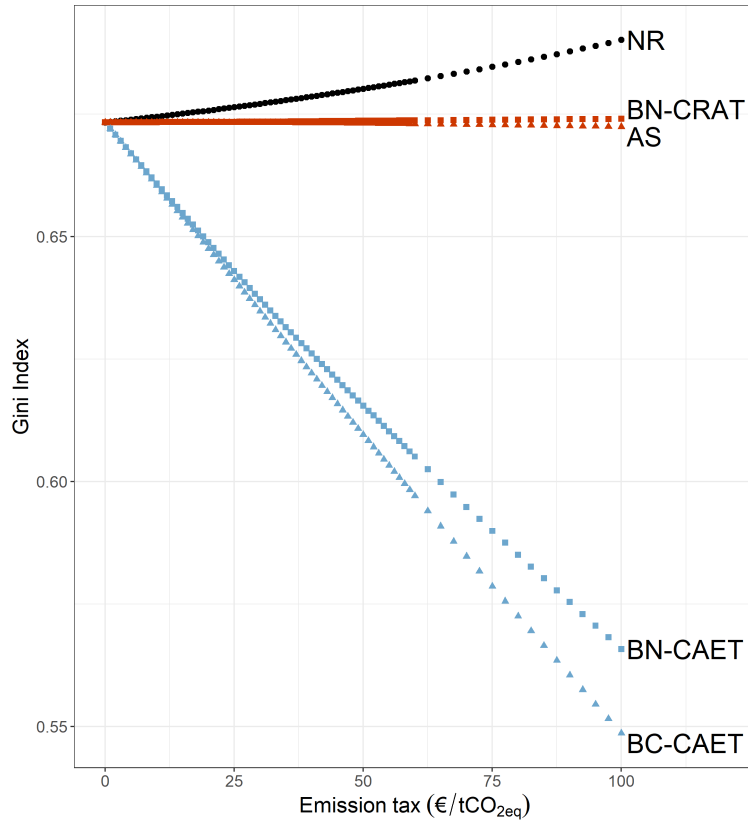


Figure 2.2: Gini index of the distribution of income (per unpaid AWU) under an emission tax from 0 to 100 €/tCO<sub>2eq</sub> and five rebate schemes.

The Lorenz curves of individual income under the pre-policy situation and three emission tax rates (30, 50, and 100 €/tCO<sub>2eq</sub>) are depicted in Figure 2.3 (left), along with the associated delta Lorenz curves relative to the pre-policy situation (right). The latter correspond to the respective changes in cumulative income share for all quantiles (Ferreira et al., 2018). Although the resulting Lorenz curves are very close to one another, the delta Lorenz curves show that the emission tax is unambiguously inequality-increasing for the three considered tax rates. These findings also indicate that the emission tax reduces (increases) the income share of the population below (above) the 9th income decile. The larger the tax rate, the larger the loss in income share for low-income agents.

These results can be further explored along the lines suggested by Proposition 1, which disentangles the influence of the distribution of initial emissions and that of abatement costs. Figure 2.4 (left) depicts the (log-transformed) distribution of individual initial emissions with respect to initial income. It shows a significantly positive

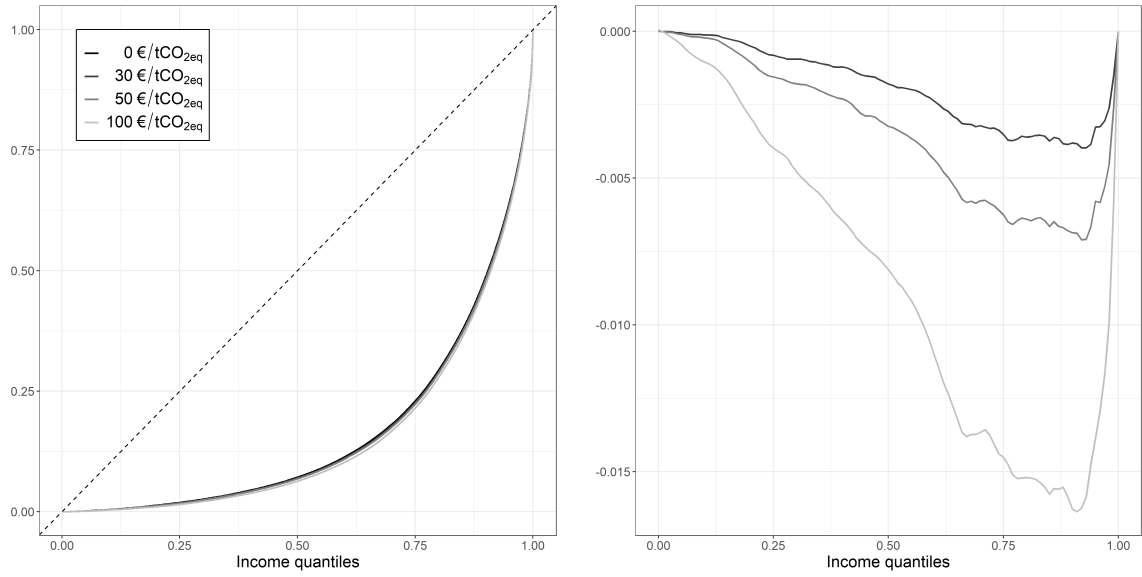


Figure 2.3: Lorenz curves of post-policy income (left) and delta Lorenz curves relative to the pre-policy situation (right) of income under the no-rebate scheme and for various emission tax rates.

association between the initial emissions (in log) and initial income (in log). The estimated slope of the (weighted, log-log) regression line shown in Figure 2.4 (left) is approximately 0.87 (significant at the 1% confidence level). On average, individual initial emissions increase slightly less than linearly with initial income. As a result, lower-income agents tend to bear a proportionally larger tax burden than higher-income agents. As seen in Section 3, this tends to make the emission tax regressive. By contrast, the (log of) net loss in income per unit of initial emissions is not significantly correlated with (log of) initial income (see Figure 2.4, right). In this context, the regressive tendency of the emission tax cannot be compensated for by the distribution of abatement costs.

The result that an emission tax with no rebate is inequality-increasing makes it all the more interesting to further investigate rebate schemes, and compare their distributional impacts for a given tax rate. For ease of exposition, we focus only on the results corresponding to  $t = 100 \text{ €/tCO}_{2\text{eq}}$ .

Figure 2.5 depicts the Lorenz curves of individual income for a  $100 \text{ €/tCO}_{2\text{eq}}$  emission tax and the five rebate schemes (left), along with the corresponding delta Lorenz curves relative to the pre-policy situation (right). The results confirm that rebate designs based on a constant relative abatement threshold (BN-CRAT and AS),

## CHAPTER 2. DISTRIBUTIONAL CONSEQUENCES OF CLIMATE POLICIES: AN APPLICATION TO EUROPEAN AGRICULTURE

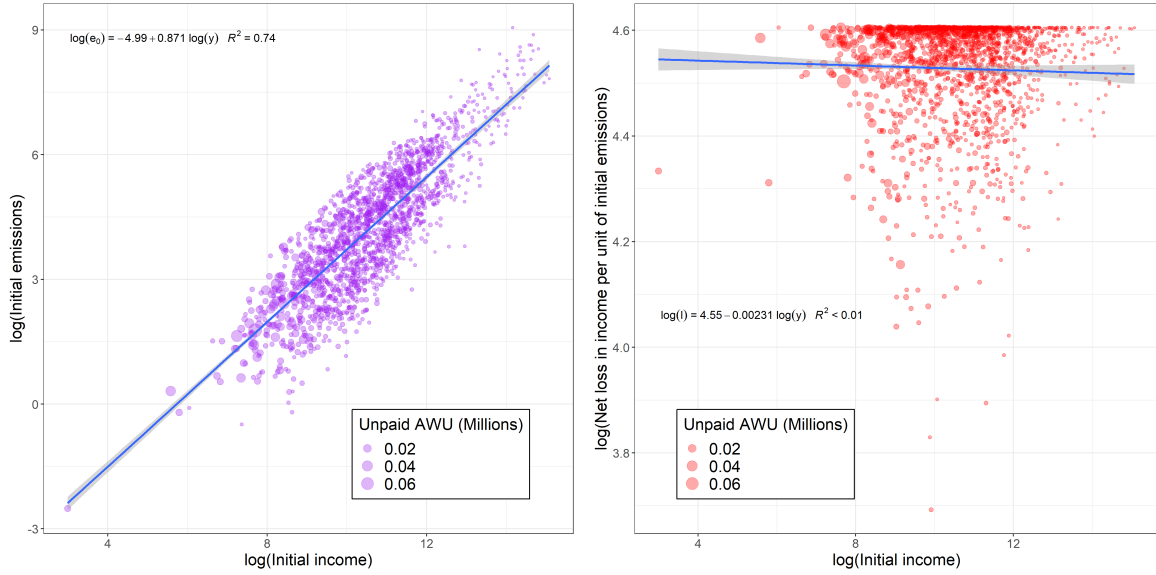


Figure 2.4: Individual initial emissions (left, in  $\text{tCO}_2\text{eq}$  per unpaid AWU) and net loss in income per unit of initial emissions (right, in  $\text{€}/\text{tCO}_2\text{eq}$  per unpaid AWU) with respect to initial income (in  $\text{€}$  per unpaid AWU) for an emission tax rate of  $100 \text{ €}/\text{tCO}_2\text{eq}$  with no rebate (NR).

Note: All variables are log-transformed. The regressions are weighted by the number of unpaid AWU.

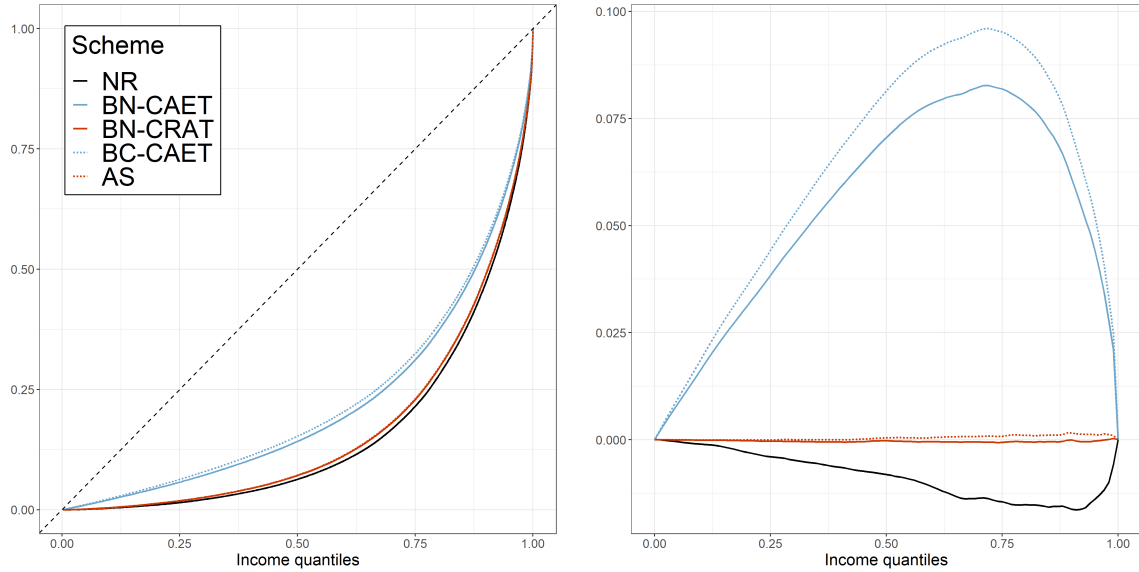


Figure 2.5: Lorenz curves of post-policy income (left) and delta Lorenz curves relative to the pre-policy situation (right) of income under the five rebate designs and for an emission tax rate of  $100 \text{ €}/\text{tCO}_2\text{eq}$ .

despite their marked impacts on the level of aggregate income, have minimal effects on income distribution relative to the pre-policy situation. By contrast, income inequality is substantially reduced (in the Lorenz sense) when the rebate is based on a constant absolute emission threshold (BN-CAET and BC-CAET). In this case, agents with



income below the seventh decile see their share in the total income increase.

The ranking of the income distributions shown in Figure 2.5 is related partly to the distribution of initial emissions (Figure 2.4, left) and partly to the distribution of abatement costs and potential, which jointly determine the individual net loss or gain in income under each rebate design. Figure 2.6 depicts the log of individual net loss or gain in income per unit of initial emissions with respect to the log of initial income for all rebate designs except NR and a 100 €/tCO<sub>2</sub>eq emission tax.

Under an abatement subsidy (AS), all agents enjoy a net gain by construction. The larger the abatement rate that the individual can attain for a given value of  $t$ , the larger the gain per unit of initial emissions. The weighted log-log regression line shown in Figure 2.6 (AS, bottom left panel) is slightly downward sloping (estimated slope -0.11, significant at the 1% level). Together with initial emissions increasing slightly less than linearly with initial income, this implies that the abatement subsidy has a very limited impact on post-policy income inequality. A similar situation prevails for BN-CRAT (bottom right panel of Figure 2.6). In that case, some agents face a net loss and others enjoy a net gain, but these two categories of agents are spread over the entire spectrum of initial income, with no clear pattern indicating that agents in any of these two categories are characterized by lower or higher initial income.

The picture is very different for rebate schemes based on a constant absolute emission threshold (BC-CAET and BN-CAET, top panels in Figure 2.6). As initial emissions are, on average, increasing with respect to initial income, farmers with low (high) initial emissions tend to be also those with low (high) income. Consequently, farmers emitting initially less than the absolute emission threshold, who unambiguously gain from the policy, are more likely to also have lower initial income, whereas farmers with initial emissions larger than the absolute emission threshold are more likely to have a large initial income and incur a net loss. The regression lines summarizing the relationship between the net loss or gain per unit of initial emissions and initial income are resultingly much steeper under BN-CAET and BC-CAET than under BN-CRAT and AS.

The quantitative results presented above substantiate and complement the analytical findings discussed in Section 3. The results show that agriculture can deliver

substantial mitigation for tax rates in the range of current carbon prices. However, if not accompanied by transfers, an emission tax would strongly affect the total farm income, mainly through the tax burden on unabated emissions. An important finding is that initial emissions increase slightly less than linearly with initial income. This has a regressive impact, which is not compensated for by the distribution of abatement costs in the absence of a rebate. Therefore, the conditions of Propositions 1 and 3 are not met, and the emission tax is inequality-increasing, all the more so that the tax rate is high. Hence, a rebate may be appealing to the regulator. If based on a sufficiently large constant absolute emission threshold, income inequality would be reduced not only relative to NR (part (i) of Proposition 2), but also relative to the initial situation (conditions of Proposition 1 are met in that case). If, for the same impact on total income, the threshold is set proportional to farmers' initial emissions, the rebate would still reduce income inequality compared to NR (first case in part (ii) of Proposition 2), but would do very little, if at all, with regard to pre-existing inequality, and thus be Lorenz-dominated by a rebate based on a constant absolute emission threshold (parts (iii) and (iv) of Proposition 2).

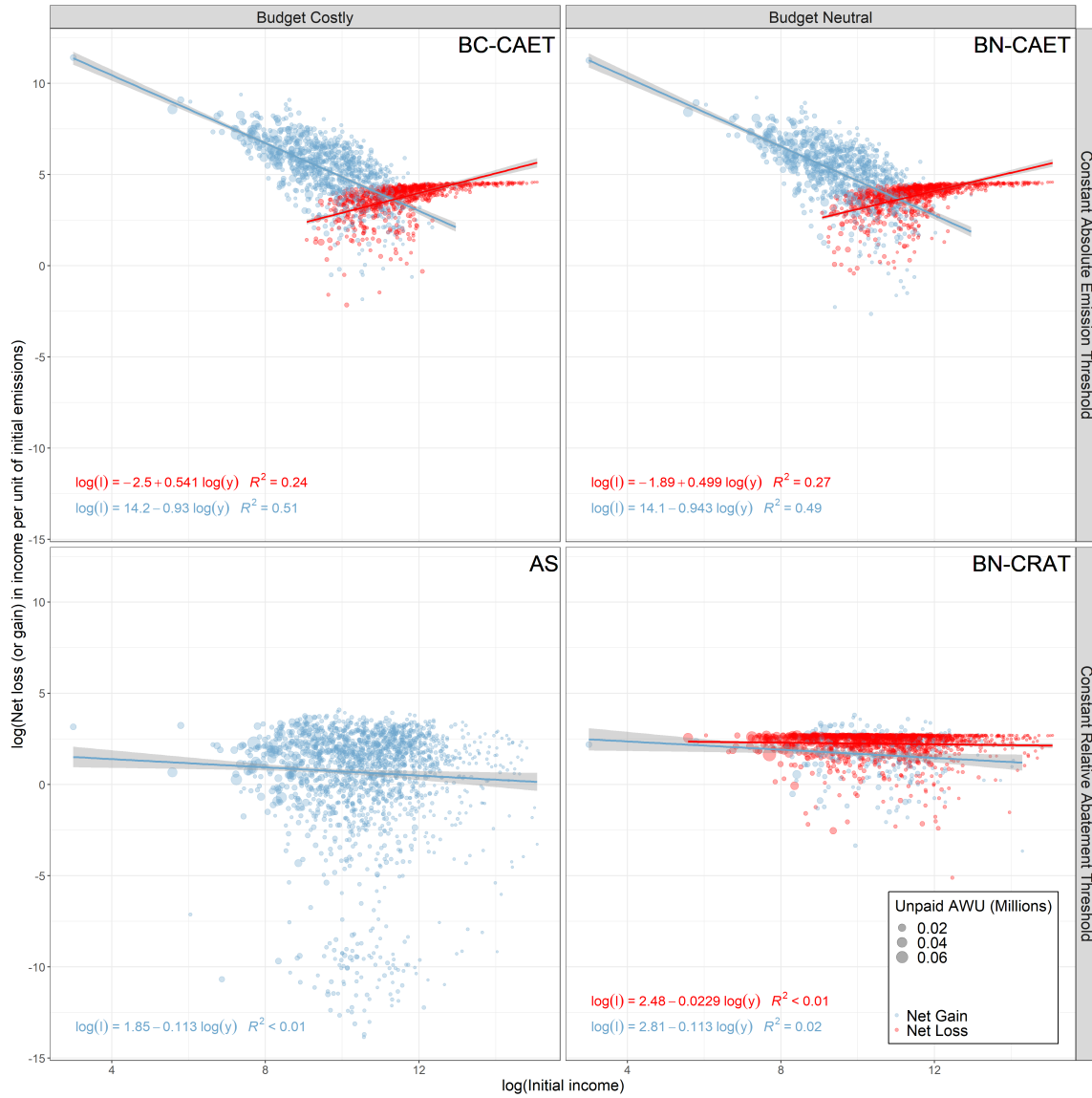


Figure 2.6: Net loss or gain in income per unit of initial emissions for an emission tax rate of 100 €/tCO<sub>2</sub>eq (in €/tCO<sub>2</sub>eq per unpaid AWU), with respect to initial income (in € per unpaid AWU).

Note: All variables are log-transformed. The regressions are weighted by the number of unpaid AWU.

## 6 Concluding remarks

In this study, the distributional consequences of various emission tax-and-rebate schemes have been investigated from both analytical and empirical perspectives.

The design of these schemes differs in the form of the rebate (based on an absolute emission or relative abatement threshold), total transfer to agents, and emission tax rate. For the same emission tax rate, all considered designs yield the same environmental benefit, but have contrasting impacts on the level and distribution of post-policy income, as well as on the regulator's budget. How individual initial emissions vary with initial income plays an important role in the distributional impacts on income and in the relative performances of various designs with regard to income inequality. However, this should be considered jointly with the distribution of abatement costs, which also influences the distribution of net changes in income.

To illustrate the policy relevance of our empirical findings, consider a policy aimed at reducing EU agricultural GHG emissions based on a social cost of carbon of 100 €/tCO<sub>2</sub>eq. Under an emission tax, total emissions would decrease by approximately 15%, from an average of about 74 down to 63 tCO<sub>2</sub>eq per individual full-time equivalent farmer. This suggests a substantial contribution of agriculture to the EU objectives in terms of GHG mitigation. However, without transfers, this would decrease average farm income by almost 20% and increase income inequality (the Gini index increases by almost 2 percentage points). These impacts on income are likely to undermine the political acceptability of such a policy.

For the same environmental benefit, the regulator may find it easier to subsidize each abatement unit. This would be equivalent to accompany the emission tax by a transfer to each individual farmer of 100 €/tCO<sub>2</sub>eq per unit of initial emissions. In this case, farm income would increase by almost 2% on average, income inequality would remain almost constant relative to the initial situation, and the total social value of abatement would be fully supported by the regulator's budget. For the same net budget cost, income inequality could be further decreased (the Gini index more than 12 percentage points below its initial level) if the regulator chooses to tax emissions with a constant rebate based on average initial emissions. This is equivalent to

accompany the emission tax by a lump-sum transfer of approximately 7,400 € to each farmer. The policy could be made budget-neutral by setting the emission threshold to 63 tCO<sub>2</sub>eq for all individual farmers (equivalent to a 6,300 € lump-sum transfer). This would still keep the Gini index 10 percentage points below its initial level. An individualized threshold set at 85% of each farmer's initial emissions would also ensure budget neutrality but have a negligible impact on pre-existing income inequality.

Rebate schemes can thus be pivotal in overcoming some of the barriers to the implementation of an emission tax that would otherwise have a strong negative and regressive impact on farm income. This is all the more important in agriculture as this sector is still largely left aside from the scope of climate policy instruments and is characterized by lower income levels than in the overall population and large income inequality. Moreover, the design of such a scheme leaves room for maneuver to the regulator. For a given value of the marginal environmental damage, the regulator can choose from a variety of designs, depending on social preferences regarding total farm income, income inequality, and considerations regarding potential budget constraints.

In the absence of a policy instrument, it is impossible to directly estimate the distributional consequences of a climate policy. In this regard, the set of simulations used in this study is unique as it informs about the response to an emission tax at the individual farm level with comprehensive coverage of the sector. However, these simulations do not account for possible changes in equilibrium prices due to changes in input and output quantities. Admittedly, this may affect the distribution of abatement costs and potential. Nevertheless, unless the changes in equilibrium prices decrease the net loss in income per unit of initial emissions much more for lower-income farms than higher-income ones, an emission tax with no rebate would remain regressive and rebates based on a constant emission threshold would still reduce income inequality.

This research can be extended in several directions. We only mention two possible directions for future research. First, the implementation costs of these schemes can be investigated further. Regardless of the chosen design, emissions from a large number of agents must be monitored and reported. To reduce the associated costs in the case of an emission tax, [De Cara et al. \(2018\)](#) propose exempting the smallest emitters. Such an exemption can be easily combined with a tax-and-rebate scheme based on a constant

emission threshold. Second, the sources of inequalities in terms of initial emissions and abatement costs can be further decomposed according to the characteristics of the farms, for instance with regard to their region and/or type of farming. This could serve as a basis for designing rebate schemes based on type-of-farming- or region-specific thresholds, which may more accurately reflect differences in terms of initial emissions and abatement costs.

## 2.A Proofs

### 2.A.1 Proof of Proposition 1

Using Eqs. (2.4) and (2.10),  $\xi^S(t, y)$  can be expressed as:

$$\xi^S(t, y) = \frac{y}{x^S(t, y)} - \frac{e_0(y)\ell^S(t, y)}{x^S(t, y)} [\varepsilon(y) + \lambda^S(t, y)] \quad (2.21)$$

Plugging Eq. (2.21) into (2.11), and rearranging gives the conditions of the proposition.

### 2.A.2 Proof of Proposition 2

Consider three continuous and non-negative income distributions  $\mathcal{X}$ ,  $\mathcal{X}_1$ , and  $\mathcal{X}_2$  with  $x_1 = h_1(x)$  and  $x_2 = h_2(x)$  both positive and monotone increasing for all  $x$  in  $\mathcal{X}$ . We know that  $\mathcal{X} \preceq_L \mathcal{X}_i$  if and only if  $h_i(x)/x$  is monotone decreasing,  $\mathcal{X}_i \preceq_L \mathcal{X}$  if and only if  $h_i(x)/x$  is monotone increasing,  $\mathcal{X}_1 \preceq_L \mathcal{X}_2$  if and only if  $h_1(x)/h_2(x)$  is monotone increasing, and that  $\mathcal{X}_2 \preceq_L \mathcal{X}_1$  if and only if  $h_1(x)/h_2(x)$  is monotone decreasing (Fellman, 1976, 2016).

- (i) For any given  $t > 0$ , take  $\mathcal{X} = \mathcal{X}^{\text{NR}}$ ,  $\mathcal{X}_1 = \mathcal{X}^{\text{BN-CAET}}$ , and  $\mathcal{X}_2 = \mathcal{X}^{\text{BC-CAET}}$  with  $h_1(x) = x + t(E_0 - A(t))$ , and  $h_2(x) = x + tE_0$  for all  $x$  in  $\mathcal{X}^{\text{NR}}$ . It is straightforward to verify that  $h_1(x) > 0$ ,  $h_2(x) > 0$ ,  $h'_1(x) > 0$ ,  $h'_2(x) > 0$ ,  $h_1(x)/x$  is monotone decreasing,  $h_2(x)/x$  is monotone decreasing, and  $h_1(x)/h_2(x)$  is monotone increasing.
- (ii) If the emission tax with no rebate (NR) is (strictly) rank-preserving, i.e. if  $x_y^{\text{NR}}(t, y) > 0$  for all  $y$  and any given  $t > 0$ , we can define  $h(x)$  as the inverse function of  $x^{\text{NR}}(t, y)$  with respect to  $y$  such that  $h(x^{\text{NR}}(t, y)) = y$ .

For any given  $t > 0$ , take  $\mathcal{X} = \mathcal{X}^{\text{NR}}$ ,  $\mathcal{X}_1 = \mathcal{X}^{\text{BN-CRAT}}$ , and  $\mathcal{X}_2 = \mathcal{X}^{\text{AS}}$  with  $h_1(x) = x + \left(1 - \frac{A(t)}{E_0}\right) te_0(h(x))$  and with  $h_2(x) = x + te_0(h(x))$  for all  $x$  in  $\mathcal{X}^{\text{NR}}$ .

We have that:

$$h'_1(x) = 1 + \left(1 - \frac{A(t)}{E_0}\right) te'_0(h(x))h'(x) \quad (2.22)$$

$$xh'_1(x) - h_1(x) = \left(1 - \frac{A(t)}{E_0}\right) te_0(h(x)) \left[ \frac{h(x)e'_0(h(x))}{e_0(h(x))} \frac{xh'(x)}{h(x)} - 1 \right] \quad (2.23)$$

Similar relations are obtained for  $h_2(x) = x + te_0(h(x))$  by replacing  $A(t)$  by 0.

As  $e_0(y) > 0$ ,  $x^{\text{NR}}(t, y) > 0$ , and  $0 \leq \alpha(t, y) \leq 1$  for all  $y$  and all  $t > 0$ , we have that  $h_1(x)$  and  $h_2(x)$  are both positive for all  $x$  in  $\mathcal{X}^{\text{NR}}$ . If  $x^{\text{NR}}(t, y)$  and  $e_0(y)$  are both monotone increasing with respect to  $y$ , we have that  $h_1(x)$  and  $h_2(x)$  are also monotone increasing. Denote by  $\xi^{\text{NR}}(t, y) = \frac{yx_y^{\text{NR}}(t, y)}{x^{\text{NR}}(t, y)}$  the elasticity of post-policy income under regime NR with respect to  $y$ . Using the definition of  $h(x)$  and the fact that  $h'(x) = 1/x_y(t, y) > 0$ , we have that  $h_1(x)/x$  and  $h_2(x)/x$  are both monotone decreasing if and only if  $\varepsilon(y) \leq \xi^{\text{NR}}(t, y)$  for all  $y$ . In addition, we have

$$\frac{h_1(x)}{h_2(x)} = 1 - \frac{A(t)}{E_0} \frac{te_0(h(x))}{x + te_0(h(x))} \quad (2.24)$$

$$\left( \frac{h_1(x)}{h_2(x)} \right)' = -\frac{A(t)}{E_0} \frac{te_0(h(x))}{(x + te_0(h(x)))^2} \left[ \frac{h(x)e'_0(h(x))}{e_0(h(x))} \frac{xh'(x)}{h(x)} - 1 \right] \quad (2.25)$$

Therefore we have that  $h_1(x)/h_2(x)$  is monotone increasing if and only if  $\varepsilon(y) \leq \xi^{\text{NR}}(t, y)$  for all  $y$ .

- (iii) For any given  $t$ , assume that the tax-and-rebate scheme BN-CAET is (strictly) rank-preserving, i.e.  $x_y^{\text{BN-CAET}}(t, y) > 0$  for all  $y$ . Define  $h(x)$  as the inverse function of  $x^{\text{BN-CAET}}(t, y)$  with respect to  $y$  such that  $h(x^{\text{BN-CAET}}(t, y)) = y$ . For any given  $t > 0$ , take  $\mathcal{X} = \mathcal{X}^{\text{BN-CAET}}$  and  $\mathcal{X}_1 = \mathcal{X}^{\text{BN-CRAT}}$  with  $h_1(x) =$



$x + t \left(1 - \frac{A(t)}{E_0}\right) (e_0(h(x)) - E_0)$ . We have that:

$$h'_1(x) = 1 + \left(1 - \frac{A(t)}{E_0}\right) t e'_0(h(x)) h'(x) \quad (2.26)$$

$$x h'_1(x) - h_1(x) = \left(1 - \frac{A(t)}{E_0}\right) t e_0(h(x)) \left[ \frac{h(x) e'_0(h(x))}{e_0(h(x))} \frac{x h'(x)}{h(x)} - \frac{e_0(h(x)) - E_0}{e_0(h(x))} \right] \quad (2.27)$$

As  $e_0(y) > 0$ ,  $x^{\text{BN-CAET}}(t, y) > 0$ , and  $0 \leq \alpha(t, y) \leq 1$  for all  $y$  and all  $t > 0$ , we have that  $h_1(x) > 0$  for all  $x$  in  $\mathcal{X}^{\text{BN-CAET}}$ . If  $x^{\text{BN-CAET}}(t, y)$  and  $e_0(y)$  are both monotone increasing with respect to  $y$ , we have that  $h_1(x)$  is also monotone increasing. Denote by  $\xi^{\text{BN-CAET}}(t, y) = \frac{y x_y^{\text{BN-CAET}}(t, y)}{x^{\text{BN-CAET}}(t, y)}$  the elasticity of post-policy income under regime BN-CAET with respect to  $y$ . Using the definition of  $h(x)$  and the fact that  $h'(x) = 1/x_y^{\text{BN-CAET}}(t, y) > 0$ , we have that  $h_1(x)/x$  is monotone increasing if and only if  $\varepsilon(y) \geq \frac{e_0(y) - E_0}{e_0(y)} \xi^{\text{BN-CAET}}(t, y)$  for all  $y$ . Since we assume that  $\varepsilon(y) > 0$  and  $\xi^{\text{BN-CAET}}(t, y) > 0$  for all  $y$ , this condition is readily verified for  $y$  such that  $e_0(y) \leq E_0$ .

- (iv) The proof proceeds exactly as in (iii) by assuming that, for any given  $t$ ,  $x_y^{\text{BC-CAET}}(t, y) > 0$  for all  $y$ , defining  $h(x)$  as the inverse function of  $x^{\text{BC-CAET}}(t, y)$  with respect to  $y$  ( $h(x^{\text{BC-CAET}}(t, y)) = y$ ), and taking  $\mathcal{X} = \mathcal{X}^{\text{BC-CAET}}$  and  $\mathcal{X}_1 = \mathcal{X}^{\text{AS}}$  with  $h_1(x) = x + t(e_0(h(x)) - E_0)$ .

### 2.A.3 Proof of Proposition 3

Differentiating  $\xi^S(t, y)$  with respect to  $t$  yields:

$$\xi_t^S(t, y) = \frac{x_t^S(t, y)}{x^S(t, y)} \left( \frac{y x_{ty}^S(t, y)}{x_t^S(t, y)} - \xi^S(t, y) \right). \quad (2.28)$$

Whenever  $\xi_t^S(t, y)$  is positive (negative), an increase in the tax rate leads to an increase (decrease) in income inequality. The sign of (2.28) depends on that of the marginal change in income  $x_t^S(t, y)$  and on whether the marginal change in income is less or more equally distributed than  $x^S(t, y)$ .

The distribution of the marginal change in income among the total population

can be summarized by:

$$\frac{yx_{ty}^S(t, y)}{x_t^S(t, y)} = \frac{-ye'_0(y)\ell_t^S(t, y) - ye_0(y)\ell_{ty}^S(t, y)}{-e_0(y)\ell_t^S(t, y)} = \varepsilon(y) + \nu^S(t, y) \quad (2.29)$$

Plugging Eq. (2.29) into (2.28) leads to the conditions given in the proposition.

## 2.B EU-FADN types of farming covered by the model

Table 2.5: Classification of main types of farming from the EU-FADN.

---

|                                                   |
|---------------------------------------------------|
| <i>Covered by the model</i>                       |
| Specialist cereals, oilseeds, protein crops       |
| General field cropping                            |
| Specialist dairying                               |
| Specialist cattle - rearing and fattening         |
| Cattle - dairying, rearing and fattening combined |
| Sheep, goats and other grazing livestock          |
| Specialist pigs                                   |
| Specialist poultry                                |
| Various granivore combined                        |
| Mixed cropping                                    |
| Mixed livestock, mainly grazing livestock         |
| Mixed livestock, mainly granivores                |
| Field crops - grazing livestock combined          |
| Various crops and livestock combined              |
| <i>Excluded from the model</i>                    |
| Specialist horticulture                           |
| Specialist wine                                   |
| Specialist orchards - fruits                      |
| Specialist olives                                 |
| Permanent crops combined                          |

---

## 2.C Robustness checks

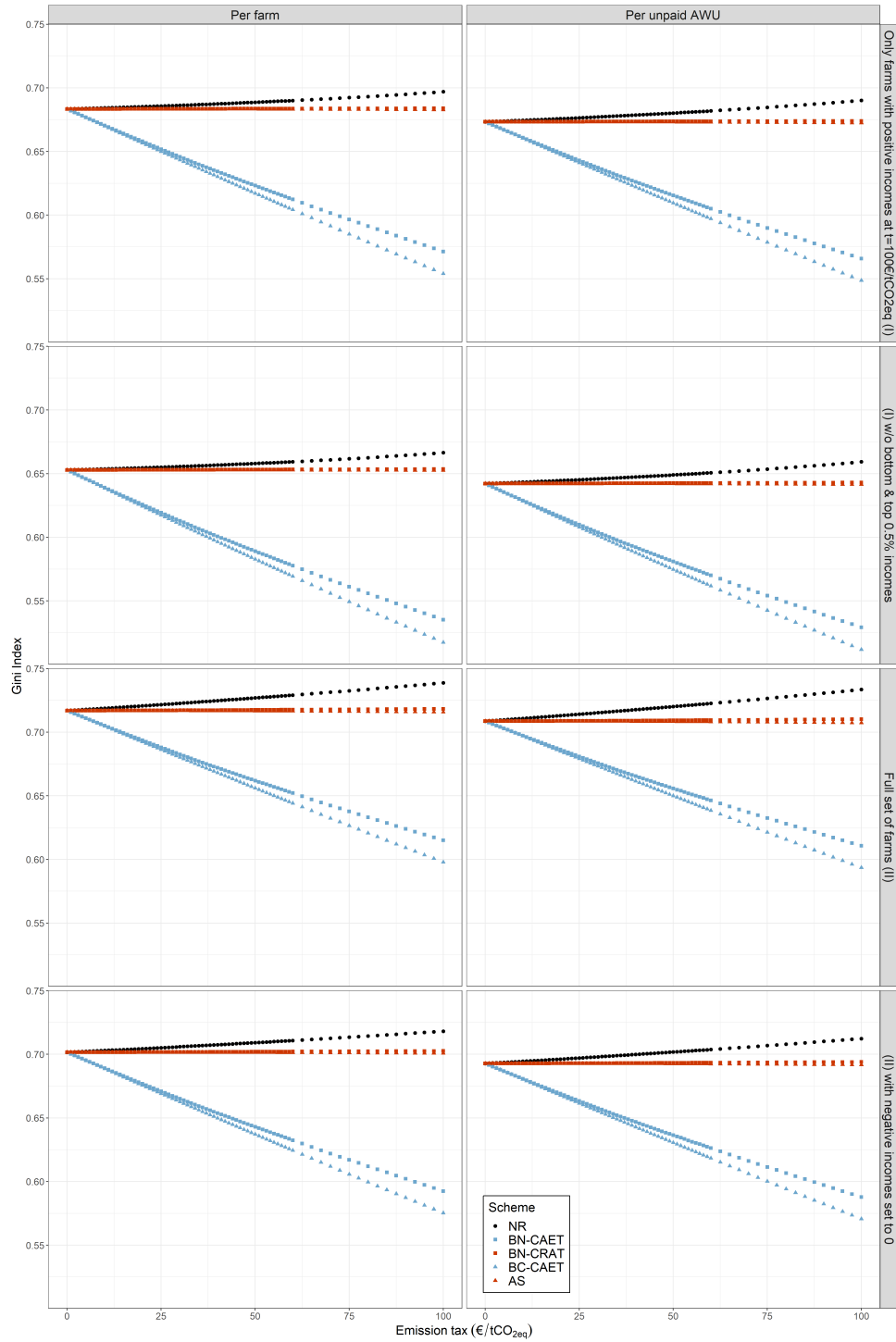


Figure 2.7: Gini index under an emission tax from 0 to 100 €/tCO<sub>2</sub>eq and five rebate schemes for two normalizations (per farm or per unpaid AWU) and four sets of farms: Only farms with positive income at  $t = 100\text{ €/tCO}_2\text{eq}$ , only farms with positive income at  $t = 100\text{ €/tCO}_2\text{eq}$  and excluding the top and bottom 0.5% of income, full set of farms (Generalized Gini Index, [Raffinetti et al. \(2014\)](#)), full set of farms with negative income set to 0.

## CHAPTER 2. DISTRIBUTIONAL CONSEQUENCES OF CLIMATE POLICIES: AN APPLICATION TO EUROPEAN AGRICULTURE

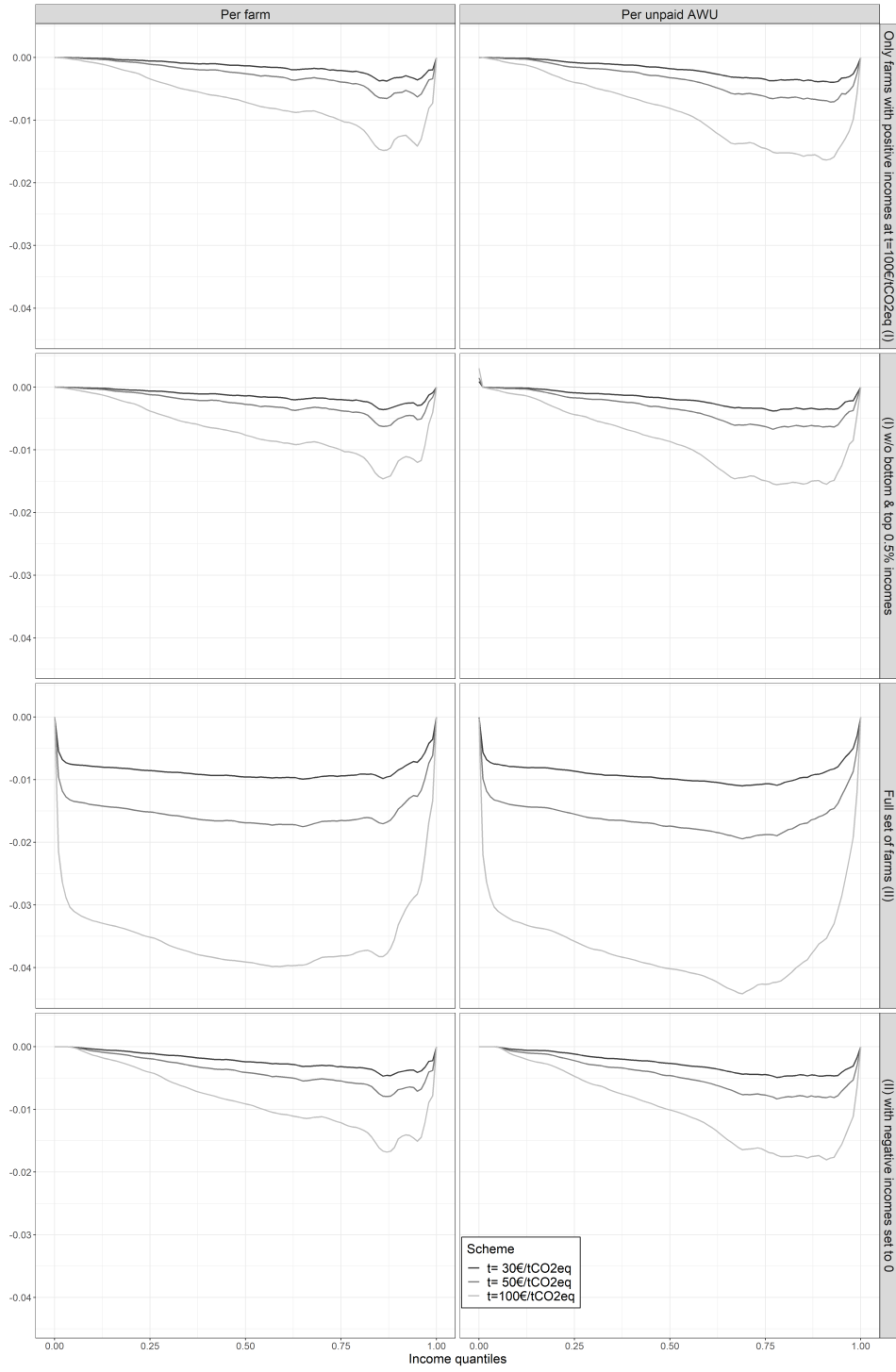


Figure 2.8: Delta Lorenz curves relative to the pre-policy situation of income under the no-rebate scheme and for various emission tax rates for two normalizations (per farm or per unpaid AWU) and four sets of farms: Only farms with positive income at  $t = 100 \text{ €}/\text{tCO}_2\text{eq}$ , only farms with positive income at  $t = 100 \text{ €}/\text{tCO}_2\text{eq}$  and excluding the top and bottom 0.5% of income, full set of farms, full set of farms with negative income set to 0.

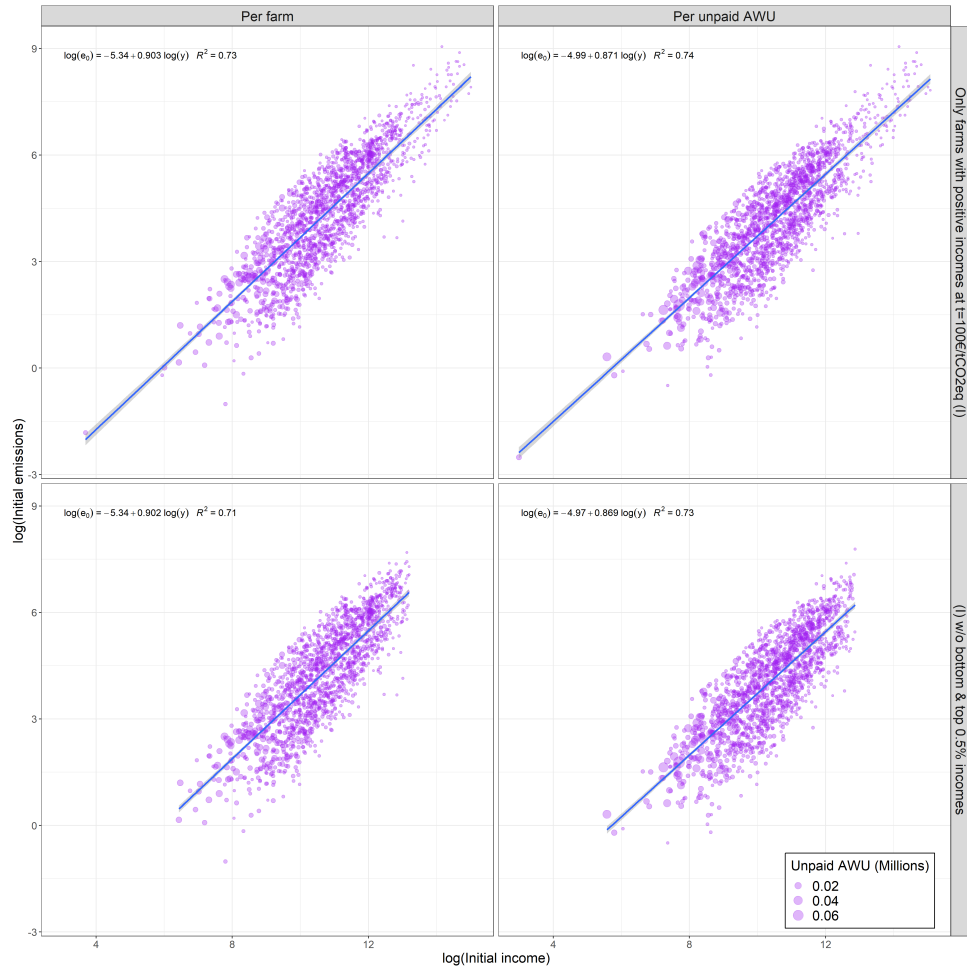


Figure 2.9: Individual initial emissions (in  $\text{tCO}_2\text{eq}$  per farm or per unpaid AWU) for two sets of farms: Only farms with positive income at  $t = 100 \text{ €/tCO}_2\text{eq}$ , only farms with positive income at  $t = 100 \text{ €/tCO}_2\text{eq}$  and excluding the top and bottom 0.5% of income.

Note: All variables are log-transformed. The regressions are weighted by the number of farms or unpaid AWU.

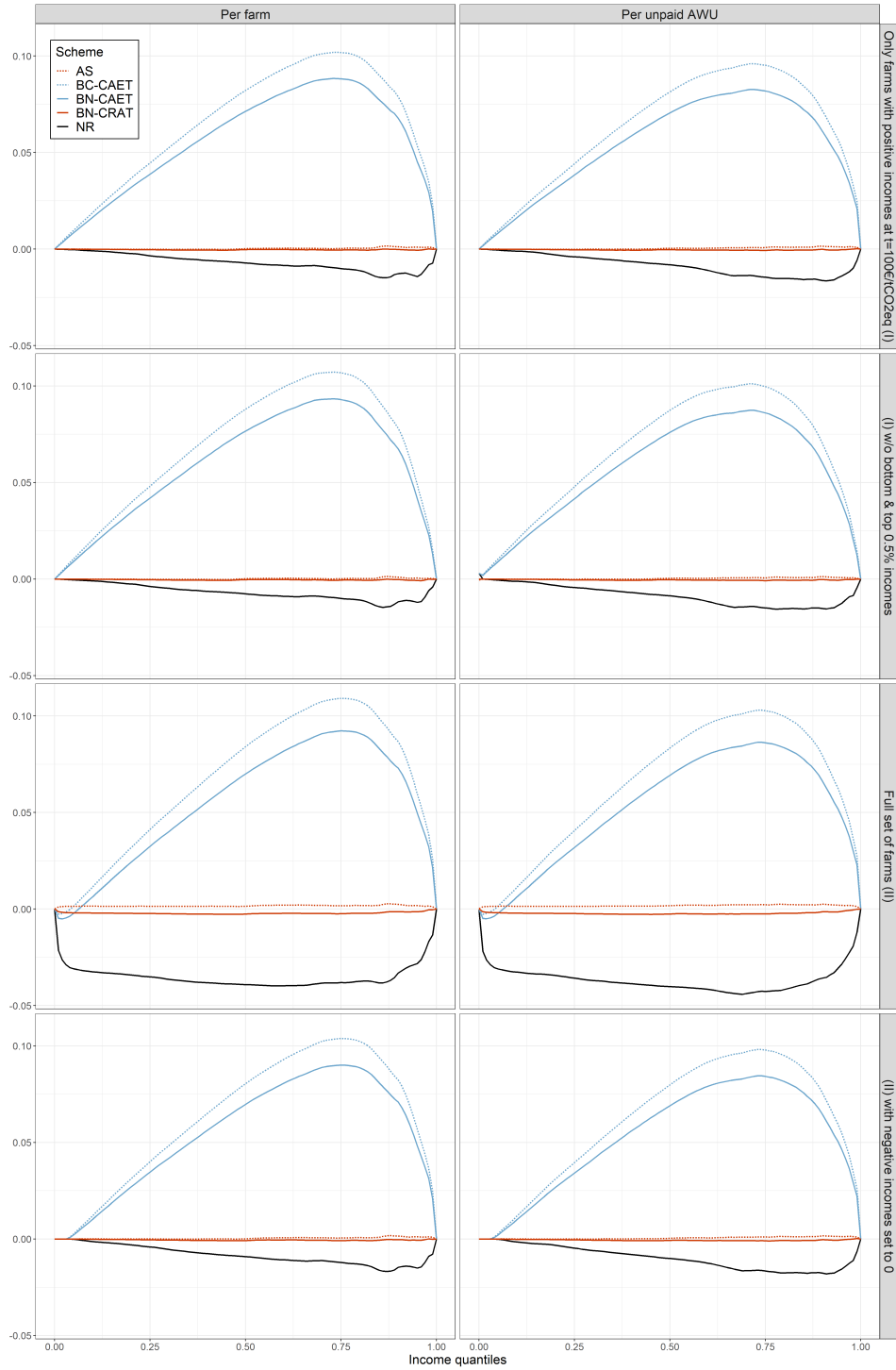


Figure 2.10: Delta Lorenz curves relative to the pre-policy situation of income under the five rebate schemes and for an emission tax rate of 100 €/tCO<sub>2</sub>eq for two normalizations (per farm or per unpaid AWU) and four sets of farms: Only farms with positive income at  $t = 100\text{ €/tCO}_2\text{eq}$ , only farms with positive income at  $t = 100\text{ €/tCO}_2\text{eq}$  and excluding the top and bottom 0.5% of income, full set of farms, full set of farms with negative income set to 0.

## 2.D Income inequality decomposition

What are the marginal contributions of farmers' individual characteristics to the overall income inequality? How do these contributions vary under a GHG emission tax-and-rebate scheme? To address these questions, we apply an inequality-decomposition framework based on the [Shapley \(1953\)](#) value ([Chantreuil et al., 2019](#)).

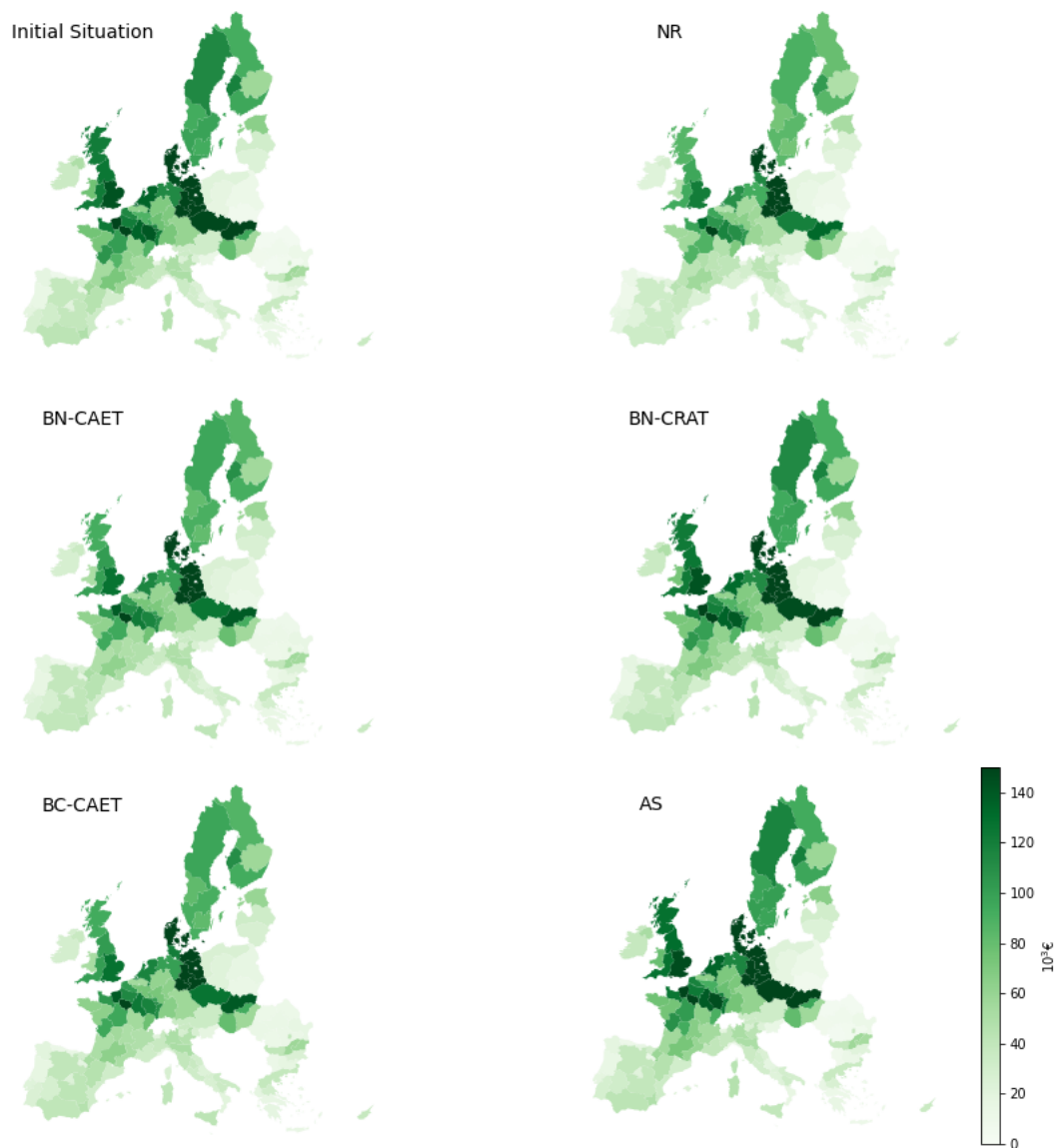


Figure 2.11: Average regional per unpaid AWU income (k€) in the initial situation and for five rebate schemes under an emission tax rate of 100€/tCO<sub>2</sub>eq.

Figure 2.11 depicts the regional per unpaid AWU mean income in the initial situation and for five rebate schemes under an emission tax rate of 100€/tCO<sub>2</sub>eq. It reveals an important heterogeneity across regions in the initial situation. Generally, per

*CHAPTER 2. DISTRIBUTIONAL CONSEQUENCES OF CLIMATE POLICIES:  
AN APPLICATION TO EUROPEAN AGRICULTURE*

unpaid AWU average incomes are higher in Northern Europe (e.g. Denmark, Northern Germany) than in Mediterranean regions (e.g. Southern Italy, Greece). Average income is about 150,000 € per unpaid AWU in Denmark whereas it is approximately 20,000 € in Greece. The different tax-and-rebate schemes do not strongly change the hierarchy between North and South of Europe. However, the tax and no rebate scheme (NR) importantly reduce the average per unpaid AWU income for some Northern regions (e.g. Austria, Netherlands, Southern England). It should be noted that regional average incomes are close to the initial situation when the tax is accompanied by a rebate based on a constant relative abatement threshold (i.e. BN-CRAT and AS), and close to the tax and no rebate scheme (NR) when the tax is accompanied by a rebate based on a constant absolute emission threshold (i.e. BN-CAET and BC-CAET).

Table 2.6: Average per unpaid AWU income (k€) by type of farming in the initial situation (IS) and for five rebate schemes under an emission tax rate of 100€/tCO<sub>2</sub>eq.

| Type of farming                                   | IS   | NR   | BN   |      | BC   |      |
|---------------------------------------------------|------|------|------|------|------|------|
|                                                   |      |      | CAET | CRAT | CAET | AS   |
| Specialist cereals, oilseeds, protein crops       | 64.4 | 58.4 | 64.7 | 63.8 | 65.8 | 64.7 |
| General field cropping                            | 41.2 | 38.3 | 44.6 | 41   | 45.7 | 41.5 |
| Specialist dairying                               | 49.6 | 38.1 | 44.4 | 48.6 | 45.5 | 50.4 |
| Specialist cattle - rearing and fattening         | 26   | 15.1 | 21.4 | 26.7 | 22.5 | 28.7 |
| Cattle - dairying, rearing and fattening combined | 28.1 | 20.6 | 26.9 | 27.9 | 28   | 29.2 |
| Sheep, goats and other grazing livestock          | 20.1 | 12.9 | 19.2 | 19.2 | 20.3 | 20.3 |
| Specialist pigs and poultry combined              | 20.1 | 15.9 | 22.2 | 19.6 | 23.3 | 20.2 |
| Mixed cropping                                    | 11.6 | 10.7 | 17   | 11.5 | 18   | 11.7 |
| Mixed livestock, mainly grazing livestock         | 7.9  | 5.9  | 12.2 | 7.7  | 13.3 | 8    |
| Mixed livestock, mainly granivores                | 14.5 | 10.9 | 17.2 | 14.4 | 18.3 | 15   |
| Field crops - grazing livestock combined          | 42.6 | 34.8 | 41.1 | 42.5 | 42.2 | 43.8 |
| Various crops and livestock combined              | 8.2  | 6.7  | 13   | 8.1  | 14.1 | 8.3  |

Table 2.6 presents per unpaid AWU average income by type of farming in the initial situation and for five rebate schemes under an emission tax rate of 100€/tCO<sub>2</sub>eq. The heterogeneity in the initial situation is less marked than for regional average incomes. Specialist cereals and specialist dairying have the most important average income (64,400 € and 49,600 € respectively) while mixed livestock, mainly grazing have the lowest average per unpaid AWU income (about 7,900 €). The tax and no rebate scheme (NR) reduces average income for all types of farming. Specialist cattle



are the most burdened (e.g. for an emission tax rate of 100€/tCO<sub>2</sub>eq, -11,500 € for specialist dairying, -10,900 € for specialist rearing and fattening, with respect to the initial situation). When the tax is combined with a rebate based on a constant absolute emission threshold (CAET), mean income increases for the lowest incomes with respect to the initial situation (e.g. +4,300 € and +5,400 € for respectively BN-CAET and BC-CAET, for mixed livestock, mainly grazing). Mean incomes are similar to the initial situation when the tax is combined with a rebate based on a constant relative abatement threshold (i.e. BN-CRAT and AS).

We then decompose farmers' income ( $x$ ) by region ( $\omega$ ) and type of farming ( $\sigma$ ). This decomposition implies to write the income of a farmer  $i$  as the sum of three elements:

$$x_i = \bar{x}_{\omega_i} + (\bar{x}_{\omega_i, \sigma_i} - \bar{x}_{\omega_i}) + (x_i - \bar{x}_{\omega_i, \sigma_i}) \quad (2.30)$$

or

$$x_i = \bar{x}_{\sigma_i} + (\bar{x}_{\omega_i, \sigma_i} - \bar{x}_{\sigma_i}) + (x_i - \bar{x}_{\omega_i, \sigma_i}) \quad (2.31)$$

where in equation (2.30) (respectively (2.31)), the income  $x$  can be expressed as the sum of (i) average farmers' income in the region (respectively type of farming) considered:  $\bar{x}_{\omega_i}$  (respectively  $\bar{x}_{\sigma_i}$ ), (ii) the difference between this average income and the average farmers' income of the type of farming in the same region:  $(\bar{x}_{\omega_i, \sigma_i} - \bar{x}_{\omega_i})$  (respectively  $(\bar{x}_{\omega_i, \sigma_i} - \bar{x}_{\sigma_i})$ ), and (iii) an individual part associated with unobserved characteristics ( $r$ ):  $(x_i - \bar{x}_{\omega_i, \sigma_i})$ . The decomposition may start by region or type of farming, and there is *a priori* no reason to choose an order over another (Chantreuil et al., 2020). We obtain three distributions (i.e. region, type of farming and residuals), the sum of which allows to meet the distribution of farmers' income. We could then apply the Shapley formula to a Gini index of different distributions where an individual characteristic can take either its exact or average value to determine the contribution of a characteristic  $j = \{\omega, \sigma, r\}$  to the overall income inequality.

$$Sh_j = \sum_{K \subset M, j \in K} \frac{(k-1)!(m-k)!}{m!} \cdot [G(\Psi(K)) - G(\Psi(K - \{j\}))] \quad (2.32)$$

where  $G$  is the Gini index,  $M$  is the set of farmers' characteristics,  $m$  the cardinality of  $M$ ,  $K$  a subset of  $M$ ,  $k$  the cardinality of  $K$ .  $\Psi(K)$  is the distribution of farmers' income among the subset  $K$ , defined by  $\Psi(\emptyset) = 0$ , and for all  $K \in 2^M$ ,  $K \neq \emptyset$ .

$$\Psi(K) = \sum_{j \in K} x_1^j + \sum_{j \notin K} \mu(x^j), \dots, \sum_{j \in K} x_n^j + \sum_{j \notin K} \mu(x^j) \quad (2.33)$$

where  $\mu(x^j)$  is the average farmers' income from farmers' characteristic  $j$ .

|     |          |       |       | BN    |       | BC    |       |
|-----|----------|-------|-------|-------|-------|-------|-------|
|     |          | IS    | NR    | CAET  | CRAT  | CAET  | AS    |
|     | $G$      | 0.673 | 0.690 | 0.566 | 0.674 | 0.549 | 0.672 |
| (1) | $\omega$ | 49.4% | 47.8% | 47.8% | 49.7% | 47.8% | 49.9% |
|     | $\sigma$ | 26.1% | 27.5% | 27.5% | 25.9% | 27.5% | 25.8% |
|     | $r$      | 24.5% | 24.7% | 24.7% | 24.4% | 24.7% | 24.3% |
| (2) | $\omega$ | 52.2% | 50.5% | 50.5% | 52.3% | 50.5% | 52.5% |
|     | $\sigma$ | 22.9% | 24.4% | 24.4% | 23.0% | 24.4% | 22.8% |
|     | $r$      | 24.9% | 25.1% | 25.1% | 24.7% | 25.1% | 24.7% |

Table 2.7: Marginal contributions of region ( $\omega$ ) and type of farming ( $\sigma$ ) to overall income inequality in the initial situation and for five rebate schemes under a 100€/tCO<sub>2</sub>eq emission tax rate.

Note: The two decomposition orders are presented when beginning the decomposition by region (1) and when beginning the decomposition by type of farming (2).

Table 2.7 details the results of the Shapley decomposition of the Gini index ( $G$ ) of the distribution of per unpaid AWU income in the initial situation and under five rebate schemes for an emission tax rate of 100€/tCO<sub>2</sub>eq. In the initial situation, the region importantly contributes to income inequality (49.4% to 52.2%), while the contribution of the type of farming is more limited (22.9% to 26.1%). Both region and type of farming explain approximately 75% of overall inequality. Under the tax and no rebate scheme (NR), the marginal contribution of region to income inequality is slightly reduced (47.8% to 50.5%) while the marginal contribution of type of farming slightly increases (24.4% to 27.5%). When the tax is accompanied by a rebate based on a constant absolute emission threshold (i.e. BN-CAET and BC-CAET), the marginal contributions are equal to the NR scheme (the transfer of the same amount to all individuals does not affect marginal contributions (Chantreuil et al., 2019)). When the

tax is accompanied by a rebate based on a constant relative abatement threshold (i.e. BN-CRAT and AS), findings are quite close to the initial situation.







## Chapter 3

# Extreme temperatures and inequality: Evidence from French agriculture





\* \* \*

Climate change is expected to alter the frequency of occurrence of extreme weather events. Applying quantile regressions on French crop farmers individual cross sectioned data over the period 2002-2017, we quantify the distributional effect of extreme temperatures on farm income. Findings indicate that both hot and cold extreme temperatures during the growing season may on average substantially reduce farm income. The distributional analysis unveil (i) an important heterogeneity between farmers and (ii) opposite effects of cold and hot extreme temperatures. While cold extreme temperatures are found to be more damaging for lowest incomes, and hence increase inequality, hot extreme temperatures are found to be more harmful for highest incomes, and decrease inequality. Two possible reasons for this antagonistic impact of extreme temperatures are explored. First, there could be a crop effect: the proportion of corn in the crop mix decreases with income, while the proportion of rapeseed increases with income. Second, there could be a region effect: the proportion of Northern farmers increases with income while the proportion of Southern farmers decreases with income.

\* \* \*

## 1 Introduction<sup>1</sup>

An increasing amount of evidence from the climate-economy literature (Dell et al., 2014) suggests that extreme temperatures may dramatically affect agricultural production. In this direction, Schlenker and Roberts (2009) for example identify critical temperature thresholds (e.g. 29°C for corn, 30°C for soybeans) from which yields start to seriously decrease. In general, the study of climate shocks on agriculture consists in estimating the marginal effect of an increase in climate variables such as temperature (Chen et al., 2016) or precipitation (Zhang et al., 2017) on agricultural outcomes such as land value (Mendelsohn et al., 1994) or profits (Deschênes and Greenstone, 2007). However, very little is known on the distributional consequences of climate change on agriculture.

The main objective of this study is to examine the potential distributional effects of extreme temperatures on French crop farmers' income. The French case is particularly relevant to illustrate the distributional impacts of climate change. First, French crop production is varied, and it is the biggest crop producer of wheat, barley, rapeseed and corn in the European Union (EU).<sup>2</sup> Hence, our study can inform on extreme temperatures consequences on crop production in mild climate regions. Second, France is part of the European Common Agricultural Policy (CAP). On the one hand, the major share of the CAP budget concerns farm income support. For the EU, farm income support amounts to 38.1 billion euros (i.e. 65.2% of total CAP allocations 58.4 billion euros).<sup>3</sup> France is the first recipient of CAP allocations with 10.21 billion euros in 2021. On the other hand, CAP has included redistributive goals since its creation. Article 39 in the Rome treaty stipulates that one of the objective of the CAP is to "*ensure a fair standard of living to the agricultural community*". This goal of equity between farmers is reaffirmed in the new CAP that will start in 2023 with the implementation of a *complementary redistributive income support mechanism*. Consequently, accounting for these distributional effects of climate shocks is crucial for many reasons. First, distributional effects of extreme temperatures are important as

---

<sup>1</sup>This chapter comes from a collaboration with Clément Nedoncelle.

<sup>2</sup>Source Eurostat: <https://ec.europa.eu/eurostat/fr/web/agriculture>

<sup>3</sup>Source Eurostat: [https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/financing-cap/cap-funds\\_en](https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/financing-cap/cap-funds_en)

they inform on the aggregate costs of weather shocks. Second, identifying losers and winners from weather shocks and understanding how these differential effects emerge allow to provide the correct public policy response to these shocks.

Our empirical analysis combines three databases. First, we use pooled cross-section data from the French Farm Accountancy Data Network (FADN) delivering individual and annual survey data for approximately 7,500 French farms in a year, representative of the French production. Second, we gather daily weather informations from *MeteoFrance* that we disaggregate at a municipality level. Third, we take advantage of the European soil database (ESDB) for providing the municipality quality, altitude and slope of land.

Our findings indicate that both hot and cold extreme temperatures may be costly for farmers. A 10% increase in cold (resp. hot) extreme degree days may cost on average 411€ (resp. 1,123€) per year to French crop farms. Our distributional analysis indicate opposite consequences of cold and hot extreme temperatures. While cold extreme degree days are more harmful for poorest than richest farmers, and may increase income inequality, hot extreme degree days are more detrimental for the richest farmers and may decrease income inequality. Two potential channels may explain these opposite effects: a crop effect (i.e. the proportion of corn area decreases with income, while the proportion of rapeseed area increases with income) and a region effect (i.e. the probability of being located in the North increases with income).

This chapter is related to three major streams of the literature, that we extensively discuss in the next section. Our contribution to the literature on the heterogeneous impacts of weather shocks is to provide evidence on the potential distributional impacts of extreme temperatures. To the best of our knowledge, this study is the first attempt to quantify the distributional impacts of extreme temperatures on farmers' income.

The remainder of the chapter is structured as follows. The literature which is related to our study is detailed in section 2. Section 3 describes the data sources and the main variables we use. Section 4 presents our empirical strategy. Aggregate and distributional impacts of extreme temperatures on French crop farmers' income are quantified in section 5. Section 6 discusses the findings with respect to the literature

and explores the potential reasons for explaining the distributional effects of extreme temperatures. Section 7 concludes.

## 2 Related Literature

In this section we detail the main fields of research related to this study: (i) agriculture and weather events, (ii) impacts of extreme weather events, and (iii) distributional impacts of weather shocks.

### 2.1 Agriculture and Weather

Our study is broadly related to the extensive literature estimating the impact of weather shocks on agriculture, yields and profit. This literature points towards large negative impact of temperatures shocks, precipitations, through changes in yields and profits. Since Mendelsohn et al. (1994) contribution, many studies have analyzed climate and weather impact on agriculture, including among others Schlenker et al. (2005); Schlenker and Roberts (2009); Deschênes and Greenstone (2007); Burke and Emerick (2016); Chen et al. (2016); Zhang et al. (2017); Fezzi and Bateman (2015); Ortiz-Bobea (2020).

For example, Moore and Lobell (2015) while focusing on Europe, show that temperature and precipitation trends since 1989 have reduced wheat and barley yields (-2.5% and -3.8% respectively) and have slightly increased maize and sugar beet yields. Closer to the geographical scope of our study, Gammans et al. (2017) suggest that French crop yields may be negatively affected by climate change.

Finally, most of these articles draw implications on future weather impact using past, historical data. The implicit assumption is that past weather shocks inform on the economic costs of climate change (Kolstad and Moore, 2020). We build on this literature by estimating the effect of extreme temperatures on French crop farmers' income.

## 2.2 Extreme weather events impact

Our work also contributes to the growing literature on extreme weather impacts, in particular on agriculture (Botzen et al., 2019). Whereas most of the seminal contributions in the field used fluctuations in temperatures or precipitations to assess the impact of weather shocks, recent progress has been made regarding the effect of extreme events. Climate projections tell us that changing extreme weather patterns are likely to be more frequent (Stephenson et al., 2008).

Following Jahn (2015), extreme events can be defined by occurrence extremity and/or by impact extremity: in the former case, the probability to observe the event is rare, whereas in the latter, the event has severe impacts. In our study, we focus on the former definition: extreme events are also rare events (independently of their impacts). Jahn (2015) provides a typology of events that can be considered as extreme: they include floods, droughts, heat waves, cold waves or storms (Strobl, 2011; Hsiang, 2010). A review of the diverse economic impacts of natural disasters is provided in Botzen et al. (2019).

The main difficulty that arises when estimating the economic impact of extreme weather events is that standard econometric approaches provide the marginal impacts of a marginal change in weather. Yet, extreme weather events are by nature non-marginal events. To overcome this, many recent articles use up-to-date event-study methodologies to assess the impacts of such events. Examples include Cavallo et al. (2011); Martincus and Blyde (2013); Gassebner et al. (2010); Paudel and Ryu (2018); Gröger and Zylberberg (2016); Hamano and Vermeulen (2019).

In the present chapter, we take a different stand and go back to marginal measures of weather shocks. Details are presented in section 3: our main measure of extreme events is the sum of degree days with extreme temperatures. It allows us to estimate the marginal impact of an additional extreme degree day. We go back a standard estimate of the marginal impact of an event (the marginal degree day of extreme temperature).

## 2.3 Distributional impacts of weather shocks

Our study builds upon recent development in the identification of the distributional effect of weather shocks. There is an emerging empirical literature on the heterogeneity of climate change effects. Early literature identified heterogeneous impact across countries (Mendelsohn et al., 2006) whereas recent literature tends to identify distributional impact even within each country (Hsiang et al., 2019).

These distributional effects usually manifest through heterogeneous damages across groups or nonlinear marginal damages along group characteristics (Hsiang et al., 2019). Regarding the impact of weather shocks on agriculture, the literature has tried to identify the sources of these heterogeneities. Among others, Annan and Schlenker (2015) find that crop insurance reduces farmers' adaptation to extreme heat in the US. Hornbeck (2012) shows that the adjustment to the 1930s American Dust Bowl occurred predominantly through large relative population declines rather than through agricultural adjustments (away from less productive crops or activities). In the Ogallala aquifer region, Hornbeck and Keskin (2014) show that after the introduction of a new irrigation technology, land use adjusted toward water intensive crops and drought sensitivity increased. On the contrary, locations without access to groundwater were more drought resistant.

Recently, DePaula (2020) estimates interquantile regressions of land value on climate using agricultural census data in Brazil. Temperatures shocks are more detrimental to high-quality (unobserved) land, whereas precipitation have the opposite heterogeneous effects. In another recent contribution, Malikov et al. (2020) estimate that, in the US, between 1948 and 2010, a given weather shock has larger, negative magnitudes at the lower yield quantiles, leading to negative distributional effects across yields quantiles.

In terms of methodology, these differential effects of climate shocks have mainly been identified using quantile regression estimators. Another less demanding approach would be to use interaction terms between weather shocks and farms characteristics to identify the heterogeneous effects. This approach has been used in a variety of context to understand the differential effects of a common shock across individuals, countries,

regions or setups.<sup>4</sup> The main difficulty lies in the choice of the farms characteristics. Another issue is that the conditional relationship between the outcome and farm characteristics is assumed to be linear in the firm characteristics. In a sense, relaxing these assumptions comes at the costs of the estimation difficulty in quantile regressions. The present study builds on recent advances in econometrics regarding the identification of quantile regression models, see e.g. Chernozhukov and Hansen (2005); Angrist et al. (2006). In particular, we control for unobserved heterogeneities using various fixed effects in a quantile regression framework. To do that, we leverage on the approach in Machado and Santos Silva (2019) and applied in Machado et al. (2021), which indirectly estimates quantiles via moment and allows for non linear specifications (thus abstracting from the incidental parameter problems, see e.g. Koenker (2004)).

### 3 Data sources and main variables

We use a dataset combining information at the farm level, daily weather informations and soil data at the municipality level. Our study focuses on the period from the year 2002 to 2017.

#### 3.1 Weather informations

**Extreme Temperatures** We gather observed daily weather informations from *Météo France* for the entire period. These are daily data available at a  $8\text{km} \times 8\text{km}$  *SAFRAN* grid, obtained from 554 weather stations across Metropolitan France and interpolated by the Centre National de Recherches Météorologique (CNRM). We disaggregate the data into municipality-level informations.<sup>5</sup> Data include daily mean temperatures, precipitations (including rain and snowfalls), and other weather outcomes. We consider the twelve years 1988-1999 as the municipality-specific climate reference. For each city  $i$ , we range all daily temperatures observations and identify

---

<sup>4</sup>A seminal article in this direction is Rajan and Zingales (1998). This article provides evidence that financial development is important for economic development by documenting that industrial sectors that are more dependent on external finance grow faster in countries with a high level of development. This estimation highlights interactions between financial development and dependency on external finance.

<sup>5</sup>Variables in the *SAFRAN* grid are representative on average for 4 municipalities.

specific thresholds in the distribution,  $T_{i,\text{ref}}^p$ . Our baseline measures are the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the observed distribution of temperatures, denoted  $T_{i,\text{ref}}^{10}$  and  $T_{i,\text{ref}}^{90}$  respectively. These are the city-specific temperatures thresholds above which observed temperatures—outside the reference period—are considered as extreme. Indeed, we consider that temperatures that are outside of this interval are unlikely events, consistently with the main definition of an extreme weather event (Stephenson et al., 2008).

Outside this reference period, we compute at the city-year  $t$  level, extreme degree days during the growing season (Deschênes and Greenstone, 2007) by calculating the cumulative sum of degree days that can be considered as extreme. Hence, we define  $H_{it}^{90}$  as the extreme degree days when temperatures were above the 90<sup>th</sup> percentile of observed past temperatures:

$$H_{it}^{90} \equiv \sum_k (T_{k,it} - T_{i,\text{ref}}^{90}) \text{ for all } T_{k,it} \geq T_{i,\text{ref}}^{90} \quad (3.1)$$

where  $k$  is a growing-season day, from April 1st to September 30th (Deschênes and Greenstone, 2007), and where  $T_{k,it}$  is the average temperature for day  $k$  in municipality  $i$ . In the same way, cold extreme degree days— $C_{it}^{10}$ —are expressed as:

$$C_{it}^{10} \equiv \sum_k (T_{i,\text{ref}}^{10} - T_{k,it}) \text{ for all } T_{k,it} \leq T_{i,\text{ref}}^{10}. \quad (3.2)$$

**Other Weather Events** Our data also allows us to identify other weather shifts that may have an impact of farmers' revenues. In particular, we compute average degree days— $M_{it}^{10-90}$ —that corresponds to the sum of degree days when temperatures were comprised between the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the observed distribution of temperatures:

$$M_{it}^{10-90} \equiv \sum_k (T_{k,it} - T_{i,\text{ref}}^{10}) \text{ for all } T_{i,\text{ref}}^{90} \geq T_{k,it} \geq T_{i,\text{ref}}^{10} \quad (3.3)$$

Finally, we capture cumulative precipitations over the growing season. All data are aggregated by city-year.



### 3.2 Farms accountancy informations

We combine the weather data at the city level with information on farmers' activities from the Farm Accountancy Data Network (FADN) dataset. We rely on the French sample of farms included in the european FADN: it provides for the studied period (i.e. 2002-2017), individual and annual survey data for 18,546 French crop farms, so approximately 1,156 crop farms per year. In FADN, farms are localised at the city level, allowing us to match this data with weather data. We thus know the weather conditions faced by farmers depending on their city.

**Farmers' incomes** For each farm, information regarding their activities, their inputs, their output values, are available and allow us to estimate an income for farmers. Following [Piet and Desjeux \(2021\)](#) we define income as the operating surplus—i.e. the total output plus the current subsidies, minus taxes and the total intermediate consumption—of the farm. We also present the results taking a per-individual basis by normalizing the operating surplus by the number of unpaid annual workforce units (AWU) of the farm.

### 3.3 Land quality informations

An analysis on the effects of climate of farmers' income may not be exhaustive without soil informations. Hence, we rely on the European soil database (ESDB) produced by the joint research centre [Panagos et al. \(2012\)](#). Data initially available at a grid with cell sizes of  $10\text{km} \times 10\text{km}$  for a large number of soil related parameters, are disaggregated to obtain the information at a municipality-level. It provides important soils characteristics such as altitude, slope, and proportions of land quality in five class of texture, presented in [3.1](#).

### 3.4 Descriptive statistics

In this section we aim at providing some descriptive statistics concerning extreme temperature events and farmers' income. We also explain the restrictions applied on our dataset.

Table 3.1: French class of soil texture.

| Class texture | Clay               | Sand          |
|---------------|--------------------|---------------|
| Coarse        | more than 18%      | less than 65% |
| Medium        | between 18 and 35% | more than 15% |
| Medium fine   | more than 35%      | more than 15% |
| Fine          | between 35 and 60% |               |
| Very fine     | more than 60%      |               |

**Evolution of Extreme Events** Figure 3.1 plots the average extreme degree days experienced by farmers, left: hot extreme degree days ( $H_t^{90}$ ) and right: cold extreme degree days ( $C_t^{10}$ ). On the one hand, our measures display year-to-year fluctuations in extreme events: indeed, we capture the 2003 European heat wave as expected, as well as the cold winter 2010–2011 in Europe. On the other hand, there seems to be a trend towards an increase in both hot and cold events over time, which can be interpreted as a manifestation of a climate change. It should be noted that extreme degree days experienced by the farmers present in the data are close from extreme degree days for all France (See Appendix A). This suggests that our farmers are randomly distributed over the country, as extreme temperatures they face are on average representative of extreme temperatures all over France.

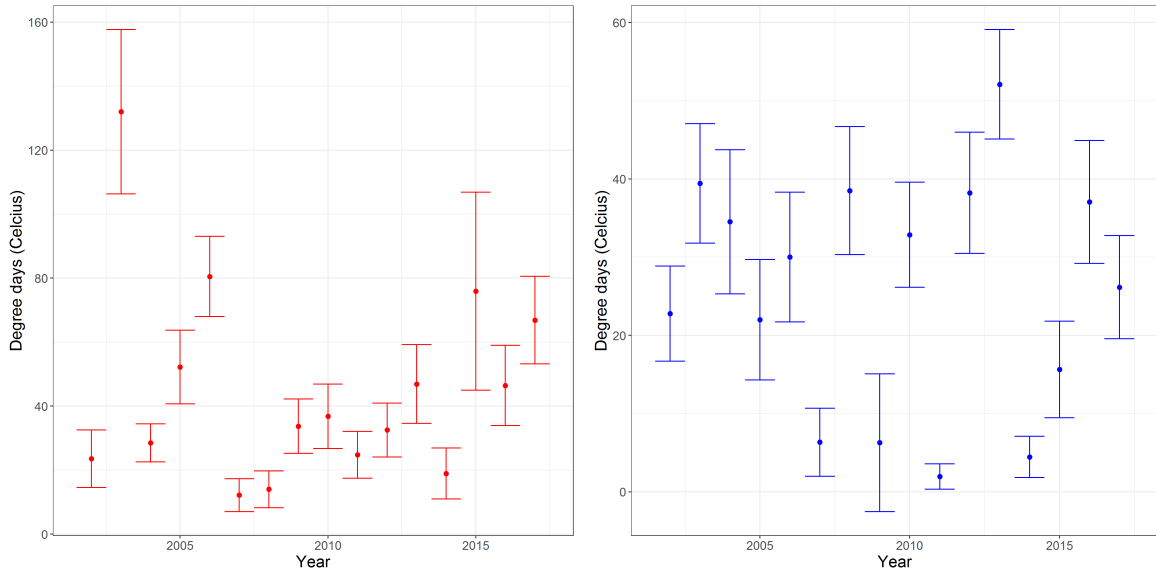


Figure 3.1: Average annual extreme degree days experienced by farmers, left: hot extremes ( $H_t^{90}$ ), right: cold extremes ( $C_t^{10}$ ).

*Note: Error bars represent standard deviation.*

### CHAPTER 3. EXTREME TEMPERATURES AND INEQUALITY: EVIDENCE FROM FRENCH AGRICULTURE

Table 3.2: Descriptive statistics of income for two normalizations and two sets of farms.

|                                                                                      | Per farm |      |       |      |       | Per unpaid AWU |      |        |      |       |
|--------------------------------------------------------------------------------------|----------|------|-------|------|-------|----------------|------|--------|------|-------|
|                                                                                      | mean     | s.d. | min   | med. | max   | mean           | s.d. | min    | med. | max   |
| <i>Full set of farms</i>                                                             |          |      |       |      |       |                |      |        |      |       |
| Income (k€)                                                                          | 83.4     | 70.7 | -93.1 | 66.7 | 938.3 | 66.0           | 58.4 | -303.8 | 54.8 | 1,162 |
| <i>Restricted set of farms with positive income and positive extreme degree days</i> |          |      |       |      |       |                |      |        |      |       |
| Income (k€)                                                                          | 85.7     | 68.2 | 0.0   | 68.8 | 700.7 | 67.3           | 53.2 | 0.0    | 56.3 | 1,162 |

Note: Income is proxied by operational surplus (see text). AWU: Annual Workforce Unit; Full set of farms: 17,267 farms and 22,575 unpaid AWU; Restricted set of farms with positive income and positive extreme degree days: 13,465 farms and 17,725 unpaid AWU.

**Data restriction** We apply two restrictions to our dataset. First, we drop out from the analysis farmers that did not experience any extreme degree days. It is possible that, during a growing season that may be locally particularly soft, farmers did not face extreme temperatures. Note that we also drop out the year 2003, exceptionally hot with respect to other years. Second, our analysis only concerns positive incomes. It is difficult to give an economic interpretation of negative incomes as their existence is mainly due to accounting procedure. Hence, it complexifies both the analysis on (i) aggregate weather impacts on income, and (ii) the distributional effects of weather. Negative incomes represent approximately 2.6% of our dataset. In accordance with [De Battisti et al. \(2019\)](#), we remove negative incomes from initial sample. Closest to our study, this restriction is also in line with [DePaula \(2020\)](#) which excludes farms with a gross revenue of less than 10 times the annual minimum wage.

Table 3.2 depicts the descriptive statistics of income for both (i) initial and (ii) restricted datasets. The removal of some farms does not significantly change the descriptive statistics. It slightly increases the median and the mean. For instance, taking a per farm basis, average income is 83,400 € for the full set of farms whereas it is 85,700 € for the restricted set of farms. It should be noted that the data restriction also slightly decrease the Gini index. For example, concerning the distribution of farm income, it goes from 0.43 for the full set of farms to 0.41 to the restricted set.

**Farms statistics** Table 3.3 depicts the repartition of the farms across four parts of France. The geographical repartition is quite heterogeneous, North-East of

Table 3.3: Regional repartition of restricted sample.

| Part of France | Number of farms | Proportion |
|----------------|-----------------|------------|
| South-East     | 1,491           | 8.6%       |
| South-West     | 4,149           | 23.8%      |
| North-East     | 8,054           | 46.2%      |
| North-West     | 3,728           | 21.4%      |

France is the most represented part (46.2%) as this contains important crop producing regions (e.g. Île-de-France, Grand Est). The North is logically more represented than the South (approximately 70% vs 30%).

## 4 Empirical Strategy

This section is devoted to the presentation of our empirical specifications. First we present our specification for estimating aggregate impacts of extreme temperatures on farmers' income. Second, we present our strategy for assessing the distributional impacts of these weather shocks.

### 4.1 Impact of extreme temperatures on farmers' income

To estimate the marginal effect of farmers exposition to extreme temperature events, we run the following OLS general model:

$$y_{j,i(j),t} = \beta_0 + \beta_1 H_{it}^{90} + \beta_2 C_{it}^{10} + \gamma X_{jt} + \delta X_{it} + \sigma_t + \lambda_d + \varepsilon_j \quad (3.4)$$

where  $y_{j,i(j),t}$  is income for farmer  $j$ , located in city  $i$ , in year  $t$ ,  $H_{it}^{90}$  and  $C_{it}^{10}$  are the two extreme degree days.  $\beta_1$  and  $\beta_2$  are coefficients of interests and capture the marginal impact of respectively hot and cold extreme degree days on farmers' revenues. We include in  $X_{jt}$  some control variables regarding the farm characteristics (e.g. land surface, perceived subventions, input consumption) and  $X_{it}$  includes city-specific variables that all affect farmers' income (e.g. other weather events, soils characteristics). We include a control variable for the year  $\sigma_t$  to exclude macro-level shocks that may affect all farmers in France in a specific year and a *département*  $d$  variable  $\lambda_d$  to absorb

unobserved geographical variance across farmers. In metropolitan France, there are 97 *départements*. On average, a département covers 5000  $km^2$ , so around 70 km  $\times$  70 km.

We expect to estimate negative  $\beta_1$  and negative  $\beta_2$  as the increase of extreme degree days should deter farmers' revenues on average, controlling for other determinants of income.

## 4.2 Distributional impacts of extreme temperatures

Beyond the average effect of extreme temperatures, we estimate the distributional effects of these extreme degree days on farmers' income. To this purpose, we adopt a linear quantile regression approach. See e.g. [Koenker and Hallock \(2001\)](#) for a review. Our specification is defined as follows:

$$Q_{y|\mathcal{X}}(\tau|\mathcal{X}) = \beta_{0\tau} + \mathcal{X}\beta_{k\tau} \quad (3.5)$$

where  $y$  is the farmer's income,  $\mathcal{X}$  is the vector of covariates we include in the linear model (3.4),  $Q_{y|\mathcal{X}}$  is the conditional quantile function of  $y$  given  $\mathcal{X}$  and  $\tau \in (0, 1)$  is a quantile.  $\beta_{k\tau}$  are the coefficients capturing the marginal effect of covariates on farmers' income across quantiles. Quantile regressions allow to inform on the variation of each quantile, respecting to the variable of interest. For instance, the estimate  $\beta_{k\tau}$  corresponds to the change of  $\tau^{th}$  of the conditional distribution of income following an increase of one unit of  $\mathcal{X}$ , *all other things being equal*. A particular attention is paid to  $\beta_{1\tau}$  and  $\beta_{2\tau}$ , providing informations on the marginal impact of respectively hot and cold extreme degree days on farmers' income, along the distribution.

## 5 Results

This section depicts our results. We first present aggregate results and then turn into the distributional analysis.

## 5.1 Extreme weather events impact on revenues

Table 3.4 presents our OLS estimation results on the marginal effects of extreme degree days (bottom and top 10%) on farmers' income. Column (1) shows the result of the average effect of a variation in weather variables (i.e. cold and hot extreme degree days, average degree days, and liquid precipitations), as well as the year and the French *département* on per farm income. We find that both extreme degree days (i.e. hot and cold) are associated with a negative impact on income. The effect is unrelated to other weather shocks (e.g. precipitations) and purged from the normal effect of average degree days. For hot extreme degree days ( $H_{it}^{90}$ ), the coefficient is equal to -0.083, significant at a 1% level, whereas for cold extreme degree days ( $C_{it}^{10}$ ), it is equal to -0.024, significant at a 10% level. Hence, hot extreme degree days seem to be more harmful than cold ones.

In columns (2) to (4), we successively add controls that could explain the sample variation of our dependent variable. In column (2), we control for variables linked to the size of the farm (i.e. the subventions perceived by the farm, the land surface) and for the irrigated land surface. We add land quality informations in column (3) by controlling for the slope and for the soil texture. In column (4) we add spending on chemical fertilizers and fuel. The coefficients estimating the effects of hot and cold extreme degree days on income slightly increase when adding control variables. In column (4), when we account for the most control variables, the model explains an important part of income (i.e. R-squared of 0.508). The average elasticity of  $H_{it}^{90}$  with respect to income is -0.131 and the average elasticity of  $C_{it}^{10}$  with respect to income is -0.048. Both are significant at a 1% level. It should be noted that we also find a significant effect of other weather variables (i.e. average degree days, and liquid precipitations). Note that we also find an elasticity of liquid precipitations with respect to income equal to 0.120.

As robustness checks, several estimation results are presented in appendix B. For instance, we change the dependant variable, normalizing the income by the number of unpaid AWU or using the farm economic gross production (i.e. total output). We also examine the marginal effect of bottom and top 5% extreme degree days. The negative

impact of cold and hot extreme degree days, and the value of estimates is robust.

To summarize, the negative impact of an increase in cold and hot extreme degree days on farms income holds when controlling for a set of variables regularly used in the literature to estimate the effect of weather on agriculture (e.g. various inputs, land quality, irrigation). The coefficient of  $H_{it}^{90}$  stands at -0.131, and the coefficient of  $C_{it}^{10}$  is -0.048 (column (4)). Both are significant at the 1% level.

This implies that a 10% increase in hot (resp. cold) extreme degree days is associated with a decline in income of 1.31% (resp. 0.48%). Thus, average per farm income over the period is 85,700 €, and a 10% increase in  $H_{it}^{90}$  implies a decline of about 1,123€ per farm, and a 10% increase in  $C_{it}^{10}$  implies a decline of about 411€ per farm.

These results suggest that an increase in cold and hot extreme temperatures is associated with a reduction in farms' income. We now turn to the distributional analysis of extreme degree days.

## 5.2 Distributional impacts of extreme temperatures

In this section we analyze the distributional impacts of extreme temperatures on farm income. We apply quantile regressions to our OLS specification.

Figure 3.2 illustrates the quantile regression estimation results for hot extreme degree days. Hot extreme degree days ( $H_{it}^{90}$ , left) have a negative impact for all quantiles. This indicates that these weather shocks globally shift down the distribution of income. The effect of  $H_{it}^{90}$  is constant up to the fifth decile and then decreases. When controlling for other variables, the reduction of the first decile of the conditional distribution of income following an increase of one hot extreme degree day is -0.125 whereas it is -0.15 for the 9<sup>th</sup>. Hence, farm income dispersion decreases when hot extreme degree days increase.

Figure 3.3 illustrates the quantile regression estimation results for cold extreme degree days on farms' income. Cold extreme degree days ( $C_{it}^{10}$ , right) have a negative impact for incomes below the eighth decile, they have a slightly positive (close to 0) non-significative effect for the top 20% of income. Contrary to  $H_{it}^{90}$ , the effect of  $C_{it}^{10}$  increases across quantiles. All other things being equal, the reduction of the

Table 3.4: Estimation results.

|                                 | <i>Dependent variable: log(farm income)</i> |                         |                         |                         |
|---------------------------------|---------------------------------------------|-------------------------|-------------------------|-------------------------|
|                                 | (1)                                         | (2)                     | (3)                     | (4)                     |
| $\log(H_{it}^{90})$             | -0.083***<br>(0.014)                        | -0.164***<br>(0.011)    | -0.154***<br>(0.011)    | -0.131***<br>(0.010)    |
| $\log(C_{it}^{10})$             | -0.024*<br>(0.014)                          | -0.031***<br>(0.010)    | -0.025**<br>(0.010)     | -0.048***<br>(0.010)    |
| $\log(M_{it}^{10-90})$          | 0.470***<br>(0.118)                         | -0.494***<br>(0.087)    | -0.357***<br>(0.088)    | -0.328***<br>(0.086)    |
| $\log(\text{precipitations})$   | 0.049<br>(0.035)                            | 0.178***<br>(0.026)     | 0.216***<br>(0.026)     | 0.120***<br>(0.026)     |
| $\log(\text{subventions})$      |                                             | 0.230***<br>(0.015)     | 0.233***<br>(0.015)     | 0.205***<br>(0.015)     |
| $\log(\text{land surf.})$       |                                             | 0.816***<br>(0.017)     | 0.805***<br>(0.018)     | 0.510***<br>(0.021)     |
| irrig. land surf.               |                                             | 0.00001***<br>(0.00000) | 0.00001***<br>(0.00000) | 0.00001***<br>(0.00000) |
| $\log(\text{slope})$            |                                             |                         | -0.033***<br>(0.004)    | -0.026***<br>(0.004)    |
| Soil text. coarse               |                                             |                         | -0.166**<br>(0.073)     | -0.134*<br>(0.071)      |
| Soil text. medium               |                                             |                         | 0.005<br>(0.069)        | 0.032<br>(0.067)        |
| Soil text. medium fine          |                                             |                         | 0.032<br>(0.067)        | 0.068<br>(0.066)        |
| Soil text. fine                 |                                             |                         | -0.034<br>(0.068)       | 0.006<br>(0.067)        |
| $\log(\text{fertilizer cons.})$ |                                             |                         |                         | 0.133***<br>(0.010)     |
| $\log(\text{fuel cons.})$       |                                             |                         |                         | 0.191***<br>(0.009)     |
| Year                            | ×                                           | ×                       | ×                       | ×                       |
| Département                     | ×                                           | ×                       | ×                       | ×                       |
| Observations                    | 13,465                                      | 13,465                  | 13,465                  | 13,465                  |
| R <sup>2</sup>                  | 0.022                                       | 0.477                   | 0.482                   | 0.508                   |
| Adjusted R <sup>2</sup>         | 0.021                                       | 0.477                   | 0.482                   | 0.507                   |

Note: \*, \*\*, \*\*\* is the significancy at 10%, 5% and 1% respectively.



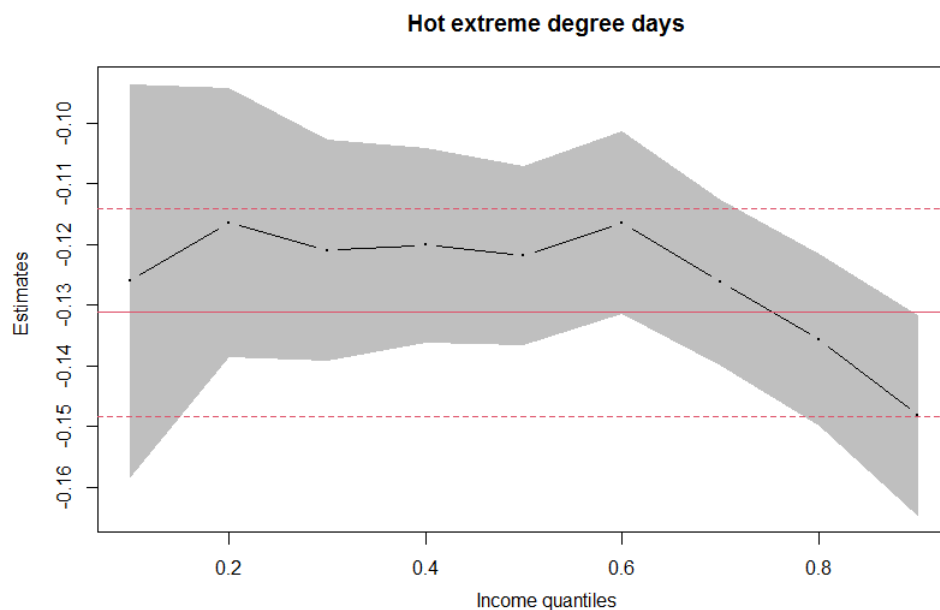


Figure 3.2: Quantile regression estimates for hot extreme degree days ( $H_{it}^{90}$ ).  
 Note: The grey ribbon represents standard deviation. The red lines represent the standard OLS estimate (plain) and standard deviation (dashed).

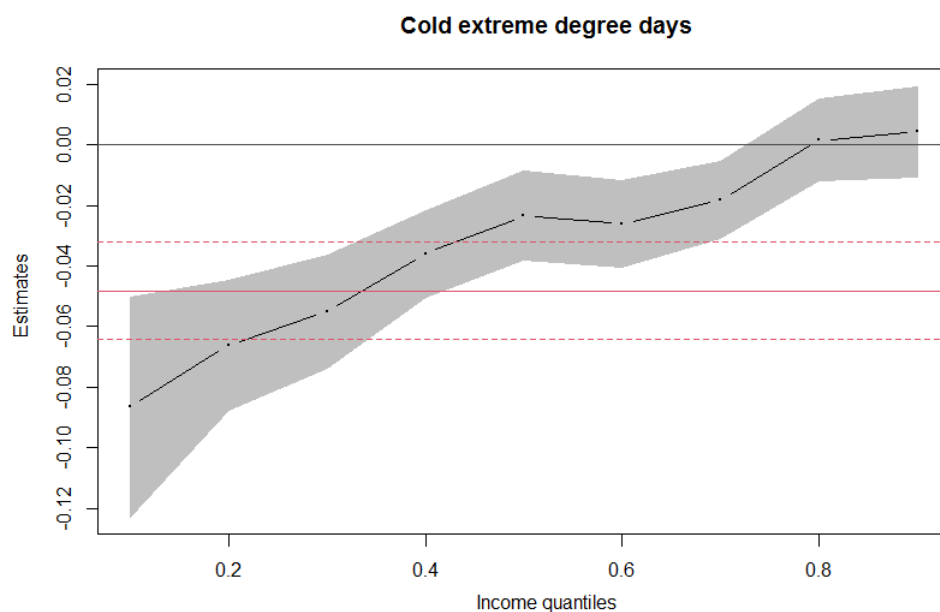


Figure 3.3: Quantile regression estimates for cold extreme degree days ( $C_{it}^{10}$ ).  
 Note: The grey ribbon represents standard deviation. The red lines represent the standard OLS estimate (plain) and standard deviation (dashed).

first decile of the conditional distribution of income following an increase of one cold extreme degree day is -0.09 whereas it is 0.005 for the 9<sup>th</sup>. The dispersion of farm

income increases when cold extreme degree days increase.

As a robustness check (see appendix C), we perform quantile regressions when changing the dependant variable (i.e. income per unpaid AWU, farm gross production). Findings seem robust. Note that the opposite distributional effects of hot and cold extreme degree days are particularly marked on the gross production.

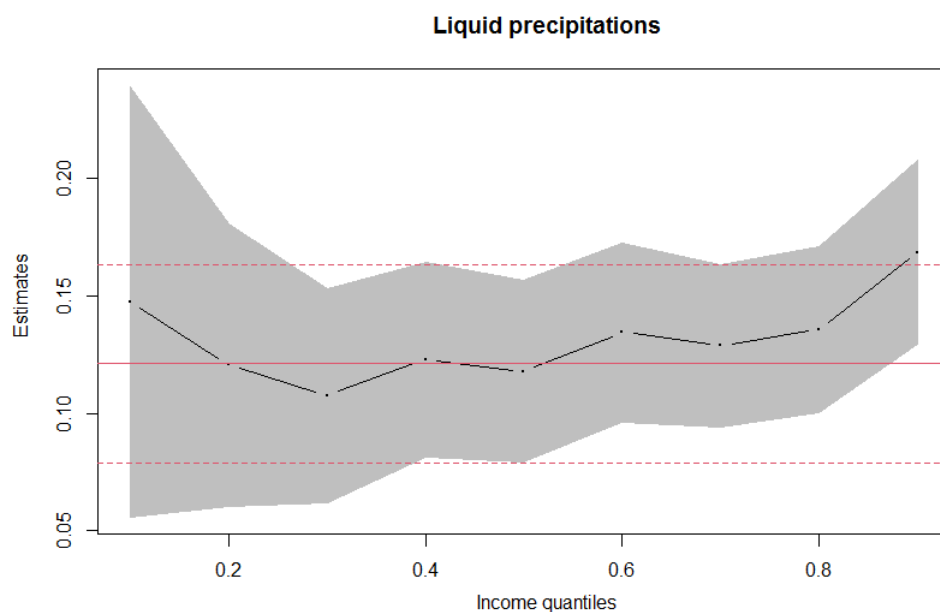


Figure 3.4: Quantile regression estimates for liquid precipitations.

*Note: The grey ribbon represents standard deviation. The red lines represent the standard OLS estimate (plain) and standard deviation (dashed).*

Figure 3.4 presents the quantile regression estimation results for liquid precipitations on farm income. Liquid precipitations have a positive impact for all quantiles. This indicates that these weather shocks globally shift up the distribution of income. The effect of liquid precipitations increases up to the third decile. When controlling for other variables, the augmentation of the third decile of the conditional distribution of income due to an increase of one unit of liquid precipitation is 0.11 whereas it is 0.17 for the 9<sup>th</sup>.

## 6 Discussion

In this section we first discuss the potential impact of extreme temperatures and climate change on inequality. Second, we provide some arguments that may explain the observed distributional impacts of extreme temperatures. Third, we discuss the consistency of our findings with respect to the literature.

Our findings indicate that both cold and hot extreme degree days have a negative impact on farms income, but they have opposite distributional effects. On the one hand, by hurting more the lowest incomes than the highest ones, an increase in cold extreme temperatures may increase income inequality. On the other hand, extreme heat appears to be more damaging for highest incomes than for lowest ones. An increase in hot extreme temperatures may decrease income inequality.

Thus, one may be tempted to say that climate change, by increasing the frequency of occurrence and the intensity of hot extreme temperatures, is likely to decrease income inequality between French crop farmers. However, the effect of climate change on cold extreme temperatures is unclear (Stephenson et al., 2008). By increasing the variance of the distribution of temperatures, climate change may also increase either the probability or the intensity of cold weather events. Also, a warm winter followed by intense late frosts occurring in the beginning of the growing season may be a consequence of climate change (Augspurger, 2013). This phenomenon, that happened in Europe in past recent years, may be particularly harmful for agriculture (Castel et al., 2017).

Figure 3.5 depicts the proportion of area allocated to major crops on the left, and the regional proportion on the right, both by income deciles. The proportion of area allocated to wheat is quite constant across income deciles (about 45%). However, area allocated to rapeseed increases with income, whereas area allocated to corn decreases with income. On the one hand, for the bottom 10% incomes of the population, corn and rapeseed represent respectively 25.6 and 14.0% of the land area. On the other hand, for the top 10% incomes of the population, corn and rapeseed represent respectively 14.0 and 23.3% of the land area. This could be a potential explanation to the distributional impacts of extreme temperatures. Corn may be more affected by cold extremes, while

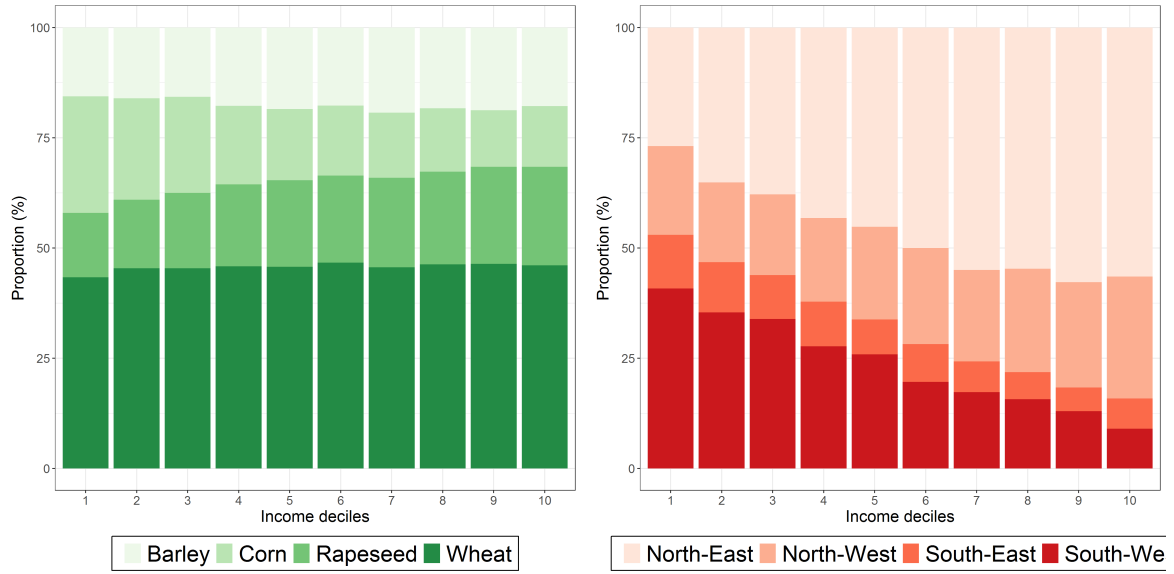


Figure 3.5: Proportion of area allocated to four major crops by income deciles (left), and regional proportion by income deciles (right).

rapeseed may be more affected by hot extremes. Another potential reason for the distributional impacts may be a region effect. The more the income increases, the more the probability of being a farmer from the north of France increases. Southern farmers represent 53.5% of the bottom 10% of incomes whereas they represent only 15.1% of the top 10% of incomes. Hence, farmers from the south may be more sensitive to cold extremes, as this part of France is the hottest one. On the contrary, Northern farmers may be more affected by hot extreme temperatures, as they are used to quite cold temperatures.

In line with the vast majority of studies assessing the effect of climate change on crop production, we find that extreme heat may have a detrimental effect on both production and income. These studies include Lesk et al. (2016); Asseng et al. (2014); Schlenker and Roberts (2009). For example, Lesk et al. (2016) indicate that droughts and extreme heat significantly reduced national cereal production across the world by 9 to 10%. We find that a 10% increase in hot extreme degree day may decrease the average production by 0.67%. Closest to the scope of our study, Gammans et al. (2017) also identify negative impacts on the French crop production for both hot and cold extreme temperatures. For instance, they find a significantly negative impact of temperatures above 32°C on crop yield growth with respect to freezing, suggesting heat

sensitivity. We also find that hot extreme temperatures may be more harmful for crop production than cold extremes. Estimates are on average -0.067 for hot extreme degree days versus -0.015 for cold extreme degree days. Very few studies attempt to estimate the potential distributional impacts of weather shocks. However, our findings may be compared with results from DePaula (2020). Studying the distributional impacts of climate on Brazilian land quality, the author finds that a 1°C of warming is more detrimental to farms with high-quality land, and that an increase in temperature could reduce inequality. He also finds that a 100-mm decrease in annual precipitation is more damaging to low-quality land, and may increase inequality. These results are quite in accordance with what we present here, an increase in exposure to extreme heat may be more damaging for high incomes, and may reduce income inequality. An increase in liquid precipitations may benefit more to high incomes than low incomes. It should be noted that unlike DePaula (2020) stating that an increase in temperatures may be more harmful to warm places, we find that farms suffering the most from an increase in extreme heat are in the coldest part of the country (i.e. the North of France).

## 7 Conclusion

An extensive empirical literature attempts to assess the effect of temperatures and/or precipitation on agricultural outcomes. The present study contributes to this research by estimating the distributional effect of both cold and hot extreme temperatures on French crop producers income.

Our work indicates that extreme temperatures are damaging for farmers. On average, we estimate that an increase in 10% of hot (respectively cold) extreme degree days may reduce per farm income of 1.31% (resp. 0.48%). Quantile regression estimations show that cold and hot extreme degree days have contrary distributional implications. Damages from cold extreme temperatures are decreasing with income and may increase farm income inequality, whereas damages from hot extremes are increasing with income and may decrease income inequality. We argue that two possible reasons may explain these antagonistic distributional impacts of extreme temperatures. First, the proportion of area allocated to corn (resp. rapeseed) reduces (resp. increases) with income. Corn could be then more affected by cold extremes while rapeseed could be more affected by hot extremes. Second, the probability of living in the North of France is increasing with income. Farmers from the North (resp. South) may be more sensitive to hot (resp. cold) extreme temperatures, as this part of France is the coldest (resp. hottest) one.

This work could be extended in several directions. First, one may be intrigued by future distributional impacts of extreme temperatures on agriculture. This study could serve as a basis for implementing extreme temperatures projections from climate scenarios, and hence quantify the consequences of a future increase in extreme temperatures. Second, it could be of major interest to study the potential adaptation to extreme temperatures. Are there practices set up by farmers that may soften these extreme shocks?

### 3.A French extreme degree days.

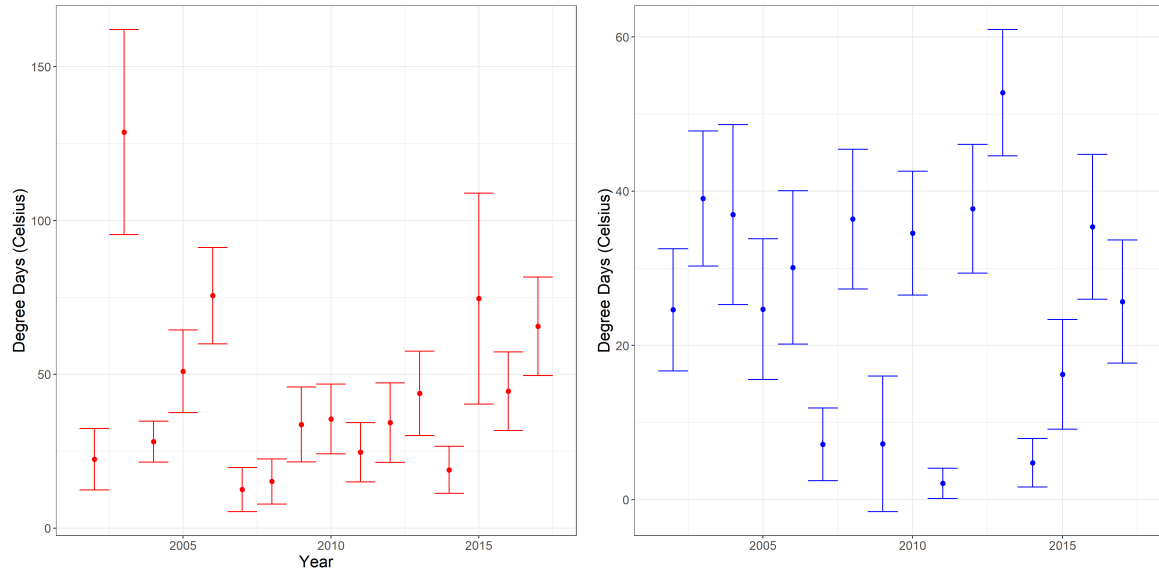


Figure 3.6: French average annual extreme degree days, left: hot extremes ( $H_t^{90}$ ), right: cold extremes ( $C_t^{10}$ ).

*Note: 36,608 metropolitan French municipalities are taking as a basis. Error bars represent standard deviation.*

### 3.B Robustness checks: OLS estimation results.

Table 3.5: Estimation results.

|                                 | <i>Dependent variable: log(farm income)</i> |                         |                         |                         |
|---------------------------------|---------------------------------------------|-------------------------|-------------------------|-------------------------|
|                                 | (1)                                         | (2)                     | (3)                     | (4)                     |
| $\log(H_{it}^{95})$             | -0.066***<br>(0.009)                        | -0.086***<br>(0.007)    | -0.082***<br>(0.007)    | -0.063***<br>(0.007)    |
| $\log(C_{it}^5)$                | -0.023***<br>(0.007)                        | -0.031***<br>(0.005)    | -0.029**<br>(0.005)     | -0.043***<br>(0.005)    |
| $\log(M_{it}^{5-95})$           | 0.154<br>(0.139)                            | -0.762***<br>(0.102)    | -0.574***<br>(0.106)    | -0.512***<br>(0.103)    |
| $\log(\text{precipitations})$   | 0.081**<br>(0.035)                          | 0.215***<br>(0.026)     | 0.251***<br>(0.026)     | 0.153***<br>(0.025)     |
| $\log(\text{subventions})$      |                                             | 0.233***<br>(0.015)     | 0.235***<br>(0.015)     | 0.206***<br>(0.015)     |
| $\log(\text{land surf.})$       |                                             | 0.811***<br>(0.017)     | 0.801***<br>(0.018)     | 0.503***<br>(0.021)     |
| irrig. land surf.               |                                             | 0.00001***<br>(0.00000) | 0.00002***<br>(0.00000) | 0.00001***<br>(0.00000) |
| $\log(\text{slope})$            |                                             |                         | -0.032***<br>(0.004)    | -0.026***<br>(0.004)    |
| Soil text. coarse               |                                             |                         | -0.162**<br>(0.073)     | -0.134*<br>(0.071)      |
| Soil text. medium               |                                             |                         | 0.006<br>(0.069)        | 0.030<br>(0.067)        |
| Soil text. medium fine          |                                             |                         | 0.032<br>(0.068)        | 0.066<br>(0.066)        |
| Soil text. fine                 |                                             |                         | -0.024<br>(0.069)       | 0.010<br>(0.067)        |
| $\log(\text{fertilizer cons.})$ |                                             |                         |                         | 0.135***<br>(0.011)     |
| $\log(\text{fuel cons.})$       |                                             |                         |                         | 0.194***<br>(0.009)     |
| Year                            | ×                                           | ×                       | ×                       | ×                       |
| Département                     | ×                                           | ×                       | ×                       | ×                       |
| Observations                    | 13,465                                      | 13,465                  | 13,465                  | 13,465                  |
| R <sup>2</sup>                  | 0.019                                       | 0.476                   | 0.480                   | 0.507                   |
| Adjusted R <sup>2</sup>         | 0.018                                       | 0.475                   | 0.480                   | 0.506                   |

Note: \*, \*\*, \*\*\* is the significancy at 10%, 5% and 1% respectively.



Table 3.6: Estimation results.

|                                 | <i>Dependent variable: log(farm gross production)</i> |                         |                         |                         |
|---------------------------------|-------------------------------------------------------|-------------------------|-------------------------|-------------------------|
|                                 | (1)                                                   | (2)                     | (3)                     | (4)                     |
| $\log(H_{it}^{10})$             | -0.021**<br>(0.010)                                   | -0.093***<br>(0.004)    | -0.084***<br>(0.004)    | -0.067***<br>(0.004)    |
| $\log(C_{it}^{10})$             | 0.004<br>(0.009)                                      | -0.003<br>(0.004)       | 0.002<br>(0.004)        | -0.015***<br>(0.004)    |
| $\log(M_{it}^{10-90})$          | 0.475***<br>(0.081)                                   | -0.402***<br>(0.036)    | -0.286***<br>(0.036)    | -0.264***<br>(0.034)    |
| $\log(\text{precipitations})$   | -0.004<br>(0.024)                                     | 0.113***<br>(0.011)     | 0.139***<br>(0.011)     | 0.072***<br>(0.025)     |
| $\log(\text{subventions})$      |                                                       | 0.131***<br>(0.006)     | 0.133***<br>(0.006)     | 0.115***<br>(0.006)     |
| $\log(\text{land surf.})$       |                                                       | 0.808***<br>(0.007)     | 0.800***<br>(0.007)     | 0.582***<br>(0.008)     |
| irrig. land surf.               |                                                       | 0.00002***<br>(0.00000) | 0.00002***<br>(0.00000) | 0.00002***<br>(0.00000) |
| $\log(\text{slope})$            |                                                       |                         | -0.020***<br>(0.002)    | -0.015***<br>(0.001)    |
| Soil text. coarse               |                                                       |                         | -0.140***<br>(0.030)    | -0.118***<br>(0.028)    |
| Soil text. medium               |                                                       |                         | -0.104***<br>(0.028)    | -0.086***<br>(0.026)    |
| Soil text. medium fine          |                                                       |                         | -0.085***<br>(0.028)    | -0.062**<br>(0.026)     |
| Soil text. fine                 |                                                       |                         | -0.153***<br>(0.028)    | -0.118***<br>(0.026)    |
| $\log(\text{fertilizer cons.})$ |                                                       |                         |                         | 0.127***<br>(0.004)     |
| $\log(\text{fuel cons.})$       |                                                       |                         |                         | 0.111***<br>(0.004)     |
| Year                            | ×                                                     | ×                       | ×                       | ×                       |
| Département                     | ×                                                     | ×                       | ×                       | ×                       |
| Observations                    | 13,465                                                | 13,465                  | 13,465                  | 13,465                  |
| R <sup>2</sup>                  | 0.010                                                 | 0.808                   | 0.812                   | 0.840                   |
| Adjusted R <sup>2</sup>         | 0.009                                                 | 0.808                   | 0.812                   | 0.840                   |

Note: \*, \*\*, \*\*\* is the significancy at 10%, 5% and 1% respectively.

Table 3.7: Estimation results.

|                                 | <i>Dependent variable: log(per unpaid AWU income)</i> |                        |                         |                      |
|---------------------------------|-------------------------------------------------------|------------------------|-------------------------|----------------------|
|                                 | (1)                                                   | (2)                    | (3)                     | (4)                  |
| $\log(H_{it}^{90})$             | -0.095***<br>(0.014)                                  | -0.158***<br>(0.011)   | -0.144***<br>(0.011)    | -0.122***<br>(0.011) |
| $\log(C_{it}^{10})$             | -0.028**<br>(0.013)                                   | -0.033***<br>(0.011)   | -0.024**<br>(0.011)     | -0.045***<br>(0.011) |
| $\log(M_{it}^{10-90})$          | 0.286***<br>(0.111)                                   | -0.446***<br>(0.093)   | -0.254***<br>(0.094)    | -0.226***<br>(0.093) |
| $\log(\text{precipitations})$   | 0.0001<br>(0.033)                                     | 0.097***<br>(0.028)    | 0.144***<br>(0.028)     | 0.058**<br>(0.028)   |
| $\log(\text{subventions})$      |                                                       | 0.186***<br>(0.016)    | 0.190***<br>(0.016)     | 0.165***<br>(0.016)  |
| $\log(\text{land surf.})$       |                                                       | 0.615***<br>(0.019)    | 0.597***<br>(0.019)     | 0.323***<br>(0.022)  |
| irrig. land surf.               |                                                       | 0.00001**<br>(0.00000) | 0.00001***<br>(0.00000) | 0.00000<br>(0.00000) |
| $\log(\text{slope})$            |                                                       |                        | -0.034***<br>(0.004)    | -0.028***<br>(0.004) |
| Soil text. coarse               |                                                       |                        | -0.273***<br>(0.078)    | -0.244***<br>(0.077) |
| Soil text. medium               |                                                       |                        | -0.148**<br>(0.074)     | -0.124*<br>(0.072)   |
| Soil text. medium fine          |                                                       |                        | -0.088<br>(0.072)       | -0.056<br>(0.071)    |
| Soil text. fine                 |                                                       |                        | -0.219***<br>(0.073)    | -0.179**<br>(0.072)  |
| $\log(\text{fertilizer cons.})$ |                                                       |                        |                         | 0.138***<br>(0.011)  |
| $\log(\text{fuel cons.})$       |                                                       |                        |                         | 0.161***<br>(0.010)  |
| Year                            | ×                                                     | ×                      | ×                       | ×                    |
| Département                     | ×                                                     | ×                      | ×                       | ×                    |
| Observations                    | 13,465                                                | 13,465                 | 13,465                  | 13,465               |
| R <sup>2</sup>                  | 0.019                                                 | 0.319                  | 0.326                   | 0.350                |
| Adjusted R <sup>2</sup>         | 0.018                                                 | 0.318                  | 0.325                   | 0.349                |

Note: \*, \*\*, \*\*\* is the significancy at 10%, 5% and 1% respectively.

### 3.C Robustness checks: Quantile regression estimation results.

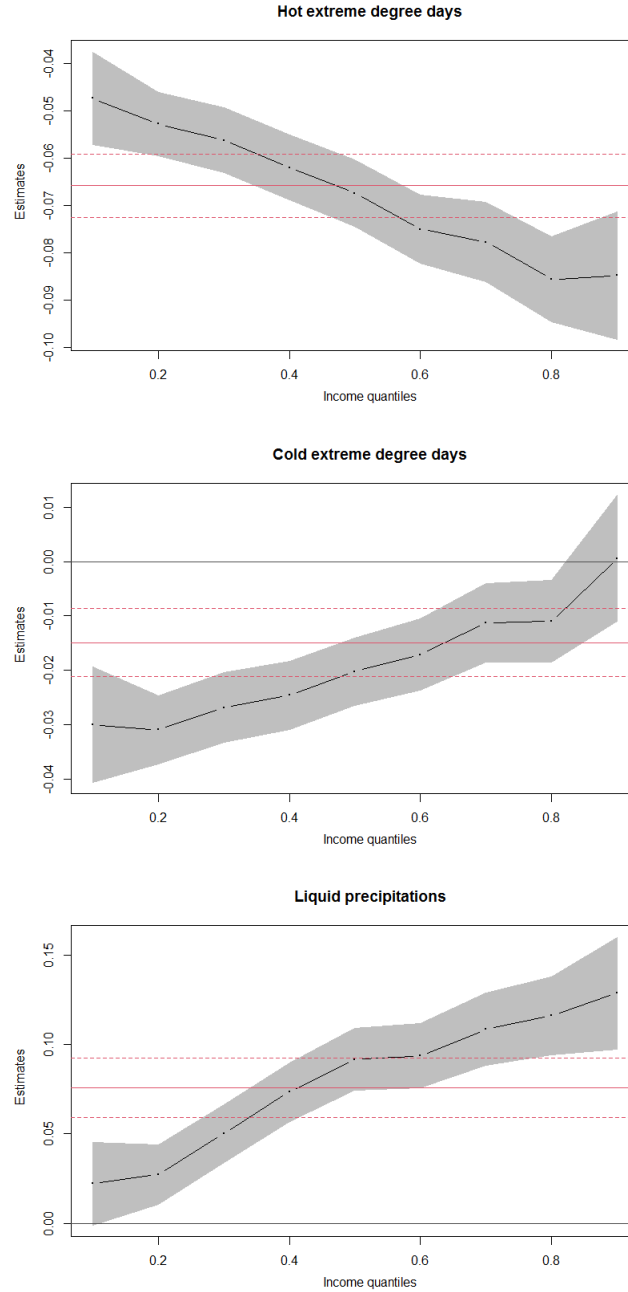


Figure 3.7: Quantile regression estimates for hot extreme degree days ( $H_{it}^{90}$ ), cold extreme degree days ( $C_{it}^{10}$ ), and liquid precipitation on farms gross production.

Note: The grey ribbon represents standard deviation. The red lines represent the standard OLS estimate (plain) and standard deviation (dashed).

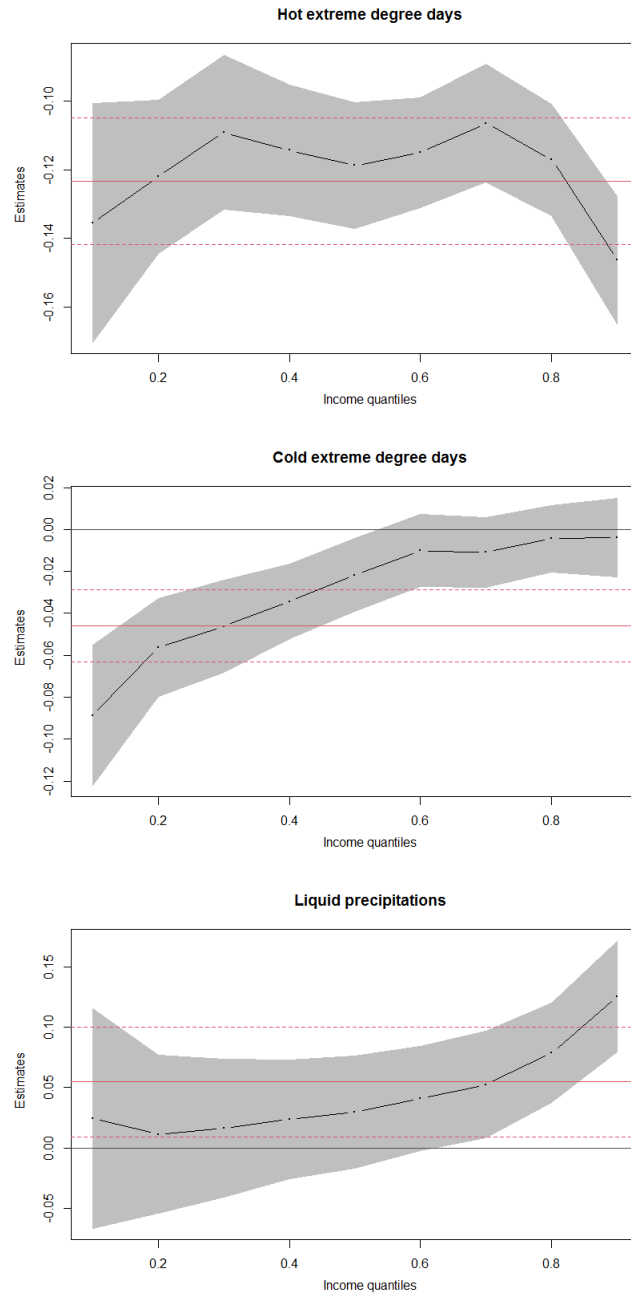


Figure 3.8: Quantile regression estimates for hot extreme degree days ( $H_{it}^{90}$ ), cold extreme degree days ( $C_{it}^{10}$ ), and liquid precipitation on per unpaid AWU farmers income.

*Note: The grey ribbon represents standard deviation. The red lines represent the standard OLS estimate (plain) and standard deviation (dashed).*





## Chapter 4

# Distributional impacts of autonomous adaptation to climate change from European agriculture





\* \* \*

Farmers facing a durable change in climate conditions may autonomously adapt through the intensive margin, the extensive margin, or through the adoption of new practices. Relying on a soft-coupling between a micro-economic model of European agriculture (AROPAj) and a crop model (STICS), this chapter investigates the potential distributional impacts of farm-level autonomous adaptation to climate change within European Union. Considering the representative concentration pathway (RCP) 4.5 from the second report on emission scenario, assessment report 5 (SRES AR5), we implement two levels of autonomous adaptation for farmers, and three time horizons. Findings indicate that, *ceteris paribus*, climate change may lead to a worse situation than the present one in terms of social welfare, in the short-term horizon but to a better situation in the long-term horizon due to (i) a stable income share for bottom quantiles and (ii) an increase in total income. Applying an inequality decomposition method based on the Shapley value, we show that income inequality is largely explained by farmers region and type of farming. Climate change slightly modify the marginal contributions of these two characteristics to overall income inequality.

\* \* \*

## 1 Introduction<sup>1</sup>

As agriculture is highly exposed to climate, the sector is expected to suffer important economic losses from climate change (IPCC, 2022). Nevertheless, IPCC (2022) highlight the existence of various agricultural adaptation options (e.g., agricultural diversification, agroforestry, irrigation expansion) quite efficient at reducing climate impacts in a 1.5°C warming world. Climate change impacts on agricultural production may be softened by farmers' autonomous adaptation. This adaptation, also known as *private adaptation* in the literature (Mendelsohn, 2000), concerns adaptation actions that farmers may take at their individual level from both the intensive margin (e.g. a change in input demand) and the extensive margin (e.g. a change in crop choice) but also from the adoption of new practices (e.g. agroforestry), more suitable to a change in climate conditions.

The present chapter addresses two main issues. First, it investigates the potential distributional impacts of farm-level autonomous adaptation to climate change on European farmers' income. To the best of our knowledge, this study is the first attempt to assess the distributional effects of farms autonomous adaptation to climate change. Second, it seeks to quantify the marginal contribution of the main individual characteristics to overall farmers' income inequality, and to analyse how these contributions vary when farmers autonomously adapt to climate change.

European agriculture provides an interesting field for our question for two main reasons. First, European agriculture is highly diverse in terms of productions and may be substantially affected by climate change (Van Passel et al., 2016). Second, the European Union (EU) has always included in the goals of the Common Agricultural Policy (CAP) to *ensure a fair standard of living to the agricultural community* (European Community, 1957) and more recently stated that CAP *should contain a more equitably distributed first pillar* (European Commission, 2010), thus European authorities may be concerned by the potential distributional consequences of farmers' adaptation to climate change.

This study builds on several streams of the literature. It borrows from the

---

<sup>1</sup>This chapter comes from a collaboration with Pierre-Alain Jayet and Pierre Humblot.

extensive literature on the measurement of inequality by a Lorenz-consistent criterion (Aaberge, 2001). In particular, we employ generalized Lorenz curves (Shorrocks, 1983) for ranking farmers' income distribution<sup>2</sup> and delta Lorenz curves (Ferreira et al., 2018) for analyzing income changes across the distribution. The study also relates to the inequality-decomposition literature (Bourguignon, 1979; Shorrocks, 1980) by adapting a framework based on the Shapley (1953) value, developed in Chantreuil et al. (2019, 2020).

Climate change has given rise to an important body of literature in environmental economics (see e.g. Dell et al. (2014) for a review), where agriculture occupies a special place (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). In particular, very recent examples try to quantify gains from adaptation, or to highlight adaptative behaviors. For example Aragón et al. (2021) find that extreme heat increase area planted, and modify crop mix among Peruvian rural households. In Meuse (a French *département*), Bareille and Chakir (2021) find that climate change increase fertilizer but reduce pesticide consumptions.

Our modeling approach broadly refers to the literature quantifying the effect of adaptation to climate change using crop simulation models and assuming some incremental adaptations (see e.g. Challinor et al. (2014) for a meta-analysis). In particular, we rely on a coupling between a supply-side micro-economic model of European agriculture (AROPAj) and a crop model (STICS). This strategy originates from Godard et al. (2008) and has been extended by Leclère et al. (2013) for assessing European farms autonomous adaptation to climate change. Humblot et al. (2017) present a theoretical framework for generating water-nitrogen yield response functions at the plot scale, then employed in bio-economic farm models. Originally implemented for maize in two French regions, yield response functions have been extended to all France for nine major crops Barberis et al. (2020). In this study, we expand the extraction of yield response function to EU for nine European crops.

Two types of farmers' autonomous adaptation to climate change are simulated. For *weak adaptation*, by modifying yield response functions, climate change shifts the

---

<sup>2</sup>Atkinson (1970) formally demonstrates that an ordering of income distributions with Lorenz curves is equivalent to an ordering of aggregate social welfare. (Shorrocks, 1983) extended the result for ranking distributions with different means.

optimal quantity of inputs and farmers can adapt through adjustments in the intensive and/or the extensive margin. However, crops remain the same as initially. For *strong adaptation*, farmers have in addition the possibility of changing the sowing date, or the crop variety. AROPAj has the main advantage of providing EU-27 aggregate results while covering an important diversity in terms of type of farming, region and economic size. Our study must be considered as an analysis of the effects of a change in climate variables on European agricultural sector *ceteris paribus*, rather than a prospective—or a forecasting—exercise of the future state of the European agricultural system.

Our contribution to the literature is twofold. First, we provide an estimate of the potential distributional consequences of farmers' autonomous adaptation to climate change. Our findings indicate that, all other things being equal, climate change could in the short-run worsen the situation compared to the present one in terms of aggregate welfare. This is due to (i) a reduction in income share for bottom quantiles and (ii) a decrease in total income. Nevertheless, in the long-term horizon, climate change may lead to a preferable situation in terms of aggregate welfare, due to (i) an income share quite stable for bottom quantiles, and (ii) an increase in total income.

As a second contribution, we identify the two main drivers—i.e. region and type of farming—of farmers' income inequality. We show that these two individual characteristics contributes approximately 73% to overall farmers' income inequality. We find region as an even more determinant characteristic than type of farming for explaining this inequality. Our results also indicate that climate change slightly impact the marginal contribution of these two attributes to farmers' income inequality.

The remainder of the chapter is structured as follows. Section 2 presents the modeling framework, the data and the inequality-decomposition framework. Section 3 depicts our aggregate and distributional results of farm-scale autonomous adaptation to climate change within the European agricultural sector. It also presents the results of our income inequality decomposition. Our findings are discussed in section 4. Section 5 concludes.

## 2 Modeling strategy

Our assessment of the potential distributional impacts of European farm-level autonomous adaptation to climate change relies on a soft-coupling between a micro-economic supply-side model of the European agricultural sector (AROPAj) and a crop model (STICS). Yield response functions, obtained from STICS for various climate and soil characteristics, are incorporated into production factors from AROPAj. This modeling framework, already used for several analysis of climate effects (Leclère et al., 2013; Humblot et al., 2017; Barberis et al., 2020) is an updated version of the one presented in Barberis et al. (2020).<sup>3</sup> An overview of the modeling framework is presented in 4.1.

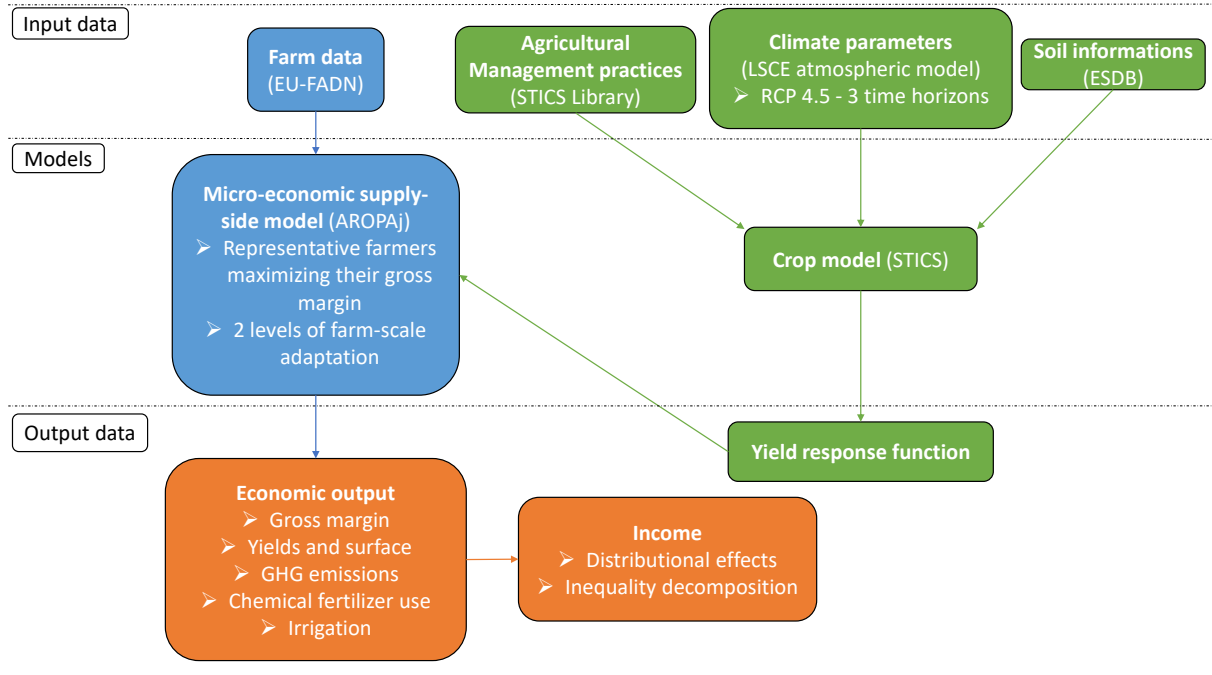


Figure 4.1: Overview of the modeling framework.

In this section devoted to methods and data, we first introduce the models, AROPAj and STICS. Second we present the climate scenario and the two levels of adaptation. Third, we describe the construction of income and the inequality-decomposition framework.

<sup>3</sup>In comparison with Barberis et al. (2020), the major update lies in the extension of the modeling framework to EU-27.

## 2.1 A micro-economic model of the EU agricultural supply

The micro-economic model (AROPAj (Jayet et al., 2021)) depicts the annual economic behavior of a set of European representative farmers in terms of farmland allocation (crops, pastures and grasslands) and livestock management (animal numbers and feeding). The model includes various agricultural productions in terms of crops<sup>4</sup> (i.e., 24 major European crops, permanent and temporary grassland) and animal husbandry (i.e., dairy and non-dairy cattle, sheep, goats, swine, poultry).

The economic behavior of each representative farmer is modeled with a static, mixed integer linear-programming model. Each farmer is assumed to maximize its gross margin<sup>5</sup> subject to technical (e.g. required crop rotations, nitrogen and water needs for associated crop yields, animal feeding requirements for milk or meat production) and economic (e.g. CAP payments, environmental policies) constraints. Farmers, assumed to be price-takers, are entirely independent one from another. It should also be noted that the herd size is bounded into a  $\pm 15\%$  range.

The representative farm results from a clustering procedure of actual surveyed farms from the European farm accountancy data network (EU-FADN). FADN provides general farm economic data, costs and prices, as well as crop and livestock yields. Farms are clustered along (i) type of farming (FADN classification TF14 Grouping<sup>6</sup>), (ii) the proportion of irrigated areas, (iii) economic size (9 categories), and (iv) location: region and altitude (3 thresholds; 0, 300, and 600 meters above sea level). The clustering procedure allows us to comply with FADN privacy policy while improving AROPAj computing time. EU-FADN year 2012 provides data for 70,000 farms (representing 3.766 millions of European farms) clustered into 1,993 representative farms, across 133 regions.

Model outcomes include farms' gross margin, input consumption (i.e., irrigation water and nitrogen fertilizers), animal products, crops yield and surface, and various environmental outputs, for instance greenhouse gas (GHG) emissions.

---

<sup>4</sup>Permanent crops (e.g., orchards, vineyards), horticulture and market gardening are not modeled.

<sup>5</sup>The gross margin is defined as the difference between farm's profit minus variable costs

<sup>6</sup>The classification can be find at <https://ec.europa.eu/agriculture/rca/detailtf-en.cfm?TF=TF14&Version=13185>.

## 2.2 A crop model providing yield response functions

The micro-economic model of European agriculture is sharpened by substituting a function linking inputs and yields at the plot scale. The major reason for incorporating dose-response functions in AROPAj production factors is to overcome the lack of exhaustivity of the EU-FADN. EU-FADN does not allow us to estimate yield functions for a large diversity of context in terms of crops and farming systems. The crop model STICS simulates the soil–atmosphere–crop system applied to a wide range of crops and pedo-climatic conditions (Brisson et al., 2003). For a given representative farm and a given crop, it provides a yield function associated with inputs in (i) nitrogen fertilizers and (ii) water. STICS crop model requires (i) climate parameters, acquired from the *Laboratoire des sciences du climat et de l’environnement* (LSCE) atmospheric model, (ii) soil information, gathered from the European Soil Database (ESDB) (Panagos et al., 2012), and (iii) data on agricultural management practices (delivered by the STICS library). It should be noted that the substitution of yield response functions from STICS to AROPAj input–yield points turns non-linear the structure of AROPAj. Thus, the optimization solving problem is in two stages. First, the gross margin is maximized for each unit of area of a crop and for each farm type. Second, yields from STICS are replaced in the linear optimization problem. Note also that the use of yield response functions allows us to come through the estimation of input prices.

In summary, STICS generates yield response functions for a specific crop in specific pedo-climatic conditions and calibrates nitrogen–water–yields relationships for crops present in a given AROPAj farm group.

## 2.3 Time horizons for climate change and autonomous adaptation

The climate scenario implemented in this study is the representative concentration pathway (RCP) 4.5 from the second report on emission scenario, assessment report 5 (SRES AR5). This climate scenario is then translated into weather variables by the LSCE atmospheric model, available at the scale of a regular grid with a mesh size of  $0.11^\circ$ —approximately 12.5 km. As a farm type is localised by a region and an

altitude, weather variables are averaged for each region and altitude levels, which leads to, at most three values per region for a variable. In order to quantify the European farm-level autonomous adaptation to climate change, we compute three time horizons. The present horizon is the representative climatic year for the period 2006-2035. The short-term (resp. the long-term) horizon is the representative climatic year for the period 2041-2070 (resp. 2071-2100).<sup>7</sup>

We simulate two levels of autonomous adaptation for farmers. In the *weak adaptation* level, farmers may adapt to a change in weather conditions through the extensive—e.g. a change in crops allocation—and the intensive—e.g. a change in input demand—margins. Farms only adapt through crops initially present in their farm type (calibrated on the 2012 EU-FADN). In the *strong adaptation* level, farmers can in addition adapt through the adoption of crop varieties more suitable to the new weather conditions, or through a change in the sowing date. None of the two levels of adaptation take into account a possible improvement in plant genomics to create new varieties more resistant to heat and/or water stress. However, autonomous adaptation remains quite important and realistic in this work.

## 2.4 Farmers' income and active population

Several difficulties lie in the estimation of an appropriate income for farmers. First, the economic outcome from the model AROPAj is the gross margin. Thus to get closer to a measure of a disposable income, we remove wages paid from the gross margin.

Second, there is possibly several unpaid workers by farms. EU-FADN data gives the amount of unpaid workers in a full-time equivalent annual workforce unit (AWU). The 3.766 millions of European farms represents 4.967 millions of unpaid farmers. It corresponds to about 1.32 unpaid AWU on average per farm, from 0.04 to 6 unpaid AWU per farm. We perform an income per unpaid AWU to analyse the income inequality per individuals. This is the farmers' income estimation in [Piet and Desjeux \(2021\)](#). Note that we present some results taking a per farm basis in [4.5](#).

Third, when using farms accounting data, a non-negligeable share of incomes is

---

<sup>7</sup>A note on the method used for the choice of a representative climatic year over a 30-year period is given in appendix A.



negative. This is clearly an issue when conducting distributional analysis, as negative incomes make it difficult to draw social welfare implications (Atkinson, 1970) and unclear to interpret delta Lorenz curves (Ferreira et al., 2018). Several authors suggest alternative Gini index to include negative values (Chen et al., 1982; Raffinetti et al., 2014), particularly used in agriculture where the presence of negative income is not rare (Allanson, 2008; Deppermann et al., 2014). However, when including negative incomes, a Gini index must be seen as a variability measure instead of the concentration measure (De Battisti et al., 2019). Thus, in line with Ravallion (2017); De Battisti et al. (2019); Piet and Desjeux (2021), we chose to remove the negative incomes from the analysis. Our distributional analysis concerns 4.702 million unpaid AWU (94.3% of initial sample) in the *weak adaptation* level, and 4.731 million unpaid AWU and (95.7% of initial sample) in the *strong adaptation* level.

Fourth, the use of individual data may favor the presence of outliers. To avoid them, Ferreira et al. (2018); Piet and Desjeux (2021) remove bottom and top 0.5% of incomes. As the farm group is made of a real-farm clustering procedure, we limit the potential presence of outliers.

## 2.5 Inequality-decomposition framework

We decompose farmers' income by region ( $\omega$ ) and by type of farming ( $\sigma$ ) (Chantreuil and Lebon, 2015). Farmers' income ( $y$ ) of a farmer  $i$  can be written in two ways, as follows:

$$y_i = \bar{y}_{\omega_i} + (\bar{y}_{\omega_i, \sigma_i} - \bar{y}_{\omega_i}) + (y_i - \bar{y}_{\omega_i, \sigma_i}) \quad (4.1)$$

or

$$y_i = \bar{y}_{0\sigma_i} + (\bar{y}_{\omega_i, \sigma_i} - \bar{y}_{0\sigma_i}) + (y_i - \bar{y}_{\omega_i, \sigma_i}) \quad (4.2)$$

According to equation 4.1 (respectively equation 4.2), individual income can be expressed as the sum of (i) income share associated with region (respectively type of farming):  $\bar{y}_{\omega_i}$  (respectively  $\bar{y}_{\sigma_i}$ ), (ii) income share associated with type of farming:  $(\bar{y}_{\omega_i, \sigma_i} - \bar{y}_{\omega_i})$  (respectively region  $(\bar{y}_{\omega_i, \sigma_i} - \bar{y}_{\sigma_i})$ ), and (iii) income share associated with unobserved characteristics (residuals):  $(y_i - \bar{y}_{\omega_i, \sigma_i})$ . The two possible decomposition orders are presented because there is *a priori* no reason to choose an order over another

(Chantreuil et al., 2020).

The contribution of a characteristic  $j = \{\omega, \sigma, r\}$  to the overall farmers' income inequality can be defined by the following Shapley formula:

$$Sh_j = \sum_{S \subset K, j \in S} \frac{(s-1)!(k-s)!}{k!} \cdot [I(Y(S)) - I(Y(S - \{j\}))] \quad (4.3)$$

where  $I$  is the chosen inequality index (Gini in this study),  $K$  is the set of farmers' characteristics,  $k$  the cardinality of  $K$ ,  $S$  a subset of  $K$ ,  $s$  the cardinality of  $S$ .  $Y(S)$  is the distribution of farmers' income among the subset  $S$ , defined by  $Y(\emptyset) = 0$ , and for all  $S \in 2^K$ ,  $S \neq \emptyset$ .

$$Y(S) = \sum_{j \in S} y_1^j + \sum_{j \notin S} \mu(y^j), \dots, \sum_{j \in S} y_n^j + \sum_{j \notin S} \mu(y^j) \quad (4.4)$$

where  $\mu(y^j)$  is the average farmers' income from farmers characteristic  $j$ .

### 3 Results

In this section we first provide aggregate results. We then go deeper in the distributional analysis. We end the section by delivering our findings in terms of region and type of farming, and by assessing their contribution to farmers' income inequality.

#### 3.1 Aggregate results

Table 4.1 presents aggregate results in terms of crops (corn and wheat), inputs (fertilizers and irrigation), GHG emissions and income for both *weak* and *smart adaptation* levels and for three time horizons. In both *weak* and *strong adaptation* levels, production (wheat and corn) and total income decrease in the short-term horizon with respect to present, -6.2% (respectively -8.5%) for *weak* (resp. *strong*) *adaptation* level. Income then increase in the long-term horizon with respect to present, +2.6% (respectively +2.0%) for *weak* (resp. *strong*) *adaptation* level.

In the *weak adaptation* level, the model computes 67.714 million tons of corn and 140.022 million tons of wheat for present, which is quite close to the actual produc-

## CHAPTER 4. DISTRIBUTIONAL IMPACTS OF AUTONOMOUS ADAPTATION TO CLIMATE CHANGE FROM EUROPEAN AGRICULTURE

Table 4.1: Aggregate results for studied sample (4.702 million unpaid AWU for *weak adaptation* vs. 4.731 million unpaid AWU for *strong adaptation*) for crop production (corn & wheat), input consumption (mineral fertilizers & irrigation water), GHG emissions, and income.

|                      |               | Unit                                | Present   | Short-term | Long-term |
|----------------------|---------------|-------------------------------------|-----------|------------|-----------|
| Weak<br>Adaptation   | Corn          | 10 <sup>3</sup> t                   | 67,714    | 47,821     | 72,192    |
|                      | Wheat         | 10 <sup>3</sup> t                   | 140,022   | 129,888    | 150,619   |
|                      | Fertilizers   | 10 <sup>3</sup> t                   | 42,124    | 39,201     | 44,416    |
|                      | Irrigation    | 10 <sup>3</sup> m <sup>3</sup>      | 4,710,097 | 4,931,883  | 5,063,983 |
|                      | GHG emissions | 10 <sup>3</sup> tCO <sub>2</sub> eq | 349,328   | 345,950    | 353,266   |
|                      | Income        | 10 <sup>6</sup> €                   | 170,932   | 160,168    | 175,365   |
| Strong<br>Adaptation | Corn          | 10 <sup>3</sup> t                   | 103,941   | 73,848     | 111,550   |
|                      | Wheat         | 10 <sup>3</sup> t                   | 169,924   | 158,427    | 173,531   |
|                      | Fertilizers   | 10 <sup>3</sup> t                   | 49,746    | 47,921     | 48,898    |
|                      | Irrigation    | 10 <sup>3</sup> m <sup>3</sup>      | 6,301,973 | 7,036,939  | 5,771,647 |
|                      | GHG emissions | 10 <sup>3</sup> tCO <sub>2</sub> eq | 353,635   | 353,031    | 352,558   |
|                      | Income        | 10 <sup>6</sup> €                   | 193,456   | 176,977    | 197,284   |

tion (i.e. for the period 2010-2020, the European Commission recorded on average 67 million tons of corn and 125 million tons for wheat per year<sup>8</sup>). It should be noted that the increase in income and production in the long-term horizon is accompanied by an increase in water (+7.5%) and mineral fertilizers (+5.4%) consumption, and GHG emissions (+1.1%).

In the *strong adaptation* level, more optimistic than the *weak adaptation* level, income and crop production are quite high, even in the present horizon. Thus, input consumption and GHG emissions are also higher than in the *weak adaptation* level. However, one may notice that input demand could decrease in the long-term horizon with respect to present, due to the adoption of less input-consuming varieties.

### 3.2 Distributional analysis

Figure 4.2 illustrates per unpaid AWU farmers' income Lorenz curves (left) and delta Lorenz curves with respect to present (right) for *weak adaptation*. Delta Lorenz curves (Ferreira et al., 2018) show the change in cumulative share of income across quantiles.

<sup>8</sup>Source: [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agricultural\\_production\\_-\\_crops](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agricultural_production_-_crops)

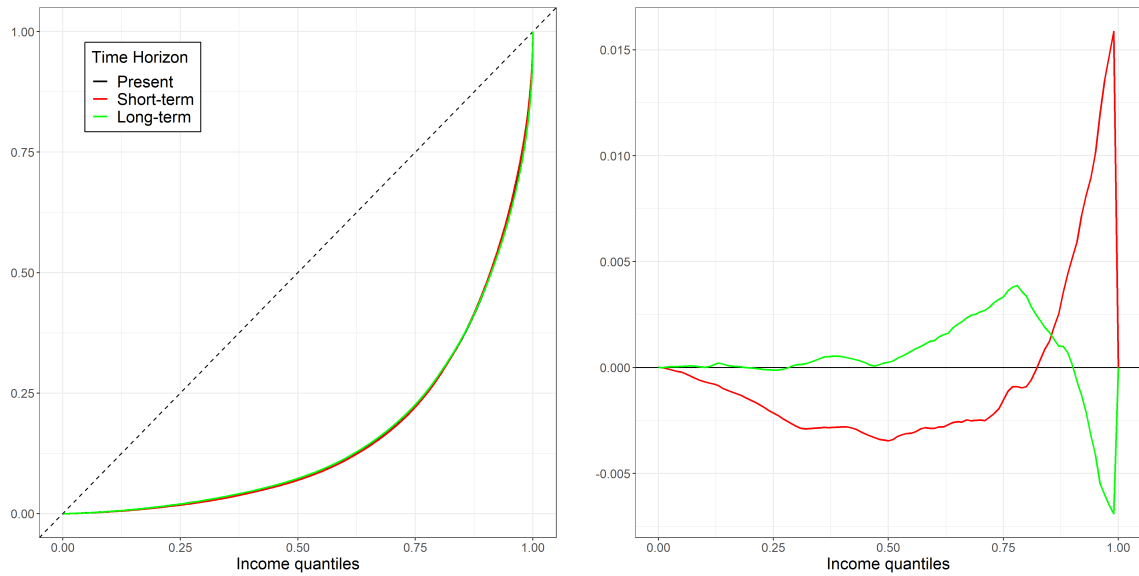


Figure 4.2: Distribution of farmers' income for *weak adaptation* level. Left: Lorenz curves. Right: Delta Lorenz curves with respect to present time horizon.

Lorenz curves are quite close: the Gini index is equal to 0.681 in the present and short-term horizon, and 0.680 in the long-term horizon. However delta Lorenz curves show that, in the short-term horizon, bottom 50% of incomes (i.e. incomes below the fifth decile) reduce their income share in total income whereas almost top 50% of incomes (i.e. incomes above the fifth decile) increase their income share in total income. It should be noted that the short-run horizon is also detrimental for the very high incomes. In the long-term horizon, income share seems quite stable (compared to present time horizon) for bottom 50% of incomes, then increases for upper middle incomes and decreases for top 20% of incomes.

Figure 4.3 illustrates per unpaid AWU farmers' income Lorenz curves (left) and delta Lorenz curves compared to present (right) for *strong adaptation*. Lorenz curves are quite close in this level of adaptation too. The Gini index is equal to 0.674 in the present, 0.680 in the short-term, and 0.674 in the long-term horizon. Delta Lorenz curves are quite similar to the *weak adaptation* level. They show that, in the short-term horizon, bottom 50% of incomes reduce their income share in total income whereas top 50% of incomes increase their income share. In the long-term horizon, income share seems quite stable for bottom 50% of incomes, then increases for upper middle incomes and decreases for top 20% of incomes. Note that the very high incomes (i.e.

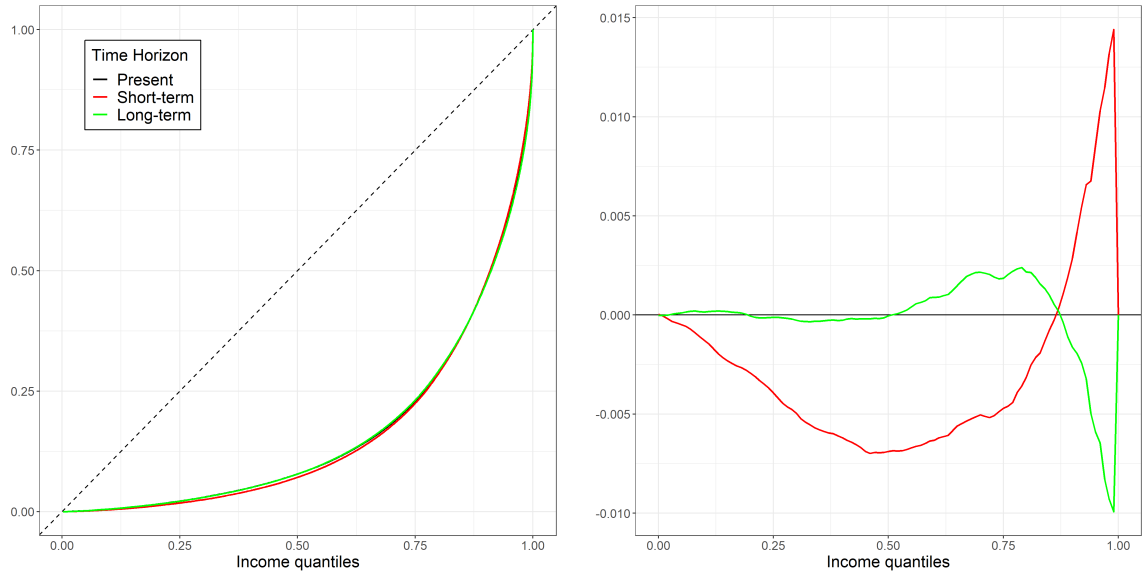


Figure 4.3: Distribution of farmers' income for *strong adaptation* level. Left: Lorenz curves. Right: Delta Lorenz curves with respect to present time horizon.

top 1% of incomes) reduce (respectively increase) their income share in the short-term (respectively long-term) horizon.

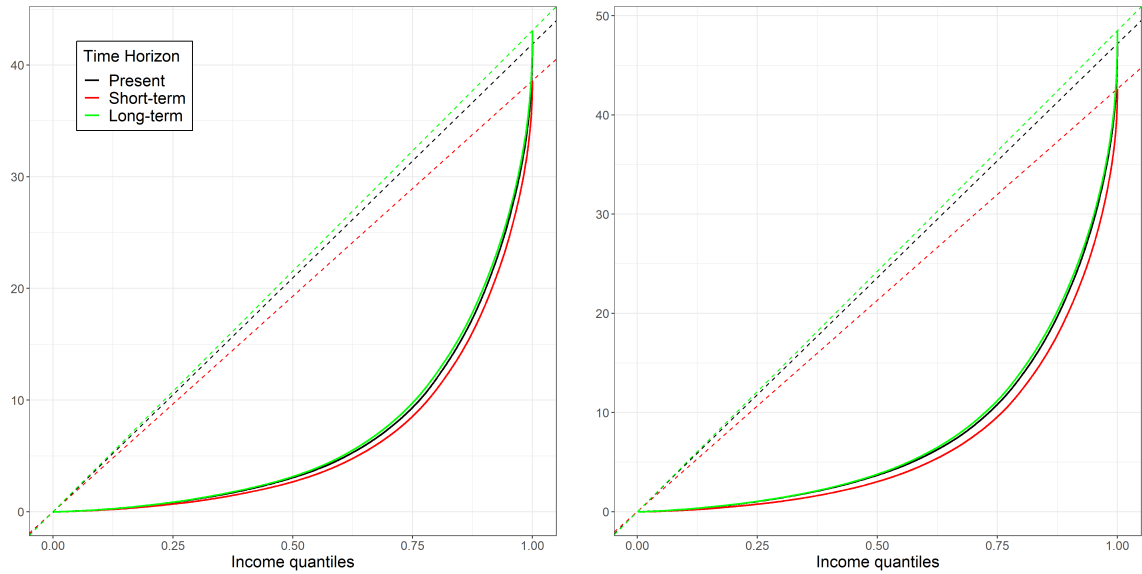


Figure 4.4: Generalized Lorenz curves of farmers' income. Left: Weak adaptation. Right: Strong adaptation.

Figure 4.4 presents the per unpaid AWU farmers' income generalized Lorenz curves (Shorrocks, 1983) for *weak* and *smart* adaptation levels, for three time horizons<sup>9</sup>.

<sup>9</sup>The generalized Lorenz curve is constructed by scaling up the Lorenz curve by the mean of the distribution:  $GL(F(x)) = \mu L(F(x))$ , with  $\mu$  the mean of the distribution and  $F$  the cumulative

For the two levels of adaptation, the generalized Lorenz curve of income lies entirely below the present generalized Lorenz curve in the short-term horizon. This result may be explained both by (i) a decrease in income share for bottom quantiles and (ii) a decrease in total income. Then in the long-run, the curve lies entirely above the present, for weak and strong adaptation. This can be explained both by (i) a constant income share for bottom quantiles and (ii) an increase in total income.

In terms of aggregate social welfare,<sup>10</sup> climate change (under RCP 4.5 scenario) may lead to (i) a worse situation in the short-run and to (ii) a preferable situation in the long-run with respect to the present situation.

### 3.3 Reranking effects

We now study the potential reranking effects (i.e., the shift of individual places in the distribution). Figure 4.5 shows future income (in the short-term and in the long-term horizon) with respect to present income, for both adaptation levels. For both short and long-term horizons, future income is quite close from income in the present horizon. Note that there is coherently more incomes that decrease with respect to present income in the short-term than in the long-term horizon.

Distributional effects of autonomous adaptation are slightly pronounced but there is an important share of the population which changes its place in the distribution. For both adaptation levels, and both short and long-term horizon, only 3% (from 1.5% to 4.3%) of the population on average keep unchanged its position in the distribution with respect to present. Approximately on average 50.3% (respectively 46.7%) of the population experience an increase (resp. a decrease) in its rank in the distribution.

We turn now into the income inequality decomposition.

### 3.4 Regional and type of farming income

What are the marginal contributions of the main individual farmers' characteristics to income inequality? How these contributions vary when farms autonomously adapt to

---

distribution function.

<sup>10</sup>The generalized Lorenz dominance is equivalent to a second-order stochastic dominance (Shorrocks, 1983; Thistle, 1989).

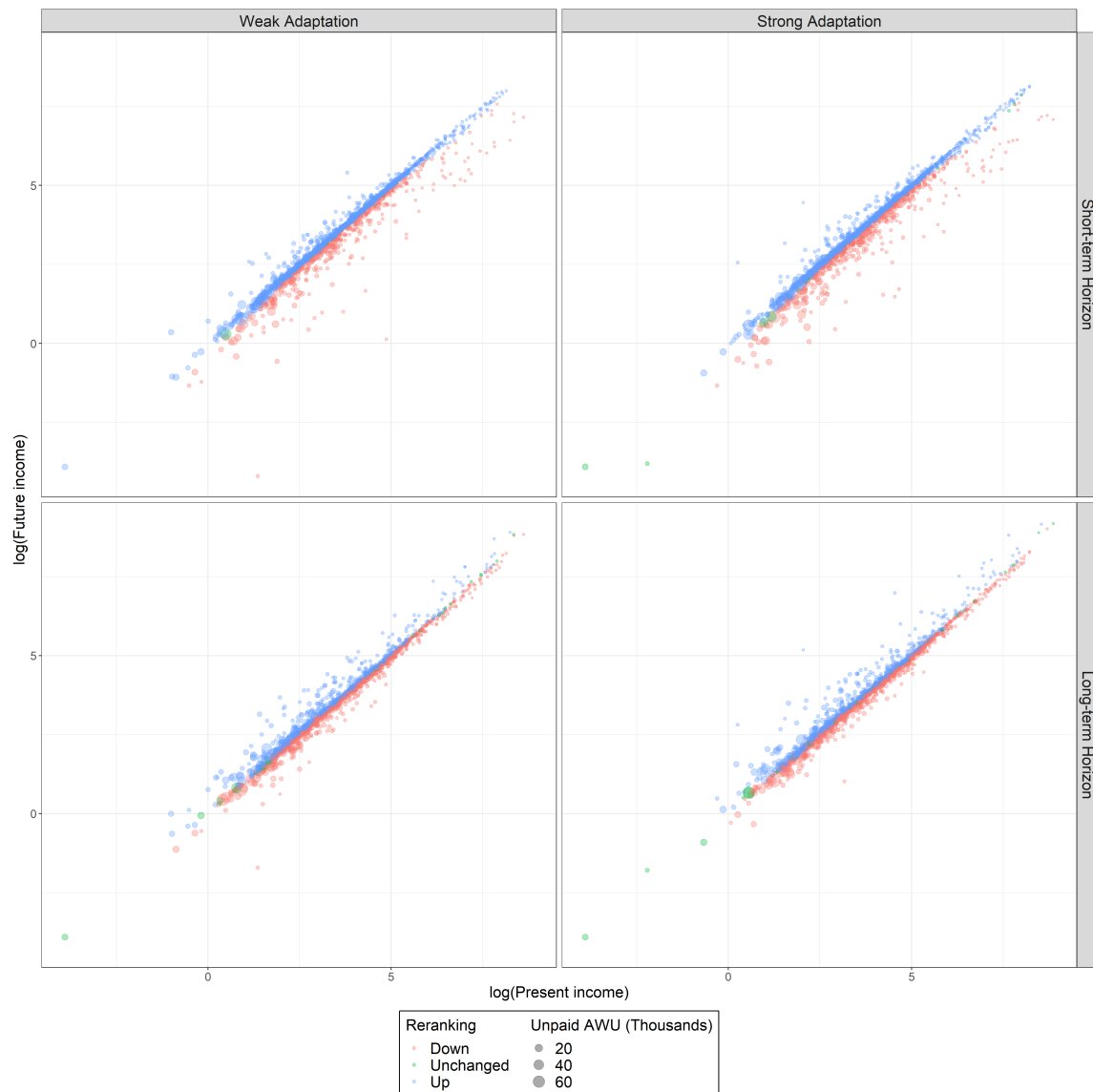


Figure 4.5: Future income with respect to present income (in logs). Top left: Short-term horizon and weak adaptation, Top right: Short-term horizon and strong adaptation, Bottom left: Long-term horizon and weak adaptation, Bottom right: Long-term horizon and strong adaptation.

climate change? To investigate these questions, we apply the inequality-decomposition framework based on the Shapley value (Shapley, 1953) introduced by Chantreuil and Trannoy (2013) to farmers' income. The method aims at assessing the marginal contribution of an individual characteristic to an overall inequality (Chantreuil et al., 2019).

Figure 4.6 depicts the per unpaid AWU average regional income for the three time horizons and two levels of adaptation. It shows an important variability among regions. For both levels of adaptation and for the three time horizons, findings are

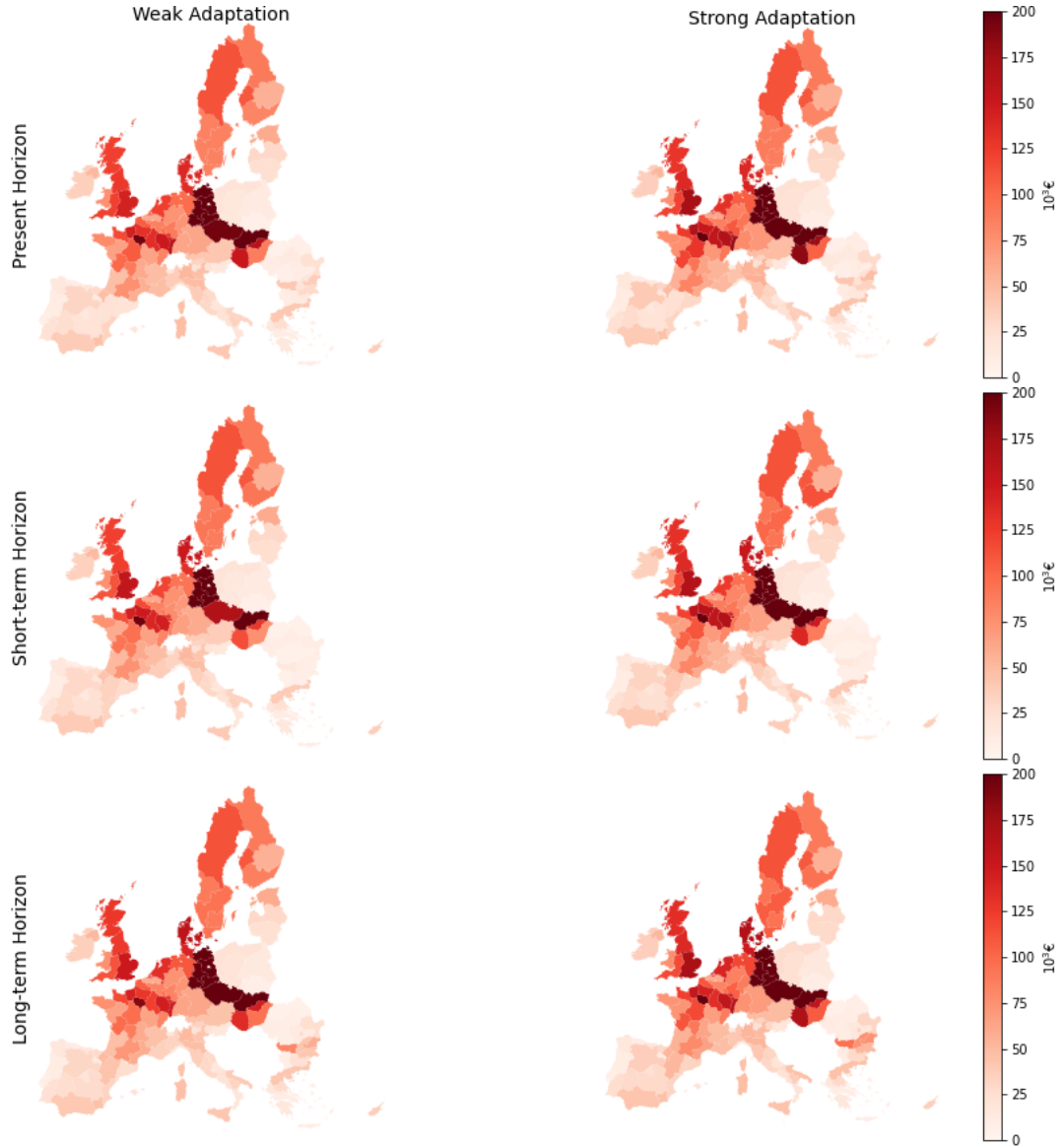


Figure 4.6: Average regional per unpaid AWU farmers' income ( $10^3\text{€}$ ). Top left: Present horizon and weak adaptation, Top right: Present horizon and strong adaptation, Middle left: Short-term horizon and weak adaptation, Middle right: Short-term horizon and strong adaptation, Bottom left: Long-term horizon and weak adaptation, Bottom right: Long-term horizon and strong adaptation.

quite close. Regions with the highest average income are concentrated in Northern Europe, for instance the North of France, Germany, Netherlands and Denmark. It should be noted that per unpaid AWU average income is particularly high in Eastern Germany and Austria, approximately 200 thousands euros. In the short-term horizon, the mean income decreases in a majority of regions with respect to present, for example in Mediterranean regions or Eastern Europe countries. It should be noted that mean



## CHAPTER 4. DISTRIBUTIONAL IMPACTS OF AUTONOMOUS ADAPTATION TO CLIMATE CHANGE FROM EUROPEAN AGRICULTURE

income increases in some regions, among them Denmark and Scandinavia. In the long-term horizon, the majority of regions experience an increase in average income with respect to present horizon. For instance, mean income increases in Eastern Europe countries (approx. +50%) and in several German, Danish, and Scandinavian regions (approx. +20%). Various French regions experience a slight reduction in mean income.

Table 4.2: Average per unpaid AWU farmers' income by type of farming for weak and strong adaptation and for three time horizons.

|                      | Type of farming                                   | Present | Short-term | Long-term |
|----------------------|---------------------------------------------------|---------|------------|-----------|
| Weak<br>Adaptation   | Specialist cereals, oilseeds and protein crops    | 73.5    | 62.7       | 77.3      |
|                      | General field cropping                            | 40.9    | 39.2       | 43.4      |
|                      | Specialist dairying                               | 50.2    | 49.5       | 50.2      |
|                      | Specialist cattle – rearing and fattening         | 24.9    | 24.8       | 25.1      |
|                      | Cattle – dairying, rearing and fattening combined | 29.9    | 28.7       | 29.6      |
|                      | Sheep, goats and other grazing livestock          | 18.2    | 17.4       | 17.8      |
|                      | Mixed cropping                                    | 13      | 12.1       | 13.7      |
|                      | Mixed livestock, mainly grazing livestock         | 8.6     | 7.8        | 9.2       |
|                      | Field crops - grazing livestock combined          | 47.3    | 44.7       | 48.3      |
|                      | Various crops and livestock combined              | 8.6     | 7.8        | 9.6       |
| Strong<br>Adaptation | Specialist cereals, oilseeds and protein crops    | 87.9    | 73.2       | 93.3      |
|                      | General field cropping                            | 50.4    | 46.3       | 51.8      |
|                      | Specialist dairying                               | 52      | 50.8       | 51.8      |
|                      | Specialist cattle – rearing and fattening         | 25.9    | 25.6       | 26.1      |
|                      | Cattle – dairying, rearing and fattening combined | 31.6    | 29.8       | 31.1      |
|                      | Sheep, goats and other grazing livestock          | 19.2    | 17.9       | 18.6      |
|                      | Mixed cropping                                    | 16.3    | 14.2       | 16.7      |
|                      | Mixed livestock, mainly grazing livestock         | 10.2    | 8.6        | 10.7      |
|                      | Field crops - grazing livestock combined          | 54.8    | 50.3       | 54.9      |
|                      | Various crops and livestock combined              | 11.1    | 9.6        | 12        |

Note: Only the main European types of farming (at least 80,000 unpaid AWU) are presented. See 4.4 for an exhaustive list of the computed types of farming.

Table 4.2 presents the per unpaid AWU average income by type of farming for two levels of adaptation and three time horizons. For both *weak* and *strong adaptation*, the reduction in mean income concerns all types of farming in the short-term horizon with respect to present. This loss is quite marked for crop producers, for example -15% (resp. -16%) for specialist cereals in the *weak* (resp. the *strong*) *adaptation* level. This loss in mean income is less marked for livestock farmers: it is on average -1.7% for specialist dairying for both adaptation levels. In the long-term horizon, average income increases for a majority of types of farming with respect to present. This increase is more pronounced for crop producers, for instance approximately +6% on average for both adaptation levels. Generally, we can see that crop producers average

income is more sensitive to climate change than livestock producers average income, which is quite stable over the different time horizons.

### 3.5 Decomposition results

Table 4.3: Shapley decompositions of per unpaid AWU farmers' income Gini index for three time horizons.

|               |                              | Time Horizon        | Present  |          | Short-term |          | Long-term |          |
|---------------|------------------------------|---------------------|----------|----------|------------|----------|-----------|----------|
|               |                              | Decomposition start | $\omega$ | $\sigma$ | $\omega$   | $\sigma$ | $\omega$  | $\sigma$ |
| Weak Adapt.   | Region ( $\omega$ )          |                     | 45.3%    | 50.2%    | 47.6%      | 51.9%    | 44.3%     | 49.7%    |
|               | Type of farming ( $\sigma$ ) |                     | 27.5%    | 22.2%    | 26.8%      | 22.1%    | 27.9%     | 22.3%    |
|               | Residual ( $r$ )             |                     | 27.2%    | 27.6%    | 25.6%      | 26.0%    | 27.8%     | 28.0%    |
|               | Gini index                   |                     | 0.6805   |          | 0.6814     |          | 0.6796    |          |
| Strong Adapt. | Region ( $\omega$ )          |                     | 44.9%    | 49.1%    | 47.9%      | 51.0%    | 43.5%     | 48.3%    |
|               | Type of farming ( $\sigma$ ) |                     | 26.9%    | 22.5%    | 26.0%      | 22.4%    | 27.7%     | 22.8%    |
|               | Residual ( $r$ )             |                     | 28.2%    | 28.4%    | 26.1%      | 26.6%    | 28.8%     | 28.9%    |
|               | Gini index                   |                     | 0.6740   |          | 0.6796     |          | 0.6743    |          |

Note: The two decomposition orders are presented, when starting the decomposition by region (order  $\omega$ ) and when starting the decomposition by type of farming (order  $\sigma$ ).

Table 4.3 illustrates the Shapley decomposition of farmers' income inequality for *weak* and *strong adaptation* levels and for present, short-term and long-term time horizon.

Region and type of farming importantly contributes to overall farmers' income inequality. Whatever the decomposition order, the level of adaptation, or the time horizon, these two characteristics explain from 71.1 to 74.4% of overall farmers' income inequality. Region seems to be the individual attribute contributing the most to farmers' income inequality (43.5 - 51.0%), whereas type of farming explains from 22.1 to 27.9% of income inequality. The contribution of farmers' region and type of farming is quite similar for all time horizon. Climate change slightly alter the marginal contribution of these two individual attributes to overall income inequality. It increases the contribution of region in the short-term horizon, and reduces it in the long-term horizon.

## 4 Discussion

In this section we first discuss the consistency of our results with respect to the literature. Second, we debate our positive findings in the long-term horizon. Third, we highlight several limits of this study.

Our results are broadly in line with the existing literature. The majority of studies assessing climate change impacts on European agriculture globally indentifies positive effects on agricultural production or revenues (Iglesias et al., 2011; Van Passel et al., 2016). These studies also find that mediterranean regions may suffer from climate change whereas regions from Northern Europe could benefit from it. Note that the increase in irrigation and chemical fertilizer use in the *weak adaptation* level is consitent with Iglesias et al. (2011) mentioning this increase in production and inputs which may have in turn unwanted environmental consequences. Also working on European agriculture, Vaitkeviciute (2018) finds that climate change may have negative impacts on the short-term, and positive impacts on the long-term. In a meta-analysis, Challinor et al. (2014) highlight that crop yields may increase from 7 to 15% under climate change with adaptation, quite close from our results (about +7% for corn and +5% for wheat, on average for both adaptation levels).

The positive findings of this study regarding farmers autonomous adaptation to climate change in the long term may be nuanced on certain points. First of all, the climate scenario used in this study (RCP 4.5) is quite optimistic. This climate scenario implies an ambitious global GHG emission mitigation policy, as overall emissions start to decrease in mid-21<sup>st</sup> century. Thus, by late 21<sup>st</sup> century the CO<sub>2eq</sub> concentration is expected to stabilized at about 650 ppm and world mean surface air temperature to increase by 1.8°C (from 1.1°C to 2.6°C). For the *weak adaptation* level, the better situation in the long-term horizon than in the present horizon in terms of social welfare is accompanied by an increase in mineral fertilizer demand. This increase may cause additionnal environmental pollution—e.g. eutrophication, GHG emissions—and degrade aggregate welfare in turn. We also note a serious increase in irrigation water consumption, which could lead to a possible tension on the resource. The slight increase in GHG emissions naturally arises the question of combining GHG emission mitigation

policies with adaptation to climate change. Does the implementation of an ambitious climate policy within European agriculture constrain the adaptation options available for farmers? How does it affect the positive long-term distributional consequences of autonomous adaptation? For the *strong adaptation* level, in the long-term horizon we also obtain positive economic results, and a decrease in input (i.e. water and mineral fertilizers) consumption. It should be noted that this adaptation level is quite optimistic as it enables farmers to procure varieties more suitable for their environment. As a consequence of this important adaptation option, the *strong adaptation* level overestimates the European production in the present horizon. Our positive findings may also be nuanced by other dimensions of climate change that we do not account for in this study. For instance, climate change could cause an increase—or an apparition—of plant disease affecting crop yields. Climate change is also certainly increasing the frequency of extreme weather events, such as droughts and floods (IPCC, 2014) that may have an important effect on agricultural production.

Although our results are conform to the existing literature, our study suffers from limitations. The first type of limitation is due to the underlying assumptions and characteristics of our modeling framework. The findings of this work strongly rely on the crop yields computed by the STICS crop model. Among the crop simulation models able to perform under various climate, soil and managements practices parameters, STICS is a well evaluated model (Palosuo et al., 2011; Rötter et al., 2012). However, the model has been found to slightly overestimate crop yields. It should also be noted that we do not consider any technical progress. Particularly, plant breeding will certainly help to obtain crops that better suit a different climate. Concerning the autonomous adaptation at the farm scale, our analysis is dependent on several assumptions. Prices for goods taken into account in the micro-economic model are exogenous. Thus we do not account for a possible change in input or output prices, due e.g. to climate change or to a change in eating habits. We also consider the structure of farms as unchangeable. We maintain the original typology (i.e. constant number of representative farms, constant farms agricultural surface). On the one hand, these assumptions enable us to assess European farmers autonomous adaptation to climate change *all other things being equal*. As we keep the agricultural population constant

across the different time horizons, we are able to quantify the distributional effects. On the other hand, this prevents us from capturing indirect effects. By modifying agricultural yields, climate change could obviously impact agricultural goods prices, and thus, farms structure.

## 5 Conclusion

Relying on a soft-coupling between a crop model and a micro-economic model of European agricultural supply, we inform the distributional impacts of EU-27 farm-level autonomous adaptation to climate change. In addition, we provide a farmers' income inequality decomposition. It allows us to identify and quantify the contribution of major farms characteristics to overall income inequality and how they vary under climate change.

Our findings indicate that, *ceteris paribus*, climate change may lead, in terms of social welfare, to a worse situation (with respect to present) in the short-term horizon. This result can be explained by (i) an decrease in income share for bottom quantiles and (ii) a decrease in total income. However, in the long-run, climate change could lead to a better situation, due to (i) a constant income share for bottom quantiles and (ii) an increase in average income. We also assess the marginal contribution of two major individual characteristics—i.e. region and type of farming—to overall income inequality. These two attributes substantially contribute to farmers' income inequality (approximately 73%). Region seems to be the most determinant characteristics. Our results show that climate change slightly influence the region and type of farming contribution to income inequality.

This work could be extended in several directions. First, the analysis could concern other regions. Distributional impacts of climate change may be different where agriculture is differently structured. One could also be interested in studying the distributional impacts of climate change on other economic sector. Second, it could consider other sides of climate change, such as the increase of the frequency of extreme weather events, or the apparition of crop diseases. Third, it could be of major interest to study the interaction of adaptation to climate change with GHG emission mitiga-

*CHAPTER 4. DISTRIBUTIONAL IMPACTS OF AUTONOMOUS  
ADAPTATION TO CLIMATE CHANGE FROM EUROPEAN AGRICULTURE*

---

tion policies, within European agriculture. How could agricultural GHG mitigation policies impact the distributional effects of adaptation to climate change across the European agricultural system? The micro-economic model used in this work could help disentangle this question.

## 4.A Modeling strategy

For selecting a representative year over a 30-year period, we measure the distance between each year's observations and the average values for the period. Each distance is calculated for the days of the year, and the FADN region and altitude class intersection (indexed by  $n$ ). The variables considered are indexed by  $k$ . We thus compare the matrice with average values ( $M$ ), and the matrice with annual observations for the year  $i$  ( $A_i$ ) as follows:

$$Distance_i = \sum_{j=1}^n \sum_{l=1}^k (M - A_i)^2 \quad (4.5)$$

Since the units of the climate variables and their variability are different, we calculate the distance with the variables normalized by their mean annual values over the 30 year period ( $avg$ ), as follows:

$$Normalized\ distance_i = \sum_{j=1}^n \sum_{l=1}^k \left( \frac{M - A_i}{avg} \right)^2 \quad (4.6)$$

Following the results obtained with the normalized distance, the year 2016 is the best choice to represent the climate in the beginning of 21st century (period 2006-2035), and the year 2073 is the best choice to represent the climate in the late 21st century (period 2071-2100).

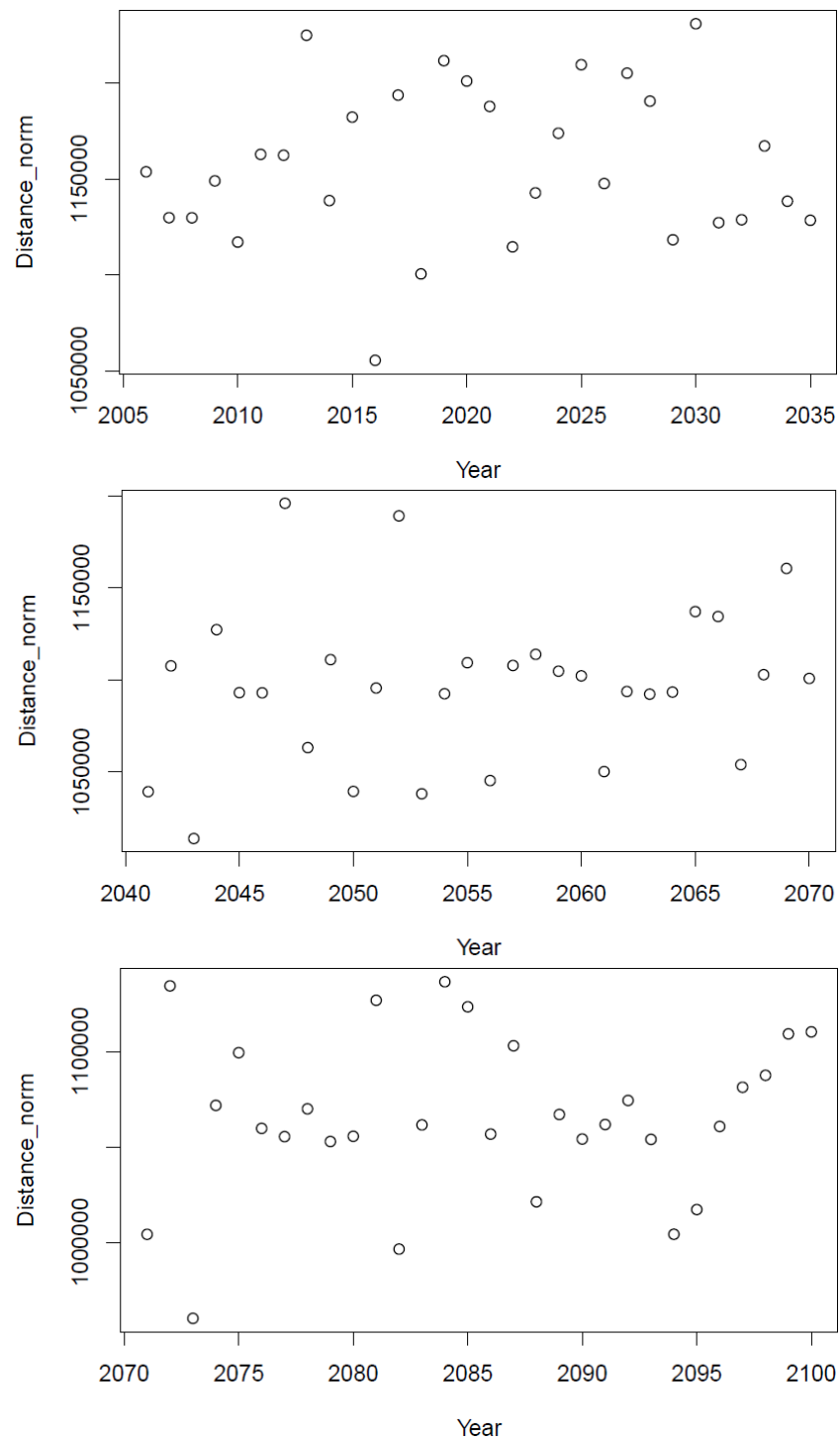


Figure 4.7: Normalized distance between year observations and average values for periods 2006-2035, 2041-2070, and 2071-2100.



## 4.B Classification of types of farming

Table 4.4: Types of farming modeled

---

|                                                   |
|---------------------------------------------------|
| Specialist cereals, oilseeds, protein crops       |
| General field cropping                            |
| Specialist dairying                               |
| Specialist cattle - rearing and fattening         |
| Cattle - dairying, rearing and fattening combined |
| Sheep, goats and other grazing livestock          |
| Specialist pigs                                   |
| Specialist poultry                                |
| Various granivore combined                        |
| Mixed cropping                                    |
| Mixed livestock, mainly grazing livestock         |
| Mixed livestock, mainly granivores                |
| Field crops - grazing livestock combined          |
| Various crops and livestock combined              |

---

## 4.C Gini index

Table 4.5: Gini index for per unpaid AWU and per farm income, for *weak* and *strong* adaptation levels, and for three time horizons.

|                      | Income         | Present | Short-term | Long-term |
|----------------------|----------------|---------|------------|-----------|
| Weak<br>Adaptation   | Per unpaid AWU | 0.6805  | 0.6814     | 0.6796    |
|                      | Per Farm       | 0.6907  | 0.6931     | 0.6885    |
| Strong<br>Adaptation | Per unpaid AWU | 0.6740  | 0.6796     | 0.6743    |
|                      | Per Farm       | 0.6840  | 0.6907     | 0.6817    |







# General Conclusion

This dissertation has explored several key aspects of climate change within agriculture in Europe. The sector is at the heart of climate change due to (i) its substantial contribution to GHG emissions, (ii) its reliance on weather and climate variables, and (iii) adaptation solutions it has to develop. These issues of emissions mitigation, weather impacts and adaptation are investigated through the prism of social justice and inequality. The guiding thread of this dissertation is to study the distributional consequences of these various aspects of climate change on farmers' income.

This conclusive section is composed of two parts. The first section summarizes the contributions of each chapter of the dissertation. The second section suggests several leads for future research.

## **Summary of contributions**

### **Chapter 2**

The second chapter investigates the distributional consequences of various climate policies, first from an analytical approach, and second applied to GHG emissions from European agriculture. Our analytical framework illustrates the importance of both distributions of (i) initial emissions and (ii) marginal abatement costs for explaining the potential regressivity of climate policies. We also show how these two distributions differently affect post-policy income inequality according to the type of policy.

We then assess the distributional effects of these climate policies on European farmers' income. Our results indicate that a single emission tax increases income inequality, and the higher the tax level, the greater the inequality. However, it is possible to offset this regressive impact through a rebate of the collected tax. A lump-sum transfer of the collected tax, neutral for the regulator's budget, is found to substantially reduce income inequality, even more than its pre-tax level. A rebate of the collected tax in proportion of initial emissions, neutral for the regulator, leaves the pre-tax income inequality level unchanged. It should be noted that an abatement subsidy delivers close distributional results.

At the moment of writing, European agriculture is not involved in any climate policies. These findings may be crucial for implementing a cost-effective instrument without fearing important and negative distributional consequences within European agriculture.

### **Chapter 3**

In the third chapter, we focus on the effect of extreme temperatures on French crop producers' income. The assessment of distributional impacts of climate change is particularly relevant for identifying the farmers most affected by the weather and, to provide the right response.

Our empirical analysis combines farms accounting, weather, and soil information. We isolate and quantify the negative effect of extreme temperatures, both cold and

hot, on farmers' income. Our distributional analysis reveals that these extremes have opposite consequences. While cold extremes are more damaging for low-income farmers and increase inequality, hot extremes are found to be more harmful for high income farmers and decrease inequality.

We suggest two hypothesis for explaining these distributional impacts. First, it may be due to the evolution of the crop mix along the distribution: the proportion of corn in the crop mix decreases with income while the one of rapeseed increases with income. Hence, corn production may be more sensitive to cold extremes and rapeseed production may be more sensitive to hot extremes. Second, a reason for these opposite distributional impacts could be the geographical distribution: the probability of being located in the North of France increases when income increases. Northern farmers may be more sensitive to hot extremes, and Southern farmers may be more sensitive to cold extremes.

## Chapter 4

The fourth chapter looks at farmers' adaptation to climate change.

In the face of climate change, farmers can adapt to a modification in weather conditions on their own scale. Our modeling framework relies on a soft-coupling between a micro-economic model of European agriculture and a crop model. We consider the climate scenario RCP 4.5 from SRES AR5 and implement two levels of autonomous adaptation for farmers. We then decompose farmers' income inequality into characteristics and explore the marginal contributions of region and type of farming to income inequality.

*All other thing being equal*, our results show that climate change may lead to a worse situation than the present one in the short-term horizon. This is due to a decrease in (i) income share for low income farmers and (ii) total income. However, the long-term horizon may lead to a better situation than the present one because of (i) a stable income share for low income farmers and (ii) an increase in total income. The decomposition of income inequality unveils the important contribution of region and type of farming to income inequality. Climate change only slightly affect their marginal contributions.

Our findings, mostly positive in the long-term under an ambitious scenario of reduction in total GHG emission (i.e., RCP 4.5), are an argument for the implementation of climate policies. A moderate warming (i.e.,  $+1.5^{\circ}\text{C}$  on average) may prevent from important distributional consequences within the European agricultural system.

## **Future research**

This section is dedicated to further research. We focus on three particular lines of research.

### **Interaction between GHG emission mitigation, climate impacts and adaptation**

In this dissertation, GHG emission mitigation policies, weather impacts and adaptation to climate change have been separately examined. However, it could be of major interest to study the effect of their interactions within the agricultural sector. For example, one may wonder how an emission tax would impact farmers' abilities to protect from weather impacts. Do climate policies constraint available adaptation options for farmers? One may also question the potential consequences of adaptation strategies on GHG emissions. Note that this question could be extended to other environmental policies, for example nitrates control, pesticides ban, or water resource constraints.

Findings from chapter 4 show that this question may be especially relevant. Farmers adaptation to climate change increases both fertilizer and water consumption, and slightly increases GHG emissions. Hence, an emission tax or a nitrates control policy may have an effect on adaptation options.

### **Characterization of the winners and losers from climate change**

Behind inequality and the distributional considerations that have been explored in this manuscript, there is the differential impacts of climate change. It appears to be an important concern to better discern how climate change impacts and mitigation affect



individuals. It can help to better understand who the losers and winners are and why. It can also help to more clearly determine good practices, both in terms of mitigation and adaptation. The increasing availability of more accurate databases will probably contribute to this development.

In particular, carbon sequestration practices have not been mentioned in this dissertation. Agricultural soils have a significant carbon storage potential that could contribute substantially to the mitigation of GHG emissions.

### **Impact of a change in demand**

One of the limitations of this study (particularly in chapters 2 and 4) is due to the underlying assumptions of the micro-economic model of the European agricultural sector. We evaluate the distributional impacts of climate policies and climate change adaptation *all other things being equal* with exogenous prices. Nevertheless, it could be interesting to investigate how a change in demand may impact the agricultural system. For instance, a change in food demand may come from a public policy promoting low-carbon food or from a shift in consumers preferences. One could wonder how a large-scale adoption of vegetarian regimes or the development of less meaty diet in school restaurants can affect the distribution of farmers income.







# Résumé long

Cette thèse traite des effets du changement climatique sur les inégalités de revenu parmi les agriculteurs européens. En particulier, elle examine successivement les conséquences distributives (i) des politiques de réductions des émissions de gaz à effets de serre (GES), (ii) des températures extrêmes, et (iii) de l'adaptation autonome au changement climatique. Elle est composée de trois chapitres indépendants, encadrés par un chapitre introductif (chapitre 1) et un chapitre de conclusion.

## Chapitre 2. Conséquences distributives des politiques climatiques: une application à l'agriculture européenne

L'objectif principal de ce chapitre est d'évaluer les impacts distributifs de divers systèmes de taxation et de remises, à partir d'une approche analytique et empirique.

Suite aux travaux de [Kolm \(1969\)](#) et [Atkinson \(1970\)](#) définissant le critère de dominance au sens de Lorenz<sup>1</sup>, une littérature théorique a émergé à partir de [Jakobsson \(1976\)](#) et [Kakwani \(1977\)](#) pour lier la progressivité de la fiscalité aux propriétés de dominance au sens de Lorenz. [Jakobsson \(1976\)](#) démontre qu'une taxe est réduit les inégalités au sens de Lorenz si et seulement si elle est progressive partout. Ce modèle a ensuite été affiné en termes d'hypothèses par [Eichhorn et al. \(1984\)](#), en ajoutant une condition sur la préservation du rang des individus, ou étendu à la fiscalité composite par [Le Breton et al. \(1996\)](#). Nous nous appuyons sur cette littérature pour aborder

---

<sup>1</sup>Une situation peut être préférée à une autre en termes de bien-être global si et seulement si la courbe de Lorenz de sa distribution se situe entièrement au-dessus de la courbe de Lorenz de l'autre distribution.

la question d'une taxe sur les émissions, éventuellement accompagnée d'une remise. Notre cadre nous permet de démêler l'importance (i) de la distribution des émissions initiales par rapport au revenu initial, et (ii) de la distribution des coûts marginaux de réduction par rapport au revenu pour que la taxe réduise les inégalités au sens de Lorenz. Nous explicitons deux types de remises de la taxe collectée : des remises basées sur un seuil d'émissions absolu constant, équivalent à des transferts forfaitaires aux agents, et des remises basées sur un seuil d'abattement relatif constant, proportionnel aux émissions initiales individuelles. Pour les deux types de remises, le régulateur peut redistribuer le montant total de la taxe collectée, ou plus. Nous comparons les propriétés de réduction des inégalités de ces différents systèmes de taxes et de remise. Nous examinons également comment ces derniers sont affectés par une augmentation du taux de taxe.

Nous appliquons ensuite ce cadre à la question de la réglementation européenne des émissions de GES dans l'agriculture. L'exploration des conséquences distributives des politiques climatiques dans l'agriculture européenne est pertinente pour plusieurs raisons. Premièrement, bien que l'agriculture européenne contribue à environ 10% des émissions totales de GES en Europe, elle n'est soumise à aucune politique climatique contraignante. Deuxièmement, la politique agricole commune (PAC) présente des objectifs d'équité pour les agriculteurs européens. Enfin, il a été démontré que les exploitations agricoles sont très hétérogènes en termes d'émissions de GES et de coûts marginaux de réduction. Notre évaluation s'appuie sur un ensemble de simulations (Isbasoiu, 2019) obtenues à partir d'un modèle micro-économique de l'agriculture européenne. Dans ce modèle, des agriculteurs représentatifs, calibrés sur des données d'exploitations réelles, maximisent leur marge brute, sous diverses contraintes. Nous construisons donc un revenu, en soustrayant les salaires versés de la marge brute, et en pondérant par le nombre de travailleurs non rémunérés sur l'exploitation. Il faut noter la présence de revenus négatifs, qui ne sont pas rares dans l'agriculture et que nous retirons pour l'analyse distributive, conformément à la littérature. Nos résultats indiquent qu'une taxe sur les émissions sans remise augmenterait les inégalités de revenu des agriculteurs. Ceci est principalement dû à une élasticité des émissions de GES par rapport au revenu inférieure à un. Cependant, nous montrons que des rabais basés sur

un seuil d'émissions bien choisi peuvent ramener les inégalités de revenu à un niveau inférieur au niveau initial (avant la taxe).

Dans une annexe, nous proposons une extension de ce travail. En appliquant une méthode basée sur la valeur de Shapley [Chantreuil et al. \(2019\)](#), nous décomposons les inégalités de revenu des agriculteurs. Nous quantifions la contribution marginale de deux caractéristiques principales, la région et le type d'agriculture, aux inégalités de revenu. Nous examinons également comment ces contributions varient, en fonction du type de politique climatique mise en place.

### Chapitre 3. Températures extrêmes et inégalité de revenu dans le secteur agricole français

L'objectif de ce chapitre est d'estimer les effets distributifs des températures extrêmes sur le revenu des producteurs céréaliers français.

Les études récentes de [DePaula \(2020\)](#) et [Malikov et al. \(2020\)](#) examinent les impacts distributifs de variables climatiques au sein des agriculteurs. [DePaula \(2020\)](#), qui étudie les fermes commerciales brésiliennes, constate qu'un réchauffement de 1°C peut être plus préjudiciable aux fermes ayant un climat chaud et des terres de haute qualité. [Malikov et al. \(2020\)](#), travaillant sur la production de maïs et de soja aux États-Unis, indiquent que les impacts du changement climatique futur pourraient être plus dommageables aux fermes qui ont de faibles rendements. S'appuyant sur ces études, ce chapitre se concentre sur les impacts distributifs des températures extrêmes au sein des producteurs céréaliers, en France. A cette fin, nous combinons trois bases de données. Premièrement, nous utilisons les informations individuelles du Réseau d'Information Comptable Agricole (RICA). Il fournit des données comptables sur les exploitations agricoles (par exemple, l'excédent d'exploitation, la production, les coûts des intrants), mais aussi des informations sur les cultures, pour 18 546 exploitations sur la période 2002-2017. Deuxièmement, nous tirons profit d'une base de données *MétéoFrance*. Elle fournit des informations météorologiques quotidiennes au niveau de la grille SAFRAN (8 km) que nous désagrégeons au niveau de la commune. Nous construisons ensuite

des variables pour capturer l'effet des températures extrêmes pendant la saison de croissance. Une période de douze ans, de 1988 à 1999, est prise comme distribution (locale) de référence. Ensuite, les jours où la température se situe dans les 10% inférieurs (respectivement supérieurs) de la distribution sont considérés comme des extrêmes froids (respectivement chauds). Leur somme cumulée est notre variable capturant les températures extrêmes. A noter que notre cadre empirique contrôle également pour l'effet des températures moyennes et des précipitations. Troisièmement, nous nous appuyons sur la base de données européenne des sols. Elle nous fournit des informations sur la qualité du sol au niveau d'une commune en cinq classes de texture.

Nous estimons ensuite l'effet des températures extrêmes chaudes et froides sur le revenu des exploitations agricoles (i.e., l'excédent d'exploitation), en contrôlant les variables météorologiques (i.e., les températures moyennes, les précipitations), la qualité des sols, les caractéristiques des exploitations agricoles (i.e., la surface des sols, l'irrigation) et les informations comptables (i.e., les dépenses en intrants, les subventions perçues). Les résultats indiquent que les températures extrêmes, tant chaudes que froides, peuvent être particulièrement coûteuses pour les agriculteurs. Nous estimons une élasticité de -0,131 (resp. -0,048) pour les degrés-jours extrêmes chauds (respectivement froids) par rapport au revenu des exploitations. En nous appuyant sur un cadre de régression quantile (Koenker and Basset, 1978; Machado and Silva, 2019), nous allons plus loin dans la distribution. Notre analyse révèle des effets opposés des températures extrêmement froides et chaudes. Alors que les températures extrêmes froides s'avèrent plus néfastes pour les revenus les plus bas, et augmentent donc les inégalités, les extrêmes chauds s'avèrent plus néfaste pour les revenus les plus élevés, et diminuent donc les inégalités. Nous explorons deux explications possibles pour ces effets distributifs opposés. Premièrement, il pourrait y avoir un effet de culture : la proportion de maïs dans le mélange de cultures diminue avec le revenu, tandis que celle du colza augmente avec le revenu. Deuxièmement, il pourrait y avoir un effet de région : la probabilité d'être situé dans le Nord de la France augmente avec le revenu.



## **Chapitre 4. Effets distributifs de l'adaptation autonome au changement climatique dans l'agriculture européenne**

L'objectif de ce chapitre est de quantifier l'impact sur la distribution des revenus de l'adaptation autonome des exploitations agricoles au changement climatique en Europe.

Face à un changement durable de leur environnement climatique, les agriculteurs peuvent s'adapter de manière autonome, à leur échelle. Cette adaptation autonome peut provenir de la marge intensive, de la marge extensive, ou encore de l'adoption de nouvelles pratiques. Notre stratégie de modélisation repose sur un couplage souple entre un modèle micro-économique de l'agriculture européenne (AROPAj) et un modèle de culture (STICS). AROPAj décrit le comportement économique annuel d'un ensemble d'agriculteurs européens représentatifs en termes d'allocation des terres agricoles (cultures, pâturages et prairies) et de gestion du bétail (nombre d'animaux et alimentation). Le modèle inclut diverses productions agricoles en termes de cultures (i.e. 24 cultures européennes majeures, prairies permanentes et temporaires) et d'élevage (i.e. bovins laitiers et non laitiers, ovins, caprins, porcins, volailles). Chaque agriculteur maximise sa marge brute sous réserve de contraintes techniques (par exemple, les rotations de cultures requises) et politiques (par exemple, les paiements de la PAC, les politiques environnementales). Pour pallier le manque d'exhaustivité du RICA, AROPAj est affiné en substituant une fonction extraite de STICS reliant les intrants et les rendements à l'échelle de la parcelle. STICS simule le système sol-atmosphère-culture appliqué à une large gamme de cultures et de conditions pédo-climatiques (Brisson et al., 2003). Il nécessite des paramètres climatiques, des informations sur le sol et des données sur les pratiques de gestion agricole.

Nous considérons la trajectoire représentative de concentration (RCP) 4.5 du SRES AR5. Le scénario climatique est ensuite traduit en variables météorologiques par le modèle atmosphérique du LSCE. Nous nous intéressons à trois horizons temporels : un horizon actuel (période 2006-2035), un horizon à court terme (période 2041-

2070), et un horizon à long terme (période 2071-2100). Nous simulons deux niveaux d'adaptation autonome pour les agriculteurs. Premièrement, un niveau d'adaptation *faible*, où les agriculteurs peuvent s'adapter à un changement de conditions météorologiques à travers les marges extensives et intensives, mais seulement avec les cultures initialement présentes dans leur type d'agriculture. Deuxièmement, un niveau d'adaptation *fort*, où les agriculteurs peuvent en plus adopter de nouvelles variétés de cultures ou changer la date de semis. Les résultats montrent que toute chose égale par ailleurs, le changement climatique peut conduire à une situation pire que la situation actuelle, en termes de bien-être social, à court terme, en raison (i) d'une diminution de la part de revenu pour les revenus les plus bas et (ii) d'une diminution du revenu total. Toutefois, la situation peut être meilleure à long terme en raison (i) d'une part de revenu stable pour les quantiles inférieurs et (ii) d'une augmentation du revenu total. Nous appliquons ensuite un cadre de décomposition des inégalités issu de Chantreuil et al. (2019) et évaluons les contributions marginales de la région et du type d'agriculture aux inégalités de revenus. Nous examinons aussi comment l'adaptation autonome des exploitations agricoles au changement climatique affecte ces contributions.





# Bibliography

- Aaberge, R. (2001). Axiomatic characterization of the Gini coefficient and Lorenz curve orderings, *Journal of Economic Theory* **101**(1): 115–132. 24, 105
- Adams, R. M., Hurd, B. H., Lenhart, S. and Leary, N. (1998). Effects of global climate change on agriculture : an interpretative review, *Climate Research* **11**(1): 19–30. 6
- Adger, W. N. (2006). Vulnerability, *Global Environmental Change* **16**(3): 268–281. 7
- Allanson, P. (2008). On the characterisation and measurement of the redistributive effect of agricultural policy, *Journal of Agricultural Economics* **59**(1): 169–187. 111
- Angrist, J., Chernozhukov, V. and Fernandez-Val, I. (2006). Quantile regression under misspecification, with an application to the U.S. wage structure, *Econometrica* **74**(2): 539–563. 77
- Annan, F. and Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat, *American Economic Review* **105**(5): 262–66. 76
- Araar, A., Dissou, Y. and Duclos, J.-Y. (2011). Household incidence of pollution control policies: A robust welfare analysis using general equilibrium effects, *Journal of Environmental Economics and Management* **61**(2): 227–243. 3, 22
- Aragón, F. M., Oteiza, F. and Rud, J. P. (2021). Climate change and agriculture: Subsistence farmers’ response to extreme heat, *American Economic Journal: Economic Policy* **13**(1): 1–35. 8, 105
- Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., Kimball, B. A., Ottman, M. J., Wall, G. W., White, J. W., Reynolds, M. P., Alderman,

- P. D., Prasad, P. V. V., Aggarwal, P. K., Anothai, J., Basso, B., Biernath, C., Challinor, A. J., Sanctis, G. D., Doltra, J., Fereres, E., Garcia-Vila, M., Gayler, S., Hoogenboom, G., Hunt, L. A., Izaurrealde, R. C., Jabloun, M., Jones, C. D., Kersebaum, K. C., Koehler, A.-K., Müller, C., Kumar, S. N., Nendel, C., O’Leary, G., Olesen, J. E., Palosuo, T., Priesack, E., Rezaei, E. E., Ruane, A. C., Semenov, M. A., Shcherbak, I., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Thorburn, P. J., Waha, K., Wang, E., Wallach, D., Wolf, J., Zhao, Z. and Zhu, Y. (2014). Rising temperatures reduce global wheat production, *Nature Climate Change* **5**(2): 143–147. [90](#)
- Atkinson, A. B. (1970). On the measurement of inequality, *Journal of Economic Theory* **2**(3): 244–263. [12](#), [24](#), [40](#), [105](#), [111](#), [139](#)
- Augspurger, C. K. (2013). Reconstructing patterns of temperature, phenology, and frost damage over 124 years: Spring damage risk is increasing, *Ecology* **94**(1): 41–50. [89](#)
- Barberis, D., Chiadmi, I., Humblot, P., Jayet, P.-A., Lungarska, A. and Ollier, M. (2020). Climate change and irrigation water: Should the North/South hierarchy of impacts on agricultural systems be reconsidered?, *Environmental Modeling & Assessment* **26**(1): 13–36. [105](#), [107](#)
- Bareille, F. and Chakir, R. (2021). Decomposing weather impacts on crop profits: The role of agrochemical input adjustments. FAERE Working Paper, 2021.09. [8](#), [105](#)
- Barreca, A. I. (2012). Climate change, humidity, and mortality in the United States, *Journal of Environmental Economics and Management* **63**(1): 19–34. [5](#)
- Bento, A. M., Goulder, L. H., Jacobsen, M. R. and von Haefen, R. H. (2009). Distributional and efficiency impacts of increased US gasoline taxes, *American Economic Review* **99**(3): 667–99. [3](#), [22](#)
- Botzen, W. J. W., Deschenes, O. and Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies, *Review of Environmental Economics and Policy* **13**(2): 167–188. [75](#)

- Bourguignon, F. (1979). Decomposable income inequality measures, *Econometrica* **47**(4). 105
- Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussi re, F., Cabidoche, Y., Cellier, P., Debaeke, P., Gaudill re, J., H nault, C., Maraux, F., Seguin, B. and Sinoquet, H. (2003). An overview of the crop model STICS, *European Journal of Agronomy* **18**(3-4): 309–332. 15, 109, 143
- Brouwer, R., Akter, S., Brander, L. and Haque, E. (2007). Socioeconomic vulnerability and adaptation to environmental risk: A case study of climate change and flooding in Bangladesh, *Risk Analysis* **27**(2): 313–326. 7
- Burgess, R., Desch enes, O., Donaldson, D. and Greenstone, M. (2011). Weather and death in India. 5
- Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture, **8**(3): 106–40. 74
- Caney, S. (2005). Cosmopolitan justice, responsibility, and global climate change, *Leiden Journal of International Law* **18**(4): 747–775. 11
- Castel, T., Lecomte, C., Richard, Y., Lejeune-H naut, I. and Larmure, A. (2017). Frost stress evolution and winter pea ideotype in the context of climate warming at a regional scale, *OCL* **24**(1): D106. 89
- Cavallo, E., Noy, I. et al. (2011). Natural disasters and the economy—a survey, *International Review of Environmental and Resource Economics* **5**(1): 63–102. 75
- Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R. and Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation, *Nature Climate Change* **4**(4): 287–291. 7, 105, 121
- Chancel, L. (2021). Global carbon inequality, 1990-2019: The impact of wealth concentration on the distribution of world emissions. World Inequality Lab, Paris School of Economics. 24

- Chantreuil, F., Courtin, S., Fourrey, K. and Lebon, I. (2019). A note on the decomposability of inequality measures, *Social Choice and Welfare* **53**(2): 283–298. [13](#), [16](#), [61](#), [64](#), [105](#), [117](#), [141](#), [144](#)
- Chantreuil, F., Fourrey, K., Lebon, I. and Rebière, T. (2020). Magnitude and evolution of gender and race contributions to earnings inequality across US regions, *Research in Economics* **75**(1): 45–59. [63](#), [105](#), [112](#)
- Chantreuil, F. and Lebon, I. (2015). Gender contribution to income inequality, *Economics Letters* **133**: 27–30. [111](#)
- Chantreuil, F. and Trannoy, A. (2013). Inequality decomposition values: The trade-off between marginality and efficiency, *The Journal of Economic Inequality* **11**: 83–98. [117](#)
- Chen, C.-N., Tsaur, T.-W. and Rhai, T.-S. (1982). The Gini coefficient and negative income, *Oxford Economic Papers* **34**(3): 473–478. [111](#)
- Chen, S., Chen, X. and Xu, J. (2016). Impacts of climate change on agriculture: Evidence from China, *Journal of Environmental Economics and Management* **76**: 105–124. [72](#), [74](#)
- Chernozhukov, V. and Hansen, C. (2005). An IV model of quantile treatment effects, *Econometrica* **73**(1): 245–261. [77](#)
- Chiroleu-Assouline, M. and Fodha, M. (2006). Double dividend hypothesis, Golden Rule and welfare distribution, *Journal of Environmental Economics and Management* **51**(3): 323–335. [22](#)
- Chiroleu-Assouline, M. and Fodha, M. (2014). From regressive pollution taxes to progressive environmental tax reforms, *European Economic Review* **69**: 126–142. [22](#)
- Citepa (2021). Inventaire des émissions de polluants atmosphériques et de gaz à effet de serre en france., *Report*, Citepa. [1](#)
- Connolly, M. (2008). Here comes the rain again: Weather and the intertemporal substitution of leisure, *Journal of Labor Economics* **26**(1): 73–100. [5](#)



- Couttenier, M. and Soubeyran, R. (2013). Drought and civil war in Sub-Saharan Africa, *The Economic Journal* **124**(575): 201–244. [5](#)
- Cronin, J. A., Fullerton, D. and Sexton, S. (2019). Vertical and horizontal redistributions from a carbon tax and rebate, *Journal of the Association of Environmental and Resource Economists* **6**(S1): S169–S208. [22](#)
- De Battisti, F., Porro, F. and Vernizzi, A. (2019). The Gini coefficient and the case of negative values, *Electronic Journal of Applied Statistical Analysis (EJASA)* **12**(1): 85–107. [81](#), [111](#)
- De Cara, S., Henry, L. and Jayet, P.-A. (2018). Optimal coverage of an emission tax in the presence of monitoring, reporting, and verification costs, *Journal of Environmental Economics and Management* **89**: 71–93. [4](#), [23](#), [37](#), [51](#)
- De Cara, S. and Jayet, P.-A. (2011). Marginal abatement costs of greenhouse gas emissions from european agriculture, cost effectiveness, and the EU non-ETS burden sharing agreement, *Ecological Economics* **70**: 1680–1690. [37](#)
- Dell, M., Jones, B. F. and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century, *American Economic Journal: Macroeconomics* **4**(3): 66–95. [4](#)
- Dell, M., Jones, B. F. and Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature, *Journal of Economic Literature* **52**(3): 740–798. [5](#), [72](#), [105](#)
- DePaula, G. (2020). The distributional effect of climate change on agriculture: Evidence from a ricardian quantile analysis of Brazilian census data, *Journal of Environmental Economics and Management* **104**: 102378. [14](#), [76](#), [81](#), [91](#), [141](#)
- Deppermann, A., Grethe, H. and 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. [111](#)

- Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather, *American economic review* **97**(1): 354–385. 6, 72, 74, 78, 105
- Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US, *American Economic Journal: Applied Economics* **3**(4): 152–185. 5
- Di Falco, S., Veronesi, M. and Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia, *American Journal of Agricultural Economics* **93**(3): 829–846. 7
- Dissou, Y. and Siddiqui, M. S. (2014). Can carbon taxes be progressive?, *Energy Economics* **42**: 88–100. 22
- Douenne, T. (2020). The vertical and horizontal distributive effects of energy taxes: A case study of a French policy, *The Energy Journal* **41**(3). 22
- Eichhorn, W., Funke, H. and Richter, W. F. (1984). Tax progression and inequality of income distribution, *Journal of Mathematical Economics* **13**(2): 127–131. 12, 30, 139
- Elster, J. (1985). *Making sense of Marx*, Cambridge University Press. 9
- European Commission (2010). The cap towards 2020: Meeting the food, natural resources and territorial challenges of the future, *Technical report*, European Commission. 104
- European Commission (2020). Farm to fork strategy for a fair, healthy and environmentally-friendly food system, *Report*, European Commission, Brussels, BE. 23
- European Commission (2021a). EU farm economics overview: FADN 2018, *Report*, Directorate-general for Agriculture and Rural Development. 23, 40, 41, 42
- European Commission (2021b). 'Fit for 55': Delivering the EU's 2030 Climate Target on the way to climate neutrality, *Report*, European Commission. 23

- European Community (1957). Treaty establishing the European Economic Community, p. 32. [104](#)
- European Environment Agency (2020). Annual European Union greenhouse gas inventory 1990–2018 and inventory report. Submission to the UNFCCC secretariat, *Report*, European Environment Agency. [1](#), [23](#)
- European Parliament (2018). Regulation (EU) 2018/842 of the European Parliament and of the Council, *Official journal of the European Union* . [23](#)
- Feindt, S., Kornek, U., Labeaga, J. M., Sterner, T. and Ward, H. (2021). Understanding regressivity: Challenges and opportunities of European carbon pricing, *Energy Economics* p. 105550. [22](#)
- Fellman, J. (1976). The effect of transformations of Lorenz curves, *Econometrica* **44**(4): 823. [24](#), [53](#)
- Fellman, J. (2016). Transfer policies with discontinuous Lorenz curves, *Journal of Mathematical Finance* **06**(01): 28–33. [53](#)
- Fellmann, T., Domínguez, I. P., Witzke, P., Weiss, F., Hristov, J., Barreiro-Hurle, J., Leip, A. and Himics, M. (2021). Greenhouse gas mitigation technologies in agriculture: Regional circumstances and interactions determine cost-effectiveness, *Journal of Cleaner Production* **317**: 128406. [23](#)
- Ferreira, F. H., Firpo, S. and Galvao, A. F. (2018). Actual and counterfactual growth incidence and delta Lorenz curves: Estimation and inference, *Journal of Applied Econometrics* **34**(3): 385–402. [44](#), [105](#), [111](#), [113](#)
- Fezzi, C. and Bateman, I. (2015). The impact of climate change on agriculture: non-linear effects and aggregation bias in ricardian models of farmland values, *Journal of the Association of Environmental and Resource Economists* **2**(1): 57–92. [74](#)
- Finger, R. and El Benni, N. (2014). A note on the effects of the income stabilisation tool on income inequality in agriculture, *Journal of Agricultural Economics* **65**(3): 739–745. [23](#)

- Finger, R. and El Benni, N. (2021). Farm income in European agriculture: new perspectives on measurement and implications for policy evaluation, *European Review of Agricultural Economics* **48**(2): 253–265. [41](#)
- Fleurbaey, M. (1996). *Théorie Economique de la Justice*, Economica. [9](#)
- Frank, S., Havlík, P., Stehfest, E., van Meijl, H., Witzke, P., Pérez-Domínguez, I., van Dijk, M., Doelman, J. C., Fellmann, T., Koopman, J. F. L., Tabeau, A. and Valin, H. (2018). Agricultural non-CO<sub>2</sub> emission reduction potential in the context of the 1.5 °C target, *Nature Climate Change* **9**(1): 66–72. [23](#)
- Gammans, M., Mérel, P. and Ortiz-Bobea, A. (2017). Negative impacts of climate change on cereal yields: Statistical evidence from France, *Environmental Research Letters* **12**(5): 054007. [74](#), [90](#)
- Garnache, C., Mérel, P. R., Lee, J. and Six, J. (2017). The social costs of second-best policies: Evidence from agricultural GHG mitigation, *Journal of Environmental Economics and Management* **82**: 39–73. [4](#), [23](#)
- Gassebner, M., Keck, A. and Teh, R. (2010). Shaken, not stirred: The impact of disasters on international trade, *Review of International Economics* **18**(2): 351–368. [75](#)
- Godard, C., Roger-Estrade, J., Jayet, P., Brisson, N. and Bas, C. L. (2008). Use of available information at a European level to construct crop nitrogen response curves for the regions of the EU, *Agricultural Systems* **97**(1-2): 68–82. [105](#)
- Gosseries, A. (2004). Historical emissions and free-riding, *Ethical perspectives* **11**(1): 36–60. [11](#)
- Goulder, L. H., Hafstead, M. A., Kim, G. and Long, X. (2019). Impacts of a carbon tax across US household income groups: What are the equity-efficiency trade-offs?, *Journal of Public Economics* **175**: 44 – 64. [22](#)
- Goulder, L. H. and Parry, I. W. H. (2008). Instrument choice in environmental policy, *Review of Environmental Economics and Policy* **2**(2): 152–174. [22](#)

- Grainger, C. A. and Kolstad, C. D. (2010). Who pays a price on carbon?, *Environmental and Resource Economics* **46**(3): 359–376. 22
- Grosjean, G., Fuss, S., Koch, N., Bodirsky, B. L., De Cara, S. and Acworth, W. (2016). Options to overcome the barriers to pricing European agricultural emissions, *Climate Policy* **18**(2): 151–169. 3, 23
- Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon, *American Economic Journal: Applied Economics* **8**(2): 123–153. 75
- Guo, C. and Costello, C. (2013). The value of adaption: Climate change and timberland management, *Journal of Environmental Economics and Management* **65**(3): 452–468. 7
- Hamano, M. and Vermeulen, W. N. (2019). Natural disasters and trade: The mitigating impact of port substitution, *Journal of Economic Geography* **20**(3): 809–856. 75
- Hanson, A. (2021). Assessing the redistributive impact of the 2013 CAP reforms: An EU-wide panel study, *European Review of Agricultural Economics* **48**(2): 338–361. 23
- Harsanyi, J. C. (1975). Can the maximin principle serve as a basis for morality? A critique of John Rawls's theory, *American Political Science Review* **69**(2): 594–606. 10
- Heal, G. (2017). The economics of the climate, *Journal of Economic Literature* **55**(3): 1046–1063. 4
- Hornbeck, R. (2012). The enduring impact of the American Dust Bowl: Short- and long-run adjustments to environmental catastrophe, *American Economic Review* **102**(4): 1477–1507. 76
- Hornbeck, R. and Keskin, P. (2014). The historically evolving impact of the Ogallala aquifer: Agricultural adaptation to groundwater and drought, *American Economic Journal: Applied Economics* **6**(1): 190–219. 76

- Hsiang, S. (2016). Climate econometrics, *Annual Review of Resource Economics* **8**(1): 43–75. 7
- Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America, *Proceedings of the National Academy of sciences* **107**(35): 15367–15372. 75
- Hsiang, S., Oliva, P. and Walker, R. (2019). The distribution of environmental damages, *Review of Environmental Economics and Policy* **13**(1): 83–103. 76
- Humblot, P., Jayet, P.-A. and Petsakos, A. (2017). Farm-level bio-economic modeling of water and nitrogen use: Calibrating yield response functions with limited data, *Agricultural Systems* **151**: 47–60. 105, 107
- Iglesias, A., Garrote, L., Quiroga, S. and Moneo, M. (2011). A regional comparison of the effects of climate change on agricultural crops in Europe, *Climatic Change* **112**(1): 29–46. 7, 121
- IPCC (2014). The physical science basis: Working group I, *Report*, Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M. M.B., Nauels, A., Xia, Y., Allen, S. K., Boschung, J., Bex, V., and Midgley, P. M. 122
- IPCC (2019). Climate change and land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems, *Report*, Shukla, P.R., Skea, J., Calvo Buendia, E., Masson-Delmotte, V., Pörtner, H.-O., Roberts, D. C., Zhai, P., Slade, R., Connors, S., van Diemen, R., Ferrat, M., Haughey, E., Luz, S., Neogi, S., Pathak, M., Petzold, J., Portugal Pereira, J., Vyas, P., Huntley, E., Kissick, K., Belkacemi, M., and Malley, J. 1
- IPCC (2022). Climate change: Impacts, adaptation and vulnerability. contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change., *Report*, Pörtner, H.-O., Roberts, D. C., Adams, H., Adler, C., Aldunce, P., Ali, E., Begum, R., Ara Betts, R., Kerr, R. B., and Biesbroek, R. 1, 104

- Isbasoiu, A. (2019). *Analyse multicritère des politiques publiques environnementales dans l'Union Européenne*, Phd thesis, AgroParisTech. 13, 24, 36, 37, 38, 39, 140
- Jacob, B., Lefgren, L. and Moretti, E. (2007). The dynamics of criminal behavior: Evidence from weather shocks, *The Journal of Human Resources* 42(3): 489–527. 5
- Jagnani, M., Barrett, C. B., Liu, Y. and You, L. (2020). Within-season producer response to warmer temperatures: Defensive investments by Kenyan farmers, *The Economic Journal* 131(633): 392–419. 8
- Jahn, M. (2015). Economics of extreme weather events: Terminology and regional impact models, *Weather and Climate Extremes* 10: 29–39. 75
- Jakobsson, U. (1976). On the measurement of the degree of progression, *Journal of Public Economics* 5(1-2): 161–168. 12, 24, 139
- Jayet, P.-A., Petsakos, A., Chakir, R., Lungarska, A., De Cara, S., Petel, E., Humblot, P., Godard, C., Leclère, D., Cantelaube, P., Bourgeois, C., Bamière, L., Ben Fradj, N., Aghajanzadeh-Darzi, P., Dumollard, G., Isbasoiu, A. and Adrian, J. (2021). The European agro-economic AROPAj model, *Report*, INRA, UMR Economie Publique, Thiverval-Grignon. 36, 108
- Jones, B. F. and Olken, B. A. (2010). Climate shocks and exports, *American Economic Review* 100(2): 454–459. 5
- Kakwani, N. C. (1977). Applications of Lorenz curves in economic analysis, *Econometrica* 45(3): 719. 12, 139
- Klenert, D. and Mattauch, L. (2016). How to make a carbon tax reform progressive: The role of subsistence consumption, *Economics Letters* 138: 100–103. 22
- Koenker, R. (2004). Quantile regression for longitudinal data, *Journal of Multivariate Analysis* 91(1): 74–89. 77
- Koenker, R. and Basset, G. (1978). Regression quantiles, *Econometrica* 46(1): 33–50. 15, 142

- Koenker, R. and Hallock, K. F. (2001). Quantile regression, *Journal of Economic Perspectives* **15**(4): 143–156. [83](#)
- Kolm, S.-C. (1969). La théorie démocratique de la justice sociale, *Revue d'économie politique* **79**(1): 138–141. [12](#), [139](#)
- Kolstad, C. D. and Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations, *Review of Environmental Economics and Policy* **14**(1): 1 – 24. [74](#)
- Labandeira, X., Labeaga, J. M. and Rodríguez, M. (2009). An integrated economic and distributional analysis of energy policies, *Energy Policy* **37**(12): 5776–5786. [22](#)
- Lambert, P. J. (1993). *The Distribution & Redistribution of Income: A Mathematical Analysis*, MANCHESTER UNIV PR. [12](#)
- Landis, F., Fredriksson, G. and Rausch, S. (2021). Between- and within-country distributional impacts from harmonizing carbon prices in the EU, *Energy Economics* **103**: 105585. [22](#)
- Le Breton, M., Moyes, P. and Trannoy, A. (1996). Inequality reducing properties of composite taxation, *Journal of Economic Theory* **69**(38): 71–103. [12](#), [40](#), [139](#)
- Leclère, D., Jayet, P.-A. and de Noblet-Ducoudré, N. (2013). Farm-level autonomous adaptation of european agricultural supply to climate change, *Ecological Economics* **87**: 1–14. [105](#), [107](#)
- Lesk, C., Rowhani, P. and Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production, *Nature* **529**(7584): 84–87. [90](#)
- Lungarska, A. and Jayet, P.-A. (2018). Impact of spatial differentiation of nitrogen taxes on French farms' compliance costs, *Environmental and Resource Economics* **69**: 1–21. [37](#)
- Machado, J. A., Parente, P. and Santos Silva, J. (2021). Qreg2: Stata module to perform quantile regression with robust and clustered standard errors. [77](#)



- Machado, J. A. and Santos Silva, J. (2019). Quantiles via moments, *Journal of Econometrics* **213**(1): 145–173. Annals: In Honor of Roger Koenker. 77
- Machado, J. A. and Silva, J. S. (2019). Quantiles via moments, *Journal of Econometrics* **213**(1): 145–173. 15, 142
- Malikov, E., Miao, R. and Zhang, J. (2020). Distributional and temporal heterogeneity in the climate change effects on U.S. agriculture, *Journal of Environmental Economics and Management* **104**: 102386. 14, 76, 141
- Martincus, C. V. and Blyde, J. (2013). Shaky roads and trembling exports: Assessing the trade effects of domestic infrastructure using a natural experiment, *Journal of International Economics* **90**(1): 148–161. 75
- Marx, K. (1867). *Le Capital*, Paris: Editions Sociales. 8
- Mathur, A. and Morris, A. C. (2014). Distributional effects of a carbon tax in broader U.S. fiscal reform, *Energy Policy* **66**: 326–334. 22
- Mendelsohn, R. (2000). Efficient adaptation to climate change, *Climatic Change* **45**(3/4): 583–600. 104
- Mendelsohn, R., Dinar, A. and Williams, L. (2006). The distributional impact of climate change on rich and poor countries, *Environment and Development Economics* **11**(2): 159–178. 76
- Mendelsohn, R., Nordhaus, W. D. and Shaw, D. (1994). The impact of global warming on agriculture: A ricardian analysis, *The American Economic Review* **84**(4): 753–771. 6, 72, 74, 105
- Mendelsohn, R. O. and Massetti, E. (2017). The use of cross-sectional analysis to measure climate impacts on agriculture: Theory and evidence, *Review of Environmental Economics and Policy* **11**(2): 280–298. 6
- Metcalf, G. E. (2009). Designing a carbon tax to reduce U.S. greenhouse gas emissions, *Review of Environmental Economics and Policy* **3**(1): 63–83. 22

- Moore, F. C. and Lobell, D. B. (2015). The fingerprint of climate trends on European crop yields, *Proceedings of the National Academy of Sciences* **112**(9): 2670–2675. [74](#)
- Nordhaus, W. (1982). How fast should we graze the global commons?, *The American Economic Review* **72**(2): 242–246. [4](#)
- Nordhaus, W. D. (1977). Economic growth and climate: The carbon dioxide problem, *The American Economic Review* **67**(1): 341–346. [4](#)
- Nordhaus, W. D. (1991). To slow or not to slow: The economics of the greenhouse effect, *The Economic Journal* **101**(407): 920. [4](#)
- Nozick, R. (1974). *Anarchy, State and Utopia*, New York: Basic Books. [9](#)
- OCDE (2021). *Effective Carbon Rates 2021*. [2](#)
- Ohlendorf, N., Jakob, M., Minx, J. C., Schröder, C. and Steckel, J. C. (2020). Distributional impacts of carbon pricing: A meta-analysis, *Environmental and Resource Economics* **78**(1): 1–42. [3](#), [22](#)
- Ortiz-Bobea, A. (2020). The role of nonfarm influences in ricardian estimates of climate change impacts on US agriculture, *American Journal of Agricultural Economics* **102**(3): 934–959. [74](#)
- Page, E. A. (2012). Give it up for climate change: A defence of the beneficiary pays principle, *International Theory* **4**(2): 300–330. [11](#)
- Palosuo, T., Kersebaum, K. C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., Patil, R. H., Ruget, F., Rumbaur, C., Takáč, J., Trnka, M., Bindi, M., Çaldağ, B., Ewert, F., Ferrise, R., Mirschel, W., Şaylan, L., Šiška, B. and Rötter, R. (2011). Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models, *European Journal of Agronomy* **35**(3): 103–114. [122](#)
- Panagos, P., Liedekerke, M. V., Jones, A. and Montanarella, L. (2012). European soil data centre: Response to european policy support and public data requirements, *Land Use Policy* **29**(2): 329–338. [79](#), [109](#)

- Parry, I. (2015). Carbon tax burdens on low-income households: A reason for delaying climate policy?, *CESifo Working Paper Series* **5482**. 3, 22
- Paudel, J. and Ryu, H. (2018). Natural disasters and human capital: The case of Nepal’s earthquake, *World Development* **111**: 1–12. 75
- Pearce, D. (1991). The role of carbon taxes in adjusting to global warming, *The Economic Journal* **101**(401): 938–948. 2
- Pellerin, S., Bamière, L., Angers, D., Béline, F., Benoit, M., Butault, J.-P., Chenu, C., Colnenne-David, C., De Cara, S., Delame, N., Doreau, M., Dupraz, P., Faverdin, P., Garcia-Launay, F., Hassouna, M., Hénault, C., Jeuffroy, M.-H., Klumpp, K., Metay, A., Moran, D., Recous, S., Samson, E., Savini, I., Pardon, L. and Chemineau, P. (2017). Identifying cost-competitive greenhouse gas mitigation potential of French agriculture, *Environmental Science and Policy* **77**: 130–139. 3, 4
- Piet, L. and Desjeux, Y. (2021). New perspectives on the distribution of farm incomes and the redistributive impact of CAP payments, *European Review of Agricultural Economics* **48**(2): 385–414. 23, 40, 41, 79, 110, 111
- Pigou, A. C. (1920). *The Economics of Welfare*, Macmillan & Co. 2, 11
- Pindyck, R. S. (2017). The use and misuse of models for climate policy, *Review of Environmental Economics and Policy* **11**(1): 100–114. 4
- Raffinetti, E., Siletti, E. and Vernizzi, A. (2014). On the Gini coefficient normalization when attributes with negative values are considered, *Statistical Methods & Applications* **24**(3): 507–521. iv, 41, 57, 111
- Rajan, R. G. and Zingales, L. (1998). Financial dependence and growth, *The American Economic Review* **88**(3): 559–586. 77
- Ravallion, M. (2017). A concave log-like transformation allowing non-positive values, *Economics Letters* **161**: 130–132. 111

- Ravigné, E., Gherzi, F. and Nadaud, F. (2022). Is a fair energy transition possible? Evidence from the French low-carbon strategy, *Ecological Economics* **196**: 107397. 22
- Rawls, J. (1971). *A Theory of Justice*, Harvard University Press. 9, 10
- Roemer, J. E. (1982). *A General Theory of Exploitation and Class*, Harvard University Press, Cambridge. 9
- Roemer, J. E. (1986). *Analytical Marxism*, Cambridge University Press. 9
- Rothbard, M. (1973). *For a new liberty*, New York: Macmillan. 9
- Rötter, R. P., Palosuo, T., Kersebaum, K. C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., Olesen, J. E., Patil, R. H., Ruget, F., Takáč, J. and Trnka, M. (2012). Simulation of spring barley yield in different climatic zones of Northern and Central Europe: A comparison of nine crop models, *Field Crops Research* **133**: 23–36. 122
- Samuelson, P. A. (1947). *Foundations of Economic Analysis.*, Harvard University Press, Cambridge, Mass. ; London, England. 7
- Schlenker, W., Hanemann, W. M. and Fisher, A. C. (2005). Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach, *American Economic Review* **95**(1): 395–406. 74
- Schlenker, W., Hanemann, W. M. and Fisher, A. C. (2006). The impact of global warming on U.S. agriculture: An econometric analysis of optimal growing conditions, *Review of Economics and Statistics* **88**(1): 113–125. 6
- Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change, *Proceedings of the National Academy of Sciences* **106**(37): 15594–15598. 72, 74, 90, 105
- Sen, A. K. (1973). *On economic inequality*, Oxford: Clarendon Press. 10
- Shapley, L. S. (1953). A value for n-person games, *Contributions to the Theory of Games* **2**(28): 307–317. 61, 105, 117

- Shorrocks, A. F. (1980). The class of additively decomposable inequality measures, *Econometrica* **48**(3): 613. 105
- Shorrocks, A. F. (1983). Ranking income distributions, *Economica* **50**(197): 3. 105, 115, 116
- Stephenson, D. B., Diaz, H. and Murnane, R. (2008). Definition, diagnosis, and origin of extreme weather and climate events, *Climate extremes and society* **340**: 11–23. 75, 78, 89
- Stiglitz, J. E. (2019). Addressing climate change through price and non-price interventions, *European Economic Review* **119**: 594–612. 2
- Stiglitz, J. E., Stern, N., Duan, M., Edenhofer, O., Giraud, G., Heal, G. M., La Rovere, E. L., Morris, A., Moyer, E., Pangestu, M. et al. (2017). Report of the high-level commission on carbon prices. 22
- Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from US coastal counties, *Review of Economics and Statistics* **93**(2): 575–589. 75
- Tebaldi, C. and Friedlingstein, P. (2013). Delayed detection of climate mitigation benefits due to climate inertia and variability, *Proceedings of the National Academy of Sciences* **110**(43): 17229–17234. 2
- Thistle, P. D. (1989). Ranking distributions with generalized Lorenz curves, *Southern Economic Journal* **56**(1): 1. 116
- Tiezzi, S. (2005). The welfare effects and the distributive impact of carbon taxation on Italian households, *Energy Policy* **33**(12): 1597–1612. 3, 22
- Tol, R. S. J. (2018). The economic impacts of climate change, *Review of Environmental Economics and Policy* **12**(1): 4–25. 4, 5
- Vaitkeviciute, J. (2018). *Econometric analysis of the impacts of climate change on agriculture and implications for adaptation*, Phd thesis, AgroParisTech. 121

- Van Passel, S., Massetti, E. and Mendelsohn, R. (2016). A ricardian analysis of the impact of climate change on European agriculture, *Environmental and Resource Economics* **67**(4): 725–760. [6](#), [104](#), [121](#)
- Vermont, B. and De Cara, S. (2010). How costly is mitigation of non-CO2 greenhouse gas emissions from agriculture?, *Ecological Economics* **69**(7): 1373–1386. [3](#), [4](#), [23](#), [36](#)
- World Bank (2020). State and trends of carbon pricing, *Report*, World Bank, Washington, DC. [2](#)
- World Bank (2022). State and trends of carbon pricing, *Report*, World Bank, Washington, DC, USA. [38](#)
- Zhang, P., Zhang, J. and Chen, M. (2017). Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation, *Journal of Environmental Economics and Management* **83**: 8–31. [72](#), [74](#)
- Zivin, J. G. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change, *Journal of Labor Economics* **32**(1): 1–26. [5](#)