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Uncertainty as a barrier to adoption of mitigation practices in the agricultural sector

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To cite this version:

Camille Tevenart. Uncertainty as a barrier to adoption of mitigation practices in the agricultural sector. Economics and Finance. Université de Lorraine, 2019. English. NNT : 2019LORR0156 . tel-02484561

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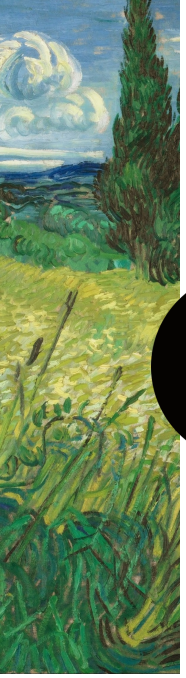

UNIVERSITÉ DE LORRAINE

BETA Bureau d'économie théorique et appliquée

École doctorale n° 79
Sciences Juridiques, Politiques, Économiques et de Gestion

Doctorat

THÈSE

pour obtenir le grade de docteur délivré par

l'Université de Lorraine

Spécialité doctorale "Sciences Économiques"

présentée et soutenue publiquement par

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le 16 octobre 2019

L'incertitude en tant que frein à l'adoption de mesures d'atténuation en agriculture

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THESE

A ma fille Andréa
Et mon épouse Nemdia

Acknowledgements

After more than three years of research, I finally have the opportunity to present the major part of my work in this thesis. All this production would not have been possible without the support of many people, who assisted me from the beginning.

I would like to thank, first of all, my supervisors Marielle Brunette, Researcher at the BETA Nancy laboratory of Lorraine University, and Caroline Orset, Professor at the Public Economics laboratory of INRA-AgroParisTech, for their constant support all along these years. Their precious advices were of great help, especially during hard times. I also want to thank Philippe Delacote, who never failed at finding practical solutions when needed. Many thanks also to Marc Baudry for his strong intellectual support and his occasional assistance when I was facing complex research problems. I would like to give particular acknowledgements to Christian de Perthuis, for his support and his ability to trust and to appreciate the work of his students. Many thanks to Antoine Poupart, from AgroSolutions (InVivo group) for his trust and his feedbacks about my work.

I would like to give thanks to Marie-Hélène Hubert, Assitant Professor at the Economics Department of Rennes University, and Arnaud Reynaud, Head of the TSE-R laboratory of Toulouse School of Economics, for having accepted to be the referees of my thesis. This is an honor for me to see my work being reviewed by them.

Further thanks go to Géraldine Bocquého, Researcher at the BETA Nancy laboratory of Lorraine University, and Pierre Dupraz, Head of the SMART-LERECO laboratory of INRA Rennes, for being examiners of my thesis. Special thanks go to Olivier Deschênes, Professor at the Economics Department of the University of California, Santa Barbara for having agreed to come from such a long distance and to be a part of my thesis jury. I am very proud to say that my thesis has been discussed by these researchers.

I want to thank a lot Professor Andrew Plantinga, from the Bren School of Environmental Sciences and Management of the University of California, Santa Barbara, for having hosted me during four months at the Bren School. Not only his scientific advices, but also his kindness, sympathy and hospitality were of a great importance for me in these last years.

Several researchers I met during these years participated, through their advices, feedbacks, cooperation or assistance, to this research. To quote some of them, Nathalie Delame, Hervé Dakpo, Raja Chakir, Serge Garcia, Danae Hernandez-Cortes, Christopher Costello, Kyle Meng, Olivier Damette, among others, deserve thanks for their support at different levels.

I would like to thank the farmers and the cooperatives' agents that agreed to have meetings with me for the field experiment, and the support of AgroSolutions' engineers for their help in the making of the survey.

I would like to give a huge thank to my partners PhD candidates and young researchers, with who I shared many good times (and some less happy times), among them, David Soares, Julien Wolfersberger, Olivier Rebenaque, Salomé Bakaloglou, Liza Dorinet, friends from the Climate Economics Chaire, the Public Economics laboratory and the BETA Nancy, people I met in France or during my visiting in the States. I won't forget your presence by my side and your active or passive support.

Last but not least, I would like to thank my wife, family and friends. And I want to express my gratitude for all that has been given and received.

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Chapter 1

Introductory chapter

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Reducing GHG emissions in the agricultural sector is nowadays considered, in France especially, as a major environmental policy challenge. In 2017, the French agricultural sector was responsible for 20.4% of the total GHG emissions in France, especially through nitrous oxide (N2O) and methane (CH4) emissions, and in a marginal way through carbon dioxide (CITEPA [16]). It is also the main sector, in parallel with forest, able to sequester atmospheric carbon and thus represents a great potential of climate change mitigation and a key feature of carbon neutrality. Kyoto (1997) and Göteborg (2012) protocols led France toward the implementation of emissions mitigation. In the same vein, the "Paquet Énergie-Climat" of the European Union, revised in 2014, asks to France a reduction of 40% of its emissions compared to 1990. The French energy market being essentially represented by the nuclear power, that is not a big emissions producers and which, in all case, is not flexible enough to adopt further important mitigations, it is important to target other sectors, like the agricultural sector, which furthermore has a important size in the country (De Cara and Jayet [17]). Regarding more specifically the agricultural sector, a succession of laws, coming from the "Grenelle de l'environnement" in 2009, and from the "Loi d'avenir" of the 2014, October 13th, about mitigation have been voted between 2005 and 2015. "Agri-environmental and Climate Schemes" (AECS) have been emphasized in 2015 (European Common Agricultural Policy, CAP), providing specifications about the subsidized measures farmers can adopt to limit their impact on the environment and develop their "integration" in their local ecosystem, but in a context of decreasing budget. The measures generally encourage farmers to diversify their activities, integrate leguminous crop, improve land rotation, develop better link between a good feeding for the livestock and vegetal protein production, and especially limit the use of pollutant inputs.

However, mitigation as well as conservation practices, are deemed far from being massively adopted nowadays. Despite the lack of complete statistics about individual efforts made by farmers, agricultural emissions have been reduced, since 1990, twice lower than the total emissions' reduction rate in France[1]. New practices can have a low speed of diffusion in the agricultural sector. We have good examples of that phenomenon: "organic farming" represented around 6% of the total French agricultural area[2], while conservation programs like Ecophyto failed to reduce chemical pesticide uses (moreover, an increase in chemicals use has been recorded during the period of the project, due, inter alia, to bad pedoclimatic conditions)[3]. Moreover new policies have been designed (AECS for instance) in order to try new ways to encourage adoption of mitigation practice at the farm level, because the farming sector is exempted from the EU-ETS and of any carbon tax on production, and the European Union's emissions targets and the pressures from the COP21 have accelerated the implementation of public intervention. While some mitigation practices are associated to a higher level of productive efficiency and related potential benefits, their spread is still limited in France, which encourages the conception of new incentives or an improvement of existing ones. There is a need for the identification and resolution of the causes of non adoption by farmers, and especially, this thesis aims at identifying the role of uncertainty as a hidden cost associated to the adoption of new practices. Since uncertainty can impact new practices' profits evaluation by farmers through different drivers, we will identify in which cases it can become a barrier of adoption. Different methodologies will be used (theoretical, empirical) in order to answer

[1] Around 9% in 2013 according to the CITEPA [16].

[2] According to the Agence Française pour le Développement et la Promotion de l'Agriculture Biologique.

[3] This State program concerned around 30000 farms, that is equal to around 5% of the amount of farms in France.

these issues. The existence of hidden costs and benefits of the main mitigation practices has to be taken into account to design efficient incentives and policies, and to improve the knowledge about the factors of non adoption. Targeting farmers with appropriate tools in order to help them adopting mitigation practices can lead to improvements in the allocation of public expenses.

In section 1.1, we briefly describe mitigation practices and the associated economic costs. In section 1.2, we show how uncertainty can lead to failures for the agricultural sector to meet the reduction targets. We present the different drivers through which uncertainty can be a barrier to adoption, how they have been treated in the literature, and the way they can be associated if necessary. In section 1.3, we sum up the contributions we will present in this thesis.

1.1 Mitigation of environmental externalities related to agricultural practices' emissions

1.1.1 Typology of mitigation practices

Mitigating GHG emissions from farming activities aims at addressing environmental externalities related to climate change, a global-scale issue generated by multiple sources. Farming productions relate to an entanglement of practices, product and a wide typology of input-output combination, from cultivations to animal productions. Emissions from the agricultural sector are embedded in this complexity, and throughout the typology of production-emission assemblages emerges the typology of mitigation practices options. There is a consensus in the literature about the main types of agricultural mitigation practices. The aim of these practices is to reduce the net emissions of GHG on the total exploitation, thus the ability of crops and livestocks to store atmospheric carbon (C) is taken into account as a way to mitigate the GHG emissions. The N2O is essentially produced by the nitrification phenomenon, that is related to the action of soil bacteria that transform ammonia and other co-products of N-fertilizer in this gaze. Mitigate N2O emissions goes through limitation of the N-concentrated products application, or limitation of the nitrification processes. CH4 is produced through the fermentation of organic maters : enteric fermentation in livestock digestive system, or fermentation of maters in humid stock of organic maters (manure for example). To mitigate CH4 emissions, it is possible to make, for instance, changes in humid zone management, livestock feedings and cattle size, manure management, inter alia (Müller et al. [52]). Basically, mitigating emissions consists of a modification brought by the producer to her production. The process is related to inputs use, outputs use, soil and waste management.

We can mention three broad types of mitigation actions: i) reducing emission; ii) enhancing removals (capturing C); iii) avoiding/displacing emissions (bioenergy instead of fossils energy) (Smith et al. [67]). We can identify seven main mitigation domains on agricultural exploitations: cropland management, grazing land management and pasture improvement, management of organic soils, restoration of degraded lands, livestock management, manure management and bioenergy related productions (*ibid.*). There is a limit with the uncertainty about the potential of reduction in net emissions that some of these mitigation practices can lead to, due to the difficulty to measure them in the agricultural sector (diffuse emissions, difficulty of measurement, stochastic nature of the pro-

ductions). Moreover mitigations can provide co-benefits like increased productivity and food safety, better water management and soil conservation, biodiversity conservation, or in the case of husbandry, a decreasing acidification of soils or eutrophication of waters (Garcia-Launay et al. [29]; Smith et al. [67]). These mitigation practices can have interactions, as the different production posts of an exploitation often interact (crops-livestock, crops-crops, livestock-livestock), and are generally related with the farmer's management and characteristics, the exploitation characteristics and with pedo-climatic conditions at a local scale. Mitigating somewhere can lead to an increase in emissions in another production spot or through another way. Some authors also emphasized the interaction between mitigation and adaptation to climate change : sometimes both go in the same direction, sometimes they have a negative impact on the other (*ibid.*). We introduce two major other distinctions between mitigation practices. First, they can be technically divisible (applicable on part of the production or the farm) or indivisible (applicable to all the exploitation). This is closely related to the classic distinction between intensive and extensive margins in agricultural productions. For instance, introducing legume in rotation in order to catch nitrogen, and by this way, improving soil quality and/avoid fertilizer application, is a divisible mitigation practice because the farmer can choose to allocate only a part of the land she disposes of, some parcels on which she will change her intensive nitrogen management practices and not others. Reversely, indivisible practices are generally related to fixed investment, for instance, improvement of energy consumption of livestock buildings, or changes in animal wastes management that imposes new storage facilities (Caswell et al. [12]). Most of mitigation practices in the agricultural sector wear a potential for divisibility, that leads to a potential partiality or sequentiality of farm transformation and transition (this phenomenon is emphasized by Leathers and Quiggin [49] and evoked by Pannell et al. [55]). The other distinction is associated to the level of irreversibility of the mitigation practices. Irreversibility is defined as a process that goes in one direction (in this case, adoption) and that can't be stopped. Irreversibility can be economic (unrecoverable costs) and physical (altering a resource that won't recover its initial characteristics). It can be simply associated to practice's adoption that requires fixed costs, equipment or human capital investment (Caswell et al. [12]). Inertia is a lower level of irreversibility that induces a difficulty to go backward after adoption, but not a complete impossibility to do so. Some mitigation can wear inertia (or "partial" irreversibility): for instance, converting a land-cover from an annual crop toward a long-run perennial crop wears strong inertia or irreversibility, especially if a contract requires the farmer to maintain the new activities on her parcel (carbon compensation programs are particularly impacted by this phenomenon). In another vein, drastically changing soil work (tillage toward no tillage) or some input use (seed or innovative fertilizers) wears some inertia, because it affects the early stages of the crop growth, that is a progressive process over time. If this new practice badly affects the crops, farmers can't change her mind and modify the setup until the next agricultural campaign, and profit losses will be experienced (the "long time lag between planting and harvest" from Pannell et al. [55]). We can say that farming practices in general can wear economic or physical inertia or irreversibility, whose level depends also on the technical path in which the farmer is already engaged and the way new practices are physically disruptive for the farm.

1.1.2 The cost of mitigating: economic point of view and adoption determinants

The economic benefits related to mitigation practices can be associated to a decreasing cost of production, and the adoption of a new production that yields higher returns. The costs related to mitigations can be associated to higher cost of production, or opportunity cost of substituting a production by another. The large majority of the literature about GHG mitigation practices in agriculture is related to estimations of the potential emissions reduction that they can lead to, and the factors of adoption of these practices. At a global, regional or national scale, authors look for the marginal abatement cost of a ton of emissions and for instance the estimated optimal level of carbon price to achieve the reduction goals (De Cara and Jayet [17]; Smith et al. [68]). The technical potential is calculated on the farms, taking into account the possible substitution between the different production posts and resources use and emissions factor for each post, then the reduction potential is targeted by varying a carbon price. The reduction of emissions is maximized relatively to the cost of abatement, under the constraint of an unchanged level of certain profits. It is thus derived from an economic point of view that assumes rationality of farmers (research of optimal management given the available resources), certainty and perfect information, and which aims to make a cost-benefit accounting in order to estimate the marginal and total abatement cost. For some mitigation practices, negative costs have been estimated, in Bamière et al. [5] for France: for instance, nitrogenous fertilizers uses reduction, increasing share of grasslands in breeding systems and modification in cattle and sow feedings, desintensification of permanent and temporary grasslands, or diverse soil use and work changes, wear negative cost on average, thus, are potentially source of benefits for farmers (see Figure 1.1 for France).

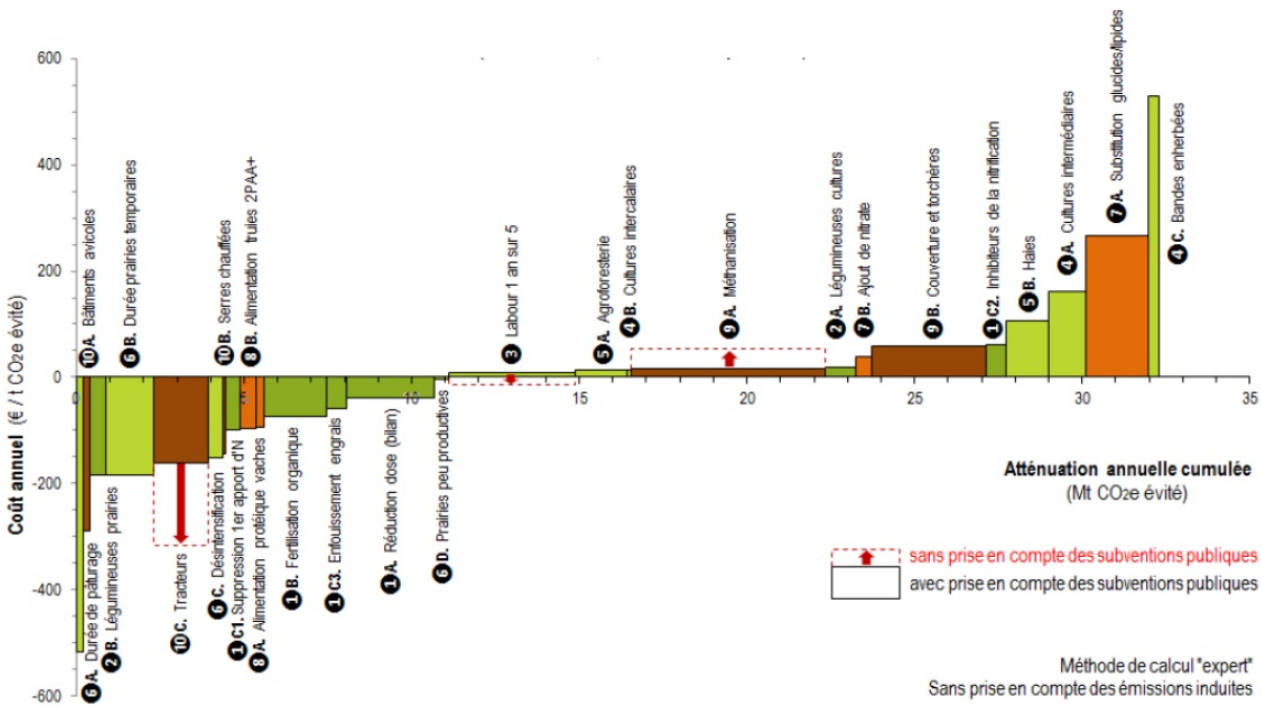

Figure 1.1 – MACC from Bamière et al. [5] -INRA

The computation result is nevertheless relatively correlated to the diverse assumptions about the production factors adjustment, market prices, the local specificities and the competition between mitigation strategies (Schneider and McCarl [65]). Furthermore, the non-adoption of mitigation by lots of "conventional" farmers is questionable, given their potential of estimated benefits, and the divergence between technical potential and actual achieved reductions. Given the importance of non-adoption of mitigations, we can assume hidden cost to adoption (or reciprocally, hidden benefits of the *status quo*) that can explain this phenomenon. Assumptions about the costs of environmentally respectful productions (mitigation and conservation agriculture) have been made but barely empirically validated : among them, the literature often identified risk attitudes of farmers, amount of training and learning about mitigations, technology diffusion, capacity building, uncertainties (related or not to prices), complexity of ecological and biological processes involved in the mitigation (which generates uncertainties about mitigation mechanism), and variability between different localities and between seasons, degree of consistency of the mitigation procedure with the conventional practices, perception of the climate-related risks etc. (Knowler and Bradshaw [46]; Schneider and McCarl [65]; Smith et al. [67]; Smith et al. [68]; Stuart et al. [69]).

The factors explaining adoption of conservation agriculture (CA) procedures, and innovations or new technologies adoptions on farms are often connected by researchers, who consider the first in the same vein that the latter (Knowler and Bradshaw [46]; Pannell et al. [55]). Mitigation practices can follow the same kind of rationale, because the underlying idea is the same: contribute to mitigate the damage on the environment related to the agricultural production while limiting the cost of the changes in production. Characteristics of the farmer and the exploitation, farm biophysical characteristics, farm financial management characteristics and exogenous factors are regularly evoked among the main CA adoption factors. These studies showed that while some variables impacted adoption across a lot of studies, "few if any universally significant variables" were empirically validated as able to explain with no doubt adoption (Knowler and Bradshaw [46]). It is often highlighted that not only profitability, but other behavioral features and characteristics explain adoption or non adoption (Caswell et al. [12]; Rogers [50]). For instance, the level of education, farm size and trialability of new practices were the most reliable variables that seem to significantly impact adoption, with a non clear-cut effect. It is important to note that results depend a lot on the nature of the analytical methods that economist used in their research, and on the observed region and context. Risk aversion and uncertainties were barely directly treated in the empirical literature of CA adoption determinants. Pannell et al. [55] showed in their review that not only relative advantages of new practices matter (profits compared to *status quo*, impact of adoption on riskiness and complexity, beliefs, etc.) but also trialability of new practices (divisibility and stepwise adoption possibility, observability, etc.) was crucial for enhancing adoption. Trialability is at the core of management of uncertainties, because it is connected to the ability to reveal true profits from adoption, which are uncertain *ex ante*. They show that CA practices adoption do not follow the same constraint than productivity-related innovation in terms of "correctness" of adoption (adoption because of clear benefits compared to the *status quo*), because CA wears a strong biophysical complexity and the benefits-costs structure is not clearly observable and can be complex. Indivisibiliy limits the trialability possibilities, and irreversibility in the same way because of its impact on the level of divisibility of adoption.

As we will see it in the following section, the impact of uncertainty and risk attitudes of farmers are often evoked in the literature concerning the level of input uses, and adoptions of innovation, or new activities on the farm: intensive as well as extensive margins are impacted by uncertainties. The relevance of this literature is related to the fact that we will adopt these rationales to the case of mitigation practices adoption, because these models allow for a good specification of the whole agricultural system on the farmer's exploitation and a possible separability between the different farm parts, where the farmer chooses to allocate divisible investments or not. It also explains intensive as well as extensive practices changes on farms. However, this literature explains some phenomena in a separated way, that we partly assembled. Moreover, while the theoretical and empirical literature show for a long time the various impacts of uncertainty on farmers adoption choices, public policies still struggle to introduce it as a specific barrier to lift.

1.2 Limitations to the adoption of new farming practices: the market failures associated to uncertainties

1.2.1 What uncertainties are we talking about?

We talk about uncertainties when the producer's profits are not perfectly forecastable, are not known with certainty. Farmers, and producers in general, are considered as facing two kinds of main uncertainties: price and production uncertainties. Beside these two main uncertainties, regulatory, political, selling capacities, and other uncertainties especially related to production costs can impact the producer. In a situation of uncertainty profits are dependent on the state-of-the-nature in which the production is set, leading to the stochastic nature of profits. Uncontrollable factors of production and timing of agricultural productions (often several months, sometimes up to one or several years) make the profits uncertain on a broad sense (Moschini and Hennessy [53]). Most of the mitigation practices proposed to farmers are selected for their ability to keep equal the level of production of a given crop or animal product. As the product still the same, and can be sold in the same competitive market, we do not assume that price uncertainties are specifically modified when a production practice for a given product changes. The stochastic changes in price that can occur, and thus lead to a specific uncertainty, would appear in the aggregation of farmers' productions, which is a scale that we do not specifically explore in this work. However, market (price) uncertainties can play the role of a background risk that is important to mention. The agricultural sector being sufficiently atomistic, we do not assume that farmers anticipate a direct effect of their production choices in a given year, on market prices. But they can act as they want to hedge against the whole set of risks they are exposed to, price risk being one of them and not the least. We won't focus on this topic here. We assume that production uncertainty is accurate in the perspective of new production practices or technologies (Isik and Khanna [38]). In this scope, we assume farmers are not certain of what they can expect from mitigation practices, which is an implicit adoption cost of these practices.

As introduced by Knight [45], microeconomists often separate uncertainty (narrow sense) and risk. The later is a situation of profit uncertainty (broad sense) where the profit probability distribution is objectively known. The profits are still not exactly forecastable, but the states-of-the-world they are associated to are expressed through objective probabilities. The former usually means that the objective probabilities are unknown, but a

subjective probabilities distribution can be associated to uncertain profits. The work of Savage [64] on the axiomatization of subjective expected utilities goes in this direction. In this setting agents develop beliefs about the uncertain profits, and act in consequence. While this distinction is only due to the difference of assumption about the nature of probabilities, both risk and uncertainty (narrow sense) are consequences of the uncertainty (broad sense) or stochasticity of profits. However both issues can lead to different conclusions. We study both in this thesis, in the frame of this distinction when necessary. The core of interest of our work is that profits of innovation are not certainly known and not perfectly forecastable. A second distinction in the nature of probabilities is often made in uncertainty analysis: probabilities can be seen as Markovian (Dixit et al. [20]; Baudry [8]) or Bayesian (Arrow and Fisher [4]; Baudry [9]; Jensen [39]). Markovian probability refers to the Markov property that all the useful information that allows forecasts is available in the current state of the stochastic process, inside the frenquency of occurence of a state-of-the-world (usual definition of a probability). Bayesian probability refers to a probability that reflects the state of knowledge or beliefs in the present that depends on the past states-of-the-world. If the first allows to observe the stochastic process of a variable and its different impacts in a tractable way, the second allows to incorporate the role of information arrival across time and the updating of beliefs or knowledges. We can conclude that the definition of uncertainty has an impact on the results and depends on the study at stake, especially the characteristics of the studied mitigation practice.

1.2.2 Risk, risk preferences and risk hedging

Risk describes a situation of uncertainty about the payoffs from economic decisions where the probability distribution of these payoffs is objectively known by the decision-maker (DM). Risk analysis are in general used in the study of assets trade or production practice adoption that exist for a long time and for which economic agents have a clue of the historical distribution of associated profits. The seminal work of Neumann and Morgenstern [54] sets that it is possible to use a utility function within the probabilistic rationale in order to describe the expected utility, or satisfaction of a DM, if some axioms are beforehand respected. The utility function distorts the payoffs and weights them in a way that follows risk preferences and the level of risk associated to the payoffs from the decisions. For a given level of risk, usually described as a greater dispersion around the mean, a risk averse agent will downweight her utility for the payoffs, and a risk loving agent will upweight them, while a risk neutral agent will consider the strict expected payoffs. The second derivative of the utility function gives the level of risk aversion. Arrow [3] and Pratt [57] developed this model, and show that it is possible to calculate the risk premium associated to decisions for the DM for different utility function and to characterize the risk preferences of the DM in absolute and relative terms. However, Markowitz [51] and Sharpe [66] conceived the first widely-used applications of risk theory in modern economics, in the field of financial management. The former developed a model of mean-variance utility applied to financial asset, and the later developed the Capital Asset Pricing Model (CAPM), showing that the risk has to be retributed within the market price of an asset in order to be bought by financial agents. These models have been the core of the financial risk analysis during decades. The level of risk and the DMs risk preferences explain the risk premium that they will ask in order to buy an asset, and it must be covered in order to hedge the risk. The inability to hedge the risk on a market is a classical market failure: if no coverage can be given, either directly in the asset price or through an insurance or options market for instance, the market is not complete and some high-potential

assets can not find any buyer. It can give rise to a suboptimal allocation of productive resources. As we will see it, the case of producers follows the same rationale when they manage their activities and their input use especially: among all the productive possibilities that the producer can use in order to reach her productive goals, the riskier ones won't be used if they are not properly covered or if the producer can't hedge against the associated risks. Other theoretical extensions of the risk theory take the form of the Prospect Theory (Kahneman [42]) or the Rank dependent expected utility (Quiggin [58]).

A lot of applications of risk theory to producer economics and specifically agricultural production economics emerged since the 1980's. It can be related to price risk for competitive firms in general (Sandmo [63]), production choices associated to marginal change in input use (Pope and Kramer [56]; Roosen and Hennessy [61]; Leathers and Quiggin [49]) or adoption of innovation on the farm (Feder [25]: Feder [26]; Just and Zilberman [40]; Just and Zilberman [41]; Ghadim and Pannell [31]; Sunding and Zilberman [70]), and price, production or cost risk in general for farmers (Moschini and Hennessy [53]). A productive practice or activity can yield high return but be associated to risks, and can be non adopted if risk is not covered. It makes higher the cost of using an innovation, or of a specific risk-increasing input, and desincentive farmer to use it. The additive profits that the new practice or the new activity is supposed to bring in a certain universe must at least cover the risk or marginal risk premium that risk preferences give rise to.

Because of the high interest of risk analysis in the agricultural sector, and the effective impact risks can have on farmers and on the economy on a broader scale, a lot of empirical studies seeked to measure the role of risk on agricultural production, through revealed or declared preferences methods. Among them, some aimed at measuring the risk attitude of farmers and their impact on land allocation (Chavas and Holt [15]; Feder and O'Mara [27]) and input use (Antle [2]; Saha [62]). They all confirmed that risk and risk preferences impact productive allocation choices. If we focus more on the adoption of mitigation practices or conservation practices and activities, more recent studies showed the negative impact of risk aversion on the reduction of nitrogenous fertilization (Bontems and Thomas [10]; Roosen and Hennessy [61]; Dequiedt et al. [19]), adoption of Site Specific Technologies in order to optimize input use and minimize adverse impacts (Isik and Khanna [38]), and adoption of conservation tillage practices with sunk costs (Kurkalova et al. [48]). All found that the issue of risks has to be taken into account if the policy maker seeks to have a comprehensive idea of the entire cost structure that face the farmers, and the correct pecuniary incentives to implement. This is the case for declared preferences methodologies that confirmed risk aversion on average, especially for French farmers (Bougherara et al. [11]; Reynaud and Couture [60]; etc.).

The nature of probabilities (objective) in the risk framework allows for specific tools that already exist but can be enhanced or promoted in order to improve the adoption of new practices by farmers. The insurance system is a good instance of a risk management tool: an insurance that would target farmers before an agreement to change their practices toward less GHG emissions could solve a part of the problem, especially in the case of excessive nitrogenous fertilization, according to Dequiedt et al. [19]. Contractualization under environmental conditions can be assumed to be an interesting tool too. Solving the issue of risk can help reach the goals that the environmental subsidies partly fail to achieve because of their incompleteness when they are calculated in a certain universe. It catches the heterogeneity in terms of risk and risk preferences among producers.

1.2.3 Uncertainty, innovations and informational externalities

Uncertainty in the narrow sense refers to a situation of uncertainty about the payoffs from economic decisions where the probability distribution of these payoffs is not objectively known, but DMs can have beliefs about this distribution. This approach fits generally the analysis of innovation adoption. These beliefs can be expressed as subjective probabilities which are attributed to the states-of-the-world associated to the likely payoffs of the economic decision. This conception of uncertainty led to two main different approaches: the first, that we will see later, is the Subjective expected utility (SEU) model à la Savage [64], which claims that the expected utility framework can be adapted to subjective probability distributions. The utility function still describes the preferences of the agent toward more or less risky choices. The second is related to the Bayesian approach, that poses that if the value of an asset is uncertain and evolves over time, beliefs are updated with information arrivals and knowledge about the true value of an asset increases. This last approach is interesting for us because it asserts that information reveals the true value of a production practice, so that farmers can wait to gather more information, which slow down the diffusion of this practice. Both approaches are often separated in economics, because the SEU approach assume preferences in the subjective risk, while the Bayesian approach, which refers usually to the real option approach, assume in general risk neutrality and aims especially at extending the Expected Net Present Value (ENPV) approach to dynamic case with information (the comparison in present and future actualized risk-neutral profits is the decision criteria). As Ghadim and Pannell [31] claim "*(...) the issue of risk in adoption has rarely been addressed adequately. The missing link is usually the dynamic nature of adoption decisions involving changes in farmers' perceptions and attitudes as information is progressively collected.*". We assume that this "missing link" can be addressed by associating the Real option approach and risk preferences of the SEU approach. Risk aversion can be an additive cost in decisions that already wears option values, and its relationship with information in dynamic choices can explain partial or sequential, and limited diffusion of new practices.

The Real option approach is able to explain non-diffusion of assets on a market (or of some productive innovations in the economy), whose adoption is irreversible or bears unrecoverable costs (Dixit et al. [20]). This approach is inspired from the option operations on financial markets, where the contractor who faces uncertainty about the value of an asset can buy an option in the future markets if she estimates that it is possible that the value of the asset increases until the expiration date. The adoption in the present can thus be delayed, in order to avoid uncoverable costs and to wait for a more favorable situation where the value of the asset exceeds the present value net from the costs. This value depends on initial beliefs and updated beliefs that evolve over time when information arrives. We assume that the value of a new practice or an innovation in terms of expected profits is subject to the same evaluation by farmers, because it presents the same characteristics (uncertainty on profits associated to adoption, irreversbility or inertia, possibility to exercise or not). The Dixit et al. [20] setting assumes that the uncertainty about the results of the asset is strictly Markovian, because it relies mainly on a Brownian motion (random walk) of the profits from the innovation. The underlying stochastic process can follow a geometric Brownian motion (Baudry [8]), or non Brownian motion for instance (Ornstein Ulhenbeck process, moving-average process). In Arrow and Fisher [4], the DM's beliefs about the uncertain yields (profits) from a resource are updated through a Bayesian conditionnal transformation of subjective probabilities attributed to the states-of-the-nature, but irreversibility is associated to the destruction of a non renewable natu-

ral resource. Other works combine options model and Bayesian probabilities in order to associate the problem of an agent confronted to an irreversible investment whose choice relies on beliefs updating, and show the impact of initial beliefs and their updating with information arrival in the diffusion of uncertain innovation (Jensen [39], Baudry [9]). We claim that the real option concept that incorporates updatings of subjective beliefs, and the classic concept of risk preferences, can be associated and lead to original contribution whose core relies on the level of inertia of mitigation practices and main results is related to informational externalities. It can explain observations that are not completely explained for the moment relative to non-diffusion of mitigation practices.

The role of information *per se* has been already studied in agricultural economics. Farmers tend to look for information about new farming practices by adopting them on a part of the farm for the biggest ones (internal information production by trials) or to observe the other farmers who already adopted them for the smaller ones (external), according to the marginal product of information acquisition modes (Feder and Slade [28]). Wozniak et al. [71] found quite similar results, and highlights the interactions between information gathering and learning-by-doing. Providing information through different complementary channels can be a cost-efficient incentive policy compared to basic subsidies, because it can enhance allocative skills of farmers and help them to make accurate predictions, while lack of information can increase risk aversion behaviors (Genius et al. [30]). Incorporating directly risk aversion in a situation of choice under uncertainty allows to explain partial and sequential adoptions that can occur, where early adopters tend to have better priors about the new practice and adopt by part on their farm (or by package), while lately adopters tend to trust the early ones and adopt later in time (Leathers and Quiggin [49]). Apart from this perspective of production and value of information, herding behaviors can also be observed. In the real option models, information source is exogenous from the action of other agents. In a general theoretical approach, Banerjee [6] shows that an agent can ignore her initial beliefs about the payoffs of different options and completely follows the choice behavior of a sufficiently high number of other agents. Information cascades can impact beliefs that a choice is a good or bad choice, and this aspect is rarely integrate in the real option framework with updating of beliefs across time. However, the literature about information acquisition from adoption or observation of others' adoption makes us believe that information can have a value and enhances or limits adoption of it, and that it can go through the valuation of the options that the farmers face. The force of the real option model being to explain lack of diffusion through wait-and-see behaviors, we expect information coming from adopters to be a key component of these behaviors if uncertainty and irreversibility interact. In this case, informational externalities will lead to non-adoption if bad signals are received, or enhance adoption if good signals correctly reach farmers which evaluate their option to adopt. Subsidizing the farmers who are the more likely to adopt in order for them to product information as a public good that will enhance diffusion can be a relevant public policy. But are positive or negative signals' impact perfectly symmetric? This is a question we propose to answer.

1.2.4 Beyond risk, ambiguity: an intrinsic limit of the agricultural advisement process and use of information

The agricultural sector is characterized by a multiplicity of actors (around 580000 farmers scattered in 101 French departments according to INSEE 2015). Each of them face heterogenous environmental conditions, and thus heterogenous interactions between nat-

ural cycles that make agricultural productions possible (crops and animals organisms, carbon cycle, microbian ecosystems, water cycle, nitrogenous cycle, etc). These evolutive pedoclimatic or zootechnic systems at the individual scale product specific knowledges and beliefs about the distribution of profits associated to conventional as well as innovative practices. A mapping of the payoffs from interactions or combinations between agricultural inputs exists in farmers' minds, and the subsequent distribution of stochastic profits depends on the past experiences, the present, the forecasts, the skills of each farmers, and their evolving local environment. The uncertainty underlying stochastic natural processes weaken the assumption that farmers have a unique distribution of profits in mind. Moreover, when another farmer or an extension agent introduces them a new farming practice, it is likely that both do not have the same distribution of production possibilities in mind regarding to this practice. We assume that when informations about an innovative farming practice is transmitted to a farmer, it introduces a new mapping of the stochastic productive possibilities associated to the production changes. This leads us to take a look behind the classical theory of uncertainty and risk with one unique subjective or objective distribution of profits, and the fact that several distributions can coexist in the decision process, for which farmers can have doubts. The advisement process aiming at spreading information and knowledges about new practices as a public policy is already implemented for some specific practices, but it did not always show good results[4].

The notion of ambiguity refers to a situation where objective probabilities are unknown. In this setting, the DM does not know what probability of occurence can be associated to each state-of-the-nature. However, some authors show that in such situations, DM will still have preferences over uncertain outcomes, preferences related to the prior they have in mind about the different scenario they can experience (Ellsberg [21], Epstein and Schneider [23]). Those priors (or beliefs, or subjective probabilities) act like second order distribution that apply to payoffs, and DMs can have preferences for more or less ambiguous outcomes. Historically, this is an extension of the Savage [64] subjective expected utility framework[5]. Ambiguity arises when the agent has doubts about what is the good distribution among her beliefs. It is related to a lack of confidence about personnal beliefs or about the information that the agent has been confronted to. The agent can be averse to this "risk of risk", which can limit her propension to bet in uncertain activities, even in the case where she is risk neutral. The link with the advisement process is straighforward. Anscombe et al. [1] compound lotteries were the first attempt since the Ellsberg experiment (Ellsberg [21]) to formalize a situation of combination of choices between risk lotteries which states-of-the-world were determined *ex ante* by lotteries with probabilistic uncertainty. Since then, several models achieved to formalize the decision process of agents facing risk and ambiguity in their uncertain choice attributes, aiming at separating attitudes toward risk from attitudes toward ambiguity[6]. Following the maxmin expected utility model in multiple prior approach of Gilboa and Schmeidler [33], we can consider

[4]The failure of FERME DEPHYS network of the Ecophyto Plan in France is a good example. The EXPE DEPHY network gathers around 170 sites that commit to drastically decrease their use of pesticide and use biocontrol approaches, and the results are communicated to all the farmers from the DEPHY network, who commit to try the new practices and are supported. During this programm, bad conjecture and natural conditions, and the lack of adaptability of informations to individual situations led the use of pesticide to increase, instead of the goal of 50% decrease from 2008 to 2018.

[5]The work of Savage already started from those of Ramsey [59] and De Finetti [18] about beliefs and probabilistic weighting of decisions' outcomes.

[6]See Etner et al. [24] for a complete review of this theory. We won't enter the NEO additive capacity theory of Chateauneuf et al. [14] here.

that expected utility can be given through a maxmin criterion, where a compounding parameter gives the weight that an agent will attribute in her choice to worse and best events wearing probabilistic uncertainty. A dynamic version of this model has been introduced by Epstein and Schneider [23]. The work of Hansen and Sargent [36] associates the Gilboa and Schmeidler model and the robust control theory, coming from the physics. The DM is not sure about what is the correct distribution of profits from her choice and fears a misspecification: there is a model that she wants to test which lead to an objective probability distribution, that she compares to subjective alternative distributions associated to the models she has in mind. The distance between distributions is expressed through an entropic index that gives the level of uncertainty in distribution, while a parameter gives the attitude toward ambiguity through the weight the DM attributes to best or worse scenarii. Hansen and Sargent [35] then provide a dynamic learning model in the vein of their robust control model. This approach better fits macroeconomic analysis with microeconomic fundations. The "Smooth ambiguity model" (Klibanoff et al. [44]) relies on the assumption that the agent has information which is *"explicitly consistent with multiple probabilities on the state space relevant to the decision at hand"*. This model is a three-steps rationale: first the expected utility of the different lotteries of the set of prior beliefs are calculated according to the objectives probabilities distribution of each (first order probabilities), and they are indexed regarding to the order of beliefs in the mind of the individual. Then, all these expected utility are transformed, by an increasing function which respects the order of prior that have been indexed, in order to apply the attitude toward ambiguity of the agent to the expectation calculus. Finally, the total expected utility is obtained by the expectation of the transformed indexed expected utility relatively to the subjective probabilities distribution (second order probabilities). It provides a separation between attitude toward risk, and attitude toward ambiguity by the weighting of the second order expectation according to the pessimism or optimism of the agent. The concavity of the second order function of transformation of the total expectation gives the level of ambiguity aversion of the agent. This approach fits well experiments aiming at eliciting preferences toward risk and ambiguity in the declared preferences method, as in Chakravarty and Roy [13] who use it in a Holt and Laury [37] setting. Gollier [34] provides an analysis of the dynamic changes in ambiguity attitudes with modification of beliefs. He shows how the demand for ambiguous asset is modified when the updating of subjective probabilities shifts the stochastic dominance of assets expected value function.

Evidences of ambiguity aversion and its impact on farmers' choices already exist, both in developed and developing countries. Engle-Warnick et al. [22] implement an experiment on Peruvian farmers aiming to observe the role of risk and ambiguity aversion in new crop varieties adoption. They observe the correlations between the result of the experiments and adoption of these varieties. It appears that ambiguity aversion significantly explains the non-adoption of varieties whose farmers do not master the yields distributions. The level of human capital (experience and education) seems to be a significant variable explaining adoption as well. The article of Barham et al. [7] deals with the effect of risk and ambiguity aversion on the adoption of herbicide or vermin resistant genetically modified crops. Herbicide use and vermin invasion are important sources of uncertainty about the effective distribution of yields for farmers. Their conclusion of the experiment is that the higher ambiguity aversion is, the higher they are likely to adopt a crop that can reduce the ambiguity. Reversely, this result is not true in a risk perspective: the risk aversion level seems to have no impact on the adoption of risk-decreasing crops. This article highlights the interest of separating attitudes toward risk and ambiguity. Ghadim et al.

[32] realize a contextualized experiment on Australian farmers. Farmers are put in situations where they have to subjectively assess the crops' yields distributions and their covariance. The authors show especially that risk aversion, risk perception and covariance between new and conventional varieties, play an important role in innovation adoption. It comforts us about our main assumption about role of the potential ambiguity associated with innovations. They also highlight that "learning-by-doing" and education are important factors to reduce uncertainties related to new crops yields, and in parallel increase the productive performance of farmers. Finally, Bougherara et al. [11] conduct an experiment on French farmers, and show that the risk aversion level is different between the gain and loss domain. The authors also extent this result to ambiguity aversion. The subjects also applied a weighting function regarding to probabilities, differently in the loss and the gain domain. Kala [43] tests the Hansen-Sargent model of ambiguity on farmers, in a context of learning about the likely date of monsoon and the optimal planting time. The author compares the updating process between farmers with more or less access to irrigation infrastructures, under the assumption that a farmer with greater access to irrigation is considered as less ambiguity averse. The results are clear: farmers with a bad access to irrigation tend, ceteris paribus, to give more weight to worst-case scenarii when updating their information and to tend to modify their planting time according to that, relative to the ones with a total access to irrigation who better hedged themselves against negative shocks. The author shows that richer farmers tend to update their choice only according to a simple expected profits rule, while poorer tend to give more weights to the past worst-case income in their updating process which is more consistent with the ambiguity aversion hypothesis. Wealth, access to infrastructures that insure yields (irrigation) in a context of uncertainty in the level of water, and information are highly embedded with ambiguity behaviors and the way information is used in the production. This corpus shows we are not the first ones to suppose a role of ambiguity aversion beside risk aversion in adoption of new practices or new farming productive activities, and the ability to use information. However, none of these papers analyze the role of ambiguity aversion as a driver of non-adoption of mitigation practices in agriculture. We assume that ambiguity aversion might be of particular interest as a direct explanation of the non-diffusion of specific practices for which knowledges about the underlying stochastic processes are particularly limited or uncertainty is deep.

1.3 Contributions

We claim that the policy makers have to take into account the externalities associated to uncertainty in order to fix them (or use them in case of positive informational externalities) and to improve the cost-efficiency of environmental economic policies. These phenomena can be seen as additive costs to adoption costs of mitigation practices (i.e. abatement costs) when they create a simultaneous market failure that makes inappropriate the incentive that were supposed to solve the climatic externality from the producers (see Figure 1.2). Introducing them in the cost-benefits analysis would help to lift barriers to the adoption and diffusion of such practices among the agricultural sector. While the Tinbergen rule states that each policy target must be associated to at least one incentive tool, if the main target is divisible in subtargets or if reaching a target is conditional to the reach of another, new tools have to be created. Imposing a carbon price (through markets, taxes or subsidies) can be limited if additional targets (here, market failures from uncertainties) are not taken into account. One target can be solved by several tools, or, a tool can have adverse impact on more than one target. Also, the less a tool is said "selective"

in the target, the less it is efficient (Knudson [47]). A first step in this direction is to identify how uncertainty can impact adoption of new practices and to quantify how much it can impact the adoption of some given practices. We will partly answer this issue in this thesis, which leads to a progress toward the correct identification of the targets in the case of policies aiming to transform the farming practices.

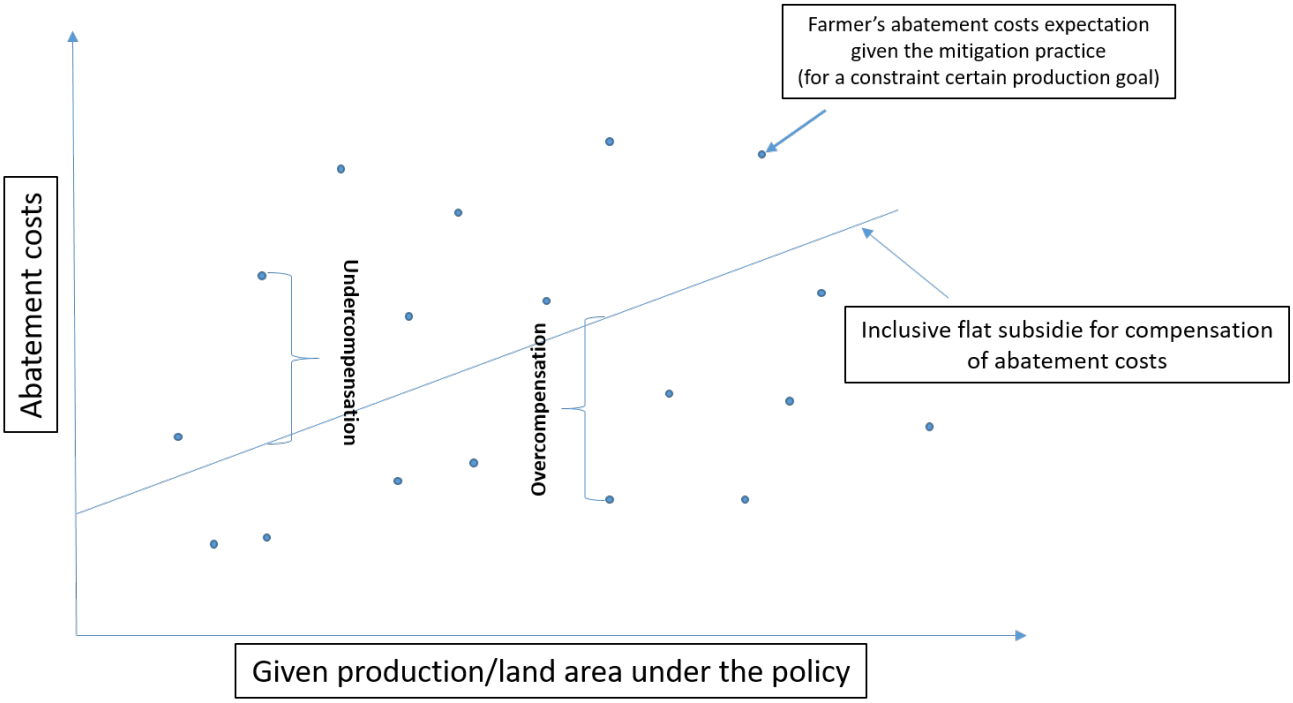

Figure 1.2 – Inefficiency of flat subsidies with hidden costs - author

In chapter 2 (based on Tevenart, Baudry, Civel 2019), we want to show how uncertainty together with risk preferences can limit adoption of new practices by farmers, and the impact that information can have at the microeconomic level. We aim at observing if real option types of behavior and risk preferences can both prevent simultaneously adoption of uncertain activities, and in which case they interact. In this purpose, we adapt the real option model in a unique theoretical setting, incorporating some specific features of agricultural productions (irreversibility, maximum land availability constraint, actual source of information). We show that options valuation by farmers and unfavorable information arrival can limit adoption at the early stages of diffusion, an effect that can be reinforced by risk aversion: the usual separation between risk analysis and real option analysis is not obvious. Our contribution is to show in a unique framework that three hidden costs associated to uncertainty can impact adoption: quasi-option values, risk premium and informational externalities. Adoption is highly embedded with relationships between risk attitudes, initial beliefs, irreversibility of adoption and negative signals, and signals can have various effects depending on the initial conditions. Risk aversion increases the adoption "costs" with a risk premium, a classic result, but moreover it explains partial, sequential adoption, a diversification phenomenon whose impact is embedded with the irreversibility of the practice, and it explains the existence of informational externalities. We illustrate our results in a numerical simulation, and we draw implications, especially in terms of public policies: the private costs associated to uncertainty may be socialized in order to achieve better results.

In chapter 3, we seek to estimate the impacts of grassland yields uncertainties on the adoption of grasslands in the cattle-feeding land-mix, which is one of the main current mitigation practice and is more and more targeted by the regulator (Tevenart 2019). To reach this goal, we apply a short model of land allocation under uncertainty, and run estimations based on the land-use econometrics specification with panel data, on a sample of French metropolitan districts, from 1989 to 2017. We deploy diverse measures of grassland yields uncertainty through their variability over time. In order to tackle endogeneity issues, we performed instrumental estimations, with meteorological data. We find diverse results, our two main variability measurements having a negative or positive, and relatively robust marginal impact on the share of land dedicated to the different types of grasslands. These results imply that yields variability and the associated uncertainty impacts significantly allocation of land to grasslands in the cattle-feeding mix. First, there can be some substitutions between land-use in terms of variability, that look like self-insurance and diversification behaviors. This type of strategies shows that the farmers' quest for stability in feedings incorporates information they observe about the level of stochasticity, and the policy maker has to add this in her plan if she wants to enhance the use of grasslands in livestock systems. The other claim we make is that if the regulation aiming at forbidding destruction of permanent grasslands protects current carbon storages (which is good), it may simultaneously prevents farmers from adopting more grasslands in their land-mix because of the regulatory irreversibility it imposes and the uncertainty related to grasslands yields. The associated option value creates an adverse effect which may limit the carbon sink potential of using more grasslands in the current and future forage land-mix. This result wears the interest to show that not only uncertainty can be a cost to cover by a subsidy, but it has to be taken into account directly in the design of the regulation itself because it can be a intrinsic direct effect of land-use changes prohibitions policies.

The chapter 4 aims at observe correlations between actual practices of nitrogenous fertilization by farmers and experimental measurement of their real risk and ambiguity preferences, in combination with several key choice variables (Tevenart, Brunette 2019). Reducing synthetic nitrogenous fertilization or improving fertilization efficiency is an important mitigation strategy that seems to present negative abatement costs. We aim at testing our assumptions about the role of risk, but also ambiguity preferences on the ability to fertilize and to apply what is advised by agronomists. We implement an experiment on a sample of French farmers and use the results to see if risk and ambiguity preferences impact the propension to use (and so to reduce) synthetic nitrogenous fertilizers and the propension to follow advices from farming cooperative agronomists. We find levels of risk and ambiguity aversion that are very close to the work of Barham et al. [7] on US Midwestern farmers. We also find two main results: risk aversion decreases the level of nitrogen fertilization over the whole agricultural campaign while ambiguity aversion increases the level of nitrogen fertilization at the first splitting. While the first result is not surprising and depends on several parameters of interactions between fertilizer use, global production plan, risk and risk preferences, the second is more original. We interpret it as an implication of the deep uncertainty that relies on application splitting practices, because it imposes a sequence of decisions where each decision's outcome induce the next decisions, but in a context embedded with natural stochastic conditions which are uncertain. The global implication of this study is to show how risk but especially its theoretical extension in ambiguity can impact the farmers' decisions about intensive margins, which are targetted by the policy maker. Our academic contribution is to associate declared prefer-

ences method and real farming practices data gathering, in order to estimate a separated effect of risk and ambiguity aversion on fertilization practices, and uses of information given through technical advices.

The three chapters partly answer the main research question through different perspectives and with different methodologies. They all allow for the conclusion that uncertainties explain a large part of farmers' behaviors, and their responsiveness to external sollicitations, public incentives or technical advices. Insuring a generalized transition toward a less emitting agriculture within the very ambitious official goals of the French policy makers will need to be approached through a complex configuration of costs and incentives, which goes beyond the strict computation of average certain abatement costs. Better results can be achieved through the consideration of the specific constraints related to agricultural productions, allowing for the incentives to reach more farmers, while catching better their heterogeneity in terms of characteristics, preferences and beliefs.

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Chapter 2

Adoption of mitigation practices in agriculture: an application of the real option theory

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2.1 Introduction

Mitigation of greenhouse gases (GHG) emissions in agriculture is generally considered as one of the most cost efficient abatement measures in Western European countries. Whereas the agricultural sector is one of the main contributors to GHG emissions in these countries, it is also the main sector able to sequestrate atmospheric carbon and thus represents a great potential of mitigation. Therefore, specific European policies have been promoted in the context of the Common Agricultural Policy (CAP), namely the Climatic Agro-Environmental Measures (CAEM). These measures incentivize farmers to diversify their activities, and to adopt new pro-climate practices on at least a fraction of the surface they cultivate. Nevertheless, the total acreage that has been switched to the targeted mitigation practices remains far below the objectives of the policy, which raises concerns about its design. The fact that farmers refrain from adopting mitigation practices whereas standard economic calculus predicts that they should be massively adopted suggests that there exist important hidden costs that are not correctly accounted for. Among them, the cost of information acquisition and, more generally, the fact that information is scarce and/or noisy probably plays a crucial role. Information is recognized as a key factor of diffusion of uncertain innovations, especially in the agricultural sector. Yet, it is rarely addressed when modelling farmers' decisions in agricultural economics.

Feder and Slade [16] introduce information as a cost supported by farmers who have a willingness-to-pay for it in order to better assess the level of profits that accrue from the use of a new input. The level of adoption is shown to depend on the level of knowledge of farmers, among which the most educated and those with the better access to information seem to adopt more easily. Bigger farmers are more willing to pay to access to this information. In another vein, Leathers and Smale [29] showed that when an uncertain innovation is proposed to farmers in the form of different complementary packages, some risk neutral farmers who do not trust the information providers tend to adopt specific part of the innovation (package) in order to learn on their own the potential results. This leads to a sequential and reversible diffusion of the innovation where late adopters tend to delay adoption in order to observe what is the outcome for early adopters in the neighborhood. By contrast, this paper focuses on the role of irreversibility in the adoption of mitigation practices by farmers in the presence of uncertainty and learning and combines it with divisibility. Whereas the two features, irreversibility and divisibility, have been disconnected in the literature, the paper highlights how they are intertwined and how their simultaneous analysis can help designing policies to circumvent informational barriers to the diffusion of profitable mitigation practices by farmers.

Irreversibility in the adoption of mitigation practices by farmers may be either physical or economic. Physical irreversibility arises when it is not technically feasible, at least in the short term, to come back to the situation that was prevailing before adoption. The seminal papers by Arrow and Fisher [5] and Henry [18] on the irreversibility effect typically address this type of irreversibility. When dealing with mitigation techniques in agriculture, it may correspond to the adoption of alternative cultural practices such as stopping or limiting the soil preparation through sowing, or burying fertilizer. The turn back to the former practice goes with a cost associated to rehabilitation or soil nutriment updating, which takes time. It is also the case for long-run land use changes, such as adoption of biofuel crops (myscanthus for instance), agroforestry development and further development of durable grasslands in herb systems. In general, mitigation pratices aiming at

storing carbon are irreversible or wear some inertia because they are associated to the impossibility to destroy the storage. Economic irreversibility follows on from the existence of sunk cost of adoption and is at the core of the real option theory popularized by Dixit and Pindyck [12]. Typically, farmers need to invest in specific physical capital and/or to be trained or more generally to increase their human capital in order to correctly handle the new practices and get used to them. If *ex post* these practices reveal to be disappointing, farmers cannot recover the expense in physical and/or human capital they have incurred *ex ante*. A third kind of irreversibility which is relevant in the agricultural sector is legal irreversibility. This type of irreversibility occurs when farmers have to commit to a practice for a long period of time in counterpart of a financial support in order to avoid time inconsistency in the decision to adopt the targeted practice. Tegene et al. [41] study for instance conservation easements and Isik and Yang [21] analyse the case of the Conservation Reserve Program. Köppl [26] propose a survey of real option problems applied to the agricultutal sector. Applications include, among others, decision to switch from conventional to organic farming (Kuminoff and Wossink [28]), decision to adopt site-specific crop management (Isik et al. [19]) or the decision to develop perennial crops (Price and Wetzstein [35]). In many applications, the decision considered is a all or nothing decision that makes the problem close to the canonical real option problem. A noticeable exception is the model of urban sprawl at the expense of a physically irreversible loss of agricultural land developed by Capozza and Helsley [8]. Many applications involve both physical and economic irreversibility. Because it aims at building a bridge with the modelling of land allocation decisions, this paper puts the emphasis on physical irreversibility rather than economic irreversibility. Nevertheless, extension of the model to the existence of a sunk cost per unit of land converted to the new practice or crop is straightforward.

Divisibility refers to the fact that farmers can choose to devote only a fraction of their total acreage rather than the whole of it to a new culture or a new practice. It is key in land allocation models under risk which assume, following Chambers and Just [9] that land is a fixed but allocatable factor in a farmer's profit maximization problem. When risk affects yields, authors have either adopted the mean-variance portfolio choice proposed by Markowitz [31] (see e.g Aradhyula and Holt [3]; Sckokai and Moro [39]) or its more general version based on expected utility and developed by Levy and Markowitz [30] and Kroll et al. [27] (see e.g. Chavas and Holt [10]). In these models, risk adverse farmers may choose to allocate their land to different crops in order to balance expected returns on the one hand and risk on the other hand. This approach follows on from the literature dealing with profit maximization under price risk, initiated by Sandmo [38] and Pope and Kramer [34] and further applied to farmers by Moschini and Hennessy [32] and Ramaswami [36] but puts the emphasis on the case of land as a quasi-fixed input. In most theoretical studies, results show that the adoption of innovations, as well as the proportion of land allocated to the use of innovation, tends to increase with the farm size, due to a decrease of the impact of risk on choices (the Decreasing Absoute Risk Aversion assumption prevails). These results have been empirically confirmed by Saha [37], Chavas and Holt [11] and Feder and O'Mara [15] for instance. Negative (resp. positive) correlations between yields from uncertain conventional and uncertain innovative productions increase (resp. decrease) the likelihood of adoption by risk adverse farmers according to the majority of articles (Feder [13]; Feder [14]; Just [1]; Just and Zilberman [23]). However, interestingly, an opposite effect related to the reduction of uncertainty through observation by the farmer of yields correlations has been developed by some authors (Ghadim and Pannell [17]). This raises the importance of distinguishing between risk and uncer-

tainty.

According to Knight [24], economic agents are facing risk on a key element of their decision problem when they know the set of possible events and the associated probability distribution of this element. If economic agents do not know the probability distribution of events but only have beliefs that lead to subjective probabilities, they are facing uncertainty. Because it focuses on assets that are traded for a long time on financial markets, so that economic agents can objectively assess the probability distribution of their return, risk is the corner stone of the portfolio theory in finance. By contrast, decisions related to innovation and its diffusion are made under uncertainty. Profit uncertainty, risk attitudes, information and potential irreversibility of adoption of new practices or land-uses in agriculture are considered as playing an important role (Sunding and Zilberman [40], Ghadim and Pannell [17], Knowler and Bradshaw [25] etc.). Uncertainties affecting profits are already known as barriers in the literature dealing with innovation adoption by producers. Concerning specifically the agricultural sector, the capacity to adopt innovations for a risk adverse farmer on the one hand, and the global management of her production on the other hand, are the two main areas of research in the field of uncertainty and risk (Isik and Khanna [20]). The perspective of receiving more information as time goes makes decisions under uncertainty tightly linked to dynamic analysis. Some authors have more specifically analyzed irreversible decisions in this context. Their work departs from the standard real option theory because the stochastic dynamics they consider does not rely on Markovian processes but explicitly refers to Bayesian learning. For instance, Baudry [6] adapts the modelling approach of standard real options to the problem of an agent having to choose between making an investment characterized by an uncertain outcome or delaying this investment in order to benefit from the arrival of information and revise her beliefs about the possible outcomes. Jensen [22] analyses the impact of initial beliefs, and their Bayesian updating as information arrives, on the diffusion of an innovation with uncertain outcomes. As outlined by Sunding and Zilberman [40], the option value rationale can be an interesting tool to analyze adoption of new technologies in agriculture if it is able to catch the dynamics of beliefs and their updating. We share the same idea but go one step further by considering that the ability of farmers to adopt only partially a new practice through land allocation choice is also crucial. This flexibility makes farmers' decisions somewhat different from the dichotomic choice generally considered in real option and calls for a joint analysis of the attitude toward risk. Indeed, land allocation is subject to two potentially conflicting forces: diversification which justifies allocating some acreage to a new crop or practice in order to take advantage of the structure of correlations between returns; irreversibility which refrains from allocating too much acreage to a new crop or practice with uncertain outcomes.

The paper is organized as follows. Section 2.2 introduces the modelling of learning in a Bayesian way. Section 2.3 applies this modelling to the decision of risk neutral farmers facing the decision to convert part or all of their land to a new, environment friendly, practice in the case of an exogenous arrival of information. The concept of irreversibility premium, or quasi-option value, is discussed as a hidden cost in this context. Section 2.4 extends the model to the case of risk averse farmers. It is shown that the risk premium also acts as a hidden cost but interacts in a non-additive way with the irreversibility premium. Section 2.5 then discusses the case of an endogenous arrival of information and focuses on the informational externality between farmers when they have to allocate some lands to the new practice to experience it. The subsidy required to internalize this informational

externality is a third type of hidden cost. In this section the different types of hidden costs are compared on the basis of a calibration of the model for adoption of myscanthus in France. The last section concludes with policy implications.

2.2 Exogenous learning process

We assume that the switch of an acreage of land from the proven practice to the new practice is irreversible because it needs for instance a soil work or an input use that radically alters the ability to turn back to the proven practice (i.e. the focus is on physical irreversibility). A ratchet effect is related to the fact that if a farmer changes drastically the cultural practice on a parcel or convert it to a new activity, it leads her to "lock herself" at least until the next agricultural session in the practice or the activity. The turn back to the proven practice or activity goes throught a cost (rehabilitation, soil nutriment updating). It is the case for alternative cultural practices such as sow reduction or fertilizer burying, whose positive effect takes time before appearing, or the delay of the first N-input. It is also the case for long-run land use changes, such as bio-fuel crops (miscanthus for instance), agroforestry development or forest, development and further adoption of durable grasslands in herb systems. Conservation practice aiming at lock a parcel in a carbon-storage intensive activity is also a possible instance. Some mitigations can thus bear a non-adjustable effect if they go wrong, or bear an implementation cost and turn back cost that would be non-recoverable. We assume the time path between two choice periods in our model to be sufficiently short for avoiding a turn back in case of adoption. The irreversibility will be modeled as an impossibility to get back directly in the next period in the land conversion in practice or use: it is closed to a form of inertia.

Let L_i be the total available land for a farmer i. We assume a continuum of farmers with $\mathrm{L}_i \in [\mathrm{L}_{min}, \mathrm{L}_{max}]$. There are two agricultural practices or activities, respectively p for "proven" (currently widely spread among farmers) and n for "new" (innovative practice or activity). l_i^p and l_i^n denote the acreage of land a farmer i allocates respectively to the proven and to the new practice.

We consider two time periods, denoted $t = 0$ (present) and $t = 1$ (futur). In $t = 0$ as in $t = 1$ the gross margin (profit per area, thus revenues net from input costs that are not explicitly modeled) from the proven practice is certain and denoted r^p. The gross margin from the new practice is uncertain. There are two scenarii as regards the true state-of-the-nature. The first scenario $\mathrm{S} = sup$ is "optimistic" and associated to a high level of gross margin r_{sup}^n. The second scenario $\mathrm{S} = inf$ is "pessimistic" and associated to a low gross margin $r_{inf}^n < r_{sup}^n$. The prior belief, in $t = 0$, in favor of the "optimistic" scenario is represented by a probability $\mathrm{X}_0 = \mathrm{P}r[\mathrm{S} = sup]$ (thus $1 - \mathrm{X}_0$ is the subjective probability $\mathrm{P}r[\mathrm{S} = inf]$ associated to the "pessimistic" scenario).

Between $t = 0$ and $t = 1$ two types of message m can be received and their probability of reception depends on the true state-of-the-nature. If the true state-of-the-nature matches the "optimistic" scenario, a positive message $m = pos$ is received with probability $\theta_{sup} > 1/2$ (and a negative message $m = neg$ is received with probability $1-\theta_{sup} < 1/2$). If the true state-of-the-nature matches the "pessimistic" scenario, a negative message $m = neg$ is received with probability $\theta_{inf} > 1/2$ (and a positive message $m = pos$ is re-

ceived with probability $1-\theta_{inf} < 1/2$). The reception of a positive message $m = pos$ corresponds to the fact that the new practice has performed well as it was implemented by some farmers or by an agricultural research center, and conversely for the reception of a negative message $m = neg$. The two probabilities θ_{sup} and θ_{sup} capture noise surrounding the reception of a message. For instance, an intrinsically performant practice, for which the "optimistic" scenario matches with the true state-of-the-nature, may perform bad due to exceptionally unfavourable weather conditions. We do not impose symmetry between θ_{sup} and θ_{inf}, so that our modelling approach admits special cases situations where one type of message is perfectly informative (i.e. the corresponding θ amounts to 1) whereas the other type is noisy.

The reception of a message affects the beliefs in a Bayesian updating process. Accordingly, the posterior belief may be computed by using Bayes' theorem. In case of a positive message received between dates $t = 0$ and $t = 1$, the posterior beliefs are given by:

$$\begin{cases} X_1^{pos} = \frac{\theta_{sup} X_0}{P^{pos}} \\ 1 - X_1^{pos} = \frac{(1-\theta_{inf})(1-X_0)}{P^{pos}} \end{cases} \tag{2.1}$$

where X_1^{pos} is used as a shortcut for $Pr[S = sup|m = pos]$ at date $t = 1$. Similarly, noting X_1^{neg} for $Pr[S = sup|m = neg]$, we obtain

$$\begin{cases} X_1^{neg} = \frac{(1-\theta_{sup})X_0}{P^{neg}} \\ 1 - X_1^{neg} = \frac{\theta_{inf}(1-X_0)}{P^{neg}} \end{cases} \tag{2.2}$$

Beliefs thus follow a stochastic process driven by the type of message received between the two consecutive dates $t = 0$ and $t = 1$. The term $P^{pos} = X_0\theta_{sup} + (1-X_0)(1-\theta_{inf})$ (resp. $P^{neg} = X_0(1-\theta_{sup}) + (1-X_0)\theta_{inf}$) is the subjective probabilities of receiving a positive (resp. negative) message whatever the true state-of-the-nature. Given that $\theta_{sup} > 1 - \theta_{sup}$ and $\theta_{inf} > 1 - \theta_{inf}$, a comparison of the likelihood of the two scenarii shows that the belief in favour of the optimistic scenario increases from $t = 0$ to $t = 1$ if a positive message is received whereas it decreases if a negative message is received. A positive (resp. negative) message thus unambiguously increases (resp. decreases) the expected gross margin from adopting the new practice. The effect on the variance of the gross margin is more ambiguous and crucially depends on the prior beliefs and/or on the noise parameters θ_{sup} and θ_{inf}. This point will be further commented latter on.

2.3 The risk neutral farmer

Because of irreversibility in the adoption of the new practice, the farmer's problem has to be solved backwards. Accordingly, we first examine the optimal allocation of her land by a farmer i at the second period $t = 1$ given the acreage l_i^n >= already devoted to the new practice at the first period $t = 0$ and conditionally on the type of message m received between the two dates. Due to irreversibility, we express this problem as the choice of the increment Δl_i^n of land eventually added at date $t = 1$. The corresponding program for profit maximization is given by:

$$\begin{cases} \max\limits_{\Delta l_i^n \in [0, L_i - l_i^n]0} X_1^m(r^p l_i^p + r_{sup}^n(l_i^n + \Delta l_i^n)) + (1 - X_1^m)(r^p l_i^p + r_{inf}^n(l_i^n + \Delta l_i^n)) \\ s.c. l_i^p + (l_i^n + \Delta l_i^n) = L_i \end{cases} \tag{2.3}$$

where X_1^m takes the value $X_1^p os$ if a favourable message has been received and $X_1^n eg$ if a unfavourable message has been received. This constraint optimization program is easily solved by substituting the land availability constraint $l_i^p = L_i - (l_i^n + \Delta l_i^n)$ in the expected profit. The linearity of the expected profit in $t = 1$ then implies that the outcome of its maximization is a corner solution:

$$\begin{cases} \Delta l_i^n = 0 & \text{if } \mathbf{E}_{X_1^m} r^n < r^p \\ \Delta l_i^n = L_i - l_i^n & \text{if } \mathbf{E}_{X_1^m} r^n >= r^p \end{cases} \tag{2.4}$$

where $\mathbf{E}_{X_1^m}$ (with $m = neg$ or $m = pos$) stands for mathematical expectation $X_1^m r_{sup}^n + (1 - X_1^m) r_{inf}^n$ of margins computed on the basis of posterior beliefs. If the farmer believes in $t = 1$ that the expected margin generated by the new practice exceeds the margin from the proven practice, then the irreversibility constraint (i.e. $\Delta l_i^n >= 0$) is not binding and the risk neutral farmer allocates all her available land to the new practice. The higher X_1^m, the more likely this choice is. Therefore, for the problem to make sense we focus on the case where full adoption is optimal if and only if a positive message has been received. The resulting maximum expected profit level is

$$\pi_1^{pos} = L_i \mathbf{E}_{X_1^{pos}} r^n \tag{2.5}$$

If a negative message is received the irreversibility constraint is binding. The risk neutral farmer would ideally reallocates all her land to the proven practice but is constrained to keep the amount of land l_i^n already devoted at $t = 0$ to the new practice and can just choose not to further adopt the new practice in $t = 1$. The resulting maximum expected profit level depends on the acreage already allocated to the new practice at $t = 0$ and writes

$$\pi_1^{neg} = r^p (L_i - l_i^n) + l_i^n \mathbf{E}_{X_1^{neg}} r^n \tag{2.6}$$

A direct consequence of our assumption that the irreversibility constraint is binding in the case a negative message is received is that the land allocation problem is dynamic.

More precisely, in $t = 0$ the farmer chooses the acreage l_i^n she will devote to the new practice, taking into account the impact of her choice in the second period according to the type of message she will get. Indeed, if and only if a negative message is received the choice of l_i^n at the first period will affect the profit flow at the second period. Formally, the problem can be written:

$$\max_{l_i^n \in [0, L_i]} \left\{ X_0 (r^p l_i^p + r_{sup}^n l_i^n) + (1 - X_0)(r^p l_i^p + r_{inf}^n l_i^n) + \beta (P^{pos} \pi_1^{pos} + P^{neg} \pi_1^{neg}) \right\} \tag{2.7}$$

where $\beta = \frac{1}{1-\rho}$ and ρ stands for the discount rate. Again, the optimization problem (2.6) admits a corner solution characterized by the following choice:

$$\begin{cases} l_i^n = 0 & \text{if } \mathbf{E}_{X_0} r^n < r^p + \beta P^{neg} (r^p - \mathbf{E}_{X_1^{neg}} r^n) \\ l_i^n = L_i & \text{if } \mathbf{E}_{X_0} r^n >= r^p + \beta P^{neg} (r^p - \mathbf{E}_{X_1^{neg}} r^n) \end{cases} \tag{2.8}$$

where $\mathbf{E}_{X_0}$ stands for mathematical expectation computed on the basis of prior beliefs. Note that (2.8) does not depend on the total land L_i farmed. The decision to adopt the new practice does not rely on the size of the farm as long as farmers are risk neutral. The last term in the right hand side of (2.8) follows on from our assumption that the irreversibility constraint is binding when a negative message is received. If the irreversibility constraint was never binding, this term would vanish and full adoption in $t = 0$ would be decided on

the basis of the sole comparison of the expected margin from the new practice in $t = t$ and that of the proven practice. Going back to (2.4), we know that the additional term induced by the biding irreversibility constraint when $m = neg$ is positive. In the terminology used by Arrow and Fisher [5] this term is the quasi-option value.

The quasi-option value as defined by Arrow and Fisher [5] is the excess of expected margin compared to the proven practice required for full adoption of the new practice in the presence of a binding irreversibility constraint. It may thus be thought of as an irreversibility premium. Actually, the corner solutions (2.4) and (2.8) make the adoption problem similar to a two periods real option problem where the farmer decides to convert all her land to the new practice if and only if the expected margin associated the new practice according to her current beliefs exceeds a optimal threshold. At the first period, the threshold is given by the right hand side of inequalities in (2.8). The fact that the threshold for expected margins from the new practice above which its development is decided exceeds the margin r^p of the proven (or *status quo*) practice is referred to by Arrow and Fisher [5] and Henry [18] as the irreversibility effect. At the second period, the optimal threshold of expected margins above which the new practice is adopted is directly given by r^p. It may be the case that the farmer decides not to develop in $t = 0$ and changes her mind in $t = 1$ if a positive message is received whereas she gives up if a negative message is received.

The quasi option value has important policy implications. In order to highlight these implications, let consider that the new practice has social environmental benefits that are known with certainty whereas the private gains that accrue to the farmer are uncertain, due for instance to the current lack of existing well-developed market where the price of the output can be observed, or a lack of knowledge about the output yields. Social benefits can be internalized thanks to a subsidy per acre of land devoted to the new practice. If this subsidy is not high enough to ensure that $\mathbf{E}_{X_1^{neg}} > r^p$, then the irreversibility effect remains: the farmer still refrains from adopting the new practice at the first period in the sense that the expected margin, even once augmented by the subsidy, has to exceed r^p augmented by the quasi option value for adoption to be optimal. Therefore the quasi option value still works as a hidden cost and the farmer still supports alone the burden of this cost. For the irreversibility effect to disappear, it is required that the farmer is also compensated for the quasi option value. Said another way, contrary to social benefits that have to be internalized, the irreversibility cost has to be socialized.

2.4 The risk averse farmer

We now assume that farmers are risk averse and that their aversion is correctly captured by an expected utility decision criteria where u is the von Neumann and Morgenstern utility function, increasing continuous and twice differentiable with respect to the profit level (see von Neumann and Morgenstern [33]). Moreover, the flow of utility is assumed to be time additive. As in the risk neutral case, the inter-temporal problem of land allocation has to be solved backwards.

At the second period, due to the irreversibility constraint, the farmer chooses whether to further adopt the new practice and add Δl_i^n acres more of land to the l_i^n acres already

devoted to the new practice at the first period or to stay with l_i^n. Substituting the land availability constraint directly in the expression of the profit flow, the problem faced by the farmer may be written as

$$\max_{\Delta l_i^n \in [0, \mathrm{L}_i - l_i^n]} \mathrm{X}_1^m u(r^p \mathrm{L}_i + (r_{sup}^n - r^p)(l_i^p + \Delta l_i^n)) + (1 - \mathrm{X}_1^m) u(r^p \mathrm{L}_i + (r_{inf}^n - r^p)(l_i^p + \Delta l_i^n)) \quad (2.9)$$

It is shown in Appendix A that if the allocation choice at the first period was not irreversible (i.e. if Δl_i^n was chosen in $\mathbf{R}$ rather than in $\mathbf{R}^+$) the optimal choice for Δl_i^n would satisfy the following first order condition

$$\frac{\mathbf{E}_{\mathrm{X}_1^m}(r^n) - r^p}{\sigma^2_{\mathbf{X_1^m}}(r^n)} = (l_i^n + \Delta l_i^n) \mathrm{A}_{\mathrm{X}_1^m}(\Delta l_i^n) \quad (2.10)$$

with

$$\mathrm{A}_{\mathrm{X}_1^m}(\Delta l_i^n) = -\frac{u''(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))} \quad (2.11)$$

the absolute index of risk aversion, and

$$\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi})) = r^p \mathrm{L}_i + (\mathbf{E}_{\mathrm{X}_1^m}(r^n) - r^p)(l_i^n + \Delta l_i^n) \quad (2.12)$$

the expected profit based on posterior beliefs conditionally on the reception of a message of type m from $t = 0$ to $t = 1$. The right hand side of (2.10) is thus the product of the absolute index of risk aversion and the total acreage devoted to the new practice. The left hand side of (2.10) is similar to the Sharpe ratio except that its denominator is the variance, instead of the standard deviation, of the margin from the new practice. This variance is computed on the basis of posterior beliefs if a message of type m ($m = pos$ or $m = neg$) has been received between the first and the second period. An alternative way to write the first order condition (2.10) is

$$\mathbf{E}_{\mathrm{X}_1^m}(r^n) = r^p + \mathbf{R}_{\mathrm{X}_1^m} \quad (2.13)$$

with

$$\mathbf{R}_{\mathrm{X}_1^m} = \mathrm{A}_{\mathrm{X}_1^m}(\Delta l_i^n) \sigma^2_{\mathrm{X}_1^m}(r^n)(l_i^n + \Delta l_i^n) \quad (2.14)$$

the risk premium applied by the farmer. For risk averse farmers $\mathbf{R}_{\mathrm{X}_1^m}$ is positive. As long as $\mathbf{E}_{\mathrm{X}_1^m}(r^n)$ is superior (resp. inferior) to r^p plus this risk premium, the expected utility increases (resp. decreases) with Δl_i^n. Note that for a CARA utility function (2.10) and equivalently (2.13) are linear equations to be solved with respect to Δl_i^n. Whereas for the left hand side of (2.13) we systematically have $\mathbf{E}_{\mathrm{X}_1^{pos}}(r^n) > \mathbf{E}_{\mathrm{X}_0}(r^n)$ and $\mathbf{E}_{\mathrm{X}_1^{neg}}(r^n) > \mathbf{E}_{\mathrm{X}_0}(r^n)$, it is unclear how the right hand side, more precisely the risk premium, evolves from $t = 0$ to $t = 1$ conditionally on the type of message received. We can distinguish three cases.

A first case with little interest occurs when the irreversibility constraint is not binding whatever the type of message received. It implies that the total land allocated at the second period systematically increases compared to that of the first period. This surface is either obtained as the solution to the first order condition (2.10) if this solution is lower than the total surface L_i available or sets equal to this total surface if the solution to (2.10) is higher than L_i. As a result, the optimal profit at the second period does not depend on the land l_n^n allocated to the new practice at the first period and the inter-temporal expected profit maximization resumes to a succession of two static equilibria. More specifically,

the optimal land allocated to the new practice at the first period solves the optimization program

$$\max_{l_i^n \in [0, \mathrm{L}_i]} \{\mathbf{E}_{\mathbf{X_0}} u(r^p \mathrm{L}_i + (r^n - r^p) l_i^n) \tag{2.15}$$

where the land availability constraint has been directly substituted in the expression of the profit flow. The corresponding first order condition may be written as[1]

$$\mathbf{E}_{\mathbf{X_0}}(r^n) = r^p + \mathbf{R}_{\mathbf{X_0}} \tag{2.16}$$

with

$$\mathbf{R}_{\mathbf{X_0}} = -\frac{u''(r^p \mathrm{L}_i + (\mathbf{E}_{\mathbf{X_0}}(r^n) - r^p) l_i^n)}{u'(r^p \mathrm{L}_i + (\mathbf{E}_{\mathbf{X_0}}(r^n) - r^p) l_i^n))} \sigma^2_{\mathbf{X_0}}(r^n) l_i^n \tag{2.17}$$

the risk premium at the first period. Equation (2.16) just states that the farmer applies a risk premium when comparing the uncertain margin from the new practice and the margin of the proven practice. In the peculiar case of a CARA utility function, (2.16) is linear in l_i^n so that the optimal acreage devoted to the new practice is easily obtained. The presence of the risk premium in (2.16) implies that compensating the farmer for the social benefits induced by the adoption of the new practice is not enough to incentivize her. If, as in our comment of the irreversibility premium, we focus on the situation where social benefits from adoption are certain, the farmer still refrains from converting land to the new practice even if the social benefits are fully internalized. Indeed the decision involves uncertainty at the farmer level so that the farmer will require the expected margin from the new practice to exceed that of the proven practice plus the risk premium before converting part of her land. The risk premium thus acts as a hidden cost and suggests that the farmer has to be compensated for it in addition to the internalization of the social benefits. Like with the irreversibility premium, the risk premium has to be socialized. Note that, according to the Arrow-Lind Theorem [4], if the risk associated to uncertainty surrounding the private costs and benefits is shared among many stakeholders, then the sum of risk premiums asked by the different shareholders tends to zero.

The second case corresponds to a binding irreversibility constraint at the second period whatever the type of message is received. It only occurs if the farmer has a high preference for the present that makes her devote a large surface of land to the new practice in the first period at the cost of systematically considering it is too large at the second period. Although this case is theoretically possible, it is not consistent with the observation that farmers rather refrain from adopting new practices.

The third case is more interesting. It corresponds to a situation where the irreversibility constraint is binding for one type of message and is not binding for the other type. The more realistic configuration, although not necessarily the only one, is when the reception of a negative message leads to a binding irreversibility constraint. It means that the farmer regrets having allocated too much land to the new practice at the first period if a negative message is received whereas she is willing to allocate more at the second period if a positive message is received. It implies that the acreage of land allocated at the first period to the new practice impacts the expected profit at the second period so that the land allocation problem is intrinsically a dynamic problem. More precisely, the optimal profit at the second period associated with the reception of a positive message is given by

$$\tilde{\pi}_1^{pos} = r^p \mathrm{L}_i + (r^n - r^p) \mathrm{Min}\{\hat{l}_i^n, \mathrm{L}_i\} \tag{2.18}$$

[1] We focus on the case of an interior solution. This first order condition is obtained following the same lines that the proof developed in Appendix A.

with $\hat{l}_i^n > l_i^n$ the solution to (2.13) for $m = pos$ that makes $\tilde{\pi}_1^{pos}$ independent of l_i^n. Conversely, the optimal profit at the second period associated with the reception of a negative message is given by

$$\tilde{\pi}_1^{neg} = r^p \mathrm{L}_i + (r^n - r^p) l_i^n \tag{2.19}$$

and depends on l_i^n. The dynamic land allocation problem that the farmer is facing is then

$$\max_{l_i^n \in [0,\mathrm{L}_i]} \begin{cases} \mathbf{E}_{\mathbf{X_0}} u(r^p \mathrm{L}_i + (r^n - r^p) l_i^n) \\ +\beta[\mathrm{P}^{pos} \mathbf{E}_{\mathbf{X_1^{pos}}} u(\tilde{\pi}_1^{pos}) + \mathrm{P}^{neg} \mathbf{E}_{\mathbf{X_1^{neg}}} u(\tilde{\pi}_1^{neg})] \end{cases} \tag{2.20}$$

where the land availability constraint has been directly substituted in the expression of the profit flow of the first period. It is shown in Appendix B that the first order condition associated to this program is[2]

$$\mathbf{E}_{\mathbf{X_0}}(r^n) = r^p + \mathbf{R}_{\mathbf{X_0}} + \beta \mathrm{P}^{neg} \frac{u'(r^p \mathrm{L}_i + (\mathbf{E}_{\mathbf{X_1^{neg}}}(r^n) - r^p) l_i^n)}{u'(r^p \mathrm{L}_i + (\mathbf{E}_{\mathbf{X_0}}(r^n) - r^p) l_i^n)} [(r^p + \mathbf{R}_{\mathbf{X_1^{neg}}}) - \mathbf{E}_{\mathbf{X_1^{neg}}}(r^n)] \tag{2.21}$$

with $\mathbf{R}_{\mathbf{X_0}}$ the risk premium at the first period, defined in (2.17), whereas $\mathbf{R}_{\mathbf{X_1^{neg}}}$ is the risk premium, defined in (2.14) at the second period when a negative message has been received. Condition (2.21) highlights how the irreversibility premium and the risk premium are combined in a non-additive way. The second term in the right hand side of (2.21) is the risk premium associated to the first period and is formally identical to the risk premium already defined in (2.17) and discussed in the first case where the irreversibility constraint is never binding. The third term in the right hand side of (2.21) is close to irreversibility premium obtained in (2.8) for the risk neutral farmer. It has a similar form except that i) the margin from the proven practice is corrected by the risk premium $\mathbf{R}_{\mathbf{X_1^{neg}}}$ before computing its difference with the expected margin $\mathbf{E}_{\mathbf{X_1^{neg}}}(r^n)$ from the new practice and ii) the weight $\beta \mathrm{P}^{neg}$ applied to the difference between the two margins is multiplied by $\frac{u'(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}$ the ratio of the marginal utility of the expected profit at the second period and the one at the first period[3]. We conclude that the total premium in (2.21) is the sum of the risk premium at the first period and the irreversibility premium corrected to account for risk aversion at the second period. This total premium has to be socialized if one wants that the hidden cost bear by the farmer vanishes. We provide a graphical example of the negative adjustment of the level of adoption in $t = 0$ in Appendix C.

2.5 Endogenous learning process

So far, information has been treated as exogenous in the sense that farmers were benefiting from messages whatever the surface of land they collectively devoted to the new practice. Such a context matches with the information provided by an agricultural research center but disregards all information produced by farmers themselves. This section thus turns to the case of farmers who self-produce information. It addresses the question of how to extend the model to this case of endogenous learning and induce from this adapted model the subsidy required to internalize the inherent informational externality. A numerical illustration to the case of miscanthus in the French departement of Eure-et-Loire is also provided.

[2]We focus on the case of an interior solution for l_i^n.

[3]This feature can be interpreted as a level of aversion towards profits inequality over time.

2.5.1 Information as a public good

The two key parameters influencing the learning process in the case of exogenous information examined *supra* are the probabilities θ_{sup} and θ_{inf} associated to the reception of respectively a positive message if the correct scenario is the optimistic one (i.e. $r^n = r^n_{sup}$) and a negative message if the correct scenario is the pessimistic one (i.e. $r^n = r^n_{inf}$). These two parameters capture the noise surrounding the reception of messages. A high value of θ_{sup} (resp. θ_{inf}) means that there is a low degree of noise surrounding the reception of a message when the correct scenario is the optimistic (resp. pessimistic) scenario. Going back to equations (2.1) and (2.2), one easily checks that higher values of both θ_{sup} and θ_{inf} imply a more drastic change in the subjective likelihood ratio $\frac{X_1^m}{1-X_1^m}$ in $t = 1$ between the two scenarios compared to the likelihood ratio in $t = 0$ whatever the type of received message (with an upward change if a positive message is received and a downward change is a negative message is received). With endogenous learning, we assume that the degree of noise depends on the scale of experiments of the new practice which is directly related to the total surface allocated to it at period $t = 0$ over all farmers. As a consequence, each farmer contributes to the production of information through the land she allocates to the new practice, even if farmers are atomistic in the sense that they are too small to consider that the land they will allocate individually to the new practice influences the learning process. Said another way, information is a public good that is unvoluntarily produced by atomistic farmers. The "production" of information is assumed to satisfy the law of positive but decreasing marginal returns in the sense that the θs are increasing and convex with respect to the total land allocated by farmers to the new practice. Formally, we capture this idea by setting

$$\begin{cases} \theta_{sup}(\bar{L}^n) = 1 - e^{-ln(\frac{1}{2})-\lambda_{sup}\bar{L}^n} \\ \theta_{inf}(\bar{L}^n) = 1 - e^{-ln(\frac{1}{2})-\lambda_{inf}\bar{L}^n} \end{cases} \tag{2.22}$$

with

$$\bar{L}^n = \int_i l_i^n di \tag{2.23}$$

As farmers are assumed to be identical in our model, this last term is equivalent to $\bar{L}^n = I * l_i^n$ where I denotes the (high) number of farmers. According to (22), if no land is allocated to the new practice at period $t = 0$ then $\theta_{sup} = 1/2$ and $\theta_{inf} = 1/2$ which in turn implies according to (2.1) and (2.2) that the beliefs remain unchanged. This is consistent with the fact that there is no information if no land is allocated to the new practice. At least a small surface dedicated over all farmers to the new practice is required to experience it and learn form that experience. It also means that endogeneous learning is incompatible with risk neutrality. Indeed it has been shown *supra* that risk-neutral farmers individually opt for a all or nothing adoption strategy. Given that all farmers are identical according to the assumption of symmetry, it induces that either all risk neutral farmers totally allocate their land to the new practice at the first period and the information produced is worthless because of the irreversibility of adoption or all farmers do not allocate any acreage of land to the new practice at the first period so that no information is produced, beliefs remain unchanged and farmers have no new element to make them revised their decision at the second period. By contrast, in the presence of risk aversion, farmers may choose to allocate part of their land to the new practice, the exact surface involved being dependent of the amount of information anticipated and thus of the total amount of land that switches to the new practice at the first period. For i symmetric farmers, the amount of

land individually allocated to the new practice is determined as a fixed point of the system formed by the solution in l_i^n to program (2.20) for given parameters $\theta_{sup} = 1/2$ and $\theta_{inf} = 1/2$ and the value of parameters θ_{sup} and θ_{inf} obtained as the functions defined (2.22) and (2.23) of the acreage l_i^n individually allocated to the new practice at the first period. Prior detailing the numerical solution obtained for this fixed point in the case of miscanthus for the French department Eure-et-Loire in the next subsection, the internalization of the informational externality characterizing the case of endogenous learning deserves some discussion.

With endogenous learning, each farmer contributes to the production of information as a public good. This contribution is unintentional because farmers do not internalized the effects of this production on other farmers, besides the fact that there are atomistic and do not even consider their decision will affect the degree of information they will benefit from at the second period. The surface of land they individually decide to allocate to the new practice is thus socially suboptimal. A subsidy to allocate more land to the practice is thus required to make individual decisions match with the collective interest of farmers and this subsidy comes in addition to the payments discussed *supra* to socialize the irreversibility premium combined with the risk premium. Contrary to these payments, the required subsidy results from cross informational externalities between farmers and is conceptually more standard: the optimal subsidy per acre of land devoted to the new practice has to be fixed to a level corresponding to the marginal increase of the expected discounted profit of each farmer at the first period that results from a marginal increase of unit of the land devoted to the new practice when total land is fixed at its social optimum (i.e. when the informational externality is internalized). However, due to the intricate impact of the total surface devoted to the the new practice on the optimal allocation choice of a farmer, we have to rely on numerical computation to asset the amount of subsidy required.

2.5.2 Numerical illustration

We simulate the farmers' optimal acreage decisions and the values of irreversibility and risk premia, and amount of subsidy for the internalization of informational externalities. We calibrate our numerical simulations with the data from Bocquého and Jacquet [7] about miscanthus and switchgrass adoption decisions by farmers in the French department Eure-et-Loire. They provide real data about yields, output prices, subsidies and variables costs for miscanthus, switchgrass and conventional crops, namely rape, winter barley and soft wheat. We use these data for the calculation of the margins from conventional and uncertain crops. They also choose a discount rate of 5% and an absolute risk aversion coefficient of $1,4.10^{-5}$. We focus on miscanthus and soft wheat as the conventional crop, the most cultivated crop in the studied region according to the public agricultural census [2]. The utility function is assumed to be on the exponential form, $u = 1 - e^{-A\Pi}$. We set:

$$r^{sup} = €500/\text{ha},$$

$$r^{inf} = €130/\text{ha},$$

$$r^{p} = €198/\text{ha},$$

$$X_0 = 0.33,$$

$$L_i = 100\text{ha},$$

$$\rho = 0.05,$$

$$A = €^{-1}1,4.10^{-5},$$

$$I = 1000.$$

We assume that 1000 farmers choose the optimal level of adoption account being taken of the parameters and their choices are included in the computation of the θ_m (2.22). The following results consider thus endogenous information. In this configuration, without irreversibility $\mathbf{R_{X_0}}$ equals €37.7 per hectare and $\mathbf{R_{X_1}}$ equals €5.1 per hectare. If we add irreversibility, the quasi-option value under risk neutrality equals zero, because the parameters are such that the expectations are high enough to induce adoption and the farmer would not experience any regrets from adoption. Reversely, under risk aversion, the irreversibility premium equals €16.4 per hectare. In this case, the total premium (risk premium in $t = 0$ plus irreversibility premium under risk aversion) equals €54.1 per hectare. This is the value of the simulated marginal private costs that farmers have to bear if they adopt miscanthus on their farm under this set of parameters. This result is interesting because it shows that information has an impact also through the irreversibility effect (around €11 per hectare), and that, only with risk aversion. Under risk neutrality, the farmer can't have any regret from adoption, due to the fact that she will either not adopt at all (no information is generated), or adopt at 100% and irreversibility makes information not relevant. Under risk aversion, partial adoption by the farmers generates information *per se*, information which in turn impacts the positive irreversibility premium. The calibration allows us to compute the level of subsidy that is needed to compensate for the marginal value of the information externality generated by adopters: 15 cents per hectare, which is very low.

Without irreversibility, the adoption in $t = 0$ equals 100 hectares as expected (adoption is maximal), whereas it equals 88.9 hectares with irreversibility and risk aversion. This result presents a quantification of the impact of irreversibility and uncertainty with endogenous information on the level of adoption, and the adoption potential if the regulator chooses to hedge the simulated total premium. Around 11% of the theoretical level of adoption in $t = 0$ is lost. It shows the partial adoption from the adjustment in the first period. The theoretical static level of adoption in $t = 1$ in case of negative message (without irreversibility) equals 16.827 hectares under the values of the endogenous θs, which is significantly under the level of adoption in $t = 0$ with irreversibility. It illustrates the impact of negative signals and risk aversion, and the adjustment of the level of adoption in $t = 0$ of the farmer who prevents herself from regretting a too high level of adoption.

2.6 Discussion

2.6.1 Implications

Diverse implications can be derived from our results. First, as we observed in the risk-neutral farmer's part with exogenous information, beliefs play an important role in the willingness to adopt, because they directly relate to the valuation of the different agricultural practices or activities' profits and thus the opportunity for farmers to adopt or not (initial beliefs and updated beliefs). The comparison between certain profits and uncertain profits is a crucial part of the choice for farmers all along the model.

A quasi real option value is associated to the presence of irreversibility, which leads to the integration of the possibility to receive a negative message. In this situation, farmers weight their evaluation of comparative margins with what they forecast about the worst scenario they can fall in, and that, from the first period. Under risk neutrality, the weighting will only change the propensity to adopt because it can increase the adoption "trigger" that is necessary to exceed the status quo's certain margin. This effect can decrease incentives to adopt the uncertain practice, and adoption follows a "go-no go" scheme. The irreversibility premium can be considered as a hidden costs that can be socialized through a public compensation. A second hidden cost arise under risk aversion: a risk premium appears at each period's choice, that corresponds to an additive cost of adoption that prevent risk averse farmers from adopting. Partial adoptions can arise in this situation because of interior solutions to the maximization program. Once again, the regulator can hedge for this premium through a public compensation: it is equivalent to say that a high number of tax payers share the risk instead of the private farmer. Finally, if the irreversibility is binding in case of negative message, and under risk aversion, choices are not divisible over time anymore, and the total irreversibility premium corresponds to the combination of a quasi-option value and a risk premium. This premium impacts the farmer's evaluation of margins and the related adoption choice from $t = 0$, and can limit her willingness to make a diversification process on the farm, while most of the current agricultural public policies aim *per se* at promoting diversification. These features impact adoption from the first period, which is a crucial result because it is directly related to the diffusion of innovations at the early stages (negative messages can "nip diffusion in the bud"). However, when information source is exogenously determined, it is impossible to assess how farmers' choices themselves can impact others adoption. A third hidden cost arises from the generation of informational externalities coming from adoption of farmers themselves. Because of our assumptions of homogeneity between farmers in the department and irreversibility, information has no influence under risk neutrality. Reversely, under risk aversion, partial adoptions induce information generation about the mitigation practice and information externalities arise. In this scope, information can be considered as a public good which production as to be guaranteed with a subsidy that encourage adoption on more land. The farmers-adopters must be compensated for the effect of the information they produce when they adopt on the group and the fact they help achieving the social goal.

We make a numerical illustration of these diverse hidden costs related to uncertainty on the case of miscanthus planting. Miscanthus is a good instance of mitigation activity that consists of a perennial fuel-crop whose yields are uncertain and fairly new for most of farmers compared to conventional crops. Our simulation relies on figures from the literature. We show that in this case, the bigger hidden cost concerns the total premium under risk aversion. This hidden cost refrains farmers from adopting, and we can say that the regulator could achieve good results if this privated cost would be socialized. This result highlights that the irreversibility significantly increases the costs associated to uncertainty and that it must be taken into account in the incentives programs: the level of subsidies may have to be strongly increased compared to the usual computation in "certain universe". Nevertheless, the level of the costs is related to the calibration we made in this simulation. Other cases must be explored, and sensitivity tests must be implemented.

2.6.2 Conclusions

We associated the portfolio management model in risk (CAPM) to the classic option value theory with Bayesian probabilities, in a structure inspired from the land allocation management models in a dynamic setting. We show that flexibility or irreversibility of new practices change drastically the uncertain margins' evaluation that farmers can make. We show that risk aversion explains both partial and sequential adoption. A farm size effect is highlighted, but depends on the risk preferences of the farmer. We show that negative information can discourage the development of practices, and thus has a non negligible impact on their massive diffusion in the agricultural sector. Negative signals can "nip diffusion process in the bud", because they impact strongly initial evaluation that farmers make. In this perspective information acts like a public good which production has to be guaranteed if the externality is positive, but that has to be limited if the externatility is negative. In this point of view, classic compensation subsidies are not necessarily the only policy option to implement in order to enhance diffusion of new practices, or can even be ineffective.

In terms of public policy, we thus can consider different potential outputs. An accurate public policy would be to cover the main hidden costs that farmers face when they evaluate adoption potential. First, we saw that quasi option values arise with irreversibility. Since irreversibility effects rely on the comparison between current uncertain expected profits and statu quo profits plus the quasi option, which is composed by a forecast of the worse scenario's expected profits in the future, this raises the question of the design of classic compensation subsidies. On the first hand, the current subsidies do not take into account the irreversibility effect, so the amount of payment may simultaneously compensate for mitigation practices that have negative abatement costs on average (which is inefficient) but do not take into account the specific presence of quasi option value at the first period for practices wearing irreversibility. The underlying question is to introduce the concept of irreversibility in the design of subsidies themselves as a particular criteria that would lead to a socialization of the irreversibility cost. On the other hand, since the most pessimist forecasts of future profits enter the quasi option value and they are necessarily lower than the expectation of profits in the first period, it induces that the dynamic evaluation of profits over time is constantly taken into account by farmers before to adopt. Adoption can be delayed until forecasts about global consequences are sufficient to induce adoption (expected profits plus public subsidies): a constant flat subsidy will not surely encourage adoption if it impacts identically the current and forecasted total profits from adoption. It could be interesting to compensate the quasi option value on the form of a much higher subsidy in the present but that tends to disappear in the next periods (temporary subsidy). The irreversibility cost is thus well socialized but a "now or never" effect can incentive quick adoption, instead of a constant subsidy that offers the same amount over a long-time horizon. Moreover, without risk aversion, adoption occurs on the whole farm so that no subsidy would be useful anymore because the "tipping point" would be exceeded. Further research should be conducted about how to introduce flexibility or irreversibility of the practices directly in the design of public subsidies. Secondly, risk by itself can be the major hidden cost from adoption and leads to partial adoption. As we saw it in part 2.4, risk premia can be socialized at a relatively low cost if many stakeholders support the private risk of adopters, who provide social benefits through adoption. The question of the compensation for individual risk taking behaviors which provide social benefits is not new. In this perpective, either the compensation subsidies directly internalize the risk premia on the form of an important overevaluation of the

current subsidies amount, or other risk management policies can be implemented like specific insurance depending on the risk sharing characteristics associated to the farmers and the practices. Researches are currently conducted about this last point. Thirdly, information production coming from first adopters plays a role from the early stages of new practices' diffusion. This public good's cost is carried by the first adopters and related benefits are shared by other farmers: a subsidy aiming at paying the first adopters for information production may be crucial to induce a mechanic motion of adoption and diffusion among the agricultural sector.

This research is part of the Agriculture and Forestry research program by the Climate Economics Chair. The authors want to thank the Climate Economics Chair for financial support. The BETA contributes to the Labex ARBRE ANR-11-LABX-0002-01.

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Appendices

Appendix A

This appendix presents the optimal choice of a farmer at the second period given that l_i^n acres of land have been allocated to the new practice at the first period but there is no irreversibility. Let first define

$$\epsilon = r^n - \mathbf{E}_{X_1^m}(r^n) \tag{24}$$

the difference between the realization of the margin of the new practice and its expected value with posterior beliefs when a message of type m is received. Let also define

$$\tilde{\pi} = r^p L_i + (r^n - r^p)(l_i^n + \Delta l_i^n) \tag{25}$$

the associated random profit at the second period.

We consider the following expected profit maximization problem:

$$\max_{\Delta l_i^n \in [0, L_i - l_i^n]} \mathbf{E}_{X_1^m}(u(\tilde{\pi})) \tag{26}$$

The associated first order condition for an interior solution writes

$$\mathbf{E}_{X_1^m}(u'(\tilde{\pi}) r^n) - \mathbf{E}_{X_1^m}(u'(\tilde{\pi})) r^p = 0 \tag{27}$$

This first order condition is transformed in two steps. In a first step, the property $\mathbf{Cov}(x, y) = \mathbf{E}(xy) - \mathbf{E}(x)\mathbf{E}(y)$ (and thus $\mathbf{E}(xy) = \mathbf{Cov}(x, y) + \mathbf{E}(x)\mathbf{E}(y)$ is applied to (27). This yields

$$\mathbf{Cov}_{\mathbf{X_1^m}}(u'(\tilde{\pi}), r^n) + \mathbf{E}_{\mathbf{X_1^m}}(\mathbf{u}'(\tilde{\pi}))(\mathbf{E}_{\mathbf{X_1^m}}(r^n) - r^p) = 0 \tag{28}$$

In a second step, it is assumed that ϵ is sufficiently small to enable the use of linear approximation of the marginal utility in the vicinity of zero :

$$u'(\tilde{\pi}) \approx u'(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi})) + u''(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))(\tilde{\pi} - \mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi})) \tag{29}$$

It follows on that we may write

$$\mathbf{E}_{\mathbf{X_1^m}}(\mathbf{u}'(\tilde{\pi})) \approx u'(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi})) \tag{30}$$

and, combining with the properties of the covariance

$$\mathbf{Cov}_{\mathbf{X_1^m}}(u'(\tilde{\pi}), r^n) \approx u''(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))\mathbf{Cov}_{\mathbf{X_1^m}}(\tilde{\pi}, r^n) \tag{31}$$

Substituting the expression of $\tilde{\pi}$ and using the notation $\sigma^2_{\mathbf{X_1^m}}(r^n) = \mathbf{Cov}_{\mathbf{X_1^m}}(r^n, r^n)$ we can also write

$$\mathbf{Cov}_{\mathbf{X_1^m}}(u'(\tilde{\pi}), r^n) \approx u''(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))(l_i^n + \Delta l_i^n)\sigma^2_{\mathbf{X_1^m}}(r^n) \tag{32}$$

Accordingly, the first order condition becomes

$$u''(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))(l_i^n + \Delta l_i^n)\sigma^{\mathbf{2}}_{\mathbf{X_1^m}}(r^n) + u'(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))(\mathbf{E}_{\mathbf{X_1^m}}(r^n) - r^p) = 0 \tag{33}$$

or equivalently

$$\mathbf{E}_{\mathbf{X_1^m}}(r^n) = r^p - \frac{u''(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_1^m}}(\tilde{\pi}))}\sigma^{\mathbf{2}}_{\mathbf{X_1^m}}(r^n)(l_i^n + \Delta l_i^n) \tag{34}$$

Appendix B

This appendix presents the optimal choice of a farmer at the first period given that l_i^n acres of land can be allocated to the new practice and there is irreversibility (program 2.20). Irreversibility is binding only in the case of the reception of a negative message. In this case, the acreage of land allocated at the first period is such that it impacts negatively the expected profits at the second period and the farmer would regret her allocation choice.

We consider the following expected profit maximization problem:

$$\max_{l_i^n \in [0, \mathrm{L}_i]} \mathbf{E}_{\mathrm{X}_0}(u(\tilde{\pi})) + \beta[\mathrm{P}^{pos}\mathbf{E}_{\mathrm{X}_1^{pos}}(u(\pi_1^{\tilde{pos}})) + \mathrm{P}^{neg}\mathbf{E}_{\mathrm{X}_1^{neg}}(u(\pi_1^{\tilde{neg}}))] \tag{35}$$

The associated first order condition for an interior solution can be written

$$\mathbf{Cov}_{\mathbf{X_0}}(u'(\tilde{\pi}), r^n) + \mathbf{E}_{\mathrm{X}_0}(u'(\tilde{\pi}))(\mathbf{E}_{\mathbf{X_0}}(r^n) - r^p) + \beta \mathrm{P}^{neg}[\mathbf{Cov}_{\mathbf{X_1^{neg}}}(u'(\tilde{\pi}), r^n) + \mathbf{E}_{\mathrm{X}_1^m}(u'(\tilde{\pi}))(\mathbf{E}_{\mathbf{X_1^{neg}}}(r^n) - r^p)] = 0 \tag{36}$$

The first order condition becomes

$$\begin{aligned} u''(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))\, l_i^n \sigma^{\mathbf{2}}_{\mathbf{X_0}}(r^n) + \mathbf{E}_{\mathrm{X}_0}(u'(\tilde{\pi}))(\mathbf{E}_{\mathbf{X_0}}(r^n) - r^p) + \\ \beta \mathrm{P}^{neg}[u''(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))\, l_i^n \sigma^{\mathbf{2}}_{\mathbf{X_1^{neg}}}(r^n) + \mathbf{E}_{\mathrm{X}_1^m}(u'(\tilde{\pi}))(\mathbf{E}_{\mathbf{X_1^{neg}}}(r^n) - r^p)] = 0 \end{aligned} \tag{37}$$

or equivalently

$$\mathbf{E}_{\mathbf{X_0}}(r^n) = r^p - \frac{u''(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}\sigma^{\mathbf{2}}_{\mathbf{X_0}}(r^n)\, l_i^n + \beta \mathrm{P}^{neg}\frac{u'(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}[r^p - \frac{u''(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}\sigma^{\mathbf{2}}_{\mathbf{X_1^{neg}}}(r^n)\, l_i^n - \mathbf{E}_{\mathbf{X_1^{neg}}}(r^n)] \tag{38}$$

Appendix C

This appendix presents a graphical illustration of the adjustement in $t = 0$ due to irreversibility and risk aversion. If we denote a the share of the portfolio that is at risk we can pose $\sigma_{\mathbf{X_t}}(\tilde{\pi}) = a\sigma_{\mathbf{X_t}}(r^n)$. Note that the first order condition in static (equation 34) can be rewritten at time t

$$\frac{\mathbf{E}_{\mathbf{X_t}}(r^n) - r^p}{\sigma_{\mathbf{X_t}}(r^n)} = -\frac{u''(\mathbf{E}_{\mathbf{X_t}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_t}}(\tilde{\pi}))}\sigma_{\mathbf{X_t}}(\tilde{\pi}) \tag{39}$$

Where the left-hand side corresponds to a Sharpe ratio and the right-hand side corresponds to the product of the absolute risk aversion and the standard error of the profit. For later purpose, we pose $\frac{\mathbf{E}_{\mathbf{X_t}}(r^n) - r^p}{\sigma_{\mathbf{X_t}}(r^n)} = \mathrm{J}_t$. At this asymptotic point the farmer is indifferent between profits expectation and risk, given that more risk must be remunerated by more profits. The arbitrage between risk and expectation is here, clear-cut, and allows for the determination of the optimal level of adoption l_i^{n*}. This result is close to the Capital Assets Pricing Model rationale: the level of remuneration of the taken risk gives the slope of the risky asset demand, that corresponds to the Sharpe ratio. We will see later the graphical illustration of that.

With irreversibility, we get back to equation (38), that can be written as a transformation of the previous equation (39) on the form

$$J_0 = -\frac{u''(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}\sigma_{\mathbf{X_0}}(\tilde{\pi}) - \beta P^{neg}\frac{u'(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_0}}(\tilde{\pi}))}\frac{\sigma_{\mathbf{X_1^{neg}}}(r^n)}{\sigma_{\mathbf{X_0}}(r^n)}[J_1^{neg} + \frac{u''(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}{u'(\mathbf{E}_{\mathbf{X_1^{neg}}}(\tilde{\pi}))}\sigma_{\mathbf{X_1^{neg}}}(\tilde{\pi})] \quad (40)$$

The last feature between brackets on the right-hand side is equivalent to the first order condition in $t = 1$ in case of the reception of a negative message. At the optimum, it equals 0 and equation (40) is equivalent to (39). If it is expected negative (which would normally induce "disadoption"), we know that the irreversibility can be binding, and it implies an adjustement of the level of adoption from $t = 0$. It is important to note that a feature $\frac{\sigma_{\mathbf{X_1^{neg}}}(r^n)}{\sigma_{\mathbf{X_0}}(r^n)}$ is added, which is a weighting component: we interpret it as a weighting of the value of potential "regrets" in the second period from too much adoption by the relative evolution of risk over time. If it equals 1, the farmer does not forecast that the risk will evolve over time and there is no impact on the level of adjustement. However, if the risk is assumed to increase between both periods, it is superior to 1 and the adjustement will be stronger. The interpretation is symmetric for the case of a decreasing evolution in the risk.

We can draw this result on Figure 1 as an example:

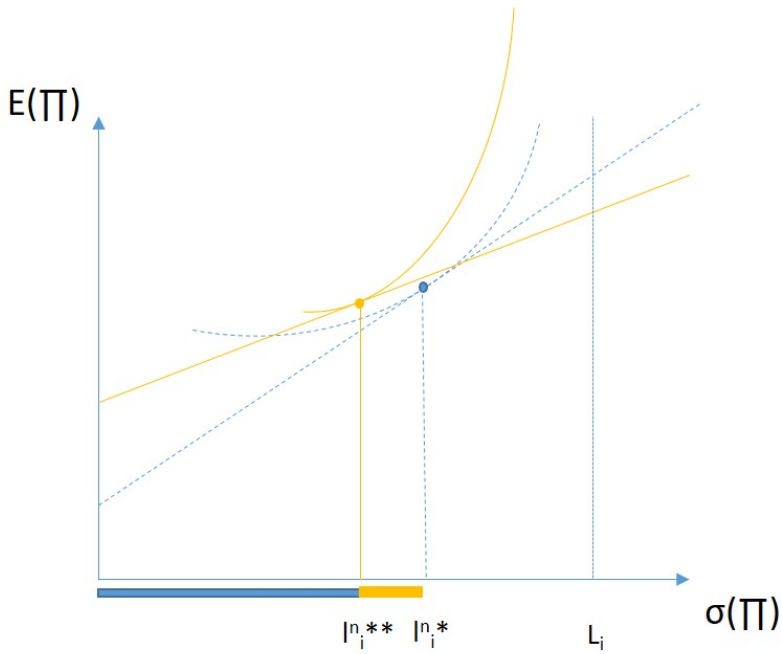

Figure 1 – Partial adjustement of adoption w.r.t. potential bad scenario - author. forecasts

This graph is similar to the Capital Asset Pricing Model rationale, whose assumptions are closed to those of Markowitz [31]. The choice of the farmer is represented on a two-dimensions graph, with the level of portfolio risk on the x-axis and the portfolio profits expectation on the y-axis. The blue dashed line represents the risky asset demand curve. The level of adoption is catched on the x-axis, through the level of risk the farmer is ready to accept. The adoption is bounded by the total farm size L_i: if adoption reaches this level, the taken risk is maximum. At the point 0 on the x-axis, the level of risk is null and the farmer does not diversify at all: she only keeps the conventional practice. The blue dot represents the asymptotic point from equation (39) in $t = 0$. In this situation we assume that there is no binding irreversibility, and the level of adoption is given by l_i^{n*}. If

the irreversibility is binding in case of negative message, the farmer will adjust her level of adoption from the first period, in order to not experience any regrets in the second period. This mechanism can be understood as a displacement of the asymptotic point (orange dot) due to a decrease in the slope of the asset demand curve (dashed orange line), simultaneous to an increase in the Arrow-Pratt "curve" with respect to the portfolio risk (orange solid line), which can be understood as a transformed marginal rate of substitution between each unit of risk and the level of profit expectation. The adjusted level of adoption is given by l_i^{n**}.

Chapter 3

Yields volatility and friction in land conversion

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3.1 Introduction

The last decades are associated to the combination of simultaneous important issues in the farming-breeding systems in France. Firstly, the importance of keeping sufficient revenues to farmers, allowing them to produce enough, aiming to feed the population and live their life in the same time, while continuing the investment in their farms in the future. The sustainability of the crop and animal products' production in economic terms is crucial, while the quick increase of the demand for meat and milk at a global scale is challenging like never before. In a second time, the increasing preoccupation for environment-related subject, especially climate change which is strongly impacted by the agricultural sector (more than 20% in France in 2016 according to CITEPA [8]), ecosystems preservation and animal condition, highlights the importance of the way farmers are practicing their activities. It is especially true concerning the farming-breeding systems, that relies on both animal feeding and animal products' production, and is an important producer of greenhouse gases: CH4 through animal eructation and dejection storage, N2O relative crop production intended to feed the cattle and animal dejection use, and carbon storage and flows related to the weight of land cover management related to the crop production. Indeed, the forage crop, as a specific land cover (that is related to forage vegetable cropping, cereal and especially ensilage maize cropping, and grass production through all the different kinds of grasslands) represents for itself 45% of the agricultural surfaces in France (Huyghe [19], TERUTI dataset). During the second half of the past century, a significant part of grasslands has been destructed in order to produce forage crops (especially cereals) because of higher productivity gains in these productions and higher advantages in terms of CAP aids (ibid.). This phenomenon led to intense carbon leakages, while grasslands' soils are able to store around 70-100tC/ha during a sufficient duration, which represents almost the same amount as forest soils (Arrouays et al. [3]). On the contrary, intensive annual cropping led to carbon losses and soils quality degradation (without taking into account the impact of cropping practices in terms of synthetic nitrogenous fertilization). Converting an annual crop into a permanent grassland is estimated to store 0.84 to 2.75 t eqCO2/ha/an (ibid.).

As a well-known public report highlighted, among the less costly and most potentially massive in terms of net GHG reduction mitigation practices, the grassland management is one of the most interesting (Bamière et al. [4]). Indeed, two main measures among those which have the better reduction/cost ratio are related to grassland: the increase of pasture duration (-€112/ha/year, around -€500/tCO2eq/year for an average farm) and of the temporary grassland duration (-€26/ha/year, around -€180/tCO2eq/year for an average farm) wear a non-negligible reduction potential, and also have negative emission unit abatement costs. The increase of the weight of pasture and/or grassland in the cattle feeding management (the "forage mix") implies a mechanic increase of their weight in the crop rotation. However, the capacity to adopt more grassland in the whole land portfolio of a farmer depends on the marginal opportunity cost of land relative to the production of inputs. Because of the potential estimated negative abatement costs, we can expect that the average marginal profitability of adoption might be positive. But if hidden costs related to uncertainty in the food production (and then risk of feeding interruptions), and its lack of reversibility, occur, one can ask for how much they impact the willingness to convert lands. Indeed, croping grasslands is complex and requires some specific knowledge from farmers, and the associated yields are significantly volatile. Uncertainty in yields would increase the shadow value of land use substitution and prevent farmer from in-

crease the extensive share of grasslands on their lands. This raises new questions: does volatility in yields lead to friction in land conversion toward grassland in the livestock system? What are the consequences in terms of public incentives policy? This preliminary study proposes a measurement of the elasticity of the use of each land-cover in livestock-oriented input production in response to uncertainty. A short land allocation framework is used, from which the empirical model is derived. An estimation on the French national territory is performed on a balanced panel dataset with different measures of uncertainty and different estimation strategies.

In Section 3.2, we made a literature review about the livestock-feeding systems (especially grasslands) and the economic methodology that should be useful in our case. In Section 3.3, we present the land-allocation model and our constructed measures of yields uncertainty. In Section 3.4, we present the empirical specification, whose results are presented in Sections 3.5, and 3.6 for the instrumental approach. Sections 3.7 is dedicated to caveats and conclusions.

3.2 Literature review

3.2.1 Grassland potential in terms of mitigation strategy

According to the BANCO report (Bamière et al. [4]), lengthen the duration of temporary grassland dedicated to graze production is a relevant mitigation: for an negative annual cost around €180/t.CO2eq for an average French breeder farm, it can achieve a carbon storage of approximatively 1.3 Mt.CO2eq in the grasslands, that corresponds to a net benefit of around M€2.3 distributed among adopters. The GHG reduction potential is due to two reasons, mainly the reduction plate (importance of this production in the agricultural sector), and the positive impact of the interrelated integration of herb product in the animal feeding (good digestibility of herb) and the dejection management if animals are in pasture (more N2O by denitrification but less CH4 because of aerobic conditions and a lot more C storage in the grassland). The negative abatement costs are related, according to the authors, to the compensation of potential loss of milk production in winter by the gains in terms of less soil work, less fertilizers costs, less ensilage and reaping work and costs, less dejection spreading costs and less concentrated feeding use (ibid.). In terms of carbon storage in soils, estimations of grasslands' significant potential have been implemented through the GES'TIM project (results are published in IDELE [20]).

The presence of negative costs is especially related to diminution of soil work and seedling preparation because the farmers do not have to sow and plant again the parcel annually (Bamière et al. [4]). However, the diffusion of this practice seems to be stable and not sustained, while the goal of the program "4 pour mille" is to increase the duration for 99% of temporary grasslands by the year 2030. A shared objective of the governmental program called "Zero Emission Nettes" (Zero net emmisions), which puts grasslands in the center of its diverse carbon neutrality goal's achieving tools. According to the report, some interviewed farmers evoked the fact that despite the possibility to decrease the cost of cattle alimentation, it can increase their level of implication in the meadows management and it can be difficult to maintain good yields of graze production. It needs a deep reform of the exploitation management, and yields can decrease after the 4th year of plantation. The complexity of the meadow management compared to a crop leads to the necessity of having adapted skills, while the lengthening of meadows duration is related

to their raising part in the farm rotation (ibid.). Furthermore, farmers tend to secure their graze provision and are chilly towards changes that can potentially impact their yields at the harvest. We can see that there are some barriers to adoption related to the intrinsic uncertainty about yields.

3.2.2 Uncertainty in input production and sources of irreversibility

Herb production is known as volatile with pedoclimatic conditions, and any mistake in the grazing planning can lead to cattle-feeding risk (O'Shea et al. [28], Coléno and Duru [9]). In the same time, put back a land that is in annual forage crop production for instance requires some changes in the practices: it is associated to specific skills and knowledges about herb production, while any big mistake in the grazing management can lead to potential losses (Bamière et al. [4]). In general, adoption of extensive as well as intensive changes, or innovation, in agricultural activities are often associated to yields uncertainty, and can be related to risk taking or risk avoidance behaviors (Sunding and Zilberman [34]; Ghadim and Pannell [16]; Knowler and Bradshaw [23]). We can expect that in a situation of uncertainty, farmers tend to seek information about the true value of yields before to make any decision. Lybbert et al. [26] show that farmers use the forecast about extreme event in order to update their beliefs about uncertain outcomes. In this situation, an option value could arise and make it more costly to adopt the forage crop that has the higher level of uncertainty. The classic Expected Net Present Value (ENPV) models consider that the value of an asset (a non-vacant land in our case), that will explain its exploitation by the owner, can be measured by the actualized net cash flow that she can expect from the exploitation. The farmer would thus compare the diverse usages she can deploy on her land and chooses the most profitable ones. But uncertainty can act like an implicit cost if the farmer values more the option to delay than the option to crop now, in order to avoid an investment in an asset whose true value of yields is difficult to forecast. We can consider in this situation that the shadow value of land cover, associated to the opportunity cost of forages crops, is distorted by yields uncertainty.

This problem has been questioned by Dixit et al. [11], as we see in the introductory chapter. If the returns from the new converted asset are uncertain and source of irreversibility, the decision maker acts like for a "call" option product on the financial market. Regarding to her expectation about new asset's returns and its irreversible cost, she can choose or not to exercise now her option on the asset. If she does not want to lock herself in an uncertain asset or thinks she does not have enough information about the expectable yields, she can postpone her option exercise and wait until favourable conditions seem to be gathered. If the "option value" raises above the present value of an asset, it is better to postpone the trade. The same rationale has been used in some works about land conversion and the result is that the conversion threshold can be increased by the uncertainty and irreversibility of new land use (Capozza and Li [6]; Plantinga et al. [30]; Schatzki [33]; Cavailhès et al. [7]). This "option value" can explain some frictions in land conversion, by improving the estimation of the conversion thresholds and optimal timing of croping, highlighting the limit of the "certain universe" model (ENPV). Basically, the land manager does not want to "lock" her land in a land-cover that is too uncertain because of the forecasts she can make about the value of production.

In another vein, the theory of decision under risk would explain the same type of fric-

tions in land allocation. Risk averse farmers would tend to adopt less of a production type if it is more spread around the expectation of yields. In this setting, the problem of the farmer corresponds to a portfolio problem under risk with an inclination toward less risky investments and a sufficient level of diversification in activities that do not covariate (Feder et al. [14]; Feder [13]; Just and Zilberman [22]). Diversification strategies thus arise depending on the covariances between the yields of the different forage crops. We can expect diverse drivers of the impact of the level of volatility in yields on the share of land dedicated to grassland.

Grasslands require some years before to be totally rentable, that causes inertia in the use of the dedicated land. Moreover, in the specific case of permanent grasslands (+6 years old), any tillage and replacement of it by other crops can lead to the suppression of the "green payment" if it is not validated by the authority, that makes it irreversible if not. Annual forage crops do not wear these problems of combination of uncertainty and inertia, and farmers have tend to replace their herb production by more flexible annual croping during a large part of the second half of the 20th century (Huyghe [19]). We thus assume that there can be an option value due to the association between uncertainties and irreversibility (or inertia) whose degree differ with the type of grassland. This is an interesting point that we will try to assess too, and it could be useful to compare the classic portfolio management approach from the option value approach. Indeed, risk premium as well as option value can potentially explain why yields volatility can prevent farmers from croping a forage instead of another. But we assume that what can really differentiate herb productions, especially old-seeded grasslands from other, is the irreversibility or at least intertia that it is related to, which can make farmers lock inside this type of land-cover if the grassland is more than 5 years old. The public regulation aiming at forbidding tillage of permanent grassland presents the advantage of preserving the actual carbon stock, that is crucial. However, if it prevents farmers from adoption more extensively sustainable grassland in land rotations, it lowers the potential in terms of new carbon storage (i.e carbon sink). This work aims at explain by which canals this regulation can limit carbon sink through grassland, and assume that uncertainty is a key issue. We do not claim that we assess the impact of the regulation *per se*.

To conclude this part, we can say that switching the production from an activity into a new one occurs when the relative returns between the two productions stand above a conversion threshold, from which the conversion brings to the farmers more expected profits than the past practice. The opportunity cost of a unit of land in a particular cover, that is related to its statistical marginal impact on final profits, equals the shadow price of this land-cover: it allows for accounting all the losses that can come from the substitution from a cover to another (Bayramoglu and Chakir [5]). Yields uncertainty, empirically defined as the level of volatility of yields, can distort the shadow value of land-cover, making it more costly to adopt the more volatile forage crops.

3.2.3 Estimating the role of uncertainty in the producer choices with joint productions

Before to define more precisely how we will measure uncertainty, the first matter is to choose a proper way to consider how uncertainty can play a role in the farmer's profits. Two main ways of estimating the economic choice criteria for land-managers exist, and

their use depends on the case study.

The first is related to the ricardian rent measure, that considers that the value of a land can be measured by the price of the land, because it integrates the net present value of all revenues that it can provide to the owner (Capozza and Li [6]; Plantinga and Birdsey [29]; Plantinga et al. [30]). The advantage of this approach is that it is tractable, in the sense that the value of land on the market equals the sum of all the productive gross margins it is related to. The disadvantage is that it assumes an equilibrium and a perfect matching between supply and demand that already met on the market, which is the reason why the price gives all the information about gross margins. In our case, we study the research for an optimal set of land use inside a producer farm, and production arbitrage that can lead to conversion, destruction of forage land cover according to the extensive capacity of it. Moreover, we do not have a robust national dataset on grasslands prices or rent in France for each type of grasslands.

A second stream of land conversion studies is agricultural production economics' models: here the value of land depends on its capacity to produce a good that enters a profit program for the owner, profit which depends also on market prices for the good and production costs structure (Fezzi and Bateman [15]; Lacroix and Thomas [24]; Bayramoglu and Chakir [5]; Moore and Negri [27]; etc.). Hotelling lemma shows that using a quasi-fixed input depends directly on the market price of the input or the per unit monetary benefit it leads to (subsidy per ha for instance). The tension on lands (through a Lagrangian multiplier) explains the repartition of lands in different productive land-covers. In our case, the second stream of studies looks more adapted to the management of cattle-feeding production by farmer-breeder. Indeed, our rationale farmers use annual forage crops or grassland as joint-technology inputs that are then used for cattle-feeding, and thus output production (milk, meat especially). Their main production posts are animal products that they try to optimize, and in this purpose they manage the input mix in the most optimal way they can.

However, we face several specific features. First, a large part of the empirically tractable models in the agricultural productions' economics (second stream) use a dual profit approach (Fezzi and Bateman [15]; Lacroix and Thomas [24]; etc.). The optimization of profits in order to find optimal choices of output and input quantity, as well as fixed factors uses, leads to estimate them through simultaneous equations related to the whole prices system. The econometric models are straightly related to this specification. In our case, we do not want the quasi-fixed factors (land allocation each year) to be only expressed through the market prices, but also through some input availability-related factors (yields' volatility expressed in diverse forms). Second, a difficulty that arises in our case is that the impact of forage on profits is very indirect: it is related to the capacity of each forage to give value to animals and animal products through its level of digestibility and different production costs (indirect multi-output technology), things that we can't observe here at all[1]. Moreover, in our case study, the markets for inputs do not play their basic incentive roles: the majority of forages are produced and consumed entirely on the farm, in the purpose of insuring input availability for the main production (animal products). The farmer seeks to have a good average forage production and the more stable as possible. We assume that she has an utility for yields that relies only on these two main components. While the preferences of the farmers for more or less volatile productions are not

[1] Especially because of a lack of data about these variables.

exactly known, we will catch the impact of uncertainty through the composition of land covers in the forage mix (extensive effect). This composition being directly related to the shadow price of land associated to forage crops yields, that encompasses yields volatility and we do not have to assume a specific form for preferences. Endogeneity problems will arise, that we will try to address in the empirical part later. Our land allocation model will thus use a mix of appropriate frameworks.

3.3 Land allocation and uncertainty measures

3.3.1 Theoretical framework of land allocation and yields

We assume a continuum of farmers (breeders) at the district level. We focus on the part of the farm dedicated to forages, where forage crops have to be allocated to lands. Assuming for the moment that their characteristics are iid, we consider that the objective function of a representative farmer can be observed and that the related production choices are additive across the department. The farmer is endowed with an initial number of forage parcels L (Σl), that we can sum to 1, and chooses at each period t the type of land-cover h that she will allocate on each parcel. Her final objective is to produce inputs in order to feed her cattle. Different land-covers h are possible, $h \in \mathrm{H}$. The forages are not directly produced in the purpose of selling them on the markets: they are entirely produced and consumed on the farm for the cattle. However, there exists a limited market for forage (especially forage maize), and we will use the prices data we obtained from it: it gives a partial idea about how is valued marketable forage in regional markets. We have no costs data for these kinds of production, so we will focus on forage crops yields. Thus, we assume that the farmer tries to manage the best way as possible the land she has at her disposal, while taking into account the yields expectation and volatility.

The first step is the following. The rationale farmer looks forward to maximize her value function V for forage crops' yields. At each period, the farmer allocates a forage crop production to different parts of the total area of her farm, in order to maximize her utility V.

$$\mathrm{V}(l_1, ..., l_h) = \sum_{h \in \mathrm{H}} l_h u(y_h) \tag{3.1}$$

$u(y_h)$ is the twice-differentiable utility function for the production and y_h are the yields of each forage crop. We assume that the utility is the same for each type of crop, only yields attributes are different. We assume that the sum of the utility on each type of crop, multiplied by the share of land in each crop, equals the total utility on the farm. We do not specify any preferences for volatility here: we just assume that the whole utility of the farmer is given by the sum of utility of what she can harvest from each productions. In static-dynamic, the choice of l_h is determined according to the maximization of the utility function for the whole farm. The constraint is related to the total land availability.

$$\max_{l1,...,l_h} \sum_{h \in \mathrm{H}} [l_h u(y_h)], \tag{3.2}$$

s.t.

$$\mathrm{L} \geq \Sigma l_h.$$

Note that the above constraint can be rewritten as $1 = \Sigma \frac{l_h}{\mathrm{L}}$ with $\frac{l_h}{\mathrm{L}} = \mathrm{P}_h$ the share of each land cover in the forage mix of the farm. In this case, the yields would be normalized by area. If we consider the Lagrangian of the objective function and the constraints, and look for an optimization of the objective function in each l_h, we find the following first order condition (FOC):

$$u(y_h) - \lambda = 0, \forall l_h. \tag{3.3}$$

Then, we can assume that the forage yields take the form $y_h = y(\mu, \sigma)_h$ where μ is the mean of yields that the farmer can expect for each forage, and σ is a measure of yields variability, both observed at each point in time. λ is the Lagrange's parameter of the land constraint and is associated to the possibility of recomposition of the forage mix in terms of quantity of land allocated to forages, or share of land allocated to the forage in the whole mix ("cost" of the constraint). The allocation is directly explained by the opportunity costs between each forage production. We can add that at the equilibrium

$$\frac{\delta \mathrm{V}}{\delta l_1} = \frac{\delta \mathrm{V}}{\delta l_2} = ... = \frac{\delta \mathrm{V}}{\delta l_{\mathrm{H}}} = \lambda, \tag{3.4}$$

for each share of crops, because of the total land constraint that leads to the equalization of each marginal value on each land. This last equation sets that the relative value function for each land cover explains the repartition of lands (allocation mix). It is a shadow price equation that tells us that the shadow price (or value) of each land under cover h depends on its relative marginal value on the farm. Finally, P_h is associated to $u(y_h)$ and the constraint.

According to the condition (3.3), we can expect that the constraint relative to the land allocation leads to a recomposition of the land covers that follows the evolution of yields in terms of expectation and volatility, the preferences of the farmers. The FOC tells us that there can be corner solutions for each l_h: the farmer chooses to totally allocate a parcel in a cover, but it is the sum of each similar cover that gives, on the total farm L and according to the total value V, a share that can be different from 0 or 1.

This simple model just allows us to observe the relationship between the allocation-reallocation of a quasi fixed factor, land, and the stochastic yields. This allocation is like an osmotic process, where the value spreads across the different lands through the choices of the farmer and according to the best valuation, that evolves over time. The hidden costs or benefits from a higher yields expectation or a higher yields volatility modify the shadow price of land covers, and impact directly the allocation of lands to each type of production. One can argue that the reallocation of land in the total land-forage mix depends on the extensive and intensive margins, and thus the physic capacities that farmers have to increase or decrease the level of cultivated (used) land. We answer that the land parameter l_h is normalized to the total available land allocated each year to forage crops in each department, that varies across time in our data. Thus the extensive capacity (or constraint) is already taken into account in the model, and the rationale we adopt (relative share of land by forage compared to one reference crop) allows to find the optimal allocation of lands ceteris paribus.

The second step is related to the option pricing equation (Hertzler [18]; Sanderson et al. [32], Dixit et al. [11]): the temporal evolution of $u(y_h)$ can be assumed to follow an

optimal process of the following "risk-adjusted" instantaneous utility function form at each t:

$$\frac{\delta u}{\delta y_h}\mu(y_h) + \frac{1}{2}\frac{\delta^2 u}{\delta y_h^2}\sigma^2(y_h) = 0. \tag{3.5}$$

Where $\mu(y_h)$ is the first moment of the yields and $\sigma(y_h)$ is the second moment of the yields[2]. This equation tells us that the utility for yields evolves following the dynamic motions of yields, whose value is known at each period. The impact of this stochastic valuation on land covers choices is subsequent, following equations (3.3-3.4). We have to precise a crucial element: we do not introduce the dynamic equation with time preferences in this work. While it is not our question, we try to emphasize the role of evolution of distribution about yields, through their level of stationarity and variability. Thus, the model is a static-dynamic model: the decision is taken again at each period, taking into account the new available information. We expect a direct marginal impact of yields motions on land cover allocation through a function F

$$P_h = F(S(y_h), Z). \tag{3.6}$$

Where Z is a vector of exogenous variables that enter the decision process (especially market prices and cattle size) and S is the vector of interest variables in terms of yields uncertainty. There exist an interior solution to the program (3.2) through (3.5) at each period t. In the purpose to validate the proposition underlying equation (3.6), we have to choose the way we measure the yields' underlying stochastic processes. Time-varying variance indicators are relevant tools to catch variability of yields over time.

3.3.2 Measuring yields uncertainty

Uncertainty is related to the fact that all the information about true yields is not available to the farmer. She does not know what exact value the stochastic yields can take on each year, and they can be above or below the expected yields. This volatility (i.e. the way exogenous shocks can affect the yields) is observable in each period of time, and each observation can be gathered to the global knowledge the farmer had about a yields deterministic part (trend, relatively predictable) and degree of walk around these trends (random or unpredictable). A large number of empirical studies that aim at estimating the role of production uncertainty go through the well-known risk econometric approach *à la* Just and Pope [21]. This framework is well-suited for the case of output stochasticity provoked by inputs use: a production function estimation is computed, where outputs are estimated by inputs, and the heteroskedasticity subsequent to the estimation is considered as a proxy for the level of risk. It is considered as a good proxy of risk because it is directly associated to the uncertainty about the results from a specific input and the distribution of errors associated to an observable distribution of state-of-the-nature by the farmer. This approach is related to the mean-variance specification of production risks. In our case, we do not want to precise the role of an input in the land cover choice, we aim at observing the global level of uncertainty of outputs. We do not need to see specifically how an input can increase or decrease the level of volatility in ouput production. The source of uncertainty is assumed to be exogenous and totally exists *per se*, but is observable by farmers. It can be directly measured on our yields dataset, under the

[2]We go further in the explanation of these elements in Section 3.3.2.

strong assumption that all farmers in each department can access the same information. However, as we will see later, we suppose an endogeneity issue between our dependent variables and our uncertainty variables, and we will test an approach that looks like the Just and Pope approach to tackle this issue. We propose different measures of uncertainty.

Below-Above the average yields

In a first attempt to measure the moves of the yields around the mean, we compute a measurement relative to the deviation of yields of each crop around their long run average within each department (Deschênes and Greenstone [10]). We calculated the distribution of yields of each type of interest forage for each district, then separated the yields at each period with a dummy variable that tells if they are in the first third, the second third (around the mean) and the third third in the yields distribution. The first category is considered as years with bad yields (negative shock), while the third one can be considered as year with very good yields (positive shock). This measure is based on a probability distribution that is not time varying. The advantage of this measure is that it is a straight way to calculate shocks (fluctuation), understood as the position of yields in their known probability distribution. The disadvantage is that this measure does not really represents the dynamic evolution of gathered knowledges by the farmer. Indeed, it does not separate a long run trend that would be perceived by farmer as deterministic and a random stochasticity of yields, that add knowledge step by step through shocks.

Yields' stochastic motions

The Dixit et al. [11] measures of uncertainty (Brownian motion and mean-reversion especially) are relevant in order to catch that stochastic motions-like phenomenon, because they rely on different interesting properties. First, they follow the Markov property, which implies that the future value of yields that can be forecasted each period only depends on its value in the current period. The consequence is that only the current available information plays a role in order to forecast the value of yields in the next period. No other information at the same period will modify the value of yields, which implies that the uncertainty is measured through an incremental value that follows the periodic shocks that percuss yields *per se* across time. The nature of the exogenous shocks are not specified in this setting. When the farmer observes the current value of yields, it thus gathers pure information about how the yields are moving and can deviate from the deterministic forecast. This type of time-varying uncertainty measures were already used in the Black-Scholes-Merton type of models, describing the value of financial options with stochastic asset prices following a Wiener process[3]. Indeed, these models of uncertainty have especially been used for asset price forecasts' estimations, more than for commodity production forecasts. We have to precise that the low stepback in time that we have in our data (28 years, that corresponds to 27 degrees of freedom) would lead to potential biases in the estimation of the uncertainty parameters. We compute the measure of uncertainty by applying the calculus of standard deviation to the yields at each period and using the past values of yields. We did that in the rest of the article, which has the advantage of being stricly in correspondance with the theory, but bears the cost that the first calculated values of the standard deviations are biased.

[3]Most of the literature using this approach assumes constant conditional variance and geometric Brownian motion processes.

The Brownian motion allows to express the dynamic motion followed by the yields through the equation (see Schatzki [33] for the below equations):

$$dy = \mu dt + \sigma dW$$

Where μ is the instantaneous first moment (or expected growing rate or trend), σ is the instantaneous standard deviation of the variable and W is a Wiener process with $E(dW) = 0$ and $Var(dW) = dt$. σ can be constant but its level updated with information accumulation, and describes an increasing variability across time (Postali and Picchetti [31]). This kind of motion is well-suited for commodities market prices' stochastic processes. The subsequent measure of volatility is given by:

$$\sigma_t^{Br} = \frac{\Sigma_{t=0}^{T-1}(y_t - y_{t-1})^2}{t}^{1/2} \tag{3.7}$$

However, for stationary variables whose stochastic value tends to revert toward the mean after experiencing shocks, the Brownian motion specification could overestimate the level of volatility and the subsequent forecast about the volatility. Indeed, if the variable looks like it tends to revert to a long run average and oscillate around it, the fact to see the stochastic motion as totally unpredictable is biased because in reality agents have a better possibility to forecast the moves of the variable across time. As we show in section 3.4.1, every test we performed shows that our yields data are stationary. In these cases, several specifications are relevant.

The Ornstein-Uhlenbeck (OU) measure is suited for mean-reverting motions. The subsequent measure of uncertainty takes the form:

$$\sigma_t^{OU} = \nu \frac{\Sigma_{t=0}^{T-1}(y_t - \bar{y})^2}{t}^{1/2} \tag{3.8}$$

Where $\bar{y}$ is a historical mean of yields (or long-run average) that we calculated on each department's time serie, and ν is a parameter of mean reversion, that gives the speed of reversion of yields toward the long run mean. We can also assume that the trend is not constant on the long run and that the farmers update their beliefs about it, which can be catched through a moving trend at each period. The moving average (MA) measure looks like the former on but the mean that is taken into account is moving at each period: it does not consider the long run "historical" mean, but an updated mean across time. The subsequent measure of uncertainty takes the form:

$$\sigma_t^{MA} = \frac{\Sigma_{t=0}^{T-1}(y_t - \tilde{y}_t)^2}{t}^{1/2} \tag{3.9}$$

Where $\tilde{y}_t = E_{t=0}^{T-1}(y_t)$ is the moving-average of yields, updated at each period, that we calculated on each department's time serie.

Schatzki [33] used these three types of uncertainty measures in his article and found very different results for his estimation of option values for forest conversion. In this article, the author attributed to Ornstein-Uhlenbeck measures an arbitrarily fixed $\nu = 0.25$ for all the sample. We assume that the level of reversion toward the long-run mean is proper to each district. According to the Euler-Maryuama discretization of the Ornstein Uhlenbeck process at time t, the parameter ν must be estimated through an AR(1) estimation of yields, on the form:

$$\Delta y_t = a + b y_{t-1} + \epsilon_t \tag{3.10}$$

With ϵ_t a white noise, and $\nu = -log(1+b)$ (Postali and Picchetti [31]).

3.4 Empirical application

3.4.1 Descriptive statistics

We have a panel of forage crops yields and land allocation for 96 French metropolitan districts, from 1989 to 2017 (Agreste [1]). For each year, we are able to calculate the share l_h of land in each type of forage crops (cereals or diverse types of grasslands) in the total of lands dedicated to forage in the agricultural sector, with $l_h \in (0,1)$ (see Table 3.1). For the whole country, the weight of managed herb production in the total forage system is around 70%[4]. An important thing to note is that the average share of land allocated to each production is not straightforwardly related to the level of yields of each production: for instance, forage maize seems not to have a huge land share across departments (around 8%). However, the average yields related to maize are much higher than herb productions in absolute terms because the production is far more intensive. The productivity by itself certainly explains the division of land in each production: while market effects migh poorly impact the cropping behaviors for forages, the most productive crop can be cropped on smaller scales. Most of the standard deviations in shares of land in the districts sample are especially following a between effect, indicating that there are mostly difference in the shares' movements across the sample, rather than within each district. It can be the sign of an heterogeneity of geographical-based characteristics that drive the land-management, as well as local specialization and other fixed effects characteristics.

The average productivity is really diverse concerning herb productions, and probably related to the level of implication and management of farmers: while the most permanent grasslands seem to have low productivity and to lower the level of global herb productivity, grasslands related to real cropping management by farmer (artificial and temporary grasslands) have much higher productivities. Within variations as well as between variations in yields are quite important for each production. However, they are not comparable in this form because they are associated to a "scale" of productivity in terms of volume that can hide the true level of variation.

[4]Some grasslands are natural and low productive, in mountains for instance, and are not considered as "managed" with farming practices even if they are part of the total forage system.

Table 3.1 – Descriptive statistics

Variable (country level)		Mean	Std. Dev.	Min	Max	Observations
Share in forage and silage maize	overall	.0831697	.0809431	0	.3456755	N=2431
	between		.0795635	0	.3147234	n=95
	within		.0176908	-.1188234	.2061766	T-bar=25.5895
Share in managed grassland	overall	.6841905	.2544402	0	1	N=2445
	between		.241909	.0785267	.9854867	n=95
	within		.0604501	.0175238	1.314501	T-bar=25.7368
Share in artificial grassland	overall	.0359801	.05417	0	.5961298	N=2445
	between		.0678475	0	.5667724	n=95
	within		.0170901	-.0365148	.1467519	T-bar=25.7368
Share in temporary grassland	overall	.1576005	.1361225	0	.5439466	N=2445
	between		.1306143	0	.4828511	n=95
	within		.0366858	-.0046349	.4379916	T-bar=25.7368
Share in non-permanent grassland	overall	.1935806	.1435085	0	.6147128	N=2445
	between		.1419873	0	.5837825	n=95
	within		.0345016	.0516038	.4961859	T-bar=25.7368
Share in natural or old-seeded grassland	overall	.4906098	.2514303	0	1	N=2445
	between		.2450163	.0686073	.9537782	n=95
	within		.0546118	-.1760568	.9022583	T-bar=25.7368
Forage maize yields (100kg/ha)	overall	108.9248	27.36707	0	400	N=2343
	between		18.71835	45	153.2018	n=94
	within		21.48015	23.01569	419.8813	T-bar=24.9255
General herb yields (100kg/ha)	overall	46.30722	21.24689	0	114.8	N=2443
	between		19.29617	8.097857	96.83182	n=95
	within		10.26511	-10.48385	94.35865	T-bar=25.7158
Artificial grassland herb yields (100kg/ha)	overall	82.1444	21.97608	8.98	160.5	N=2398
	between		17.03947	45.47643	127.9227	n=94
	within		14.966	9.964042	156.3265	T=25.5106
Temporary grassland herb yields (100kg/ha)	overall	67.91604	18.56736	0	139	N=2394
	between		13.87018	37.27321	104.43	n=94
	within		13.27152	-7.621107	122.6518	T=25.4681
Natural and old seeded grassland herb yields (100kg/ha)	overall	46.90751	16.83583	0	110	N=2437
	between		13.60912	9.961538	79.26364	n=95
	within		10.58169	1.390366	98.94597	T-bar=25.6526

As we show in the previous part, there are different ways of measuring the level of uncertainty in yields depending on the characteristics of the variables of interest and the objective of the researcher. A crucial point to explore before to choose the proper measure is the level of stationarity of the yields: it tells us if the yields tend to come back to the mean after experiencing a shock. We use different tests in order to observe the level of stationarity of our panel and use the appropriate expression of the subsequent process (Postali and Picchetti [31]). These tests show the (non) stationarity of department-wide panel variables (for yields of maize and all types of herb). In our case the interest variables being non strongly balanced, the Fisher-type test of unit root was the more relevant. The null hypothesis is that the variable has a root that equals 1 with its lagged values. H1 considers thus that at least one panel is stationary, which means a parameter lower than one for the lagged value, thus past shocks have a transitory effect on the variable (it follows a certain degree of stationarity), which tends to go back to the mean if there is a mean-reversion or moving-average process. We specified those tests for our yields in the case of maize, temporary grassland, artificial grassland, natural and old-seeded grassland and all

types of grassland yields, in order to know better what kind of stochastic process they follow across time (see Tables 2 to 13). They are all stationary in the scope of the Fisher-type test of unit root. Im-Pesaran-Shin unit-root tests have been conducted too (reported in Appendix) and confirm that fact for all the same variables, except for forage maize yields because the test could not be applied (at least one of our panel individual has less than 10 observations). The stationarity of yields is a relevant clue for considering that they follow mean-reversion or moving-average stochastic processes, with a quick resilience of yields toward shocks and a relatively stable trend, and reject the Brownian motion. We thus assume that our measure of variance will follow a Ornstein-Uhlenbeck or a moving-average process in the form we described in section 3.3.2.

3.4.2 Computation of the uncertainty measures

Despite the limitations in degrees of freedom, we performed panel regressions for the yields of each land cover and integrate the estimated coefficient of mean reversion ν for each crop in each department, expecting a gain of information because of the cross-sectional dimension. The average parameter ν across departments is equal to 1.437 for temporary grasslands' yields, 1.377 for artificial grasslands' yields, 1.005 for natural and old-seeded grasslands' yields. We also ran it for maize yields (1.225). These low levels of parameters indicate that b is closed to -1, so that the reversion toward the long run mean is not so quick. To sum up, we can measure uncertainty through different ways that allow us to take into account the degree of volatility and in the same time to respect the degree of "forecastability" (available information) given by the observation of each new value of yields at each period. These measures respect the Markov properties.

Some questions arise from the measures we propose. First, there is a potential issue related to the chaotic nature of our computed exogenous measures of uncertainty [5]. Indeed, if the volatility coevolves with a lot of interconnected variating drivers of yields (incremental technical progress, interconnected markets fluctuations, information and rumors about a future public policy, etc.), uncertainty can be related to so much sources that the coefficients that we will estimate can go in every direction. Even if shocks occur on yields, these multiple variables shocks are comprised in the volatility measures and can impact the related share of land in the forage mix. This is a specific omitted variables issue, that is often related to time-varying multiple sources. In the situation of mathematical chaos, the value of a variable at each t is very dependent on the initial conditions and the future values of yields are difficult to predict. Nevertheless we assumed that the volatility measure, recomputed at each t, give an idea of the predictions farmers can have about yields in order to make their choices: thus, the scope of observation (initial t of observation and observation temporal window) may be loose of its relevance with time. Secondly, when we plot our measures of uncertainty we can see that most of the time, they tend to be very widespread for the first periods and then converge toward a horizontal line, showing a lower variability across time. This is related to the natural properties of the variance, which tends toward a constant level when observations increase (Property of the convergence of the variance). The issue is that the within variability of the measure is decreasing over time. We can address these problems by computing our measures' computations by temporal windows (5-years time windows) instead of updating them every year. This will lower the difference between the variance calculated in the first periods

[5] Sometimes referred to as the "volatility vortex" problem in financial markets.

(with a low number of years so a low stepback, which leads to a high potential bias) and the variance computed with cumulated observations, and it adjusts for real forecasts that farmers can do with information they gather in the few past years. Moreover, it can address a part of the "volatility vortex" problem previously mentioned: allowing for volatility measurement by temporal windows can filter for interconnected time-varying trends and shocks' impacts. These measures can be interesting in order to observe what can be the short scope uncertainty impact, and they allow us to add time fixed effects to our panel regression without taking the risk of yield highly biased estimates. We will use both basic volatility measures and the same volatility measures recomputed by 5-years windows in our estimations. We also estimated the marginal impacts of time-dummies for each year on our volatility measures, in order to observe the strength of statistical relationships of our measures with time (Table 14). Our moving-average measure by 5-years windows (MAW) for each department then take this form:

$$\sigma_{it}^{\mathrm{MAW}} = \frac{\Sigma_{k=t}^{t-5}(y_k - \tilde{y}_k)^2}{5}^{1/2} \tag{3.11}$$

Where $\tilde{y}_k = \mathrm{E}_{k=t}^{t-5}(y_k)$ is the yields average recalculated for each temporal window. It is more complex in the case of the Ornstein-Uhlenbeck measure because it is theoretically associated to short-term fluctuations around the long-run average. In its basic form $\sigma_{it}^{\mathrm{OU}}$, the OU measure can be embedded in the "volatility vortex" problem because the dynamic of the measure is connected to each y_t. We computed an Ornstein-Ulhenbeck measure by windows (OUW) equals to the average fluctuation of the average yields by windows relative to the long-run average, on the following form:

$$\sigma_{it}^{\mathrm{OUW}} = \nu\frac{\Sigma_{k=t}^{t-5}(\tilde{y}_k - \bar{y})^2}{5}^{1/2} \tag{3.12}$$

Where $\bar{y}$ still the historical mean of yields. To sum-up, we have four different measures of volatility: σ_t^{OU} the time-varying fluctuations around the long-run (historical) average yields; σ_t^{OUW} the 5-years windows-varying fluctuations around the long-run (historical) average yields; σ_t^{MA} the time-varying fluctuations around the moving-average (recomputed at each t) average yields; σ_t^{MAW} the time-varying fluctuations around the moving-average (recomputed for each 5-years windows) average yields.

3.4.3 Econometric model

Based on Hardie and Parks [17], and Ahn et al. [2] we use a linear logistic probability model specification. This model considers that the estimated relative shares of land in each cover are like the conditional probability to withdraw a land cover in the sample, given the independent variables that we have about each land cover (and a reference land cover) characteristics. If the static estimated proportion of land in use h is given by P_{ih} and we denote x the vector of all explanatory variables and β the vector of parameters to estimate, we can write P_{ih} in the following form:

$$\mathrm{P}_{ih} = \frac{e^{\beta_{ih}.x}}{1 + \sum\limits_{h\in \mathrm{H}-1} e^{\beta_{ih}.x}} \tag{3.13}$$

This ensures for the estimated shares of land covers to lay between 0 and 1. The explanatory variables are related to the land cover optimal choice model that we expressed in section 3.3.1 (interest variables plus other exogenous explanatory variables). Our first

linear estimation model is directly associated to equation (3.6). The logistic specification links the conditional probability to observe the relative share of a land cover to a reference land cover that plays the role of a common forage substitution option and a good comparison point: we assume that ensilage maize is a relevant reference forage crop, because it is the intensive alternative option for substitution in cattle feeding compared to all the diverse herb-related forage systems for which we assume a particular uncertainty issue. Thus, we assume that $\mathrm{P}_{iht} = \frac{l_{iht}}{l_{imt}}$. The estimation model is expressed as:

$$\mathrm{P}rob(l_{iht}) = ln(\mathrm{P}_{iht}) = \beta_0 + \beta_h.x_{iht} - \beta_m.x_{imt} + f_i + \epsilon_{it} \tag{3.14}$$

Where m is for ensilage maize, the reference forage crop, i is the district, βs are the parameters to estimate for the intercept and our variables of interest, f_i represents district fixed effects and ϵ_{it} is the error term. β_m is constraint to be equal to 0 for a correct identification of the model. District fixed effects are straightforward in our setting, due to the important role that can play each district's fixed characteristic that we can't control for, in the estimation of the dependent variable. Moreover, we controlled for potential heteroskedasticity and serial correlations in each estimation by computing a weigthing matrix of correction *à la* White [35] and provide heteroskedasticity consistent standard errors estimations. The final linear model takes the following form:

$$ln(\mathrm{P}_{iht}) = \beta_0 + \beta_{1h}.\mathrm{S}_{iht} + \beta_{2h}.\mathrm{Z}_{iht} + f_i + \epsilon_{it} \tag{3.15}$$

3.5 Results assuming exogeneity of explanatory variables

We have two control variables at our disposal. The first one is the selling price index in each department for forage. As we said in section 3.2.3, the impact of this price is not clear-cut: markets for forage are not like usual markets, and we can't expect farmers-breeders to behave in the usual way. Nevertheless, because forages are inputs that are produced and consumed on the farm, if the price of ensilage maize for instance, increases, it will incentive farmers to produce more of it. Indeed, selling on the market is more attractive, and buying it is less attractive so it can incentive farmers to produce more by themselves and self-consume more of it. Furthermore, this price index is essentially composed with the price of ensilage maize. We can expect that its marginal impact on the relative shares of land dedicated to grasslands is negative. The second control variable is a spatialized index for animal costs, that is a constructed proxy for the unit cost of bovines. Bovines are the main animal that farmers-breeders use to produce meat and milk, which are the two main productions from animals in France. Raw data for animal price in each department are only accessible by region (RICA dataset) and not for each department. In order to introduce spatial variability in the index at the department level, we weight each regional price index by a representative variable of the weight of the production volume in each department (following Lewbel and Pendakur [25] kind of index). We obtain a composite index, that is a good proxy of the bovines buying cost in volume per year, where variability is catched through the variation in volume. We accessed data about the cattle size (bovines) for each department per year. Overall our index is a factor of the regional price index for buying bovine and the share of bovine lifestock in the department relative to the national lifestock. We expect this variable to be a good proxy for intensive costs of production, since the price of an animal integrates its production cost as well as the stream of value-added it can lead to. The regulation of grasslands in France and Europe

followed straighly the CAP reforms. As it is a key explanation for variations in grasslands allocation, we can be tempted to ran regressions with time effects: it allows for catching the effect of policies that were homogeneously applied on all the country over time, and thus the impact of public policies, that is likely to be non-negligeable. However, we found high levels of colinearity between our uncertainty measures and time dummies, which can lead to strong multicolinearity biases in our final estimations. This phenomenon is probably related to the fact that our time-varying uncertainty measures have a significant dynamic nature and structurally depend on past periods.

We ran the regressions for three types of land covers: Temporary grasslands and Artificial grasslands (land covers supposed to be less perennials or non-permanent), and Natural or old-seeded grasslands (land covers supposed to be totally perennials or permanent)[6]. The old-seeded grasslands correspond to grasslands older than 6 years. The results are different according to the type of uncertainty measure and between both types of forage. We regressed our dependent variables on the measures of yields fluctuation below-above average measures (section 3.3.2) and on the measures of volatility (section 3.3.2). We ran Hausman post-estimation tests for all regressions: departement fixed effects are validated for all regressions. Our results are thus with department fixed effect. We will only comment the significant coefficients (minimum confidence level: 10%). Our regression is in log-level, thus the coefficients are in percentage. However, while coefficients can be surprisingly high or sometimes low, they correspond to a level of average relative elasticity, and the total impact depends on the value of the independent variable and the value of the dependent variable (ratio of land) for individual observations. Due to format issues, the results for regressions with control variables are split in distinct tables for each type of grassland. We provide the Fisher tests of global significance for all our regressions and the R-squares. All the results are available in the appendices.

3.5.1 Test for colinearity with time variables

The Table 14 in appendix shows the estimated marginal impact of time dummies for each year on our volatility measures. The goal of these regressions is to assess the potential multicolinearity of time effects and uncertainty measures that can emerge in the main regressions. Not only individual covariates' coefficients are important, but the level of global significance of regression through Fisher p-value (last row) and the explanatory power of regression with R-squared. It is interesting to note that σ_{TG}^{OUW}, σ_{AG}^{OUW} and σ_{NOS}^{OUW} are not colinear with time dummies, contrary to all the classic OU measures: it can be the sign that the goal of computing uncertainty measures by temporal windows in order to fix chaos in the volatility has eventually been achieved. Note that σ_{TG}^{MAW} is disconnected to time-effects too. These results show that in our panel regression, when we will add time fixed effect to catch purely time-varying exogenous processes, we will avoid multicolinearity bias for these four variables.

3.5.2 Regressions with below-above average yields variable

We regressed the ratio of land in each type of grasslands by our categorical variables of yields shocks for each type of grass. Positive or negative shocks are the categories that we consider in the regressions, with the 2nd category as the reference variable. We also made estimations with the lagged value of this shocks variable $(t-1)$. Tables 15 to 17 are naive

[6]All the regressions have been ran with Stata 12.1®.

regressions by type of shocks on grasslands' yields. Table 18 show regressions of all the shocks together on the three types of grasslands. We add ensilage maize shocks in these regressions, in order to try this new control and see the relationship with the reference "asset" represented by maize.

Tables 15 to 18 presented in Appendix lead to the following summary result:

Result 1: Positive shocks on Natural and old-seeded grasslands' yields seem to be associated with a global persistent positive impact on adoption of all types of grasslands (relative to maize). It can be the sign that the yields of the most massive share of grasslands in the whole grasslands in the country (NOS) is a global indicator of the good years for herb production, and the willingness to develop herb systems (role in terms of information). Negative shocks on Temporary grasslands' yields seem to lead to a contraction in the other types of grasslands on the short-run. We also shows a clear substitution diversification strategy between Artificial grassland and ensilage maize.

The estimations of yields' shocks impacts on grasslands adoption are limited because the shocks do not catch real time-varying uncertainties (stochastic motion) and they suppose perfect uniform information access over time. They present the advantage of giving a first idea of the role of stochastic deviations on land-use decisions.

3.5.3 Regressions with volatility variables - without controls

Tables 19 to 24 presented in Appendix lead to the following summary result:

Result 2: OU measures show a relatively robust negative impact on Temporary grasslands' ratio, while positive for Artificial grasslands' ratio. MA measures always show a positive (but weakly robust) impact on Temporary and Artifical grasslands' ratios. Time-effects always affect the results and make coefficients not significant anymore, except in the case of OU measures by 5-years windows for Temporary grasslands, which is confirmed with time fixed effects.

3.5.4 Regressions with Volatility variables and controls

Tables 25 and 26 presented in Appendix lead to the following summary result:

Result 3: Only basic yields' volatility indicators for Temporary and Artificial grasslands are robust when we add controls. The impacts of control variables are, for their part, relatively robust: the selling price index for forage always displays a highly significant negative impact on the ratio of land dedicated to grasslands, while the spatialized index for animal costs displays a positive impact in the case of Temporary and Natural and old-seeded grasslands.

Results 1 to 3 are interesting in two manners: firstly, they show that fluctuations are taken into account by farmers in their portfolio management. We observe some interactions between land covers and the yields shocks, and trade-offs between forage land covers. They allow us to have a measure of the marginal impact of volatility across time on land cover allocation, that corresponds to the elasticity of land cover allocation with respect to uncertainty. However, these results show diverse degrees of robustness, which

especially raise questions about potential endogeneity issues.

We also may have a potential omitted variable: the covariance between yields of different forages. For instance, if the the volatility of herb yields in temporary grasslands is high but negatively covariates with other type of forage production, farmers may tend to adopt it more in order to diversify their portfolio, thus insuring themselves against shortages. We catch it in our regression of yields shocks from maize yields and grasslands yields. The results show diverse portfolio allocation strategies in terms of risk and production efficiency. The first effect looks like a diversification-specialization strategy: farmers allocate lands in crop that do no covariate in order to insure their feeding capacity. The more maize and artificial grassland (legume crops) yields will covariate, the less it is interesting for them to adopt both on the farm (specialization). The role of diversification as a self-insurance is clear in this situation (see Just and Zilberman [22]). The second effect shows a different phenomenon. The more Natural and old-seeded grasslands and Temporary grasslands (mix of classic gramineous and sometimes legume crops) yields will covariate, the more farmers will adopt both: in this situation diversification is not a risk management strategy. If ensilage maize and gramineous are perceived by farmers as complementary (and not substitute), more covariance is good because a variation in the yields of one crop gives informations about how can evolve the other. This informational learning effect is the other explanation of diversification strategy that is not directly related to risk management but related to improvement in the accuracy of prediction of yields (Ghadim and Pannell [16]).

Finally, it is likely that there are some endogeneity biases that reduce the accuracy of our estimations. Indeed, some variables probably explain simultaneously the choice of land covers and the yields (farmers' average ability, lands characteristics, etc.), and the former maybe explains the later (precedent crop effect, etc.). The farmer tries to optimize every posts of production on her farm at the same time, that can lead to omitted variable and simultaneity bias. We also observed the impact of adding time fixed effects. In order to correct that biases, we want to perfom an IV regression where our yields would be instrumented by a totally exogenous variable. The weather seems to us as a straightforward solution: indeed, meteorological shocks are totally exogenous, explain a large part of yields variability, and we can expect that they are exogenous from the dependent variable because the potential effect they could have on land use choice goes directly through the yields.

3.6 Instrumental regression

3.6.1 Limits of the exogeneity assumption

We assumed until now that our independent variables of interest were exogenous and that the estimated marginal impacts, catched through coefficients β_h, were unbiased. This assumption is quite strong: variables that we didn't introduce in the model can simultaneously impact dependent and independent variables. First, the volatility of yields can go through multiple sources, proper to the farmers and their behaviors, that can explain the land cover choices too: abilities, distribution of lands in term of quality, diverse farming strategies and objectives, can be endogenous to both dependent variables and volatility variables. These variables are omitted in our model. Secondly, land covers choices can

explain a part of the actual yields at the end of the croping campaign, and both variables are probably embedded in a productive cycle that can lead to simultaneity biases. The bias can be written in the general form that follows:

$$\frac{\delta P_h}{\delta z_{iht}} = \beta_{1h} + \frac{\delta \epsilon_{it}}{\delta z_{iht}} \tag{3.16}$$

This bias can be either positive or negative and lead to significant fallacies. A first strategy used to tackle this bias is to use a lag operator of the endogenous explanatory variable. The endogenous variable is estimated with its lagged values. The error terms are assumed to be not autocorrelated in order to respect the Gauss Markov theorem. An issue arises in our case: we cannot assume that there are no autocorrelation over time between our error terms because all the elements that impact our uncertainty variables over time can still have an impact in t, then the estimated coefficient may not be BLUE anymore[7]. Another common methodology that allows to tackle this endogeneity issue is instrumentation with an exogenous variable. We follow this strategy in this section. We do not presuppose a bias with certainty, but we want to hedge against all the possible fallacies in order to provide robust results. We provide post-estimation tests for endogeneity for each regression.

3.6.2 Instrumental (IV) regressions

Meteorological data are the natural exogenous variables that we focused on. Indeed, they are totally exogenous and we assume that they strongly impact yields. Moreover, we assume that if they could have an impact on land use, it wouldn't be outside of yields: the impact of meteorological shocks on land allocation to forage crops can only go through yields and how they are impacted by them. We gathered meteorological data from Meteo France by town by day from 1990 to 2017. They mainly consist of data about precipitations, temperature, level of humidity, evapotranspiration, and minimum and maximum temperatures. We computed the mean and standard deviation of these variables per year for each city. Then, we average these variables by department by attributing each town to its department. We thus balanced our panel with aggregated meteorological data which are assumed to be homogeneously distributed within the spatial units (we assume a potential aggregation bias). The vector of meteorological variable is denoted I.

An instrument is considered as good if it is strongly correlated with the instrumented variable and not much correlated with the error terms. For each dependent and independent variable, we selected the instruments by computing pairwise correlation matrices between each variable, then trying to find the best regressions as possible. We keep only variables which are relevant (i.e. correlated with the endogenous variables), and for which pairwise correlations were significant at the 10% level. Coefficients are comprised between -1 and 1. Our protocole is the following, and has been determined with respect to the limits of what our dataset was able to provide: first, we selected the instruments (meteorological variable) that yield a pairwise correlation coefficient (in absolute terms) higher than 0.20 with the endogenous variables. If we did not find such coefficient, we tried instrumentation with the most correlated meteorological data. We also prioritized variables that yield a pairwise correlation coefficient (in absolute terms) lower or equal to 0.10 with the dependent variables. However, we also tested instruments which can

[7] Best Linear Unbiased Estimator.

have a higher level of correlation with these dependent variables, because of our assumption that the impact goes essentially through yields. We added instruments, if necessary, and dropped some of them, in order to catch the best estimation results. This is why for few instrumental regressions, the most correlated meteorological variable is not our final choice, if another strongly correlated variable yield better regression result, after controlling for good fit of the instrumentation obviously. We thus have selected specific instruments for each volatility variable.

The resulting models are two-stage least-squares (2SLS) generalization of fixed-effects panel-data regressions with instrumentation, of the form:

$$\left\{ \begin{array}{l} ln(\mathrm{P}_{iht}) = \beta_0 + \beta_{\mathrm{IV}h}.\hat{\mathrm{S}_{iht}} + \beta_{2h}.\mathrm{Z}_{iht} + f_i + \epsilon_{it} \\ \\ \hat{\mathrm{S}_{iht}} = \beta'_0 + \beta_{3h}.\mathrm{I}_{iht} + \beta_{4h}.\mathrm{Z}_{iht} + \epsilon'_{it} \end{array} \right\}$$

Where the second step is estimated first, and the subsequent estimates are introduced in the first step. For each regression, we computed an endogeneity post-estimation test (Sargan Hansen-Hausman test). If the test is significant, then the uncertainty variable is validated as endogenous because H0 poses that the variable is exogenous. We also computed an underidentification test (Kleibergen-Paap LM statistic) that tests if the instruments are sufficiently good in the first step. The null hypothesis is that we have underidentification, so we have to reject it in order to validate the instrumentation. We also presented overidentification test (Sargan Hansen J stat) for which the null hypothesis is that the instrumental equation is not overidentified, so our 2SLS is validated if H0 is not rejected. Finally, we show the Fisher tests for each regression is order to observe the level of global significance of each model. Sometimes our R-squared are negative, that is not a problem in terms of significance of the estimation, but highlights some big caveats about the explanatory power of the estimation.

3.6.3 Results of IV regressions

We only estimated IV regressions for the cases that we selected according to the protocole described in section 3.6.2 (if a correct instrument is available). Thus, as we did not find any good instrument in our criteria for the moving average uncertainty measure for Temporary grasslands and Natural and old-seeded grasslands, we do not have regressions for them. If the tests aiming at observing the goodness of the instruments were not validated, we made again the estimation while changing the instruments, until we yield the best results. We will only comment the significant coefficients (at least 10% of significance) and the regressions that have been validated in terms of instrumentation (see section 3.6.2) and global inference (last rows of tables 29 and 30).

Tables 27 and 28: We provided the results of correlations coefficient matrix between our volatility measures and the diverse aggregated meteorological variables we gathered. The star indicates a 10% significance level. The final instruments that we selected appear in bold.

Tables 29 and 30 presented in Appendix lead to the following summary result:

Result 4: The negative impacts of σ_{TG}^{OU} and σ_{TG}^{OUW} on the Temporary grasslands' ratio is confirmed. The negative impact of σ_{AG}^{MA} and the positive impact of σ_{AG}^{OU} on the Artificial grasslands' ratio is confirmed. We show that our diverse measures of volatility imply diverse results on Natural and old-seeded grasslands.

Our regressions yield very low R-squared in most of the cases. We also found negative R-squared in some of our instrumental regressions. It shows that our estimation sometimes has a low explanatory power in terms of summed squared estimation errors. However, the global (Fisher tests) or local (student-t by variable) levels of our estimations were most of the time very high. The main explanation of the negative R-squared is that the instrumental panel regressions with fixed effects do not yields the constant covariate (intercept) estimation, unlike the basic fixed effects panel regressions for which Stata attributes average value of the fixed effects. In this scope, we please the readers to focus more on the Fisher global tests of significance.

Summary of main results: The regressions with yields shocks of the different types of forages show some degrees of diversification strategies between forage in the "forage mix". While maize and artificial grasslands seem to be "stochastically" substituable, permanent grasslands and non-permanent grasslands seem to be "stochastically" complementary. The OU volatility impact negatively temporary grasslands ratio and positively articifial grasslands ratio, but the more robust impact is associated to the OU measure negative impact on temporary grasslands ratio, even with our measures by 5-years windows and with time fixed effects. The MA volatility presents the reverse results: the impact is positive for temporary grasslands ratio and negative for artificial grasslands ratio. These main results are relatively robust to control variables for basic volatility measures (not those by 5-years windows). Before IV regressions, we can say that the level of volatility globally impact non-permanent grasslands ratios. Instrumental regressions generally confirm them and also show new impacts on permanent (natural and old-seeded) grasslands ratio. Volatility measures (OU as well as MA) present a very strong positive impact, while the MA measure by 5-years windows present a negative impact on the permanent grasslands ratio. This can be the sign of a strong endogeneity (stronger than for other regressions) that were hiding real impacts of yields volatility.

3.7 Conclusion

We developed a short land cover allocation model and a related econometric model in order to explain the impact that can have yields uncertainties on the forage mix in France. We developed different measures of uncertainty, from a basic assumption of shocks along the yields distributions, to average fluctuations measures in line with the stochastic variables motions' theory (*à la* Dixit et al. [11]).

Shocks on natural and old-seeded grasslands' yields seem to provide information about "herb" yields and impact the allocation of all kinds of grasslands. Some diversification strategies have been identified between complementary grasslands. The general proposition of these results is that complementarity or substitution between crops in terms of stochasticity has to be taken into account if the regulator wants to enhance grassland adoption in rotations. Grasslands have to be an "interesting option": farmers-breeders tend to secure their forage yields, and thus try to manage their forage production following the yields volatilities and covariations between them. It also reinforces the evidences

that it is necessary to incorpore uncertainty in dynamic croping plan decisions modelling, which aims at improving simulation models (Dury et al. [12]).

Uncertainty measured as volatility (variability) of yields has diverse impacts according to the way we calculated it. But it is clear that it seems to impact more non-permanent grasslands ratio relative to maize. Ornstein-Uhlenbeck uncertainty measures especially (related to a long-run average assumed to be known by the farmer) show a behavior of avoidance for adoption of Temporary grassland. This particularly sounds like a real option behavior, associated to the aversion of farmers to lock themselves in Temporary grasslands that can become permanent after 5 years, and can't be destroyed. Prohibiting the replacement of old-seeded grasslands may lead to less and less adoption of temporary grassland, and artificial grassland to a lesser extent. However, our diverse measures sometimes provided very different results when we assume exogeneity of the independent variables: it is due to some limits that we partly address with instrumental regressions. Most of the time, OU measures have a negative and relatively robust marginal impact on Temporary grasslands' ratios. Forbidding the tillage of old grassland is well-suited for the conservation of existing carbon stocks. But it interacts with the carbon flows in grasslands if it prevents farmers from creating new grasslands, which are huge carbon sinks. This arbitrage between carbon sink and stock in grassland and the policy assessment must be addressed with *ex ante* and *ex post* public policy evaluation methods.

Yields uncertainties impact the opportunity costs of land covers, sometimes positively and sometimes negatively, but mainly non-permanent grasslands. First observation, one could assume that these diverse effects are related to the difference between our uncertainty measure: the OU measure is associated to variability around the long run mean, while moving-average, variability around the short run mean. It could have an impact on the role that play each measure in the forecastability of yields: the first one would be related to long run strategies and adaptation to external conditions in general, while the second one would be more related to year-to-year adjustment to secure the livestock's feeding with local adjustments. Second observation: option value is associated to a situation of uncertainty with irreversibility of adoption; however without irreversibility, it is difficult to infer a specific behavior from farmers, who can tend to love this uncertainty or avoid it (depending on their preferences and beliefs).

Our work present some caveats. The first caveat is related to our micro-economic land-allocation model: it neither relies on ricardian rent theory (widely used), nor on economics of agricultural production models of land use (with dual profits function). We attempt to make a clear model of static-dynamic choices combining uncertainty in an instantaneous utility functional form and optimal land use choice in a utility maximization. This allows to stay general in terms of mathematical results and expectation in terms of empirical results, thus we do not have to specify preferences or a form for the utility function. Moreover, the way forage markets work do not follow the usual input markets assumptions (there is a high level of self-consumption), and the utility between forage production and animal production is not completely separable for all farmers: it would be interesting to go farther in this direction. Also, we make strong assumptions to go from the micro-level to the department-aggregated model, and when we choose not to introduce any time preferences. Finally, we observe extensive margins, because we assume we can control for most of intensive margins through our cattle-size spatialized index in the regressions with controls (section 3.5). It is still a possible additional limit of the model.

We assume that intensive margins are already optimally developed. A second caveat is that there is an intrinsic limit in the assumption of constant conditional variance, essentially because the forage yields present leptokurtotic distributions in our sample (same limit as in the Black-Sholes (B-S) models, that aims at providing optimal option pricing). In the B-S case, the value (or price) of an option or an asset is conditional to the value of its underlying asset (the distribution is thus conditional). This model fits perfectly options markets, especially if the distribution is also assumed to be conditional to past shocks (stochastic persistance of shocks on the financial markets). In our case, we do not look at conditional variance *per se*, we look at the totally exogenous variability or volatility of yields. Moreover, our volatility measures are not constant over time because they are updated each year. Another caveat is associated to the fact that the linear logistic econometric specification in the form we used it can require that we perform all regressions in the same time (SUR model) in order to tackle simultaneity of land-cover allocation choices. We tried it with naive regressions but the estimations were computationaly very costly and it was almost impossible to add any control variable or time effects. It would be interesting to go farther in this direction in another work. Finally, the choice of ensilage maize as the reference crop relies on *ad hoc* assumptions: we did not test for the relevance of this choice. This crop also has been choosen because data on maize were available.

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This research is part of the Agriculture and Forestry research program by the Climate Economics Chair. The author wants to thank especially Professors Andrew Plantinga, Olivier Deschênes, and all the Environmental Markets Laboratory team from the Bren School of Environmental Sciences and Management (University of California, Santa Barbara). The author also thanks Nathalie Delame for her help with the dataset (Public Economy Laboratory, INRA AgroParisTech, France). The author is grateful to the Climate Economics Chair for financial support. The BETA contributes to the Labex ARBRE ANR-11-LABX-0002-01. Last but not least, the author thanks all the researchers that provided a precious help with their recommendations, in research seminars as well as in bilateral discussions.

Appendices

Unit root Fisher tests (URT) based on augmented Dickey-Fuller tests - applied on forage yields. These test assume that yields dynamics have no drift and no trend, or trend and no drift, or no trend and drift.

Table 2 – URT1

Fisher-type unit-root test for Maize yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 24.93	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1149.6639	0.0000
Inverse normal Z	-24.5149	0.0000
Inverse logit t(469) L*	-32.3385	0.0000
Modified inv. chi-squared Pm	49.5940	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 3 – URT2

Fisher-type unit-root test for Maize yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 24.93	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1069.1797	0.0000
Inverse normal Z	-22.3609	0.0000
Inverse logit t(469) L*	-29.8946	0.0000
Modified inv. chi-squared Pm	45.4434	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 4 – URT3

Fisher-type unit-root test for Maize yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 24.93	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1402.11	0.0000
Inverse normal Z	-30.3047	0.0000
Inverse logit t(469) L*	-40.0399	0.0000
Modified inv. chi-squared Pm	63.0524	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 5 – URT4

Fisher-type unit-root test for Artificial grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 25.51	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1314.2409	0.0000
Inverse normal Z	-27.4870	0.0000
Inverse logit t(469) L*	-36.9915	0.0000
Modified inv. chi-squared Pm	58.0814	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 6 – URT5

Fisher-type unit-root test for Artificial grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 25.51	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1059.4200	0.0000
Inverse normal Z	-23.2950	0.0000
Inverse logit t(469) L*	-29.5221	0.0000
Modified inv. chi-squared Pm	44.9401	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 7 – URT6

Fisher-type unit-root test for Artificial grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 25.51	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1518.3537	0.0000
Inverse normal Z	-32.1668	0.0000
Inverse logit t(469) L*	-43.1689	0.0000
Modified inv. chi-squared Pm	68.6078	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 8 – URT7

Fisher-type unit-root test for Temporary grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 25.47	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1288.5141	0.0000
Inverse normal Z	-27.4658	0.0000
Inverse logit t(469) L*	-36.3218	0.0000
Modified inv. chi-squared Pm	56.7547	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 9 – URT8

Fisher-type unit-root test for Temporary grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 25.47	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1048.2891	0.0000
Inverse normal Z	-23.0975	0.0000
Inverse logit t(469) L*	-29.0752	0.0000
Modified inv. chi-squared Pm	44.3660	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 10 – URT9

Fisher-type unit-root test for Temporary grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 94	
Ha: At least one panel is stationary	Avg. number of periods = 25.47	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1516.6980	0.0000
Inverse normal Z	-32.2471	0.0000
Inverse logit t(469) L*	-43.1281	0.0000
Modified inv. chi-squared Pm	68.5224	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 11 – URT10

Fisher-type unit-root test for Natural and old-seeded grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 95	
Ha: At least one panel is stationary	Avg. number of periods = 25.65	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1067.7273	0.0000
Inverse normal Z	-23.1330	0.0000
Inverse logit t(469) L*	-29.4048	0.0000
Modified inv. chi-squared Pm	45.0265	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 12 – URT11

Fisher-type unit-root test for Natural and old-seeded grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 95	
Ha: At least one panel is stationary	Avg. number of periods = 25.65	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Included		
Drift term: Not included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	967.4256	0.0000
Inverse normal Z	-21.0058	0.0000
Inverse logit t(469) L*	-26.2248	0.0000
Modified inv. chi-squared Pm	39.8811	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 13 – URT12

Fisher-type unit-root test for Natural and old-seeded grassland yields		
Based on augmented Dickey-Fuller tests		
Ho: All panels contain unit roots	Number of panels = 95	
Ha: At least one panel is stationary	Avg. number of periods = 25.65	
AR parameter: Panel-specific	Asymptotics: T -> Infinity	
Panel means: Included		
Time trend: Not included		
Drift term: Included	ADF regressions: 0 lags	
	Statistic	p-value
Inverse chi-squared(188) P	1356.0125	0.0000
Inverse normal Z	-29.5818	0.0000
Inverse logit t(469) L*	-38.2666	0.0000
Modified inv. chi-squared Pm	59.8152	0.0000
P statistic requires number of panels to be finite.		
Other statistics are suitable for finite or infinite number of panels.		

Table 14 – Control regressions for time effects and multicolinearity

VARIABLES	σ^{OU}_{TG}	σ^{OUW}_{TG}	σ^{MA}_{TG}	σ^{MAW}_{TG}	σ^{OU}_{AG}	σ^{OUW}_{AG}	σ^{MA}_{AG}	σ^{MAW}_{AG}	σ^{OU}_{NOS}	σ^{OUW}_{NOS}	σ^{MA}_{NOS}	σ^{MAW}_{NOS}
Dummy t_{1991}	-5.555***		3.163***		-6.881**		3.231***		-2.734***		1.521***	
	(-2.610)		(4.704)		(-2.413)		(3.904)		(-3.025)		(3.295)	
Dummy t_{1992}	-8.427***		5.984***		-10.36***		6.092***		-4.007***		3.552***	
	(-4.181)		(8.827)		(-3.873)		(6.847)		(-4.671)		(7.238)	
Dummy t_{1993}	-10.00***		6.510***		-12.58***		6.698***		-4.868***		3.941***	
	(-5.119)		(9.782)		(-4.852)		(7.425)		(-5.851)		(7.971)	
Dummy t_{1994}	-11.11***	-0.0574	6.411***	-2.099	-13.70***	0.596	6.862***	-1.184	-5.435***	-0.505	3.926***	-0.275
	(-5.751)	(-0.0829)	(9.679)	(-1.607)	(-5.396)	(0.737)	(7.613)	(-0.801)	(-6.643)	(-0.726)	(7.948)	(-0.282)
Dummy t_{1995}	-12.17***	-0.808	5.839***	-1.996	-14.85***	0.333	6.328***	-1.551	-5.935***	-1.037	3.570***	-0.296
	(-6.379)	(-1.227)	(9.219)	(-1.541)	(-5.943)	(0.448)	(7.282)	(-1.092)	(-7.386)	(-1.502)	(7.671)	(-0.307)
Dummy t_{1996}	-12.49***	-0.673	5.662***	-1.732	-14.96***	0.733	6.312***	0.470	-5.902***	-0.387	3.638***	0.696
	(-6.576)	(-0.920)	(9.112)	(-1.323)	(-6.026)	(0.991)	(7.450)	(0.332)	(-7.328)	(-0.539)	(7.870)	(0.663)
Dummy t_{1997}	-13.32***	-0.811	5.292***	-1.987	-15.65***	0.454	6.192***	-1.328	-6.252***	0.0673	3.405***	-0.159
	(-7.054)	(-1.142)	(8.747)	(-1.511)	(-6.354)	(0.609)	(7.547)	(-0.894)	(-7.836)	(0.0959)	(7.620)	(-0.159)
Dummy t_{1998}	-14.02***	-1.429**	5.064***	-2.135	-16.25***	0.186	6.162***	-0.761	-6.492***	-0.903	3.334***	-0.731
	(-7.466)	(-2.024)	(8.474)	(-1.579)	(-6.636)	(0.257)	(7.553)	(-0.513)	(-8.182)	(-1.364)	(7.497)	(-0.732)
Dummy t_{1999}	-14.10***	-0.473	5.275***	-3.018**	-16.37***	0.910	6.422***	-2.391*	-6.544***	-0.696	3.480***	-0.145
	(-7.509)	(-0.647)	(8.678)	(-2.505)	(-6.696)	(1.235)	(7.800)	(-1.793)	(-8.255)	(-1.026)	(7.744)	(-0.152)
Dummy t_{2000}	-13.93***	-0.627	5.477***	-0.349	-16.20***	0.695	6.657***	-0.395	-6.420***	-0.525	3.689***	0.228
	(-7.393)	(-0.919)	(8.824)	(-0.254)	(-6.631)	(0.916)	(8.051)	(-0.259)	(-7.998)	(-0.737)	(7.880)	(0.214)
Dummy t_{2001}	-14.42***	-0.283	5.228***	-1.215	-16.78***	0.769	6.351***	-0.425	-6.634***	-0.442	3.568***	0.569
	(-7.680)	(-0.403)	(8.528)	(-0.839)	(-6.893)	(1.073)	(7.796)	(-0.287)	(-8.306)	(-0.657)	(7.709)	(0.557)
Dummy t_{2002}	-14.84***	-0.377	5.042***	-1.434	-17.22***	0.984	6.148***	-0.535	-6.817***	0.00370	3.482***	1.249
	(-7.920)	(-0.539)	(8.277)	(-1.121)	(-7.094)	(1.385)	(7.621)	(-0.368)	(-8.551)	(0.00557)	(7.573)	(1.145)
Dummy t_{2003}	-13.40***	-0.917	6.192***	0.560	-15.95***	0.336	7.222***	2.042	-6.089***	-0.170	4.337***	2.185**
	(-7.161)	(-1.309)	(10.11)	(0.439)	(-6.564)	(0.452)	(8.966)	(1.463)	(-7.657)	(-0.228)	(9.355)	(2.326)
Dummy t_{2004}	-13.70***	-0.713	6.184***	-2.139	-16.34***	1.202	7.070***	-0.141	-6.165***	0.0205	4.588***	1.355
	(-7.344)	(-0.948)	(10.35)	(-1.608)	(-6.751)	(1.556)	(8.927)	(-0.0999)	(-7.764)	(0.0292)	(10.16)	(1.362)
Dummy t_{2005}	-13.88***	-0.881	6.112***	-0.803	-16.63***	0.343	6.920***	0.447	-6.249***	-0.735	4.632***	-0.639
	(-7.450)	(-1.259)	(10.27)	(-0.622)	(-6.880)	(0.457)	(8.805)	(0.316)	(-7.869)	(-1.025)	(10.26)	(-0.621)
Dummy t_{2006}	-14.12***	-0.216	6.024***	-1.099	-16.93***	0.600	6.773***	1.152	-6.352***	-0.143	4.648***	1.859*
	(-7.590)	(-0.312)	(10.22)	(-0.813)	(-7.015)	(0.792)	(8.693)	(0.727)	(-8.003)	(-0.195)	(10.36)	(1.878)
Dummy t_{2007}	-13.92***	-0.373	6.315***	-0.0772	-16.97***	0.826	6.871***	1.837	-6.213***	0.477	5.013***	2.197**
	(-7.472)	(-0.542)	(10.59)	(-0.0595)	(-7.038)	(1.102)	(8.828)	(1.203)	(-7.829)	(0.653)	(11.30)	(2.189)
Dummy t_{2008}	-13.90***	-0.464	6.399***	-0.258	-16.99***	0.696	6.941***	1.375	-6.125***	0.0431	5.225***	0.956
	(-7.437)	(-0.682)	(10.55)	(-0.202)	(-7.046)	(0.950)	(8.877)	(0.924)	(-7.694)	(0.0647)	(11.68)	(0.891)
Dummy t_{2009}	-14.14***	-0.339	6.282***	-1.530	-17.31***	0.0171	6.751***	-2.289	-6.236***	0.301	5.180***	1.304
	(-7.572)	(-0.465)	(10.37)	(-1.094)	(-7.188)	(0.0236)	(8.660)	(-1.548)	(-7.844)	(0.408)	(11.63)	(1.265)
Dummy t_{2010}	-14.27***	-0.923	6.228***	-1.591	-17.31***	0.471	6.784***	1.200	-6.292***	0.0195	5.168***	1.634
	(-7.646)	(-1.380)	(10.29)	(-1.149)	(-7.173)	(0.581)	(8.615)	(0.793)	(-7.913)	(0.0266)	(11.63)	(1.547)
Dummy t_{2011}	-14.13***	-0.735	6.363***	-0.448	-17.14***	0.717	6.949***	0.356	-6.245***	-0.548	5.236***	1.599
	(-7.556)	(-1.018)	(10.44)	(-0.351)	(-7.097)	(0.935)	(8.804)	(0.236)	(-7.838)	(-0.867)	(11.73)	(1.588)
Dummy t_{2012}	-14.25***	-0.994	6.325***	-1.574	-17.24***	0.518	6.926***	1.202	-6.294***	0.178	5.220***	0.232
	(-7.634)	(-1.396)	(10.45)	(-1.180)	(-7.147)	(0.654)	(8.803)	(0.810)	(-7.909)	(0.238)	(11.71)	(0.219)
Dummy t_{2013}	-14.32***	-0.695	6.310***	0.256	-17.34***	0.188	6.899***	-0.471	-6.263***	-0.129	5.284***	2.257**
	(-7.698)	(-1.002)	(10.56)	(0.196)	(-7.213)	(0.264)	(8.910)	(-0.337)	(-7.864)	(-0.175)	(11.85)	(2.178)
Dummy t_{2014}	-14.15***	-0.415	6.470***	0.186	-17.06***	0.614	7.161***	0.438	-6.054***	-0.0391	5.522***	0.895
	(-7.603)	(-0.595)	(10.78)	(0.146)	(-7.096)	(0.828)	(9.224)	(0.290)	(-7.551)	(-0.0524)	(12.28)	(0.874)
Dummy t_{2015}	-14.17***	-0.453	6.492***	-1.699	-17.09***	0.684	7.177***	-1.381	-6.023***	0.316	5.559***	-0.624
	(-7.605)	(-0.634)	(10.75)	(-1.302)	(-7.102)	(0.907)	(9.187)	(-0.925)	(-7.451)	(0.426)	(12.15)	(-0.599)
Dummy t_{2016}	-14.14***	-0.341	6.537***	-0.690	-17.22***	0.568	7.106***	0.932	-6.008***	-0.00680	5.576***	1.075
	(-7.591)	(-0.515)	(10.82)	(-0.526)	(-7.171)	(0.735)	(9.187)	(0.619)	(-7.408)	(-0.00978)	(12.14)	(1.107)
Constant	31.68***	8.745***	4.959***	17.97***	36.05***	8.724***	5.760***	18.55***	15.83***	7.982***	3.525***	12.29***
	(17.90)	(17.43)	(10.79)	(18.95)	(15.64)	(16.91)	(9.321)	(18.22)	(21.52)	(16.98)	(10.77)	(17.01)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,565	2,074	2,565	2,018	2,565	2,078	2,565	2,022	2,565	2,111	2,565	2,057
R-squared	0.166	0.005	0.098	0.012	0.141	0.003	0.073	0.015	0.141	0.006	0.139	0.020
F	7.200	0.454	8.850	1.197	5.387	0.315	6.250	1.456	6.247	0.593	15.79	1.917
p Fisher	0	0.988	0	0.236	0	0.999	0	0.0746	0	0.936	0	0.00549

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15 – Yields shocks' impact on Temporary grasslands ratio

VARIABLES	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)
Negative shocks TG	-0.0281					
	(-0.848)					
Positive shocks TG	0.0469					
	(1.623)					
lag(1) Negative shocks TG		0.0356				
		(1.182)				
lag(1) Positive shocks TG		0.0544**				
		(1.994)				
Negative shocks AG			-0.0217			
			(-0.535)			
Positive shocks AG			0.0351			
			(1.047)			
lag(1) Negative shocks AG				-0.00275		
				(-0.0753)		
lag(1) Positive shocks AG				0.0134		
				(0.371)		
Negative shocks NOS					0.209	
					(0.736)	
Positive shocks NOS					0.839***	
					(2.828)	
lag(1) Negative shocks NOS						0.437
						(1.477)
lag(1) Positive shocks NOS						-0.130
						(-0.626)
Constant	1.037***	1.032***	1.039***	1.061***	0.835***	0.632**
	(53.49)	(56.78)	(43.66)	(43.91)	(2.971)	(2.156)
Observations	2,314	2,221	2,314	2,221	2,314	2,221
R-squared	0.005	0.002	0.003	0.000	0.005	0.004
Number of geo	94	94	94	94	94	94
F	3.192	1.996	1.632	0.189	12.47	
p Fisher	0.0456	0.142	0.201	0.828	1.60e-05	
Robust t-statistics in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Table 16 – Yields shocks' impact on Artificial grasslands ratio

VARIABLES	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)
Negative shocks AG	0.00322					
	(0.0834)					
Positive shocks AG	0.00475					
	(0.150)					
lag(1) Negative shocks AG		0.0309				
		(0.765)				
lag(1) Positive shocks AG		-0.0185				
		(-0.514)				
Negative shocks TG			-0.0444			
			(-1.252)			
Positive shocks TG			-0.0409			
			(-1.110)			
lag(1) Negative shocks TG				0.0352		
				(1.220)		
lag(1) Positive shocks TG				-0.0284		
				(-0.674)		
Negative shocks NOS					0.321***	
					(6.006)	
Positive shocks NOS					0.921***	
					(4.405)	
lag(1) Negative shocks NOS						0.477***
						(17.60)
lag(1) Positive shocks NOS						0.271***
						(14.30)
Constant	-0.786***	-0.806***	-0.753***	-0.804***	-1.103***	-1.274***
	(-37.16)	(-33.33)	(-33.78)	(-35.14)	(-20.76)	(-47.42)
Observations	2,317	2,224	2,316	2,224	2,316	2,224
R-squared	0.000	0.001	0.001	0.002	0.004	0.003
Number of geo	94	94	94	94	94	94
F	0.0115	0.904	0.964	2.155	18.64	
p	0.989	0.408	0.385	0.122	1.56e-07	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 – Yields shocks' impact on Natural and old-seeded grasslands ratio

VARIABLES	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)
Negative shocks NOS	-0.0153					
	(-0.113)					
Positive shocks NOS	1.189***					
	(3.114)					
lag(1) Negative shocks NOS		0.464				
		(1.650)				
lag(1) Positive shocks NOS		1.326***				
		(6.743)				
Negative shocks TG			-0.0459*			
			(-1.720)			
Positive shocks TG			0.0278			
			(1.272)			
lag(1) Negative shocks TG				0.0254		
				(1.068)		
lag(1) Positive shocks TG				0.0379		
				(1.268)		
Negative shocks AG					-0.0175	
					(-0.499)	
Positive shocks AG					0.0425	
					(1.543)	
lag(1) Negative shocks AG						0.000478
						(0.0136)
lag(1) Positive shocks AG						0.0202
						(0.657)
Constant	2.432***	1.957***	2.425***	2.395***	2.410***	2.410***
	(18.08)	(7.025)	(168.5)	(136.3)	(123.2)	(115.3)
Observations	2,316	2,223	2,316	2,223	2,316	2,223
R-squared	0.017	0.014	0.008	0.002	0.006	0.001
Number of geo	94	94	94	94	94	94
F	28.03		3.483	0.861	2.326	0.308
p Fisher	2.97e-10		0.0348	0.426	0.103	0.735

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18 – All yields shocks' impact on the three types of grasslands

VARIABLES	P(AG)	P(TG)	P(NOS)	P(AG)	P(TG)	P(NOS)
lag(1) Negative shocks maize	0.115***	-0.0285	0.0305			
	(0.0366)	(0.0399)	(0.0282)			
lag(1) Positive shocks maize	-0.105***	0.0228	-0.0233			
	(0.0358)	(0.0301)	(0.0196)			
lag(1) Negative shocks TG	-0.0107	0.0348	0.0166			
	(0.0420)	(0.0304)	(0.0249)			
lag(1) Positive shocks TG	-0.00124	0.0512	0.0368			
	(0.0510)	(0.0330)	(0.0291)			
lag(1) Negative shocks NOS	0.209	0.162	0.291			
	(0.129)	(0.139)	(0.190)			
lag(1) Positive shocks NOS	0.442***	0.0406	1.439***			
	(0.0844)	(0.0887)	(0.117)			
lag(1) Negative shocks AG	0.00256	0.00174	-0.00726			
	(0.0491)	(0.0405)	(0.0363)			
lag(1) Positive shocks AG	0.00866	-0.00897	0.0119			
	(0.0476)	(0.0429)	(0.0342)			
Negative shocks maize				0.0945**	-0.0413	-0.00388
				(0.0428)	(0.0379)	(0.0269)
Positive shocks maize				-0.107***	0.0385	-0.0108
				(0.0338)	(0.0295)	(0.0193)
Negative shocks TG				-0.0854*	-0.0248	-0.0549**
				(0.0480)	(0.0362)	(0.0227)
Positive shocks TG				-0.0225	0.0350	0.0163
				(0.0459)	(0.0335)	(0.0265)
Negative shocks NOS				0.274***	0.259	0.0111
				(0.0705)	(0.278)	(0.136)
Positive shocks NOS				0.899***	0.842***	1.180***
				(0.225)	(0.312)	(0.399)
Negative shocks AG				0.0180	0.0149	0.0191
				(0.0484)	(0.0474)	(0.0373)
Positive shocks AG				0.0261	0.00120	0.0220
				(0.0411)	(0.0398)	(0.0315)
Constant	-1.029***	0.863***	2.090***	-1.026***	0.776***	2.411***
	(0.128)	(0.141)	(0.195)	(0.0787)	(0.270)	(0.132)
Observations	2,218	2,215	2,217	2,316	2,314	2,316
R-squared	0.031	0.005	0.021	0.028	0.015	0.026
Number of geo	94	94	94	94	94	94
F	-	-	-	5.665	4.732	9.091
p Fisher	-	-	-	7.34e-06	6.84e-05	3.75e-09

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19 – Yields volatility (Ornstein-Ulhenbeck)'s impact on Temporary grasslands ratio

VARIABLES	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)
σ_{TG}^{OU}	-0.0192***		0.00157					
	(0.00319)		(0.00582)					
lag(1) σ_{TG}^{OU}		-0.0159***		0.00440				
		(0.00358)		(0.00644)				
σ_{TG}^{OUW}					-0.00483*		-0.00383	
					(0.00286)		(0.00240)	
lag(1) σ_{TG}^{OUW}						-0.00626**		-0.00540*
						(0.00309)		(0.00280)
Constant	1.449***	1.409***	0.569***	0.531**	1.201***	1.245***	0.859***	0.934***
	(0.0640)	(0.0720)	(0.211)	(0.226)	(0.0338)	(0.0365)	(0.0500)	(0.0509)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,221	2,128	2,221	2,128	1,944	1,852	1,944	1,852
R-squared	0.049	0.036	0.320	0.302	0.003	0.005	0.274	0.267
Number of geo	94	94	94	94	94	94	94	94
F	36.05	19.66	12.13	12.74	2.849	4.112	13.05	11.29
p Fisher	3.69e-08	2.53e-05	0	0	0.0948	0.0455	0	0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20 – Yields volatility (Ornstein-Ulhenbeck)'s impact on Artificial grasslands ratio

VARIABLES	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)
σ_{AG}^{OU}	0.0111***		-0.00182					
	(0.00254)		(0.00352)					
lag(1) σ_{AG}^{OU}		0.0130***		-0.000256				
		(0.00290)		(0.00370)				
σ_{AG}^{OUW}					-0.00163		-0.00136	
					(0.00197)		(0.00204)	
lag(1) σ_{AG}^{OUW}						0.000691		-0.000211
						(0.00193)		(0.00200)
Constant	-1.047***	-1.103***	-0.447***	-0.489***	-0.822***	-0.867***	-0.474***	-0.543***
	(0.0560)	(0.0642)	(0.166)	(0.166)	(0.0250)	(0.0245)	(0.0606)	(0.0637)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,224	2,131	2,224	2,131	1,947	1,855	1,947	1,855
R-squared	0.016	0.022	0.163	0.159	0.000	0.000	0.144	0.132
Number of geo	94	94	94	94	94	94	94	94
F	19.28	19.98	13.88	14.11	0.686	0.128	14.16	15.03
p Fisher	2.99e-05	2.21e-05	0	0	0.410	0.721	0	0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21 – Yields volatility (Ornstein-Ulhenbeck)'s impact on Natural and old-seeded grasslands ratio

VARIABLES	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)
σ^{OU}_{NOS}	-0.00795		-0.00611					
	(0.00481)		(0.00703)					
lag(1) σ^{OU}_{NOS}		-0.00134		0.000510				
		(0.00496)		(0.00678)				
σ^{OUW}_{NOS}					0.00366		0.00340	
					(0.00225)		(0.00209)	
lag(1) σ^{OUW}_{NOS}						0.00157		0.00152
						(0.00229)		(0.00226)
Constant	2.500***	2.434***	2.442***	2.363***	2.399***	2.417***	2.388***	2.398***
	(0.0497)	(0.0513)	(0.131)	(0.125)	(0.0166)	(0.0169)	(0.0454)	(0.0456)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,223	2,130	2,223	2,130	1,946	1,854	1,946	1,854
R-squared	0.003	0.000	0.043	0.042	0.001	0.000	0.045	0.047
Number of geo	94	94	94	94	94	94	94	94
F	2.735	0.0734	9.075	9.124	2.642	0.470	9.668	8.708
p Fisher	0.102	0.787	0	0	0.107	0.495	0	0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22 – Yields volatility (Moving average)'s impact on Temporary grasslands ratio

VARIABLES	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)	P(TG)
σ^{MA}_{TG}	0.0451***		0.00889					
	(0.00702)		(0.00739)					
lag(1) σ^{MA}_{TG}		0.0434***		0.00925				
		(0.00693)		(0.00788)				
σ^{MAW}_{TG}					-0.00100		-0.00202	
					(0.00145)		(0.00136)	
lag(1) σ^{MAW}_{TG}						0.000552		-0.000841
						(0.00126)		(0.00116)
Constant	0.565***	0.610***	0.575***	0.628***	1.161***	1.161***	0.849***	0.885***
	(0.0779)	(0.0765)	(0.0619)	(0.0602)	(0.0249)	(0.0217)	(0.0409)	(0.0444)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,221	2,128	2,221	2,128	1,944	1,852	1,944	1,852
R-squared	0.071	0.070	0.321	0.303	0.000	0.000	0.273	0.264
Number of geo	94	94	94	94	94	94	94	94
F	41.26	39.27	13.31	13.61	0.475	0.193	13.61	13.70
p Fisher	5.59e-09	1.14e-08	0	0	0.492	0.662	0	0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23 – Yields volatility (Moving average)'s impact on Artificial grasslands ratio

VARIABLES	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)	P(AG)
σ_{AG}^{MA}	-0.0178*		0.00765					
	(0.00987)		(0.0111)					
lag(1) σ_{AG}^{MA}		-0.0165*		0.00859				
		(0.00937)		(0.0104)				
σ_{AG}^{MAW}					-0.000402		-0.000493	
					(0.00175)		(0.00150)	
lag(1) σ_{AG}^{MAW}						-0.000326		-0.000445
						(0.00179)		(0.00160)
Constant	-0.577***	-0.608***	-0.560***	-0.549***	-0.835***	-0.852***	-0.482***	-0.537***
	(0.125)	(0.118)	(0.0959)	(0.0896)	(0.0337)	(0.0346)	(0.0626)	(0.0605)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,224	2,131	2,224	2,131	1,947	1,855	1,947	1,855
R-squared	0.009	0.008	0.163	0.160	0.000	0.000	0.144	0.132
Number of geo	94	94	94	94	94	94	94	94
F	3.241	3.092	14.00	14.43	0.0530	0.0330	15.58	15.65
p Fisher	0.0751	0.0820	0	0	0.818	0.856	0	0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24 – Yields volatility (Moving average)'s impact on Natural and old-seeded grasslands ratio

VARIABLES	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)	P(NOS)
σ_{NOS}^{MA}	0.00827		-0.00518					
	(0.00593)		(0.00869)					
lag(1) σ_{NOS}^{MA}		0.00740		-0.00338				
		(0.00581)		(0.00903)				
σ_{NOS}^{MAW}					0.00186		0.00181	
					(0.00138)		(0.00143)	
lag(1) σ_{NOS}^{MAW}						-0.000649		-0.00104
						(0.00109)		(0.000953)
Constant	2.353***	2.363***	2.363***	2.382***	2.402***	2.436***	2.392***	2.422***
	(0.0467)	(0.0454)	(0.0415)	(0.0354)	(0.0172)	(0.0137)	(0.0453)	(0.0466)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,223	2,130	2,223	2,130	1,946	1,854	1,946	1,854
R-squared	0.003	0.002	0.043	0.043	0.001	0.000	0.045	0.047
Number of geo	94	94	94	94	94	94	94	94
F	1.946	1.621	8.861	9.181	1.826	0.354	8.395	8.877
p Fisher	0.166	0.206	0	0	0.180	0.553	0	0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25 – Yields volatility (Ornstein-Uhlenbeck)'s impact with controls on all grasslands ratio

VARIABLES	P(TG)	P(TG)	P(AG)	P(AG)	P(NOS)	P(NOS)
σ_{TG}^{OU}	-0.0251***					
	(-4.642)					
σ_{TG}^{OUW}		-0.00333				
		(-0.926)				
σ_{AG}^{OU}			0.0147***			
			(2.948)			
σ_{AG}^{OUW}				-0.00234		
				(-0.710)		
σ_{NOS}^{OU}					-0.00829	
					(-1.176)	
σ_{NOS}^{OUW}						-0.00226
						(-0.804)
Selling price index for forages	-0.00112***	-0.00189***	-0.00196***	-0.00184***	-0.00141***	-0.00179***
	(-4.742)	(-6.498)	(-5.353)	(-5.371)	(-5.003)	(-6.561)
Spatialized index for animal costs	0.283**	0.220**	0.101	0.0789	0.201***	0.167***
	(2.144)	(2.089)	(0.507)	(0.393)	(2.678)	(2.749)
Constant	1.370***	1.131***	-0.940***	-0.611***	2.461***	2.495***
	(8.163)	(9.592)	(-4.676)	(-2.661)	(28.92)	(32.85)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,107	985	1,107	985	1,107	985
R-squared	0.061	0.024	0.055	0.019	0.022	0.030
Number of geo	62	62	62	62	62	62
F	19.96	21.19	13.77	10.92	15.25	17.02
p Fisher	3.92e-09	1.60e-09	5.77e-07	7.78e-06	1.63e-07	3.83e-08

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26 – Yields volatility (Moving average)'s impact with controls on all grasslands ratio

VARIABLES	P(TG)	P(TG)	P(AG)	P(AG)	P(NOS)	P(NOS)
σ_{TG}^{MA}	0.0353***					
	(3.123)					
σ_{TG}^{MAW}		-0.00142				
		(-1.000)				
σ_{AG}^{MA}			-0.0150*			
			(-1.720)			
σ_{AG}^{MAW}				-0.00103		
				(-0.689)		
σ_{NOS}^{MA}					0.00728	
					(1.278)	
σ_{NOS}^{MAW}						0.000478
						(0.398)
Selling price index for forages	-0.00133***	-0.00189***	-0.00194***	-0.00183***	-0.00144***	-0.00179***
	(-5.048)	(-6.726)	(-4.990)	(-5.427)	(-5.323)	(-6.540)
Spatialized index for animal costs	0.0767	0.224**	0.167	0.0873	0.168**	0.166***
	(0.814)	(2.147)	(0.816)	(0.435)	(2.615)	(2.742)
Constant	0.743***	1.124***	-0.512**	-0.623**	2.364***	2.473***
	(4.800)	(9.598)	(-2.021)	(-2.652)	(24.10)	(32.54)
Observations	1,107	985	1,107	985	1,107	985
R-squared	0.045	0.024	0.032	0.019	0.022	0.029
Number of geo	62	62	62	62	62	62
F	9.662	18.06	11.56	11.28	16.39	16.70
p Fisher	2.62e-05	1.68e-08	4.27e-06	5.55e-06	6.35e-08	4.92e-08

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27 – Correlation coefficients table for volatility measures (Ornstein-Uhlenbeck) and meteorological data

	σ^{OU}_{TG}	σ^{OUW}_{TG}	σ^{OU}_{AG}	σ^{OUW}_{AG}	σ^{OU}_{NOS}	σ^{OUW}_{NOS}
Average temperature	0.0832*	0.1258*	0.0124	-0.0696*	0.1925*	**0.2665***
Average effective rainfall	-0.1226*	-0.1078*	-0.0857*	-0.0503*	-0.1518*	-0.1545*
Average liquid precipitation	-0.1605*	-0.0653*	-0.1343*	-0.0634*	-0.1574*	-0.1164*
Average minimum temperature	0.2270*	0.0014	0.1590*	-0.0419*	0.1938*	0.0283
Average maximum temperature	-0.1830*	0.0905*	-0.1475*	0.0059	-0.0955*	0.1577*
Average real evapotranspiration	0.0084	-0.1124*	0.0081	-0.0800*	-0.0732*	-0.1663*
Average potential evapotranspiration	-0.1904*	0.0736*	-0.1563*	-0.0382*	-0.1048*	0.1846*
Average atmospheric radius	**0.2508***	-0.0431*	**0.2292***	-0.0241	0.1948*	-0.0717*
Average visible radius	-0.0985*	-0.0277	-0.0338	**-0.0749***	-0.0810*	0.0151
Average specific humidity	0.1624*	0.0981*	0.0601*	-0.0605*	0.1915*	0.1654*
Average relative humidity	0.1866*	-0.0361	0.0813*	-0.0061	0.0880*	-0.1324*
Std dev temperature	-0.2234*	-0.1118*	-0.1646*	-0.0674*	**-0.2566***	-0.1295*
Std dev effective rainfall	-0.2156*	-0.1722*	-0.1283*	-0.0687*	-0.2311*	-0.1462*
Std dev liquid precipitation	-0.1407*	-0.1184*	-0.0499*	-0.0401*	-0.1761*	-0.1314*
Std dev minimum temperature	**-0.2449***	-0.0349	-0.1909*	-0.0533*	**-0.2536***	-0.0823*
Std dev maximum temperature	-0.2327*	-0.0989*	-0.1642*	-0.0073	-0.2415*	-0.1478*
Std dev real evapotranspiration	-0.2154*	-0.0643*	-0.1921*	-0.0717*	-0.2053*	-0.0488*
Std dev potential evapotranspiration	0.0972*	-0.0159	0.0845*	-0.0467*	0.0470*	-0.0785*
Std dev atmospheric radius	0.2470*	-0.0417*	0.2239*	-0.0322	0.1911*	-0.0741*
Std dev visible radius	-0.0120	**-0.1242***	0.0480*	0.0226	-0.1188*	-0.1885*
Std dev specific humidity	-0.1397*	-0.1119*	-0.1336*	-0.0755*	-0.1772*	-0.0769*
Std dev relative humidity	0.1104*	-0.0716*	0.1267*	-0.0222	0.0215	-0.1228*

Table 28 – Correlation coefficients table for volatility measures (Moving average) and meteorological data

	σ^{MA}_{TG}	σ^{MAW}_{TG}	σ^{MA}_{AG}	σ^{MAW}_{AG}	σ^{MA}_{NOS}	σ^{MAW}_{NOS}
Average temperature	0.0754*	0.0745*	0.0222	0.0913*	0.0916*	0.1183*
Average effective rainfall	-0.1219*	-0.1338*	-0.0985*	-0.2007*	-0.0992*	-0.1651*
Average liquid precipitation	-0.0174	-0.0893*	-0.0151	-0.1095*	0.0328	-0.1093*
Average minimum temperature	-0.0659*	-0.0155	-0.0989*	-0.0038	-0.1678*	-0.0432*
Average maximum temperature	0.1112*	0.0881*	0.1331*	0.1188*	0.2130*	0.1403*
Average real evapotranspiration	-0.0029	-0.1257*	-0.0047	-0.0953*	-0.0057	-0.1454*
Average potential evapotranspiration	-0.0705*	-0.0852*	-0.0380*	-0.0292	0.0048	-0.0413*
Average atmospheric radius	-0.1329*	-0.0710*	-0.1199*	-0.0697*	-0.2474*	-0.0939*
Average visible radius	-0.0986*	-0.2159*	-0.0423*	-0.1538*	-0.0608*	-0.1970*
Average specific humidity	0.1443*	0.1494*	0.0673*	0.1172*	0.1203*	0.1358*
Average relative humidity	**0.2497***	0.1923*	0.1643*	0.1335*	0.1898*	0.1332*
Std dev temperature	-0.2294*	**-0.2827***	-0.1848*	-0.2692*	-0.2141*	**-0.3243***
Std dev effective rainfall	-0.2114*	-0.2284*	-0.1465*	-0.2657*	-0.1824*	-0.3027*
Std dev liquid precipitation	-0.1995*	-0.1830*	-0.1441*	**-0.2048***	-0.2194*	-0.2652*
Std dev minimum temperature	-0.1451*	-0.1855*	-0.1162*	-0.1983*	-0.1091*	-0.2230*
Std dev maximum temperature	-0.1994*	-0.1919*	-0.1625*	-0.1858*	-0.1757*	-0.2602*
Std dev real evapotranspiration	-0.2090*	-0.2034*	-0.1975*	-0.1896*	-0.1811*	**-0.2920***
Std dev potential evapotranspiration	-0.2089*	-0.1438*	**-0.1858***	-0.1361*	**-0.2895***	-0.1979*
Std dev atmospheric radius	-0.1310*	-0.0724*	-0.1205*	-0.0782*	-0.2456*	-0.1010*
Std dev visible radius	-0.0081	-0.0329	0.0483*	-0.0247	-0.0246	-0.1772*
Std dev specific humidity	-0.1479*	-0.2079*	-0.1508*	-0.2350*	-0.1561*	-0.2679*
Std dev relative humidity	-0.1275*	-0.1243*	-0.0974*	-0.1001*	-0.2607*	-0.1869*

Table 29 – Instrumentation of yields volatility (Ornstein Uhlenbeck)'s impact on all grasslands ratios

VARIABLES	P(TG)	P(TG)	P(AG)	P(AG)	P(NOS)	P(NOS)
σ_{TG}^{OU}	-0.120***					
	(0.00989)					
σ_{TG}^{OUW}		-0.170***				
		(0.0581)				
σ_{AG}^{OU}			0.0761***			
			(0.00768)			
σ_{AG}^{OUW}				-0.779		
				(1.050)		
σ_{NOS}^{OU}					0.396***	
					(0.152)	
σ_{NOS}^{OUW}						-4.291
						(57.75)
Observations	2,167	1,274	2,170	1,274	1,274	1,274
R-squared	-1.356	-2.457	-0.532	-23.162	-1.349	-1,650.212
Number of geo	92	77	92	77	77	77
F	146.5	8.592	98.20	0.549	6.821	0.00552
P Fisher	0.0000	0.0034	0.0000	0.4587	0.0091	0.9408
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						
Overidentification test						
Hansen J stat - Chi2 p value	0.8025	-	-	-	0.9835	-
Underidentification test						
LM test - Chi2 p value	0.0000	0.0004	0.0000	0.4481	0.0022	0.9409
Endogeneity postestimation test						
Sargan Hansen test - Chi2 p value	0.0000	0.0000	0.0000	0.0036	0.0010	0.0013
Validation in terms of instrumentation	Yes	Yes	Yes	No	Yes	No
Validation in global inference (Fisher)	Yes	Yes	Yes	No	Yes	No

Table 30 – Instrumentation of yields volatility (Moving average)'s impact on all grasslands ratios

VARIABLES	P(TG)	P(TG)	P(AG)	P(AG)	P(NOS)	P(NOS)
σ_{TG}^{MA}	0.0602**					
	(0.0267)					
σ_{TG}^{MAW}		-0.854				
		(4.646)				
σ_{AG}^{MA}			-0.155***			
			(0.0187)			
σ_{AG}^{MAW}				-0.483		
				(0.635)		
σ_{NOS}^{MA}					0.0296***	
					(0.00822)	
σ_{NOS}^{MAW}						-0.140**
						(0.0615)
Observations	2,167	1,274	2,170	1,899	2,169	1,274
R-squared	0.064	-318.104	-0.552	-44.334	-0.015	-5.535
Number of geo	92	77	92	92	92	77
F	5.091	0.0337	68.72	0.579	12.92	5.199
p Fisher	0.0242	0.8543	0.0000	0.4470	0.0003	0.0228
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						
Overidentification test						
Hansen J stat - Chi2 p value	-	-	-	-	-	0.9392
Underidentification test						
LM test - Chi2 p value	0.0000	0.8542	0.0000	0.4397	0.0000	0.0354
Endogeneity postestimation test						
Sargan Hansen test - Chi2 p value	0.5672	0.0032	0.0000	0.0000	0.0044	0.0000
Validation in terms of instrumentation	No	No	Yes	No	Yes	Yes
Validation in global inference (Fisher)	Yes	No	Yes	No	Yes	Yes

Chapter 4

Role of farmers' risk and ambiguity preferences on fertilization decisions: an experiment

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4.1 Introduction

Reducing GHG emissions in the agricultural sector is a major environmental policy challenge in France, where the sector was responsible in 2017 for 20.4% of the total GHG emissions (CITEPA [15]). The agricultural sector, associated to the forest one, is the main sector able to sequester atmospheric carbon, so that it represents a great potential of mitigation. Mitigation practices that are proposed to farmers in the context of the European Common Agricultural Policy (CAP) encourage farmers to diversify their activities, integrate leguminous crop, improve land rotation, develop better link between a good feeding for the livestock and vegetal protein production, and especially limit the use of pollutant inputs. In this context, reducing synthetic nitrogenous fertilization or improving fertilization efficiency is an important mitigation strategy.

However, farmers poorly adopt such practices, even when they are associated to negative abatement costs such as the reduction of nitrogenous fertilization (Pellerin et al. [33]). Several determinants of the non-adoption have been identified in the literature. For example, the level of education and the farm size were the most reliable variables that seem to significantly positively impact adoption. Our idea is that hidden costs linked to the existence of uncertainty may explain (almost partly) the non-adoption of fertilization reduction to mitigate climate change. Indeed, adoption of new practices generate production uncertainty on the farmer's profits[1]. The farmers are not certain of the efficiency of the practices, and the resulting outcome is uncertain. For example, fertilization is a risk-decreasing activity, so that changing the farmer's habits may be difficult, in particular because the reduction of fertilization is associated to uncertain effect on the profit. As a consequence, the farmer's preferences toward risk and ambiguity should also play a role in this adoption process. In this context, the question that we address is the following : What is the impact of farmer's preferences towards risk and ambiguity on fertilization choices ? In line with that question, the role of the follow-up advices (in terms of fertilization) provided by the agent of the agricultural cooperative will also be analyzed.

This research question refers to two different literatures aiming at the elicitation of farmer's risk and ambiguity preferences. The first literature gathers studies based on revealed preferences method, which provides an estimate based on real farmer's choices (production, input). The second literature is composed with articles using stated preferences method. This method provides a quantification of the risk attitude through experiment based on simple decisions taken in a controlled environment to provide a pure measurement. In this paper, we propose to elicit risk and ambiguity aversion parameters through simple lottery choices, and then, to use these parameters as potential explanatory variables for farmer's fertilization choices. We then combine experimental data on risk and ambiguity aversion with real data on the fertilization choices and follow-up advices[2].

The rest of the paper is organized as follows. In Section 4.2 we precisely position our research as regard to the two literatures briefly evoked above, the one using revealed preferences method and the other based on stated preferences method. Section 4.3 presents

[1] In addition to production uncertainty, a price uncertainty may also appeared. However, as the mitigation practice considered (fertilization) does not imply a change of the agricultural product or a change of market, we only focused on production uncertainty.

[2] A similar approach has been proposed in Brunette et al. [11] where risk preferences parameter has been estimated through lottery choices and then used to explain the probability to harvest of foresters.

the questionnaire. The results are presented in Section 4.4, and Section 4.5 provides the discussion and conclusion of the paper.

4.2 Literature review

Following the modeling approaches of Moschini and Hennessy [32], Pope and Kramer [34], and Roosen and Hennessy [36], inter alia, the use of an input by a producer can be impacted by risk if the input is risk-increasing or decreasing (in yields), depending on the producer's risk preferences: a risk averse agent will use less of a risk increasing input than a risk neutral one, and reciprocally. This result has been specifically extended in the case of input use and agricultural policies by Leathers and Quiggin [28] who show that a policy can be partly inefficient if the risks associated to the input and producer's preferences toward risk are not taken into account. For instance, taxing a risk-increasing polluting input in order to disincentive its use by farmers can lead to disappointing results because risk averse farmers can try to maintain a sufficiently high level of its use to avoid risk. This phenomenon can explain why yields risk and risk preferences are hidden costs of pollution policies, especially for agricultural policies, and low level of participation can be observed.

The relationships between nitrogenous fertilization and risk is well-documented in empirical studies, that especially use revealed preferences methods or agronomic simulations. Stuart et al. [38] show that applying more nitrogenous fertilizer is a risk-decreasing activity, and depends on farmers' perception about risk and their trust in the information provided about fertilization reduction. Financial insertion and background risks, as well as the level of competition and the dependency toward contractors create risks that prevent farmers from reducing their use of nitrogenous fertilizer to maintain a sufficient level of yields. Sheriff [37] shows that all farmers put a nitrogenous fertilizer rate according to the yields expectation independently of risk preferences, thus uncertainty impacts this rate. Moreover, risk aversion and risk perception impact fertilizer use by farmers, in the same way than in the Pope and Kramer [34] rationale: it depends on the risk-decreasing or risk-increasing nature of the input. Bontems and Thomas [8] study the role of risk aversion and additional information on nitrogenous fertilizers applications, and found that a large proportion of their sample of farmers was risk averse, and risk aversion led to an over-fertilization accounting for 7.1% of total fertilizer costs per hectare on average. The value of information, associated to the practice of fertilization splittings and observation of nitrogen availability between splits, account for 23.53% of fertilizer costs per hectare. Dequiedt and Servonnat [17] developed the mathematical conditions for risk aversion to lead to higher rate of fertilization. They tested their results on a sample and found that an important proportion of French farmers were risk averse and that these preferences led to 29.4% more nitrogenous applications by hectare. This account for approximately €75.8/ha, and increase the marginal abatement costs of fertilization reduction. The gains that farmers can receive if the application recommendations by extension agents would take into account risk and risk aversion have been studied by Gandorfer et al. [22]. Through different measures of risk, they compute the optimal level of nitrogenous rate in different scenarii in order to reach certainty equivalents in the same perspective than objective yields. Among their results, they found that fertilization decreases especially the probability of negative profits, and for the scenarii of high risk aversion the consideration of risk premia leads to an average gains per hectare for the farmers. Monjardino et al. [31] also show that the risk and risk preferences sig-

nificantly modify the level of optimal nitrogenous fertilization to apply in order to close the gap between certain yields goals and actual yields. Globally, the theoretical results of the modeling approaches are often validated by empirical studies, showing that risk perception, risk preferences and arbitrage between yields mean and variance, impact the level of nitrogenous fertilization. This relationship depends on natural conditions, but is relatively robust in one direction: risk aversion seems to incentive farmers to apply more fertilizer rate on their crops, and consequently increases the cost of reducing applications. Other elements related to uncertainty and information, trust in information sources and risk profile of farmers have also a role to play.

More recently, another literature emerged based on experimental economics and proposed to elicit risk and ambiguity aversion parameters through simple lottery choices. Measuring directly risk attitudes through experiments offers diverse advantages. It allows for the specific isolation of risk attitudes from other behavioral parameters because of the design of the experimentation: contextualized or not, it aims to purely measure the risk attitudes, and not estimating them like with the revealed preferences methods. It thus prevents some endogeneity biases related to the simultaneous contribution of perceptions, context and individual preferences to the final decision. Binswanger [4] is the first to submit lotteries to samples of farmers in order to elicit their risk preferences. The experiment presents a comparison of lotteries from the less to the riskier, and ask farmers to choose their preferred lotteries. The more they like risky lotteries, the more risk loving they are, and reciprocally. The author found that Indians farmers were on average risk averse, and that it can have an influence on a lot of phenomenon (investment, credit, innovation adoption etc.). These initial researches served as an impulse in the literature, so that lots of elicitation procedures appeared. One of the famous procedure, the Multiple Price List (MPL) method, was popularized by Holt and Laury [25]. The idea is to submit to the subjects ten paired-lottery choices, and to observe the switching point, i.e. the choice for which they switch from the safe option to the risky one. This switching point allows then to infer a coefficient of relative risk aversion, supposing a power utility function[3]. This MPL method has already been used to elicit the farmer's risk preferences. Reynaud and Couture [35] implemented an experiment with French farmers aiming to compare three different elicitation procedures among which the MPL one. They show that the estimate of risk aversion is procedure-dependent. Bocquého et al. [6] conducted an experiment on a sample of 100 French farmers, and show that they exhibited attitudes in accordance to expected utility preferences assumption, and that they were risk averse. Chakravarty and Roy [14] extended this MPL procedure to ambiguity aversion elicitation. Their respondents were risk averse but ambiguity neutral in the gain domain, but risk seeking and ambiguity seeking in the loss domain. Bougherara et al. [9] elicited the risk and ambiguity preferences of 197 French farmers. They show that farmers are risk and ambiguity averse.

The estimates provided by experimental economics are often used to explain real agricultural decisions. The studies that did this provided divergent results. Ghadim et al. [23] showed that Australian farmers adopt new crops depending on their risk aversion, risk perceptions and the perceived covariance between the yields of the different crops. Cotty et al. [16] found that impatient farmers tend to secure their current consumption by fer-

[3]Other procedures follow with for example the Ordered Lottery Selection (OLS) method popularized by Eckel and Grossman [19]. In this procedure, the subject has to indicate at which lottery she accepts to play among five ones.

tilizing more if they are risk averse, while patient farmers do the reverse if they are risk averse because they need to smooth their consumption over time. Hellerstein et al. [24], through a Holt and Laury's experiment, found that more risk aversion led to less diversification, less likelihood to adopt an insurance contract. Liu [29] shows that risk aversion can lead to significant delay in adoption of new varieties of crops. Engle-Warnick et al. [20] and Barham et al. [1] both observed with experiments (respectively in Peru and in the US) that ambiguity aversion decreases the probability to adopt a new crop variety if farmers are not sure of the associated distribution of yields or if the new variety increases the level of ambiguity about yields. In the latter, the authors even show that risk aversion has no impact on adoption of risk-decreasing crop, suggesting that ambiguity alone can sometimes has an effect *per se*.

4.3 Questionnaire

The questionnaire was in three parts (see Appendix 4.5). The first one was composed of lottery choices to elicit risk aversion and ambiguity aversion parameters. The second part is related to the farmers' practices in terms of fertilization and also contains some information about their property. The last part is dedicated to socio-demographic characteristics.

4.3.1 Part 1 of the questionnaire: Elicitation of preferences

The preferences are elicited through a MPL method, as proposed by Holt and Laury [25] for risk, and Chakravarty and Roy [14] for ambiguity. Appendix 4.5 presents the lottery choices under risk and ambiguity. For each task, individuals are presented with ten decisions between two lotteries (Option A and Option B). For each decision, the subject has to choose between a safe option (Option A) and a risky one (Option B) for risk (Table 8), and between a risky decision (Option A) and an ambiguous one (Option B) for ambiguity (Table 9). The number of safe choices allows to infer a coefficient for the relative risk aversion coefficient assuming a power utility function as: $\mathrm{U}(x) = x^r$ with r the relative risk aversion coefficient and x the wealth. The expected utility is given by $\mathrm{E}u(x) = p\mathrm{U}(x)$ with p the objective probability associated to a set of risky outcomes. Table 4.1 presents this classification. Under the same assumption, Table 4.2 presents the classification for ambiguity aversion following Chakravarty and Roy [14] for their ϕ function representing ambiguity preferences. Given s the subjective probability belief over a set of ambiguous outcomes, the total expected value function over outcomes can be written as $\mathrm{V}(x) = s\phi[\mathrm{E}u(x)]$, with $\phi(z) = z^a$. The concavity of U gives the level of risk aversion, while the concavity of ϕ gives the level of ambiguity aversion.

From these tables two indicators may be extracted. The first one is the number of safe choices to represent risk aversion and the number of risky choices to represent the ambiguity aversion. In both cases, the higher the number is, the higher the strength of the aversion will be. The second indicator that may be computed is an individual's average risk and ambiguity coefficient. Indeed, using the center of the interval, we can attribute to each subject their corresponding coefficient. These two indicators are then used as a farmer's characteristic and considered as a potential explanatory variable for fertilization choices.

Table 4.1 – Risk aversion classification based on lottery choices

Number of safe choices	Bounds for relative risk aversion	Classification
0 and 1	$r < -0.95$	Highly risk-loving
2	$-0.95 < r < -0.49$	Very risk-loving
3	$-0.49 < r < -0.15$	Risk-loving
4	$-0.15 < r < 0.15$	Risk-neutral
5	$0.15 < r < 0.41$	Slightly risk averse
6	$0.41 < r < 0.68$	Risk averse
7	$0.68 < r < 0.97$	Very risk averse
8	$0.97 < r < 1.37$	Highly risk averse
9 and 10	$1.37 < r$	Stay in bed

Table 4.2 – Ambiguity aversion classification based on lottery choices

Number of risky choices	Bounds for relative ambiguity aversion	Classification
0	$s > 1.92$	Extremely ambiguity-loving
1	$1.92 < s < 1.59$	Highly ambiguity-loving
2	$1.59 < s < 1.35$	Very ambiguity-loving
3	$1.35 < s < 1.15$	Ambiguity-loving
4	$1.15 < s < 1$	Slightly ambiguity-loving
5	$1 < s < 0.86$	Ambiguity neutral
6	$0.86 < s < 0.75$	Slightly ambiguity averse
7	$0.75 < s < 0.66$	Ambiguity averse
8	$0.66 < s < 0.43$	Very ambiguity averse
9	$0.43 < s < 0.30$	Highly ambiguity averse
10	$s \geq 0.30$	Extremely ambiguity averse

4.3.2 Participants, order effect and incentives

The questionnaire was submitted to a sample of 45 French farmers from four French agricultural cooperatives. The questionnaire was realized during meetings organized by the cooperatives, between November 2018 and March 2019. The researchers were present during the meeting to present the questionnaire and answer to any potential questions from the farmers.

The first part of the questionnaire used methodology from experimental economics to elicit farmer's preferences. In this part, we don't use financial incentives as traditionally done in such tasks in experimental economics. Several reasons explain this choice. First, this is a common practice to not incentivize the elicitation task when experiment used "real subjects" as farmers (see Reynaud and Couture [35]) or forest owners (Brunette et al. [10]; Brunette et al. [11]). In addition, Camerer and Hogarth [13] and Beattie and Loomes [3] showed that, since questions are related to simple lottery choices, monetary incentives do not seem to significantly affect the decisions. In the same vein, some papers show the absence of difference in terms of decisions between lottery choices using hypothetical or real payoffs (Battalio et al. [2], Wik et al. [40]).

Another concern when using elicitation task from experimental economics is the or-

der effect, i.e. the order in which the subjects answer to the various tasks. In order to control for order effect, half of the distributed questionnaire begun with the elicitation of preferences towards risk first and then, the elicitation of ambiguity preferences, and the opposite occurs for the other half.

4.3.3 Parts 2 and 3 of the questionnaire: fertilization and socio-demographic characteristics

The survey specifically focuses on the bigger parcel of the farmer's exploitation (except grasslands). The bigger parcel is more likely to host the main crop of the exploitation during the agricultural campaign and the crop for which the farmer expects to grow most of her profits (scale effect, intensity effect). Specific questions associated to parameters that can explain the nitrogenous needs, and the nitrogenous fertilization decisions are asked in order to provide relevant control variables: spreadable area on the parcel, type of precedent crop, soil type, potential organic fertilizer use and fertilizer tillage. Parcel locations (department, municipalities) as well as the status of the farmer with this parcel (owner, tenant) and the potential cropping contract are asked too.

The actual and expected yields are crucial for the farmers since the risk the farmer would face relative to fertilization is related to how she seeks to reach this yields objective. Since actual yields give us vague general information about the level of efficiency of fertilization decisions, the yields goal before the end of the campaign is a proxy of what yields could have be expected at the beginning and the difference between both is a proxy of the actual shocks that farmer faces on the crop. We expect to use this proxy as a potential explanatory variable of the fertilization's level, in interaction with risk and ambiguity preferences.

Concerning the synthetic nitrogenous fertilization, precise questions have been asked. The synthetic nitrogenous fertilization and its potential N2O emission depends on multiple parameters: the dose of fertilizer, the spreading method type, the splitting of spreading according to the plant needs, all those elements being related to the current regulation on nitrogenous fertilization. We thus explore all these elements in order to have a complete view of how can synthetic nitrogenous be used, and we associated these elements to the regulation, and more important, to the advices farmers received about them from their cooperative agent. To sum-up the fertilization part, as we want to test the way risk and ambiguity preferences can impact N2O emission from synthetic nitrogenous fertilization and the capacity to follow the official advices about fertilization, we seek quantity and quality variables about actual fertilization, and also quantity and quality variables about advices in order to construct difference variables. In order to gather more control variables, we asked farmers the amount they receive from CAP subsidies (and the specific part associated to "green" behaviors), if they contracted an optional yields insurance, the total area of their farm and their possible participation in a farmers union.

In a last part we asked classical questions about socio-demographic variables that can impact risk and ambiguity preferences as well as global economic behaviors and characteristics of the farmers. Age, marital status, education as well as revenues (inter alia) were asked, and two last questions with free text answer about opinion of the farmer about fertilization and fertilization regulation, and about the present survey. The survey is totally anonymous, in order to ensure farmers that their response concerning fertilization

(a sensitive topic) will not be associated to them.

4.4 Results

4.4.1 Elicitation of risk and ambiguity preferences

These graphs show the results of risk and ambiguity preferences elicitation for all the sample (35 non empty answers).

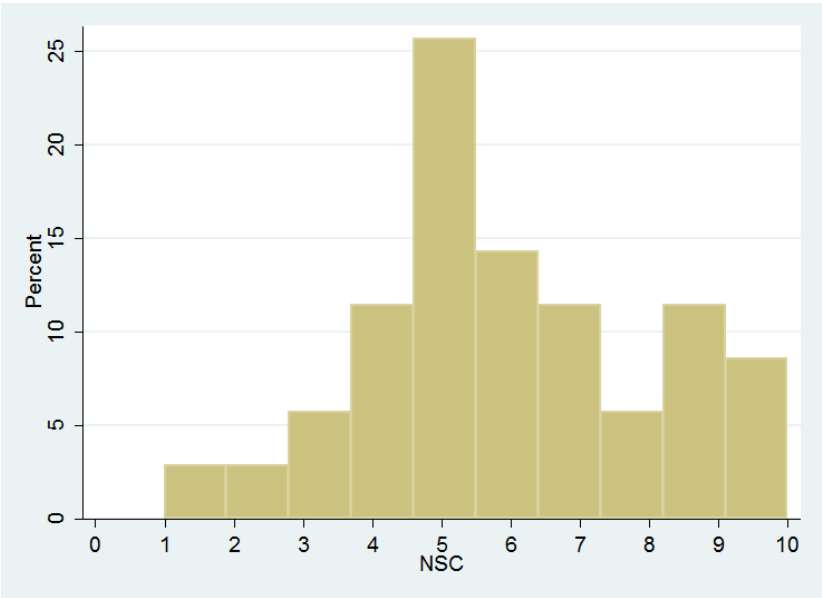

Figure 4.1 – Number of safe choices selected by the farmers

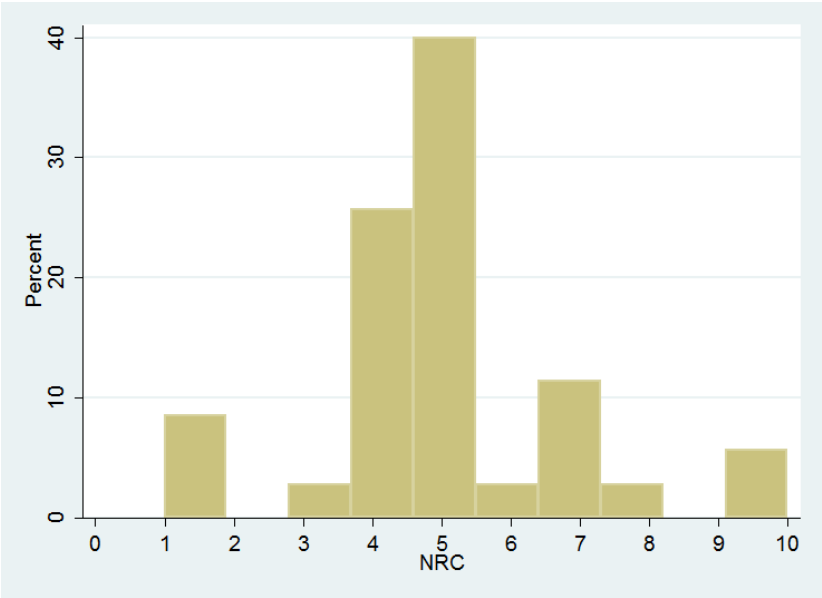

Figure 4.2 – Number of risky choices selected by the farmers

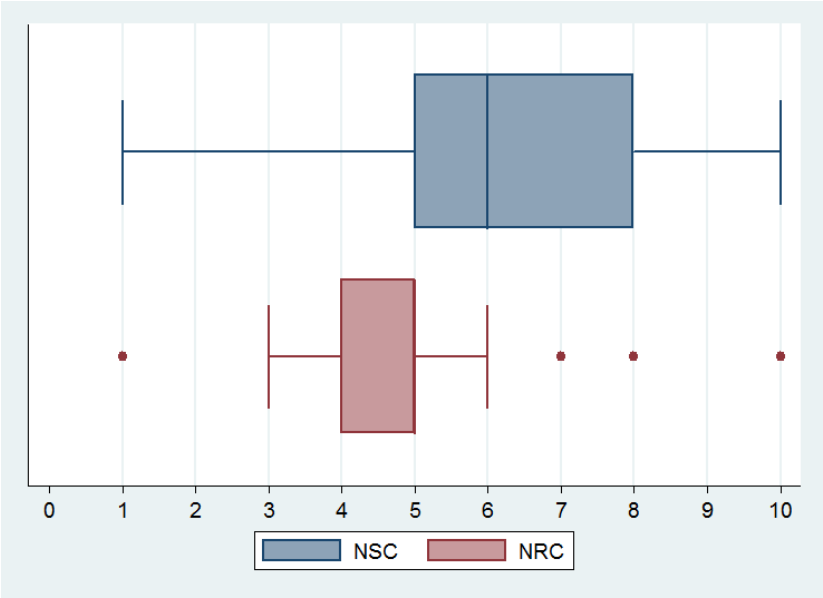

Figure 4.3 – Number of risky choices selected by the farmers

Figures 4.1 and 4.2 show the distributions of preferences in our sample. The average Number of Safe Choices (NSC - risk) is 6, while the average Number of Risky Choices (NRC - ambiguity) is around 5. The major part of respondents is risk averse (70.27%) while 14.86% of farmers are risk neutral and the remaining 14.86% are risk loving. The major part of respondents is ambiguity neutral (38.24%) and ambiguity loving (38.24) and 23.5% are ambiguity averse (34 non empty answers). Each number of safe (risky) choices corresponds to a range of coefficients of risk (ambiguity) aversion. We attribute a coefficient to each number of safe (risky) choices by taking the midpoint of each class, so that each respondent has a coefficient[4]. The average coefficient of risk aversion is 0.615 (prevalence of risk aversion) and the average coefficient of ambiguity aversion is 0.91 (close to ambiguity neutrality). These results are in line with the findings of Bougherara et al. [9] for risk aversion (0.614), but not for the ambiguity aversion (0.722), where the French respondents farmers were more ambiguity averse. The results are very close from those of Barham et al. [1], finding a prevalence of risk aversion preferences in terms of population proportion, and 38% of ambiguity neutrality, 38% of ambiguity loving and 24% of ambiguity aversion on a sample of Midwestern (US) farmers. The good fit of our measures with some results from these previous researches is an important outcome, in terms of replicability and external validity of the elicitation methodology. The Figure 4.3 presents box plots of the dispersion of preferences for risk and ambiguity in our sample. We can see that the risk lottery's responses are more spread than for the ambiguity lottery's responses, but the later present some outliers.

We constructed a categorical variable with three modalities: if the respondent is risk (ambiguity) loving it takes the value 1, if the respondent is risk (ambiguity) neutral it takes the value 2, if the respondent is risk (ambiguity) averse it takes the value 3. The modality 2 is attributed if the farmer made 4 safe choices in the risk experiment and 5 risky choices in the ambiguity experiment. If the answer is below this neutrality number, the farmer is

[4]For the extreme categories we assume 2 and -2 under risk (as Reynaud and Couture [35]), which correspond to 2.55 and -0.75 under ambiguity if we assume the same computation method.

assumed to be risk (ambiguity) loving, and the farmer is assumed to be risk (ambiguity) averse if the answer is above this neutrality number. We produced the cross Table 4.3 of risk and ambiguity preferences according to these categories (45 answers with the missing values).

Table 4.3 – Cross table function of the modality

	Ambiguity			
Risk	Inclination	Neutrality	Aversion	Total
Inclination	2	1	1	4
% row	50	25	25	100
%column	15.38	7.69	12.50	11.76
Neutrality	2	2	0	4
% row	50	50	0	100
%column	15.38	15.38	0	11.76
Aversion	9	10	7	26
% row	34.62	38.46	26.92	100
%column	69.23	76.92	87.50	76.47
Total	13	13	8	34
% row	38.24	38.24	23.53	100
%column	100	100	100	100

We can see the proportion (frequencies and percent) in each crossed modality. It seems that the fact to be risk averse and ambiguity averse is positively correlated. However, we performed independence tests that all failed to reject the independence hypothesis: both variables cannot be considered as significantly dependent. In order to reinforce our conclusions about correlation between risk and ambiguity measures, we proposed pairwise Pearson correlations estimations. We will link three variables of preferences: the previously mentioned categorical variable, the initial variable of NSC and NRC, and the coefficients associated to the midpoint of each class. Associated results are presented in Table 4.4 (* p<0.1).

Table 4.4 – Pearson correlation coefficients

	Categ. (risk)	Categ. (amb.)	Midpoint (risk)	Midpoint (amb.)	NSC	NRC
Categ. (risk)	1.0000					
Categ. (amb)	0.2358	1.0000				
Midpoint (risk)	0.6791*	0.0471	1.0000			
Midpoint (amb.)	−0.7532*	-0.0335	−0.9895*	1.0000		
NSC	0.7106*	0.0482	0.9767*	−0.9893*	1.0000	
NRC	0.0998	0.8510*	0.0894	-0.0855	0.1343	1.0000

The positive significant correlations in the case of risk are not surprising because they always correspond to variables that covariate by construction. The interesting thing to note is the significant and strong negative correlation between the Midpoint variable for ambiguity and all the variables related to risk. The coefficient of ambiguity aversion being a descending variable, this result shows that more risk aversion is correlated with more ambiguity aversion.

4.4.2 Descriptive statistics

Crops and yields.

Our sample is constituted by farmers cropping mainly cereals for at least 75.72%, more than 10% by oilseed and the remaining part in other crops (vineyards, chestnut, etc.). In France, arable lands are constituted by 2% in vineyards, 34.56% of cereals (together with seeds productions), 1.1% of oilseeds, 0.73% of fruit trees, 5.47% of annual forages (especially ensilage maize) (MAA [30]). We have a special crop composition that deviates from the national figures and is widely represented by cereals. This is directly associated to the cooperatives we had access to (through InVivo group). The BANCO report (De Cara et al [12]), that is at the origin of the MACC estimation, was focused on annual crops, that in France is essentially represented by cereals. The work of Dequiedt and Servonnat [17] about risk and fertilization reduction was only treating cereals and oilseed, on a sample of farmers coming from the same group of cooperatives than ours (the advantage relies in the replication potential of the sample selection). The composition bias is thus limited in the fact that the perimeter of the abatement potential and costs estimation study corresponds a lot to these crops, and do not apply to all the crops that can be found in France. We still have to take it into account in our regressions if it leads to estimation bias.

We only show the descriptive statistics about yields for the main crops of our sample, wheat (15 answers) and maize (7 answers). The average level of actual harvested yields for wheat is 61.16 qt/ha (std 15.12 qt/ha) and the average level of yields objective is 67.16 qt/ha (std 14 qt/ha). The average level of actual harvested yields for maize is 118.7 qt/ha (std 35.5 qt/ha) and the average level of yields objective is 123.43 qt/ha (std 30.24 qt/ha). The rate of difference between actual yields and objectives is -5% for wheat and -4% for maize. We asked farmers the reason of the difference according to their perception. They said that meteorological conditions were the main explanation especially the quantity of rain that was too low or too high (71% of cases for maize and wheat farmers).

Figure 4.4 plots the relationship between actual yields and what was the objective at the beginning of the agricultural campaign. The bisectrix (green line) shows a hypothetical situation where there would be a perfect matching between the *ex ante* objective and the actual realization of yields. We can observe a positive and slightly convex relationship between both (red line), which is a sign that in our sample the higher the goals, the harder they are achieved, with a better matching for the highest goals.

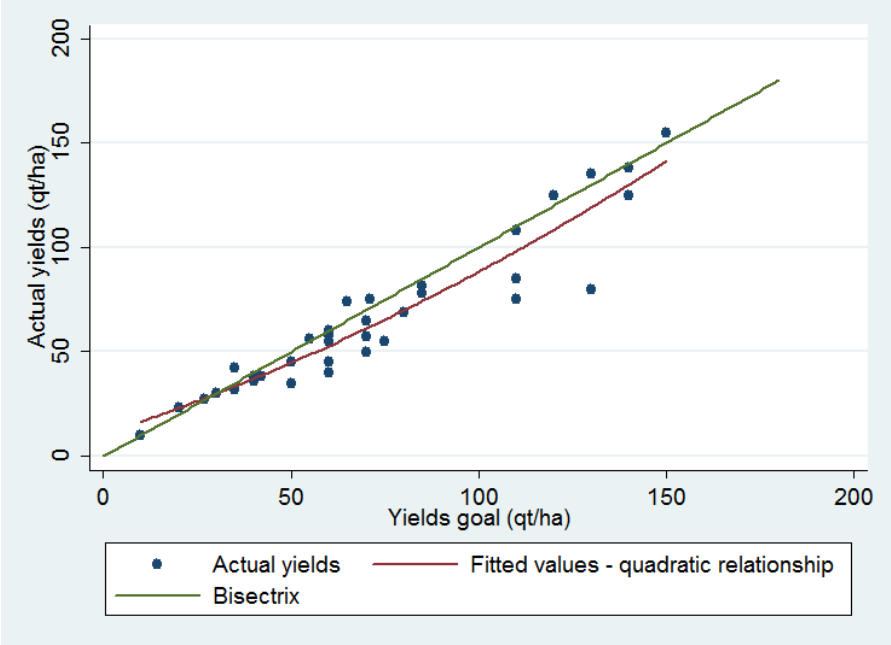

Figure 4.4 – Relationship between actual and objective yields

We constructed a rate of deviation on the form $\frac{actualyields-goals}{goals}$ in order to observe the level of deviation on a normalized basis, which allows volume comparisons. Results are presented in Figure 4.5.

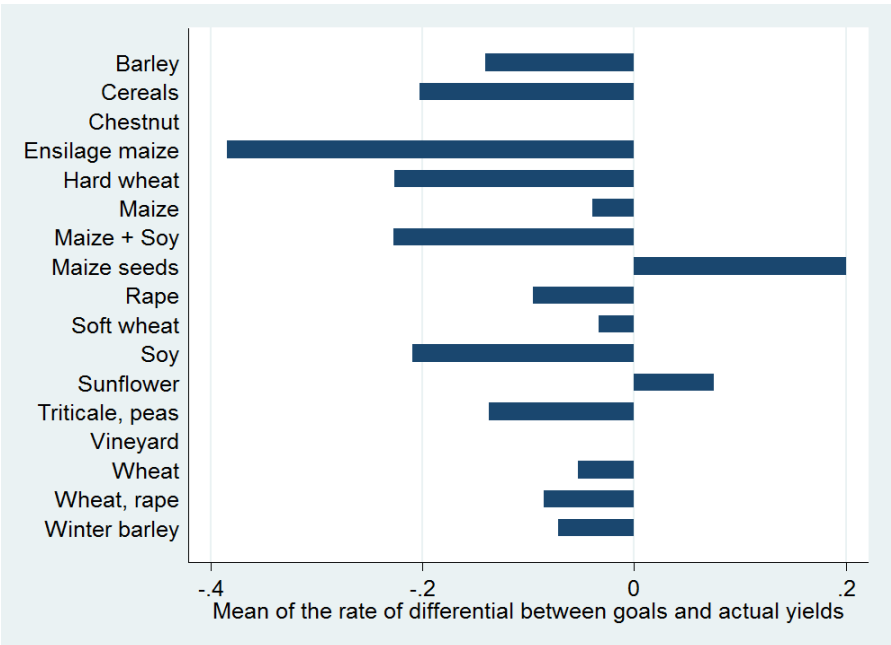

Figure 4.5 – Deviation rate between actual and objective yields

The average rate is -8.24% (std 0.14%, 37 answers). We can observe that the average

rate of yields objective achievement by crops is most of the time negative, strong for some crops (ensilage maize especially), and positive for two crops (maize seeds and sunflower). The 2018's agricultural campaign was particularly difficult for a lot of farmers all over the country. We can't deny that it could have an impact on lot of variables, and maybe also those related to uncertainty.

Synthetic nitrogen fertilization.

95.6% of the respondents applied synthetic nitrogen fertilizers on their parcel. The share of operational costs associated to synthetic nitrogen fertilizers use on the declared parcels is 26% on average (24 answers). This is important if we set that in general, labor (wage), mechanical soil work (fuel, etc.), seeds, other fertilizers, phytosanitary products and potentially irrigation might be contingent operational costs on the same parcel.

The nitrogen balance sheets give the total nitrogen fertilizers application on the parcel during the agricultural campaign (in kgN/ha). It does not make a lot of sense to observe the general statistics for this variable because it highly depends on the crop, and inter-crop comparisons have no actual interest in our topic. We still can say that the average level of fertilization is around 151 kgN/ha (std 72.5 kgN/ha, 37 non-empty answers) as indicated on Figure 4.6. This graph shows how farmers tend to follow advices from their cooperative agent in terms of fertilization for the annual cropping. We can observe that farmers relatively apply as much fertilizers as the advice, except some outliers. We still can say that there are more deviations when the advice is higher.

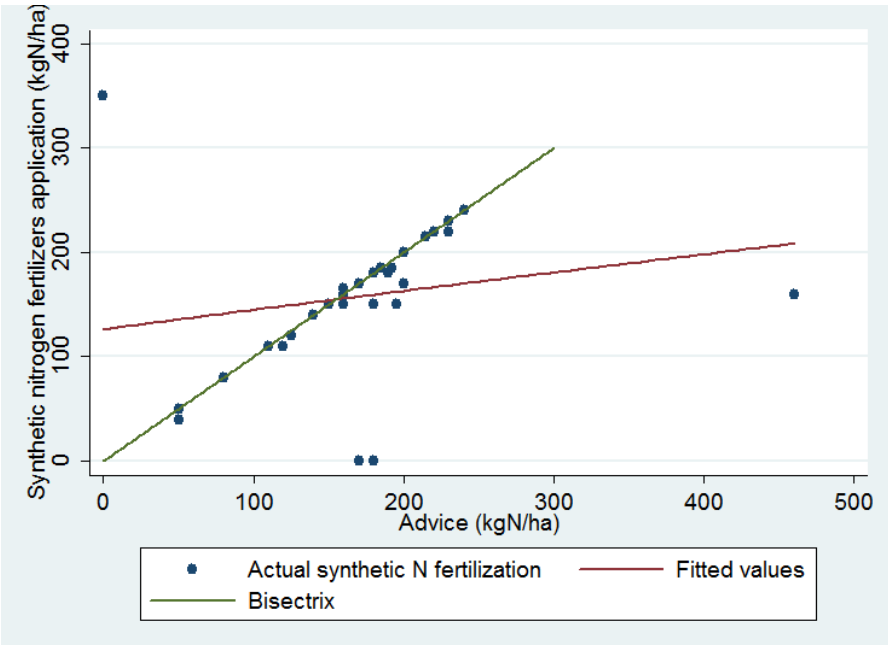

Figure 4.6 – Relationship between actual and adviced fertilization

Reducing the global synthetic nitrogen application balance sheet is an important mitigation practice. But it relies on the actual nitrogen rates in the soils, and depends on the alternative practice in case of insufficient nitrogen rate. While alternatives (like legume

crop in intermediary cropping) are not always applicable or efficient enough, another approach is to split the applications and to modulate each application in order to optimize the leaching by crops according to their needs over time, and thus to reduce the loss by non-absorption and the emission of N2O by volatilization. This is especially the first application at the beginning of the campaign (during the crop growth cycle) that can be source of modulation, and advisers try to push farmers to put less nitrogen fertilizers at the beginning and if needed, to compensate with more fertilizer at the next application. Moreover, the first application is associated to much more emissions (Sheriff [37]). Technically, the reduction of fertilization at the first splitting relies on the fact that it can still be nitrogenous from the last campaign and the precedent crop if soils are correctly managed between campaigns. In another vein, the first application is crucial and source of uncertainty if badly implemented: the beginning of the growth cycle is very important for the remaining of the campaign and for the yields goals to be reached (as well as quality goals). Moreover, it can be impossible to make sidedressing applications of nitrogen in the advanced stages of the growing-blooming cycle depending on uncertain water access and field work conditions, so that risk averse farmers would tend to apply more nitrogen than risk neutral farmers at the first application (Sheriff [37]; Bontems and Thomas [8]; Feinerman et al. [21]). However, the assumption that farmers attribute clear objective profits distribution to the fertilization practices is weak, since the issue may fairly be that the uncertainty can be deeper about the future states-of-the-nature, due to the embeddedness of several uncertain bio-physical factors in the forecasts related to sidedressing possibilities. We seek to see how splitting is implemented by the farmers from our sample, and also if it deviates from the advices coming from the cooperative agents, in relationship with risk and ambiguity preferences. The average level of fertilization at the first application is around 50.5 kgN/ha (std 24.7 kgN/ha, 37 non-empty answers). Once again, it depends a lot on crops and inter-crop comparisons are not our interest. We compute the same graph than Figure 4.6 for the first application of fertilizer. The same kind of behaviors is observable in Figure 4.7.

We developed indicators about the degree to which farmers tend to follow advices in terms of total synthetic nitrogen fertilizers application, of fertilizer application for the first application, and for the number of splitting. Farmers' preferences under uncertainty may impact the willingness to follow advices, if the assumption of uncertainty associated to their consequences is valid. The two first indicators share the same structure: $\frac{actualpractice-advice}{advice}$. They are a normalized rate of matching, that is negative if farmers put less than advised, positive if they put more, null if they perfectly match the advice. The more they go far from 0, the more the farmer deviated from the advice. The average rate of matching for the total fertilization is -0.08 (std 0.21, 33 answers), and for the first application it is -0.043 (std 0.28, 23 answers). For the number of splitting and the related advice, that is a relative integer, the indicator is just a difference between the actual number and the advised number. 0.5 means a semi-split: it is a situation where two different splittings were possible for the adviser (2 or 3, 4 or 5 for instance), and the farmer had the choice. The average number of difference between advices and actual practices is 0.1 (std 0.5, 29 answers). 79% of farmers applied exactly what they were told to in terms of splitting.

17 respondents have been placed in a "vulnerable zone" for the questioned parcel, a specific recognition of environmental quality on the parcel and the risk in terms of ecological destruction if certain farming practices are used (around 37% but there are a lot of

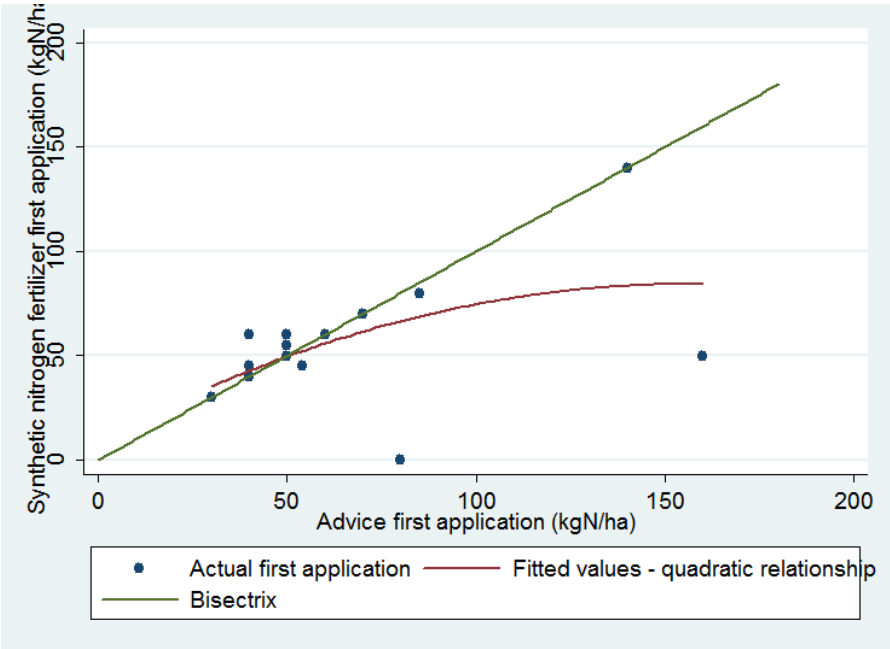

Figure 4.7 – Relationship between actual and adviced first application

missing answers). This official zoning implies obligation and forbidden practices, especially in terms of nitrogen fertilization. In our sample, the average maximum authorized quantity of nitrogen fertilization is 154.6 kgN/ha (16 answers). 20.6% declared having a mandatory fertilization method, such as using only organic fertilizer, liquid product, ovine manure (34 answers). These statistics give an idea of the weight of regulation on respondents, despite the regular lack of answers to these questions.

Other practices and characteristics.

We asked farmers who applied organic fertilizer (manure for instance) on the parcel how they did take into account the amount of nitrogen contained in this product. Among the 34 answers we collected, 35.56% only used the reference table (very generalist in terms of information), 20% only used an analysis of the product (the most precise source of information), and 4.4% both, while 15.56% did not take the amount of nitrogen into account. This application of organic-based nitrogen was taken into account for the synthetic nitrogen application by 90.32% of respondents (31 answers). Thus, we can see that the precise level of nitrogen that is applied is not always known by farmers before they apply fertilizer on their parcels. 59.38% of farmers that applied organic fertilizer buried it through tillage (32 answers). Only 4.9% of farmers did not apply any nitrogen fertilizer. 56% applied both on their parcel, while 39% applied only synthetic fertilizer and none of the farmers applied only organic fertilizers (41 answers).

Respondents come from Drôme (31.71%), Meuse (21.95%), Tarn (21.95%), Charente Maritime (12.20%), Isère (7.32%), and Meurthe (4.88%). We can see that we have a wide geographic dispersion with a non-homogeneous composition. This presents the advantage of getting us a control for some fixed local characteristics that can be catched through the department membership (or the town, that we know too). The disadvantage is that we

can't control for crucial heterogeneous unobservable variables that impacted diversely the locations and can explain individual farming choices. 43.9% of respondents own the parcel and 66.1% are tenant. 36.59% of farmers were cropping their parcel under a contract, mainly about seed production, product quality and industry-related sales. This characteristic can be important, especially for the case of quality contracts, because in some cases a good quality in terms of protein of the product (especially for wheat) requires specific amount of nitrogen level (less than for the "quantity-focused" cases). 32.5% of respondents had a crop insurance during the campaign (40 answers), which is closed to the national level. The average size of the parcel is 15.34ha. The average total area of the farms is 149.7ha, which is more than twice of the national average of around 58ha in 2013 according to Eurostat. The composition in terms of crop, as well as location specificities, and selection effects associated to the cooperative (InVivo group and its affiliations) may partly explain this difference. The average perceived CAP annual subsidy was 34 276 euros in our sample, and the average subsidy specifically related to environment was 3524 euros (10.3% of the total).

Socio-demographic statistics.

97.6% of our sample is composed by males (41 answers). The average age is 45.3 years old, in a range from 16 to 66 years old. In France, the average age of male farmers is 49 years old (53 years old for females) and 61% of farmers are aged between 40 and 60 years old (INSEE [27]). According to our data, 82% of our respondents are between 40 and 60 years old. Our sample is more concentrated in terms of age, and it may be related to the fact that being a part of the cooperative and being motivated about meetings create a selection of farmers. 45% of the respondents are married, 42.5% are single, 10% are in Civil Solidarity Pact and 2.5% are divorced (40 answers). In terms of education level, 77% of the respondents own a Baccalaureate (39 answers). At least 41% are Bac+2 and not beyond, which may correspond to a Agricultural post-bac technical diploma. 23% stopped school after the Bac. 18% only have a middle school certificate. In France, farmers who went above the Baccalaureate are 17%. 44% of French farmers stopped after middle school (MAA [30]). It shows our sample is constituted of farmers better educated than the general population at a country level. This is partly due to the composition in terms of age of our sample (32% are less than 40 years old against 23% for France), because younger farmers access a better education that the former generations (MAA [30]). 41% of the households in our sample are constituted of at least four people, 30.8% are constituted by the farmer alone, the remaining part is two or three people in the household (39 answers). 52% of respondents have two childrens, 20% have no childrens, 12% have three childrens and the rest have one, or more than three childrens (25 answers). Table 4.5 presents the farmer's revenues ranges for our sample:

Table 4.5 – Distribution of farmer's revenues

	Frequencies	Percent	Cum.
< €1000/month	3	8.11	8.11
from €1000 to €1500/month	9	24.32	32.43
from €1500 to €2000/month	4	10.81	43.24
from €2000 to €2500/month	8	21.62	64.86
from €2500 to €3000/month	4	10.81	75.68
> €3000/month	9	24.32	100

4.4.3 Pairwise correlations and marginal impact estimations

Correlations.

We performed pairwise correlations estimations (Pearson or Spearman) between all our measures of risk and ambiguity attitudes with interest variables: the total level of nitrogen fertilization, the level of fertilization at the first application, the number of splitting in fertilizers application, the rate of differential between the total advised application and what has been actually applied, the rate of differential between the actual and advised first application, and the rate of differential between the number of advised and actual splitting. We found no significant correlations with the Pearson coefficient applied on continuous variables. The Pearson coefficient fails at estimating correlation coefficient for ordinal or categorical variables. The Spearman rank-order coefficient is suited to estimate correlation coefficients with categorical variables. We found only one almost significant (p-value = 0.13) positive Spearman correlations between the NRC (ambiguity) and the level of fertilization at the first application (Spearman = 0.28). This would be the sign that farmer applies more nitrogen at the first fertilization splitting when they are ambiguity averse. Sheriff [37], and Bontems and Thomas [8] show that sidedressing nitrogen fertilization can be cost-efficient (better use of input) but depends on the propensity of farmers to take the risk that future natural conditions can prevent them from doing other applications after the first splitting. We find a negative relationship between our categorical variable of risk aversion and the number of fertilization splitting, but the coefficient is not significant. The main result with the Spearman rank-order coefficient shows a new relationship: ambiguity aversion leads farmers who agreed to split applications to apply more at the first stage in a situation where they are totally uncertain about what the future conditions will be. That can be the sign that when the risk of splitting is taken, ambiguity aversion encourages farmers to hedge against the probabilistic uncertainty that they are exposed to. However, lot of other factors can explain that phenomenon, that we can't test since we are not *ceteris paribus*. Moreover, the low level of observations and the unbalanced nature of the answers between respondents and questions make the estimations and tests limited.

Taking into account sampling design in regressions.

The observations of our sample were not individually selected: we performed our experiment randomly on the farmers that we had at our disposal in usual meetings that occured in the cooperatives. However, the probability of being "selected" in our sample directly depends on individual characteristics of the respondents (crop, soil, etc.) that lead them to be a part of these experiment groups and can simultaneously impact individuals' decisions. Those characteristics are heterogeneously repeated in the sample, so that the composition of the sample is not the same as for the total population. Any regression that would be runned without correcting for these sampling selections would attribute false phenomenons to the whole population of farmers, while the results would be only accurate for the sample at stake. Ignoring selection weight can thus lead to biases in estimation, and it is possible to fix this issue by attributing probability weight to each observation. Finding the proper variables that can be used to make good sampling weights depends on the available data and on the assumption we can make about the probability of selection. The crop the farmers choose on their parcel seems to us a good weighting variable, since the composition of our sample is widely determined by crops and targeting cooperative that work with annual non-perennial crop was one of our selection criteria.

The composition bias can be important, since two main crops compose our sample and wear specific agronomic and economic characteristics (wheat and maize). Moreover, this question has been generally well-filled by respondents. Adding probability weighting is feasible with Stata: the dependent and independent variables of each row is multiplied by a weight that corresponds to the inverse of the probability of having put each crop on the parcel and the variance-covariance matrix is estimated through a robust sandwich estimator. The more a crop represents a big proportion in the sample, the smallest will be the multiplied factor.

Our observations were collected by group (local cooperatives) so that there can be correlation between error terms between observations in a same group, leading to a failure of the homoskedasticity assumption. These clustering can be taken into account in the regressions by applying adjustment weighting coefficients to subgroups standard errors covariance matrix in order to correct heteroskedasticity. We can assume that the local cooperative groups from which the farmers come are natural clusters among which respondents are concentrated, and some unobservable phenomena can affect the group uniformly. This subgroup catches correlation between behaviors as well as a part of exogenous natural hazards. We can also use a White [39] heteroskedasticity consistent standard errors estimation in order to fix for heteroskedasticity issues, but it does not allow for clustered variability to be corrected, and the adjustment is at the individual level. We will compare both.

Regressions results.

We will only comment regression with significant coefficients. Given the limited number of observations, most of the relevant regressions were the ones with at least thirty observations. This is the higher average number of observations we obtained. Given the low number of degrees of freedom, we limited our regressions to one independent variable.

Table 4.6 – Total fertilization

VARIABLES												
Risk lovers	-28.25	-50.60	-50.60									
	(54.07)	(41.58)	(49.03)									
Risk averse	-58.16	-48.84**	-48.84***									
	(41.43)	(19.57)	(5.471)									
Ambiguity lovers				-12.25	18.80	18.80						
				(32.17)	(28.91)	(14.96)						
Ambiguity averse				-30.70	-14.52	-14.52						
				(37.48)	(40.08)	(21.10)						
NSC							3.754	6.827	6.827			
							(6.278)	(4.775)	(5.393)			
NRC										-3.424	-6.235	-6.235
										(6.794)	(6.461)	(4.430)
Constant	191.2***	186.9***	186.9***	157.4***	142.4***	142.4***	122.7***	103.5***	103.5*	162.6***	177.0***	177.0***
	(38.24)	(8.863)	(4.501)	(22.75)	(25.72)	(8.803)	(39.03)	(34.51)	(35.30)	(36.34)	(33.83)	(22.89)
Weighting (crop)	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Clustering (cooperative)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	31	31	31	31	31	31	31	31	31	31	31	31
R-squared	0.074	0.047	0.047	0.023	0.031	0.031	0.012	0.042	0.042	0.009	0.030	0.030
F	1.121	3.595	117.5	0.336	0.610	1.590	0.357	2.045	1.603	0.254	0.931	1.982
p-Fisher	0.340	0.0408	0.00142	0.717	0.550	0.338	0.555	0.163	0.295	0.618	0.342	0.254

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We can see in Table 4.6 that in the most robust regressions that we have (third column), the fact to be in the risk averse category leads to a significant lower level of total

Table 4.7 – Fertilization at the first splitting

VARIABLES												
Risk lovers	1.750	1.825	1.825									
	(19.35)	(6.614)	(7.242)									
Risk averse	-0.207	-4.310	-4.310									
	(14.82)	(6.873)	(5.037)									
Ambiguity lovers				-3.667	6.471	6.471						
				(8.682)	(8.172)	(6.882)						
Ambiguity averse				3.762	4.886	4.886						
				(10.11)	(12.61)	(2.738)						
NSF							0.732	1.529	1.529			
							(2.171)	(1.567)	(1.198)			
NRC										2.094	1.422	1.422*
										(1.796)	(2.005)	(0.527)
Constant	51.25***	53.14***	53.14***	48.67***	45.44***	45.44***	47.07***	41.02***	41.02***	37.76***	41.08***	41.08***
	(13.68)	(3.747)	(4.580)	(6.139)	(6.655)	(2.332)	(13.50)	(10.77)	(6.668)	(9.606)	(10.03)	(4.301)
Weighting (crop)	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Clustering (cooperative)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	31	31	31	31	31	31	31	31	31	31	31	31
R-squared	0.001	0.009	0.009	0.019	0.019	0.019	0.004	0.020	0.020	0.045	0.018	0.018
F	0.00873	0.318	0.537	0.277	0.315	8.685	0.114	0.953	1.628	1.360	0.503	7.282
p-Fisher	0.991	0.730	0.632	0.760	0.732	0.0565	0.738	0.337	0.292	0.253	0.484	0.0739

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

fertilization compared to the reference category of risk neutral farmers (coeff. = -48.84 significant at the 1% level). Reversely, the fact to be more ambiguity averse (NRC) has a positive marginal impact on the quantity of nitrogen fertilizers applied at the first split (coeff. = 1.422 significant at the 10% level). These results have to be interpreted simultaneously.

The first one indicates a phenomenon that is symmetric to numerous common assumptions about the positive impact of risk aversion on nitrogenous fertilization. While the role of risk aversion on fertilization, as we saw in the literature review, is not clear-cut and depends on the risk-increasing or decreasing nature of the input (and thus depends on the natural states-of-the-nature in terms of meteorological conditions, and complementarity with water and pesticide uses), nitrogen fertilizers seem to be not considered as a risk-decreasing input in our sample. This lowers the assumption that risk aversion can be a barrier to adoption of practices that reduces the total quantity of fertilizers use, because it reversely looks like a driver of reduction. However, it is notable that the risk aversion variable at stake is the categorical one: the reference category that we choose for comparison is the category 2, for risk neutrality. The coefficient is thus the average level of fertilizers of risk averse farmers in general compared to risk neutral farmers in general.

The second result is the most original. Ambiguity aversion leads to put more fertilizers at the first application split (see Table 4.7), which is equivalent to say that having an aversion for making bets on outcome whose probabilistic distribution is uncertain encourages farmers to hedge against future possible nitrogen lacks. We interpret this result as follows: if cooperative agents ask farmers to split their application, the first application is the most crucial, not only because it happens at the beginning of the growing stage for the crop, but especially because the farmer does not know if it will be possible for her to fertilize again at the future stages, because future states-of-the-nature are deeply uncertain. The possibility to make future splittings is dependent on this inability to make complete forecasts about entangled natural conditions. If we want to connect more the interpretation to the lotteries experiment, we can say that the ambiguity averse farmers insure themselves by

putting more fertilizers at the first splitting, which is exactly the thing cooperative agents do not want them to do, because they prefer to bet on a risky practice than an ambiguous one[5]. That would be the sign that the result confirms the risk-increasing nature of fertilizers, but farmers are sufficiently ambiguity averse so that they prefer to bear this risk, in order to cover themselves compared to the ambiguous situation. However, this impact is much smaller than the negative impact of risk aversion on total fertilization. Moreover, splitting practices induce dynamic evaluation of profits and optimal input uses, as shown in Bontems and Thomas [8], which implies other potential explanations, like information value. We do not test for that in this study. The benefits from splitting is, according to Bontems and Thomas [8], to allow the farmers to gather information about the true nitrogen needs of the crops and to be more efficient in their first and sidedressing application, thus reducing the production costs. We show in this study that ambiguity aversion may impact the total benefits from information value, and is a complementary driver of fertilization decisions.

The low number of observation for each regression (31) nuances our results. Adding control variables for crops (17 modalities), soil quality (21 modalities), precedent crops (22 modalities), interactions between risk and ambiguity preferences, differences between actual yields and yields goals and the perception of experienced risks at the last campaign by farmers, and several controls for agricultural practices and socioeconomic and demographic variables would produce more robust results and limit the biases that we may experience. Because each modality of the categorical variables represents a covariate, the necessary number of observations would have to be significantly higher. The dependent variables related to fertilization being directly explained by obvious variables like the crop that has been put on the parcel by the farmers or the soil quality, which are information that we asked in the questionnaire, it would be crucial to make our regression with these controls. This is an important caveat of our econometric analysis.

The indicators about the degree to which farmers tend to follow advices in terms of total synthetic nitrogen fertilizers application, of fertilizer application for the first application, and for the number of splitting were not sufficiently matched with answer about risk and ambiguity preferences, so that a too limited number of observations were gatherable. It reinforce our willingness to have more observations.

4.5 Conclusion

We implemented an experiment on farmers in collaboration with their cooperative group (InVivo group) in order to test on real data our main assumption: uncertainty may be a barrier to nitrogen fertilization reduction. We test two levels of preferences toward uncertainty, risk attitudes (known probability) and ambiguity attitudes (unknown probability). In the scope of our goal to estimate the interactions between those measures and the mitigation potential associated to fertilizer reduction, we seeked to test the role of these individual behavioral attitudes on diverse practices related to fertilization, about the fertilization practices directly (global level of fertilizer, level of fertilization at the first splitting, number of splittings) and the farmers' willingness to follow advices from their cooperative agents who try to lead them toward less emitting production practices. We also planned to estimate the role of several agricultural, regulatory and socioeconomic

[5]Adding variables of interactions between risk and ambiguity preferences is an extension we plan to do.

characteristics, and their embedded with uncertainty preferences, on fertilization practices and propensity to follow advices.

We found that our respondents were mostly risk averse, and ambiguity neutral or inclined. Our measures are closed to some previous studies on farmers. The representativeness of our sample in terms of crops is low (with comparison to French farmers) but is closed from the previous studies about nitrogen fertilization reduction, which often test the same kind of crops, cereals and oilseeds. The last campaign were globally not a good year for our respondents, who slightly failed on average to reach their yields goals. Our respondents did not follow perfectly what was advised in terms of fertilization, and an important part of them has to be in compliance with fertilization regulatory rules on their parcel. They present some important statistical differences with the national farmers population, in terms of size of farm (bigger), age (younger) and education (more educated).

We performed OLS regressions with considerations of sampling design in order to produce the most robust estimations as possible. We found significant marginal impacts only for two dependent variables (when sample weights and clustering are introduced), the total quantity of nitrogen fertilizer use, and the quantity of fertilizer use at the first splitting. Being risk averse is associated to a lower level of total fertilization (-48.8 kgN/ha on average) with respect to the reference category (risk neutrality). This result is interesting but difficult to analyze, because it can be the sign that nitrogen fertilizers are perceived as risk-increasing by farmers, or risk-decreasing (or neutral) but the global level of risk were perceived as very low by farmers who self-insure with fertilizers. It could be the sign of diverse water and fertilizer use characteristics (Feinerman et al. [21]) and interaction between pest invasion risk with good growing conditions and crops growth level related to fertilizer use (Horowitz and Lichtenberg [26]). However, we can say that the total level of fertilization may be always associated to yields goals and agricultural knowledge of farmers for which they might have an objective probabilistic "mapping", and a clear *ex ante* stochastic production plan for the whole campaign. The second main result is the positive marginal impact of ambiguity aversion (NRC variable) on the level of fertilization at the first splitting (+1.42kg/ha for each higher level of risky choice). While this result is unique to our knowledge, it echoes some previous researches that highlighted the deep uncertainty that lay behind the splitting practice. Indeed, splitting fertilization is a good way to adapt the fertilizer application to the crops' needs, but it relies on technical feasibility of postponed applications, which itself directly depends on unpredictable pedo-meteorological conditions, and their short-term deeply uncertain fluctuations. Uncertain evolution of states-of-the-nature can't be *ex ante* forecasted at the time of the first application, but the farmer can have subjective priors and be more or less pessimistic about what can be expected. In this scope, ambiguity aversion impacts positively the level of fertilization at the first application. However, the marginal impact is low, implying that even the global effect is negligible compared to the first result. The net total estimated impact of our preferences measures on the total fertilization is negative. Moreover, the first result is significant because of sampling weight, while the second is significant because of clustered heterosckedastic-robust standard errors. The first case is not surprising. On the other hand, the second fact indicates that the significance of the result depends on the consideration of specific cluster-dependent unobservable variables, like very local fluctuations and characteristics. It is interesting because it can echo our interpretation about the NRC result, that ambiguity associated to the first splitting is embedded in the indi-

vidual deep uncertainty about technical and natural feasibility of postponed splittings, which may be essentially local-specific and thus, partly shared by farmers from a given cooperative. In another vein, it is possible that the cluster-corrected standard errors fixes unobserved shocks on group-variations that are directly related to the differences that could have appear in the measurement processes between cooperative. While we tried to make exactly the same experiment on each farmers, it may have had slight differences which provoked group-specific measurement errors (day, time in the day, context etc.). This is specific to field experiments compared to laboratory experiments.

We have several external and internal validity issues. We are limited by the number of respondents and the subsequent number of valid answers in our estimations. This limits the external validity of our results. Our experiment may be seen as a pilot for a wider experiment, in order to observe if our current results are robust or not to all the necessary controls. In terms of internal validity, it would be an interesting extension associated to the fact that we do not test for time preferences impact in this study. Time preferences explain choices at each step of the production, as well as decisions in terms of practices and production goals. Secondly, the use of the MPL procedure entails advantages and caveats. These lotteries rely on the widely accepted assumption of a CRRA (power) utility function, and its form (chained lotteries with switching point) allows for the precise measurement of the level of risk aversion on the continuous distribution of gains. Moreover, its wide use in the literature allows for a good level of comparativeness of our results. The main caveats entangle the limit in identification of the actual preferences of the respondent. First, if the preferences of the agent do not follow a CRRA utility function, or more generally, if the individual has preferences not in line with expected utility framework, then the method is not relevant. This would lead to the risk that our subsequent regressions would have a limited internal invalidity and thus, limited results. Second, as we mentioned in the literature review, some critics have been developed by Drichoutis and Lusk [18]. However, these caveats did not prevent several studies to produce creditable results (see literature review).

There are two main implications in terms of public policies. First, this study partly shows that risk and ambiguity attitudes impact abatement costs associated to nitrogen fertilization reduction. While ambiguity aversion is a hidden costs of innovative fertilization practices like splitting, risk aversion can be a "hidden abatement benefit" for global reduction of nitrogen application. We can conclude that these phenomena question the optimality of flat rate subsidies. Fluctuations in production conditions can make fluctuate the abatement costs mechanically, and subsidies aiming at offsetting potential losses from reduction can become a windfall for farmers that would, in their majority, adjust their use of fertilizer by themselves. This feature induces a questioning of usual recommendations under risk consideration, like subsidized crop insurance that would cover yields risk and by this mean, encourages farmers to lower their fertilization: it depends on the interaction between nitrogen fertilizers and the environment they are applied in, and the crop, thus it can even have counter-productive effects on N2O mitigation (Sheriff [37]). If we get back to the work of Bontems and Thomas [7], we can say that fertilization splitting wears a huge benefit in terms of information value. This explains why farmers would be not so reluctant to adopt this practice. However, if ambiguity aversion increases the level of application at the first splitting and thus, increases emissions, it could be good to rather reducing uncertainty through generalized soil testing in order to securize information while developing new methods to ensure that sidedressing will be certainly mak-

able later in the campaign. Trials can also be offered under diverse forms in order to improve farmers knowledges about the reaction of crops to these new forms of nitrogen management over the growing period.

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Appendices

The ten-paired lottery-choice

Table 8 – The ten-paired lottery-choice decisions under risk

Decisions	Option A				Option B			
	Proba.	Payoff	Proba.	Payoff	Proba.	Payoff	Proba.	Payoff
1	10%	€ 7	90%	€ 5	10%	€ 13	90%	€ 0
2	20%	€ 7	80%	€ 5	20%	€ 13	80%	€ 0
3	30%	€ 7	70%	€ 5	30%	€ 13	70%	€ 0
4	40%	€ 7	60%	€ 5	40%	€ 13	60%	€ 0
5	50%	€ 7	50%	€ 5	50%	€ 13	50%	€ 0
6	60%	€ 7	40%	€ 5	60%	€ 13	40%	€ 0
7	70%	€ 7	30%	€ 5	70%	€ 13	30%	€ 0
8	80%	€ 7	20%	€ 5	80%	€ 13	20%	€ 0
9	90%	€ 7	10%	€ 5	90%	€ 13	10%	€ 0
10	100%	€ 7	0%	€ 5	100%	€ 13	0%	€ 0

Table 9 – The ten-paired lottery-choice decisions under ambiguity

Decisions	Option A: urn A		Option B: urn B	
	In urn A, the distribution of balls is 5 black and 5 white		In urn B, the distribution of balls is not known	
	Chosen color obtained	Chosen color not obtained	Chosen color obtained	Chosen color not obtained
1	€ 13	€ 0	€ 9	€ 0
2	€ 12	€ 0	€ 9	€ 0
3	€ 11	€ 0	€ 9	€ 0
4	€ 10	€ 0	€ 9	€ 0
5	€ 9	€ 0	€ 9	€ 0
6	€ 8	€ 0	€ 9	€ 0
7	€ 7	€ 0	€ 9	€ 0
8	€ 6	€ 0	€ 9	€ 0
9	€ 4	€ 0	€ 9	€ 0
10	€ 2	€ 0	€ 9	€ 0

Questionnaire

Survey on the use of synthetic nitrogen fertilizers

The survey you are going to participate aims at studying the climate change mitigation measures of the French agricultural sector. In particular, the survey focuses on farmers' fertilization decisions. Nitrogen fertilization is one of the main greenhouse gas emissions in the agricultural sector. The aim is to improve the understanding and determinants of fertilization decisions, particularly by focusing on an economic parameter reflecting individual preferences for risky choices.

This survey is conducted as part of a joint project between the INRA (National Institute for Agronomic Research), the Climate Economics Chair (CEC), and InVivo. More specifically, this work is part of a thesis in Economics, conducted within INRA.

The questionnaire will consist of three parts. In the first part, it will be necessary to make hypothetical choices between two options. These choices will help measure your

individual attitude towards risk. This method is widely used in economics to reveal to individuals their preferences for more or less risky situations. The second part will be composed of questions relating to your management decisions and, more particularly, fertilization. The final part of the survey will focus on your socio-economic characteristics.

There are no good or bad answers during the survey, just different behaviors to observe. For the purposes of the survey, you must answer all the questions. The confidentiality of the information contained in this questionnaire is ensured by the anonymity of the respondent. Your answers will remain confidential. The results will be presented in synthetic form in scientific publications with scrupulous respect for the anonymity of the respondents. Once the data is processed, it will be returned to you individually and you can compare your results to the average of our sample and your cooperative.

The lack of communication between participants is a guarantee of success. We ask you not to discuss with other participants during the survey.

1st part: Choice between two options

This first part is composed of two series of 10 decisions represented by two tables.

All questions correspond to fictitious situations for which we ask you to answer as if you were facing a real situation, taking the necessary time to choose the answers that best correspond to your preferences.

First table:

For each of the 10 decisions (lines) you must choose which of the two options (A or B) you prefer. Let's take an example. Decision 1 of the table reads as follows:

- Option A: get €7 with 10% chance or €5 with 90% chance.
- Option B: get €13 with 10% chance or €0 with 90% chance.

This decision 1 can also be represented in the form of a circular graph as well:

The following decisions read in the same way, only the probabilities associated with earnings change. Please complete the boxes below the table.

- I choose option A for decisions 1 to ☐.

You can answer with a number between 1 and 10. If you choose 3 it implies that option A is chosen for the first three lines, then B for the following ones. If you choose 1 it implies that you choose A only for the first line, and B for the others. If you do not put anything that implies that you choose B for all lines: you will have to answer 1 in the next question.

- I choose option B for decisions ☐ at 10.

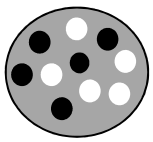
Decisions	Option A				Option B			
	Proba.	Payoff	Proba.	Payoff	Proba.	Payoff	Proba.	Payoff
1	10%	€ 7	90%	€ 5	10%	€ 13	90%	€ 0
2	20%	€ 7	80%	€ 5	20%	€ 13	80%	€ 0
3	30%	€ 7	70%	€ 5	30%	€ 13	70%	€ 0
4	40%	€ 7	60%	€ 5	40%	€ 13	60%	€ 0
5	50%	€ 7	50%	€ 5	50%	€ 13	50%	€ 0
6	60%	€ 7	40%	€ 5	60%	€ 13	40%	€ 0
7	70%	€ 7	30%	€ 5	70%	€ 13	30%	€ 0
8	80%	€ 7	20%	€ 5	80%	€ 13	20%	€ 0
9	90%	€ 7	10%	€ 5	90%	€ 13	10%	€ 0
10	100%	€ 7	0%	€ 5	100%	€ 13	0%	€ 0

Second table:
For each of the 10 decisions (lines) you must choose which of the two options (A or B) you prefer. This time, both options are likened to a draw in an urn composed of 10 balls of black or white colors. Option A corresponds to an urn composed of 5 black balls and 5 white balls. If you choose this option, you know that you have 5 chances out of 10 (or 1 chance out of 2) to win. In other words, the probability of winning is equal to 50%.

Option B corresponds to an urn whose exact composition is not known. If you choose this option you do not know exactly your chance to win. This varies between 0 chance out of 10 (for example, you choose the white ball, and the urn contains only black balls) and 10 chances out of 10 (for example, you choose the white ball and the urn contain only white balls). In other words, the probability of winning is between 0% and 100%.

Prior to the 10 decisions, you will have to choose the color that you consider as winning, black or white.
Choose a color: BLACK ☐ or WHITE ☐

Let's take an example. Decision 1 of the table reads as follows:
- Option A: get €13 with 1 chance out of 2 (50%) or €0 with 1 chance out of 2 (50%).
- Option B: get €9 or €0, but you do not know the chances of winning associated.
This decision 1 can also be represented in the form of an urn as here:



Urn A : 5 white balls and 5 black balls.

- Chosen color obtained : €13

- Chosen color not obtained: €0

Urn B : 10 balls, distribution not known.

- Chosen color obtained : €9

- Chosen color not obtained: €0

The following decisions read in the same way, only the potential gains for Option A change. Please complete the boxes below the table.

Decisions	Option A: urn A		Option B: urn B	
	In urn A, the distribution of balls is 5 black and 5 white		In urn B, the distribution of balls is not known	
	Chosen color obtained	Chosen color not obtained	Chosen color obtained	Chosen color not obtained
1	€ 13	€ 0	€ 9	€ 0
2	€ 12	€ 0	€ 9	€ 0
3	€ 11	€ 0	€ 9	€ 0
4	€ 10	€ 0	€ 9	€ 0
5	€ 9	€ 0	€ 9	€ 0
6	€ 8	€ 0	€ 9	€ 0
7	€ 7	€ 0	€ 9	€ 0
8	€ 6	€ 0	€ 9	€ 0
9	€ 4	€ 0	€ 9	€ 0
10	€ 2	€ 0	€ 9	€ 0

- I choose option A for decisions 1 to ☐.

You can answer with a number between 1 and 10. If you choose 3 it implies that option A is chosen for the first three lines, then B for the following ones. If you choose 1 it implies that you choose A only for the first line, and B for the others. If you do not put anything that implies that you choose B for all lines: you will have to answer 1 in the next question.

- I choose option B for decisions ☐ at 10.

Part 2: Management decisions on the largest plot of your farm, excluding pasture

We wish to remind you that all the answers to this questionnaire will be totally anonymous and will not be treated in any way outside the scientific publication for which they are intended.

For this part of the questionnaire, we will refer to the largest plot of your farm, excluding pasture. We would like to know more about your farming practices on this plot during the last crop year.

• Location:
→ Which department?
→ On which commune is your parcel located?

• What is your status vis-à-vis the parcel in question? ☐ Owner ☐ Tenant

• What is the main crop?

• Is it a contract crop? ☐ No ☐ Yes
→ If yes, what kind of contract?

• What is the smallest area spread on the plot (in hectares)?

• What is the type of precedent (previous crop on the plot)?

• What is the type of soil on the plot?

• What was your target for early returns (in qt/ha)?

• What were your real yields after harvest (in qt/ha)?

→ If objective and real returns have been different, please explain why:

• Have you applied one (or more) organic nitrogen fertilizer on this plot? ☐ No ☐ Yes
→ If yes, how much (in kg/ha)?
→ How was the amount of nitrogen contained in this (these) intake (s) taken into account?
☐ Analysis ☐ Reference table ☐ It was not taken into account
→ Does mineral nitrogen fertilizer advice take into account this quantity? ☐ No ☐ Yes

• Have you buried the fertilizer? ☐ No ☐ Yes

In terms of mineral nitrogen fertilization:

• Please indicate the amount of mineral nitrogen recommended by your nitrogen advisory agency on this plot (in kgN/ha)?

• Was there any advice on the first nitrogen intake? ☐ No ☐ Yes
→ If yes, how much (in kg/ha)?

• Have you been advised to split contributions? ☐ No ☐ Yes
→ If yes, how much ?

• Did you split the contributions? ☐ No ☐ Yes
→ If yes, how much ?

Regulatory Doses:
• Is there a maximum that you should not exceed on this parcel? ☐ No ☐ Yes.
→ If yes, how much (in kg/ha)?

• Is there a type of spreading that you must follow? ☐ No ☐ Yes
→ If yes, which one?
→ If yes, what is this regulatory constraint related to? ☐ Vulnerable area ☐ MAE ☐ Other

Actual decisions of mineral nitrogen fertilization:
• How much did you actually apply to this parcel in total (in kgN/ha)?

• And at the first intake (in kgN/ha)?
→ Explain the reasons for your choice:

• What is the share of synthetic nitrogen fertilizer costs in your total expenses for this parcel (in %)?

Some additional questions on your farm:

• How much PAC assistance do you receive in total (in €/year)?

→ Of this total amount, which amount corresponds to specific environmental aids and the reduction of the chemical spreading do you perceive (MAE or other) (in €/year)?

• Have you signed this year a voluntary agricultural yield insurance? ☐ No ☐ Yes

• What is the total area of your farm (in hectares)?

• Are you part of an operator's union? ☐ No ☐ Yes
→ If yes which?

Part 3: Socio-economic characteristics

Answers to these questions are essential to properly analyze your decisions. We remind you that your answers will be treated anonymously.

• What is your age in years ?

• Sex: ☐ Man ☐ Woman

• Marital status: ☐ Single ☐ Married ☐ Pacsé

• Level of studies :
☐ Without diploma ☐ Brevet ☐ Bac
☐ Baccalaureate + (specify the number of years of study after baccalaureate:....)

• Number of people in the household: ☐ 1 ☐ 2 ☐ 3 ☐ 4 and more
Among them, how much children ?

• In what interval are the total monthly incomes of your household (net of taxes)?
☐ < €1000/net/month ☐ from 1000 to €1500/net/month
☐ from 1500 to €2000/net/month ☐ from 2000 to €2500/net/month
☐ from 2500 to €3000/net/month ☐ > €3000/net/month

• Here you can express your opinion on synthetic nitrogen fertilizers and policies to regulate their use:

• Here you can give us your opinion on the survey (strengths, possible difficulties encountered, etc.):

Email address for the return of the results:

THANKS FOR YOUR HELP
WE WILL TRANSMIT YOUR INDIVIDUAL RESULTS WHEN THEY WILL BE PROCESSED

Chapter 5

Concluding comments

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This thesis focuses on the role of uncertainty as a barrier to adoption of mitigation practices in the agricultural sector. The literature explicitly shows that most of these practices may be of high technical quality and source of benefits for farmers. However, these mitigation practices can wear uncertainty and farmers can have misperceptions of the potential profits. This uncertainty prevents them from adopting if it negatively impacts the farmers profits evaluation or the utility they expect from their farming activities. Identifying the drivers of uncertainty's effect on adoption and quantifying it about some given practices is a first step that we did in this thesis. Our findings contribute to a better understanding of individuals' adoption choices drivers and a better identification of the environmental and agricultural policies targets and design.

The effect of uncertainty on agents' microeconomic choices is often introduced through separated channels in the litterature. We adopted a strategy of merging these diverse concepts, that can be associated in order to produce improvements in the comprehension of farmers' adoption decisions. This approach leads us to do three main studies which partly answer the main question in an eclectic way.

5.1 Uncertainty, irreversibility and information at the core of farmers' reluctance to adopt

We show that in a situation of uncertainty, typically with mitigation sufficiently disruptive or innovative in the usual farm management, uncertainty generates three different (possibly coexistent) hidden costs, and bad information can limit diffusion from early stages. We merge the diversification processes toward environmental friendly practices with a real option approach embedded with information through beliefs updatings. This framework allows us to take into account specific (physical) constraints of agricultural productions: the maximum land available constraint and the portfolio of land allocation in different activities. Irreversibility is introduced progressively. We introduce risk preferences and risk premia, while it is rarely used in real option theory. More precisely, we show that irreversibility makes dynamic choices non-separable, and negative signals are potentially lowering the willingness to adopt through the worse forecasts farmers can make. Under risk neutrality, a quasi-option value arises with irreversibility, which is a first hidden cost. Under risk aversion, risk premia are added as a second hidden cost at each period, that depends on individual preferences toward risk. Thirdly, with irreversibility and risk aversion, an irreversibility premium composed by risk premia plus quasi-option value that coexist, weights the profits evaluation from the first period and act like a hidden cost. Irreversibility and the choice dynamic create an asymmetry between bad and good signals' impact on profits evaluation. Bad signals at early stages can "nip diffusion in the bud". While most of current agricultural public incentives target diversification of farming practices toward mitigation practices, we claim that policy makers should take into account flexibility or irreversibility of these practices in their design, and socialize the costs associated to uncertainty in order to unlock diffusion of practices with negative abatement costs.

Different extensions can be done later on. First, we want to append a farm internal signal production into the information function. This extension would allow us to show arbitrage than can be made by farmers between adopting and taking benefit from their own information production about the potential good new practice, or not adopting and

observe external signals. The role of risk aversion and irreversibility may be of a great importance in this decision process, and may allow us to make a clear distinction in the driver of being a early or a lately adopter, with all the subsequent implications in the diffusion process. Secondly, the cost-efficiency of our political propositions has to be assessed. We claim that given the fact that some mitigation practices wear negative abatement costs, issues can arise from other perspectives than a classic matter of compensation from losses, and alternative policies can suffice to unlock adoptions if they reduce uncertainty and provide knowledge about practices quality to farmers. In this purpose, targeting one region where conditions seem reunited for high level of adoption and success of farm transformation, and spread good information around, can be a solution that lower the cost for the policy maker and achieve better results than current measures (flat inclusive subsidies). The cost-efficiency of providing higher but decreasing and temporary subsidies for mitigations wearing irreversibility, must be checked too.

5.2 Volatility in grass yields can prevent us from taking benefits from the potential of grasslands carbon sink

Increasing the share of grasslands into rotations of farmers-breeders can induce potential huge benefits for them. But volatility of herb yields, their high level of interaction with meteorological conditions and the lower number of technical levers associated to herb management with respect to this meteorological dependency compared to annual forage crops is a well-known issue in the topic of herb systems promotion. We develop a short static-dynamic model of stochastic land allocation and different measures of uncertainty, related to yields shocks and to yields volatility. We test empirically our assumptions through a classic land-use econometric panel model estimation with fixed-effects, and ran several regressions in order to check the robustness of results with respect to diverse assumptions : naive regressions, time dummies, control variables, and finally instrumentation method in order to tackle endogeneity. We show that Natural and old-seeded grasslands' yields shocks impact positively land-use ratio of each type of grasslands in the forage mix, as well as the alternative annual crop (ensilage maize) whose yields shocks impact Artificial grasslands like in a risk-hedging diversification strategy. This result shows how yields fluctuations lead to arbitrage between grasslands and strongly impact their use. We show that the temporary grasslands ratio in the forage mix is negatively impacted by OU measures and positively by MA measures, while the Artificial grasslands ratio in the forage mix is positively impacted by OU measures and negatively by MA measures, while the results are not clear-cut for Natural and old-seeded grasslands. We interpret this difference by the fact that OU measures can be attributed to long-term volatility forecasts while MA measures can rather be associated to short-term volatility forecasts. Given the estimated marginal impact of uncertainty, it is a crucial component of farmers-breeders choices, and has a non-negligible effect on the possibility of further development of grasslands in rotations. This impact must be hedged by the regulator in order to reach the political goal of grasslands promotion.

A tension can arise between policies aiming at conserving the carbon stocks of permanent grasslands by forbidding their destruction, and the potential of carbon sink related to adopting new grasslands for the current livestock. Uncertainty may induce that this environmental policy has a perverse effect, leading farmers not to lock into grasslands, whose yields are too uncertain compared to annual intensive crops, if they increase too

much the duration of non-permanent grasslands. This conclusion leads to a clear proposition for an extension: in order to check this assumption, it would be interesting to make a complete assessment of sustainable carbon storage in soil in grasslands over time and sequestration potential across years, together with integrating abatement costs, uncertainty and irreversibility. Making parameters associated to regulation move (especially considering grasslands destruction and subsidies design) can be a good simulation of the processes involved and the impact on GHG net emissions. Simulating the impact of providing centralized forage stocks in case of negative shocks, other insurance strategies, or the impact of the development of new levers aiming at improving herb production stability can be of interest too.

5.3 Not only risk but ambiguity aversion impact N2O emissions mitigation related to nitrogenous fertilization practices

Individual's preferences in a situation of uncertainty are known to impact practices associated to intensive margins. Nitrogen fertilization is a good example of that. Meanwhile, farmers together with cooperatives agents try to find margins in fertilization practices that can allow to achieve yields goals while limiting N2O emissions, and policy makers encourage farmers to reduce nitrogen fertilization by compensating the average potential loss due to nitrogen limitation. Nitrogen fertilizers have an effect on the stochasticity associated to yields, and farmers already know well the probabilistic distribution of yields related to input uses. Then, depending on the risk-decreasing or increasing nature of the fertilizer and farmers' preferences, nitrogen will be more or less applied, so that reciprocally emissions abatement will be enhanced or limited. Ambiguity preferences would catch a deeper level of uncertainty and adopting new practices of fertilizer application can fall in this particular situation, if you multiply the number of possible outcomes embedded with different states-of-the-nature. We test experimentally if there exist significant impacts of risk and ambiguity preferences on fertilization practices: total fertilization and fertilization at the first splitting. We used a MPL approach and a questionnaire for farming practices and socio-economics variables on a sample of 45 French Farmers. Some of our results are close to previous results in the literature, and we find that our sample is slightly statistically different from French farmers at the national level for some characteristics. We find that risk averse farmers apply less nitrogen fertilizer than risk neutral one in total. However, we also find that the more farmers are ambiguity averse, the more they apply nitrogen fertilizer at the first splitting.

We interpret the first result as a consequence of the possible risk-increasing nature of fertilizer with respect to the meteorological conditions during the last agricultural campaign. The second result would be related to the deep uncertainty which is associated to the splitting practice, because it relies on a difficulty to forecast future natural conditions that will allow or not sidedressing. Because risk aversion decreases whole fertilization it can be interpreted as a abatement co-benefit, while ambiguity aversion can be considered as a hidden abatement costs because splitting practice is a well-known approach to decrease N2O emissions from fertilization. However, we have not enough observations to control for crucial variables, like the cultivated crop on the parcel, the precedent crop and soil type. We can't either make parallel analysis with key variables, like insurance coverage or sales contracts types, or other interactions and control variables. Other extensions are

possible and can be done in future works: controlling for discounting behaviors, doing a contextualized experiment, testing for prospects and probabilities transformation are all extensions that we are currently considering. Developing a theoretical behavioral model that explains the ambiguity aversion effect we found experimentally, as well as finding innovative policies that can have an impact on ambiguity-related behaviors will be needed.

Chapter 6

Summary of the thesis (French)

L'incertitude en tant que frein à l'adoption de mesures d'atténuation en agriculture

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16 octobre 2019

Cette thèse porte sur le rôle de l'incertitude en tant que frein à l'adoption de mesures d'atténuation par les agriculteurs. Le changement climatique est un enjeu de poids face auquel de nombreuses politiques publiques ont été mises en place dans les différents secteurs de l'économie, notamment en France. Son atténuation est l'un des principaux challenges auquel les producteurs de biens et services font face, et l'agriculture n'est pas en reste compte tenu du niveau de ses émissions et de son potentiel de réduction d'émissions nettes. Plusieurs mécanismes incitatifs ont été mis en place afin d'encourager les agriculteurs à mener individuellement des actions d'atténuation de leurs émissions, via les changements d'un certain nombre de pratiques de production agricoles. La théorie économique classique visant à internaliser le coût du changement climatique dans les productions agricoles conduit à mesurer le coût d'abattement de pratiques dites de références et d'établir le niveau de taxe optimal permettant d'atteindre des objectifs de réduction fixés par les pouvoirs publics. Dans le cas de taxes "négatives" (subvention), il s'agit de rémunérer les agriculteurs pour des actions de réduction des émissions en compensant l'ensemble des coûts supportés par ceux-ci s'ils modifient leurs pratiques par rapport aux pratiques conventionnelles. C'est ainsi que fonctionne la quasi-totalité de la politique d'atténuation du changement climatique en agriculture en France, notamment du fait de la non-participa-tion du secteur au marché EU-ETS et de la difficulté de mettre en place un système de régulation stricte des pratiques qui augmenterait les charges opérationnelles des agriculteurs, dont un nombre important supporte déjà des charges élevées et une concurrence accrue sur les marchés internationaux : en effet, le développement rural et agricole est un enjeu collatéral fort des politiques agro-environnementales.

Dans cette perspective, un certain nombre de questions se sont posées récemment à propos de ces politiques incitatives. Premièrement, leur efficacité est remise en cause d'un point de vue *ex post*. En effet, si les résultats en terme d'adoption concrète de nouvelles pratiques dans la constellation d'exploitations agricoles sont difficilement mesurables, les émissions totales du secteur agricole sont en revanche celles qui diminuent le moins tous secteurs confondus, rendant les objectifs de réduction des émissions de plus en plus éloignés. Par ailleurs, le secteur peine souvent à se transformer, comme le montrent l'échec du programme Ecophyto concernant l'utilisation de produits phytosanitaires, ou autre exemple, le lent taux de progression de l'agriculture biologique dans l'ensemble du secteur. L'agriculture semble être le secteur économique national le plus inerte en terme de changements de pratiques liés à l'atténuation. Deuxièmement, l'estimation des coûts d'abattement associés aux principales pratiques d'atténuation a montré qu'un nombre significatif de pratiques présentent des coûts négatifs, autrement dit des bénéfices nets pour les agriculteurs qui les adopteraient sur leur exploitation. Ce résultat n'est pas unique, en agriculture comme dans d'autres secteurs, en France comme ailleurs. La présence de bénéfices nets potentiels à la réduction des émissions pose cependant la question des freins qui peuvent limiter la diffusion de pratiques d'atténuation. Ces freins économiques, qui cohabitent avec des freins sociologiques et comportementaux, agissent comme des coûts "cachés" qui sont non seulement absents du calcul des coûts d'abattement car non pris en compte pour l'instant dans les coûts mesurables, mais surtout mènent à des défaillances potentielles des politiques publiques qui ne les intègrent pas dans leur design. Les subventions étant censées permettre de corriger des défaillances de marchés, se retrouvent inefficaces sans cette correction, ce qui limite l'atteinte des objectifs politiques environnementaux. Différents coûts "cachés" sont évoqués dans la littérature portant sur l'adoption de nouvelles pratiques en agriculture, et parmi eux, l'un des principaux est l'incertitude. Cette thèse se propose d'explorer ce sujet, en montrant com-

ment l'incertitude peut, via différents canaux, limiter l'adoption de pratiques d'atténuation par les agriculteurs. Les méthodologies adoptées sont éclectiques : passant de la modélisation théorique, à l'économétrie, à l'expérimentation, nous nous proposons d'aborder la question de recherche sous différents angles, théoriques comme empiriques.

Le premier chapitre (1) constitue un état de l'art stylisé de la littérature portant sur le rôle de l'incertitude sur les choix de changement de production des agriculteurs. Après avoir caractérisé les principales pratiques d'atténuation du changement climatique en agriculture de manière générale, nous passons en revue les principaux canaux par lesquels l'incertitude peut engendrer des freins aux changements de pratique agricole. Ces canaux sont ceux que nous empruntons au cours de la thèse, selon les besoins du sujet d'étude de chaque chapitre. Nous les présentons tels qu'ils sont presque toujours présentés dans la littérature, c'est-à-dire séparés et faisant l'objet de conclusions parfois très différentes. La distinction Knightienne entre risque et incertitude (que nous appelons ici, incertitude au sens stricte) a beaucoup compté dans cette dichotomie historique. Le risque et les comportements face au risque sont les premiers drivers que nous présentons : présents dans la littérature d'économie agricole depuis très longtemps, ils constituent une explication fondamentale de nombreux comportements de production des agriculteurs. Les agriculteurs ayant de l'aversion pour le risque cherchent à se couvrir contre celui-ci ou à éviter de prendre de nouveaux risques qui ne seraient pas couverts par suffisamment de profit supplémentaire ou par un mécanisme de couverture du risque. Ces comportements, qui sont fortement liés aux caractéristiques des pratiques en terme de prise de risque, peuvent constituer un coût caché qui, s'il n'est pas intégré dans les incitations économiques, empêche les exploitants d'adopter de nouvelles pratiques. L'abondante littérature sur cette question montre que le sujet mérite d'être appliqué aux pratiques d'atténuation, afin d'améliorer la conception des subventions et autres politiques incitatives. Le risque correspond cependant à des cas où les profits sont incertains mais probabilisables objectivement, ce qui correspond à un niveau de connaissance élevé des pratiques associées. C'est le contraire dans le cas de l'incertitude au sens stricte (suivant la distinction de Knight) qui est associée à des cas où la pratique d'atténuation est suffisamment innovante pour que les agriculteurs n'aient pas assez de recul et de connaissance sur les profits associés. Il s'agit du deuxième canal que nous présentons. L'incertitude est en général modélisée dans cette situation via des croyances subjectives que les agents peuvent former sur les distributions de profits des nouvelles pratiques. Ce second courant de littérature, moins abondant en agriculture, met l'accent sur la dépendance des producteurs à leurs croyances initiales mais également à ce qu'ils peuvent observer de la vraie valeur des profits engendrés par l'innovation, donc, à l'information reçue par l'exploitant. Généralement étudiée dans le prisme de la théorie des options réelles, elle donne un rôle profond à l'irréversibilité de l'adoption d'innovation, dans ce qu'elle conduit à un regret potentiel si celle-ci se révèle moins profitable que la pratique conventionnelle. L'agriculteur ne sachant pas initialement la distribution réelle des profits de la nouvelle pratique, il peut être poussé à recueillir suffisamment d'information afin de déterminer son choix optimal. Contrairement au risque, où l'accent est donné à la forme de la distribution connue des profits et aux préférences individuelles pour certaines formes de distributions (plus ou moins dispersées notamment), l'incertitude au sens stricte met l'accent sur les croyances et les anticipations sur les profits espérés, ainsi que leur mise à jour au cours du temps et leur comparaison face au statu quo. Nous introduisons le fait que si la distinction knightienne est généralement cruciale car chaque courant de pensée se développe sur des hypothèses, fonctionne sur des méthodologies, et mène à des conclu-

sions et préconisation bien différentes, elle peut cependant être allégée dans l'étude de certaines pratiques d'atténuation selon les besoins méthodologiques du chercheur. Le dernier canal par lequel l'incertitude peut constituer un frein à l'adoption de nouvelle pratique est l'ambiguïté. Elle correspond à une situation dans laquelle un "risque de risque" pèse sur les profits des pratiques agricoles, c'est-à-dire, que les probabilités associées à la distribution objective des profits sont elles-mêmes incertaines. Des pratiques relativement connues des agriculteurs, associées à des connaissances suffisantes sur le risque qu'elles revêtent, peuvent devenir source d'une incertitude plus profonde si des modifications qu'on y apporte entraînent un doute sur la distribution de profits qui peuvent en être générés. Imaginons qu'une pratique courante et connue soit remise en cause par un conseiller agricole afin de modifier le mode d'administration d'un intrant déjà utilisé ou le mode de gestion d'une culture déjà cultivée sur la ferme, dans le but de tirer parti d'un gain d'efficacité à la marge : ce changement de pratique peut conduire simultanément à des économies et à une réduction des émissions de gaz à effet-de-serre. Les processus biophysiques inhérents à la production agricole, qui sont une interconnexion complexe de phénomènes naturels stochastiques dans lesquels l'agriculteurs doit normalement apporter des leviers agronomiques, mènent à une remise en cause de ce que l'agriculteur croit être la distribution correcte de ses profits. Dans ce cas, plusieurs distributions peuvent cohabiter dans l'esprit de l'exploitant, une situation qu'il peut déprécier et vis-à-vis de laquelle il peut chercher à se prémunir et se couvrir. La littérature est assez récente sur le sujet, et particulièrement limitée dans le cas de l'adoption de pratiques d'atténuation en agriculture. Nous introduisons l'intérêt que cette approche revêt, en tant que troisième canal. Enfin, nous présentons les contributions de chaque chapitre.

Le second chapitre (2) constitue une approche théorique de la question de recherche, dont la principale caractéristique est d'introduire l'irréversibilité de l'adoption d'une nouvelle pratique au cœur de la préoccupation de l'agriculteur, du fait de l'incertitude, conjointement aux préférences face au risque. Ici, les probabilités associées aux profits incertains sont considérées comme des croyances subjectives bayésiennes, mais les profits sont cependant susceptibles d'être considérés comme risqués par l'agriculteur. Cela implique la conjonction d'un phénomène de type option réelle induisant une prime d'irréversibilité et de l'apparition de primes de risque, ainsi que la possibilité d'externalités informationnelles liées à la mise-à-jour bayésienne des croyances. La structure du modèle nous permet d'extraire les coûts "cachés" liés à la valeur d'option et au risque de manière séparée, mais pouvant cohabiter ou être liés selon les caractéristiques de l'exploitant et de la nouvelle pratique. L'externalité informationnelle notamment, n'est supposée possible que dans le cas d'adoption partielle que nous expliquons grâce à l'aversion au risque. Il est ainsi possible que l'effet de l'irréversibilité ne limite pas l'adoption sans aversion au risque, mais que ce soit le cas avec aversion au risque si cela conduit à une externalité informationnelle générée par les premiers adoptants. Nous illustrons ces résultats dans une simulation avec calibration sur données réelles dans le cas de l'adoption de miscanthus, une culture servant à la production de bio-fuel, qui est une culture pérenne aux profits incertains. Nous présentons une situation originale permettant de mesurer les différents coûts et l'impact sur le niveau d'adoption, mais aussi d'illustrer ce phénomène spécifique d'externalité informationnelle en cas d'aversion au risque.

Le troisième chapitre (3) s'attache à mesurer empiriquement l'impact de l'incertitude sur l'allocation de terres fourragères aux prairies en France. En effet, l'adoption de plus de prairies dans les rotations (pour fauche ou pâturage) constitue une pratique d'atténuation

à très forts potentiels et co-bénéfices environnementaux, et à coût d'abattement négatif. Nous partons de l'hypothèse que l'incertitude sur les rendements herbagers peut constituer un frein à leur plus ample adoption en ce qu'elle peut réduire la valeur implicite de l'usage "prairies" des terres agricoles à destination fourragère, vis-à-vis de cultures annuelles étant moins complexes et pour lesquelles l'agriculteur a plus de leviers de stabilisation tel que le maïs ensilage. Devoir verrouiller une partie de ses terres dans des prairies, même temporaires, peut ainsi être difficile du fait de la volatilité des rendements herbagers. Nous nous proposons de mesurer l'impact de l'incertitude sur les rendements grâce à un modèle économétrique d'usage des terres en panel sur les départements métropolitains, dans le cas des trois principaux types de prairies fourragères : les prairies temporaires et artificielles (non permanentes) et les prairies naturelles ou semées depuis plus de 5 ans (permanentes). Un avantage de cette distinction dans les données et que chaque type de prairie n'est pas de la même nature et ne revêt pas le même niveau d'irréversibilité. L'incertitude est mesurée via différents indicateurs que nous avons voulu complémentaires. Des problèmes d'endogénéité nous conduisent à employer la méthode instrumentale en utilisant des données météorologiques agrégées, et à chercher par différents moyens les résultats les plus robustes. Ceux-ci montrent que l'incertitude impacte différemment les parts relatives des divers types de prairies fourragères dans les rotations départementales, de manière souvent symétrique. L'incertitude impacte surtout l'allocation de terres aux prairies non-permanentes, parfois positivement et parfois négativement. Certains effets de complémentarité entre les diverses options de fourrages en cas de chocs sont aussi visibles. L'ensemble de ces phénomènes conduit à la conclusion que l'incertitude joue un rôle particulièrement fort dans la propension à adopter des prairies dans les rotations, rôle qui doit être pris en compte dans les politiques publiques dans le but d'inciter correctement à leur déploiement. Par exemple, l'allocation aux prairies temporaires, qui sont destinées à devenir des prairies permanentes protégées si elles ne sont pas déplacées ou détruites au bout de cinq ans (et doivent donc stocker du carbone), est particulièrement impactée négativement par notre mesure de volatilité de long terme : plus la volatilité est intense et plus nous mesurons une désallocation dans ce type de prairie, ce qui pourrait remettre en cause la production de nouvelles prairies permanentes et donc le puit de carbone associé, à cause d'un effet d'irréversibilité.

Dans un quatrième chapitre (4) nous abordons le cas de la réduction de la fertilisation azotée, mesure d'atténuation fondamentale, qui concerne une pratique déjà bien connue des agriculteurs. La modulation des apports en fertilisants azotés peut conduire à des gains d'efficacité et une réduction des émissions de N2O. Portés par de précédentes recherches sur le rôle des préférences face au risque sur le niveau de fertilisation, nous tentons d'apporter une confirmation ou non des précédents résultats sur le sujet mais aussi d'étendre l'étude aux préférences face à l'ambiguïté. Nous utilisons pour ce faire des méthodes expérimentales de mesure des préférences suffisamment validées dans la littérature et les combinons avec des questions économiques et agronomiques sur les décisions de fertilisation. L'étude a été réalisée sur un échantillon de 45 agriculteurs. Différentes techniques économétriques sont appliquées afin de prendre en compte le plan de sondage complexe et extraire du mieux possible des résultats significatifs. Il est montré que les agriculteurs ayant de l'aversion pour le risque fertilisent moins sur l'ensemble de la campagne agricole que les agriculteurs neutres au risque. Cela implique que les fertilisants azotés doivent être perçus comme impactant positivement le niveau de risque, et dans ce cas l'aversion au risque n'est pas un coût "caché" à la réduction de la fertilisation azotée. Le niveau d'aversion à l'ambiguïté n'impacte pas le niveau de fertilisation

totale. En revanche, nous montrons qu'il conduit à mettre significativement plus de fertilisants azotés au premier apport en cas de "splitting", une technique visant à ajuster les apports aux besoins des plantes en séparant les applications, ce qui fait partie des pratiques d'atténuation possibles liées à la fertilisation azotée. Ainsi, mettre plus de fertilisants pourrait conduire à émettre plus de N2O et donc réduire l'intérêt environnemental d'une telle pratique. Nous interprétons ce résultat comme une conséquence directe de l'incertitude profonde qui règne en cas de "splitting" sur les possibilités d'application postérieure et la réponse des cultures à ce type de procédé. Ce résultat montre que les pratiques d'atténuation, selon leurs caractéristiques spécifiques en terme d'interactions entre les conditions pédoclimatiques et les décisions de production, peuvent se révéler ambigües, ce qui impliquerait un coût "caché" de type nouveau à prendre en compte.

Le dernier chapitre (5) conclut la thèse. Après avoir replacé le travail dans la question de recherche globale, nous résumons les contributions de chaque chapitre en ouvrant les perspectives futures que nos résultats impliquent. Nous rappelons l'intérêt de ce travail : mieux comprendre les comportements des agriculteurs, démontrer que l'incertitude peut mener à des freins à l'adoption de pratiques d'atténuation via différents vecteurs, et qu'elle doit impérativement être prise en compte par les politiques publiques afin d'atteindre les objectifs environnementaux que les pouvoirs publics ont fixé.