Productivity, Price Volatility, and Dynamic Choices in French Agriculture

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THESE DE DOCTORAT DE

AGROCAMPUS OUEST
COMUE UNIVERSITE BRETAGNE LOIRE

ECOLE DOCTORALE N° 597
Sciences Economiques et sciences De Gestion
Spécialité : « *Sciences Economiques* »

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Thèse présentée et soutenue à Rennes, le 30 Novembre 2018
Unité de recherche : INRA, UMR SMART-LERECO
Thèse N° : 2018-26 E51

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Abstract

The EU has adopted many reforms of the Common Agricultural Policy (CAP) in the past decades. Price support has decreased, and decoupled payments have been introduced. As a result, European agricultural prices have become more volatile, in line with world prices.

This dissertation measures the evolution of the productivity of French agriculture in a dynamic stochastic farm decision model in the new economic context with increased price volatility. On this basis, it studies the dynamic link between price risk, farmer decisions, and productivity in the structural estimation framework. The literature review in Chapter 2 describes productivity as a residual and emphasizes the measurement issues from the unobserved capital data series and the endogeneity problem in primal estimation. Chapter 3 compares the numerical methods to solve and estimate nonlinear dynamic stochastic general equilibrium (DSGE) or DSGE-like models, in which capital and productivity are latent state variables. Chapter 4 estimates productivity in a dynamic stochastic decision model based on the generalized maximum entropy (GME) approach. We show that the productivity growth in French agriculture has slowed down and become much more volatile following the increase in price volatility. Overall, price risk has an impact on productivity in the way that when exposed to high risks, farmers change their production, consumption, investment and financial borrowing decisions, which in turn affects the realized productivity negatively. Chapter 5 simulates the market impacts of the CAP instruments in a dynamic GTAP-AGR CGE model with risks. We show that risk and risk attitude matter when assessing the impacts of the CAP reforms.

Keywords: agricultural productivity; price volatility; dynamic decisions under risk; agricultural policy; structural estimation

Productivité de l'Agriculture Française et Volatilité des Prix

Mots clés: productivité de l'agriculture ; volatilité des prix ; choix dynamique ; politique agricole ; estimation structurelle

Résumé

À la suite des réformes successives de la Politique Agricole Commune (PAC), les soutiens publics européens par des prix nominaux constants ont diminué au profit de soutiens directs aux revenus agricoles. Cela a exposé les agriculteurs français à une grande volatilité des prix, reconnectés avec les prix mondiaux.

Cette thèse mesure l'évolution de la productivité de l'agriculture française dans un modèle dynamique stochastique en intégrant la récente augmentation de la volatilité des prix. Nous étudions le lien dynamique entre le risque de prix, les décisions des agriculteurs et la productivité dans le cadre de l'estimation structurelle. La revue de la littérature présentée dans le chapitre 2 décrit la productivité comme un résidu et souligne les problèmes de mesure des données du capital et le problème de l'endogénéité dans l'estimation primale. Le chapitre 3 compare les méthodes numériques permettant de résoudre et d'estimer les modèles d'équilibre général dynamique stochastique (DSGE) ou de type DSGE, dans lesquels le capital et la productivité sont des variables d'état latentes. Le chapitre 4 estime la productivité dans un modèle dynamique stochastique en utilisant l'approche de maximum d'entropie généralisée (MEG). Nous trouvons que la croissance de la productivité de l'agriculture française a diminué après la réforme de la PAC, à cause de l'augmentation de la volatilité des prix. En effet, le risque de prix impacte la productivité négativement à travers les choix de production, de consommation, d'investissement et d'emprunt des agriculteurs. Le chapitre 5 simule les impacts de marché des instruments de la PAC dans le modèle d'équilibre général calculable GTAP-AGR où est introduit la dynamique et le risque. Nous montrons l'importance du risque et de l'attitude vis-à-vis du risque pour l'évaluation des réformes de la PAC.

Remerciements

I want to express my gratitude to my advisor Alexandre Gohin. During my first interview with Alex for an internship position, I told him that I want to do research in economics such to contribute to some “common good” to the public. A simple OK opened my academic adventure in the following years. This Ph.D. project, which started three years ago, would not exist without Alex’s trust in me. I thank Alex for sharing his knowledge and understanding in economics with me, and for supporting me in every possible way to develop my thesis and my career. I enjoyed many discussions with Alex - I have always been inspired by his creative thinking and his insight in agricultural markets.

It has been a privilege to have Christoph Heinzel as a co-advisor. I am grateful to his constant supply of patience, encouragement, new knowledge, and helps in academic writing. In addition to the great answers I had from Christoph every time I came for advice, I am in particular thankful for his friendship.

I thank the INRA SAE2 department and the region of Brittany for funding this thesis.

I would like to thank all the members of the committee for their constructive evaluation of the thesis. I am especially grateful to Jean-Christophe Bureau and Sergio Lence for accepting to be the rapporteurs, for their attentive review of the manuscript, and their insightful comments. I would like to thank Stéphane Auray, Michel Juillard, Catherine Laroche-Dupraz, and Katheline Schubert for accepting to be the examiners and for their highly valuable questions.

Many people have given valuable comments during the different stages of the thesis. I would like to thank the members of my thesis monitoring committee, Alban Thomas, AJ Bostian, Irz Xavier, and Jean-Christophe Poutineau. Special thanks to AJ for his high-quality guidance in numerical computing. I have spent a snowy spring at Iowa State University, where I was warmly hosted by Sergio Lence. I have benefited intellectually from every conversation with Sergio. I also want to thank Nicolas Treich for inviting me to seminars at TSE when I had the opportunity to travel to Toulouse.

The INRA SMART-LERECO laboratory has created an ideal environment for me to do this thesis. I want to express my sincere thanks to all the members of SMART-LERECO. I thank Alain Carpentier, for his presence and encouragements in almost all my presentations in the international conferences, Carl Gaigné, for the help in supporting me to teach at Université de Rennes 1 and the career suggestions, Fabienne Féménia, for her help with my third paper and the French abstracts, Angela Cheptea, who has been a great neighbor and drove me home when we worked late. I have also benefited, academically and personally, from the interactions with Pierre Dupraz, Chantal Le Mouël, Elodie Letort, Stéphane Turolla, Nicolas Legrand, and Laurent Piet. I would like to thank the administrative help from Françoise Auffray and Cécilia Elléouet, and the library and IT support from Christine Mesquida, Lise Frappier, and Anne Chauvel.

I spent much joyful time with my peer colleagues and have shared my frustrations and achievements with them. Special thanks to Romain Gaté, François Bareille, Théophile Bassène, Philippe Koutchadé, Löic Lévi, Julia Jouan, and Elodie Marajo-Petitzon. I would not have accomplished my thesis without the supports from my life-long friends, Su Wei, Su Zhi, Li Xiaoxu, and Sherry Li.

Last, I want to thank my partner, Yin Yang, for your love, and for the happiest time we have had, and will have together.

Contents

Chapter 1

General Introduction

1.1 Motivation

The French agriculture is confronted with several economic, environmental, and social challenges. Among the economic challenges are the increasing competition from the foreign countries, which is partly a result of the trade reforms under the Common Agricultural Policy (CAP) and in bilateral agreements. Competition also rises from other European countries, especially in northern Europe. Moreover, French farmers face an increasing price volatility in agricultural outputs and inputs. This is partly due to the CAP reforms which reduce price supports and introduce direct payments that impose fewer market interventions. The environmental challenges include the more constrained natural resources, and also the pressure from regulation, which aims at generating fewer negative impacts on the environment while increasing its positive externalities.

Like for other productive sectors, a key element for the French agriculture to meet these challenges is its ability to improve productivity. This is because productivity growth is the principal driver of output growth, and it is an important factor for the competitiveness of the economy (Ball et al. 2015, Andersen et al. 2018). Persistent productivity growth has been realized in all industries, including in agriculture, thanks to the major innovations in information technology and automation. However, according to the total factor productivity (TFP) index of the European Commission (2016), in line with the EU-15 member states, agricultural productivity growth in France has been slowing down over the past decades.

Productivity and its dynamics are not only reflections of technology growth, but also the choices regarding technology adoption, resource allocation, incentive, and structural adjustments. From the perspective of policymakers, these choices, along with innovations, are related to policies that influence market conditions and investments in research and education. Because productivity is not directly observable, the economists' task is to understand productivity, identify the sources of productivity growth, and develop unbiased productivity measures.

This dissertation aims, first, at measuring the evolution of productivity in French agriculture using a dynamic structural model, accounting for the increasing price volatility in the new economic and regulatory context. Second, we study the dynamic link between price volatility, farmer decisions, and productivity in the structural estimation framework. These two objectives are realized by developing dynamic structural models in which economic incentives and prices influence the economic agents' decisions, and considering structural change in price volatility. We estimate productivity and the behavioral parameters in the dynamic structural model. We build on estimation methods that are well developed for estimating state-space models and dynamic stochastic general equilibrium (DSGE) models. The estimation contributes to alleviate the measurement issues related to the unobserved capital input, and the endogeneity issue with estimating a production function.

The third objective is to assess market impacts of the policy instruments in the context of volatile prices. This is made based on developing a dynamic stochastic version of a computable general equilibrium (CGE) model. The econometric evidence of the effect of price risks on agricultural production, and especially on productivity, provides the empirical basis for the policy analysis.

In the following, we motivate the research objectives.

Policy Reforms and the New Price Volatility Pattern

To ensure a stable income for farmers, a stable supply of affordable food for consumers and to enhance the competitiveness of EU agriculture, the CAP in the EU has been successively reformed over the past decades. Figure 1.1 illustrates the evolution of CAP expenditures since 1990: it gradually reduces the price instruments (export subsidies and other market support) and coupled payments and introduces direct payments. The major reform in 2003 introduces the "Single Farm Payment" policy to decouple the subsidies from production, and the direct payments are mostly linked to land use. The new CAP 2014-2020 increases the focus

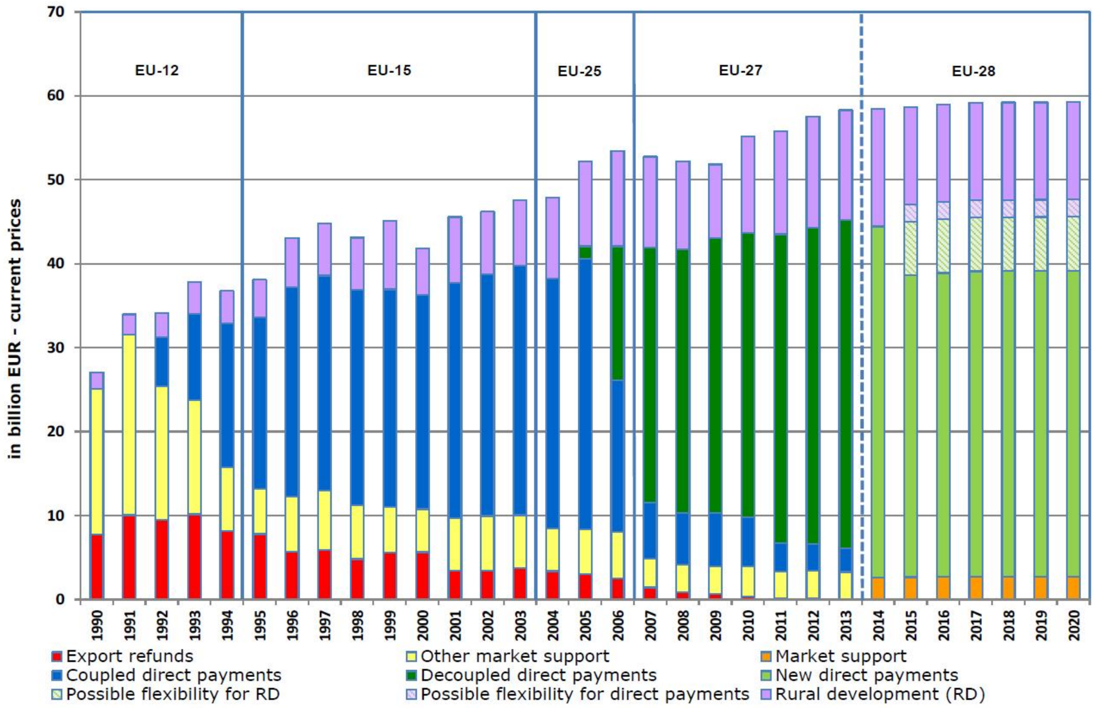
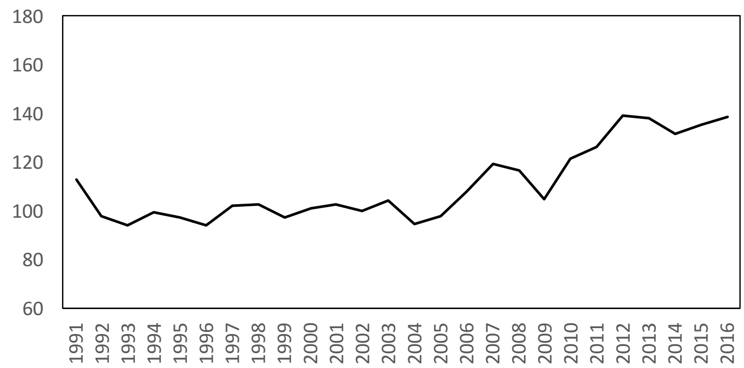


Figure 1.1: The path of CAP expenditures by calendar year (in current prices) (Source: European Commission 2013)

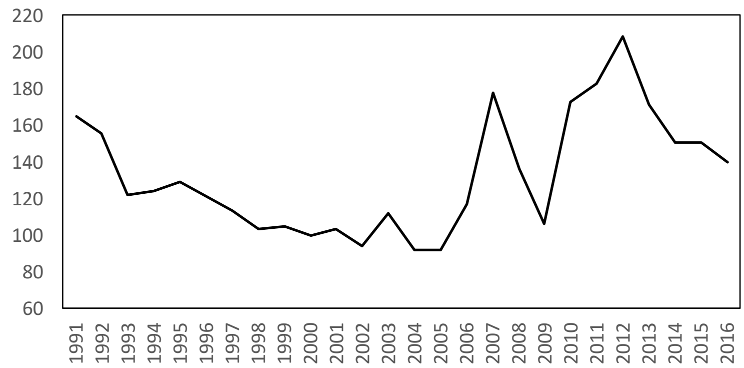
on environmental and risk-related issues, and seeks to target support to the farmers who are active in production. Land subsidies shift gradually to new direct payments which are designed for active farms, with encouragement for young farmers and small farms, and with increasing conditions for environmental criteria and risk-management measures. Moreover, an increasing amount of the budget is spent on rural development, aiming to foster knowledge transfer and technology innovations in order to improve productivity.

At the national level, there is an increasing political will aiming at changing the practices in agriculture to reduce certain negative externalities, such as those from the use of the pesticides for crops and antibiotics for livestock.

The succession of CAP reforms, especially the major reform in 2003, have resulted in greater exposure of European agriculture, including the French agriculture, to the highly volatile world prices. The level and volatility of the world prices increased significantly after 2000. The agricultural prices in France, which for a long time had been stable and had a declining trend in cereal products, started



(a) Producer price indices in France: agriculture (Source: FAO-STAT)



(b) Producer price indices in France: cereal (Source: FAOSTAT)

Figure 1.2: Producer annual price indices in France (Source: FAOSTAT)

to increase and fluctuate much more after 2003 (Figure 1.2).[1] Taking the average cereal price of $2004 - 2006$ as a baseline, the cereal price has increased by 52% in 2008, then dropped by 24% in 2009, and increased sharply again by 61% in 2010. A similar pattern exists for aggregate agricultural prices.

The rising price volatility introduces higher risks for farmers. They may change their decisions to deal with the increasing risks, and these decisions may in turn impact productivity. For example, due to high risks, farms may refrain from long-term investment, which results in a negative effect on productivity. There have been some studies which point to a negative impact of greater price volatility on investment and productivity (Pietola and Myers 2000, Odening et al. 2013).

This new market context leads to the first two research questions of the disser-

[1]The policy reforms are certainly not the only factor that causes the price fluctuations. However, the sources of price volatility and the formation of agricultural prices are not the focus of this dissertation. They are discussed in detail in Gouel (2011).

tation:

1. How does productivity evolve with the new structural changes?
2. What are the dynamic links between productivity, farm decisions, and price risks?

These two questions correspond to the first two research objectives. In order to answer them, we need to develop unbiased productivity measures that allow to account for the policy reforms and increasing price risks. Moreover, we need to develop a structural model which allows us to study the link between price risks, farmer decisions, and productivity.

Measuring Productivity

Productivity measures are sensitive to data and methods. This point is discussed in more detail in the literature review in Chapter 2. Above all, obtaining an unbiased measure of productivity evolution is generally difficult. First, inputs and outputs are measured with error. This is especially true for quasi-fixed factors, including family labor and capital in agriculture. Andersen et al. (2011) point out the difficulties of accurately measuring the capital service flow and associated returns in U.S. agriculture. Second, measuring productivity is basically equivalent to estimating the production function, which has been a classical problem in agricultural economics and industrial organization. Different methods, parametric and non-parametric, have been developed to measure productivity, each method has its pros and cons (Van Biesebroeck 2007). All methods need to deal with the endogeneity problems, data measurement problems, and different market assumptions. Besides, comparing productivity evolution or differences also depends on the consistency of the adopted method. To circumvent these two difficulties, the ideal suggested in the economic literature is to obtain better data. Novel approaches have also been proposed for better productivity estimates (De Loecker et al. 2016, Plastina and Lence 2018)

We propose a new approach to measure agricultural productivity, in which productivity is modeled and estimated jointly with the behavioral parameters. This approach is based on estimation methods relying on the maximum entropy principle and the particle filter. The generalized maximum entropy (GME) method has been used to estimate state-space models. The filtering methods are well developed to estimate DSGE models in the modern macroeconomic literature. Both methods are applied to recover the hidden states in state-space model estimation. In our case, productivity and capital are the hidden states. These estimation techniques allow us to estimate productivity in a dynamic stochastic framework, in which we are able to integrate price volatility and risk-management instruments. We consider the quasi-fixed input capital as a latent state variable by recognizing that we do not have an exact measure of it.

Policy Assessment

Our third objective is to assess the market impact of the CAP policy instruments in a context where prices are volatile. The corresponding research question is:

3. How do risk and risk attitude matter for the CAP policy assessments?

In recent economic models for agricultural policy analysis, for example, the computable general equilibrium (CGE) models, the static behaviors of the agents are modeled through profit maximization and cost minimization frameworks, but the dynamic and risk dimensions are largely ignored. Despite the power of the large-scale CGE models for the comprehensive modeling of the entire market system, it is impossible to analyze the farmers' dynamic responses to the increasingly risky environment in such static models. Alternatively, based on the microeconomic principles, the DSGE models are widely used to understand economic growth and business cycles. This opens the possibility to integrate dynamic and risk dimensions into agricultural models. Indeed, in this dissertation, productivity and its link to price volatility are modeled and estimated based on the concept of DSGE modeling, while policy assessment is performed within the CGE framework.

1.2 Approach

We develop dynamic structural models to accomplish the three research objectives of measuring productivity with structural change, studying the dynamic link among price volatility, farmer decisions and productivity, and the policy assessment with risks. These models reflect that both productivity and price evolution are dynamic processes, and risky events are generally situated in the future. Compared to reduced-form models, the structural models are developed based on agents' behavioral principles. They allow us to integrate the agents' decisions, price volatility, and productivity in one framework, and are better suited to assess policy reforms.

1.2.1 Dynamic Modeling

Two kinds of dynamic models are constructed in this dissertation. The first is a DSGE-like farm decision model, in which a forward-looking farmer makes production, consumption, capital investment, and financial borrowing decisions to maximize the discounted utility of consumption. This model falls into the family of dynamic programming models. Compared to the DSGE models, this model focuses on the producers' side, so that prices are exogenous. Besides, it is at a less aggregate level. Second, we develop a recursive dynamic CGE model with a succession of short-term equilibria. This model extends the recent CGE models by integrating the risk and intertemporal dimensions.

The model dynamics pass through the channel of capital accumulation and the price/productivity evolution. In agriculture, the sources of risk include the price and productivity in the future periods. They affect current investment decisions in the way that the agent makes expectations about the future returns. In addition, a particularity in agriculture is that risks also play a role within one period, between the growing season and the harvesting season. This risk is modeled in the recursive dynamic CGE model.

Structural change Above all, dynamic structural models describe the agents' behavior through economic principles. While the agents' interactions constitute the market, we expect the structural models to rationalize the market outcomes. Important traits of structural models are the mathematical consistency of the model structure and the stability of the fundamental “deep" parameters. Policy changes affect the market conditions, but the agents' optimal behavioral principles stay independent from the policy changes. So, the structural models pass the Lucas critique (Lucas 1976) and can be useful for policy analysis. For this reason, the farm decisions model is eligible to analyze the new market context with the CAP reforms. Structural change is imposed in the parameters describing price and productivity evolution, but not the deep parameters which determine the agents' decision rules.

1.2.2 Structural Estimation

Given that the structural model describes the market, the estimation goal is to find optimal parameter sets whose model output can best explain the historical data. The estimation allows to depict the production techniques, farmer preferences, and also the latent capital accumulation and the productivity evolution process. Estimating these models is technically difficult because a numerical solution process is needed to obtain an explicit state-space model, then the structural parameters and the latent states in the state-space model are to be estimated with observed data.

Bayesian techniques are applied to the estimation both for the parameter estimation and the hidden-state estimation. Regarding the parameters, we possess prior information on the deep parameters since they have corresponding economic meaning. The parameter posteriors are estimated given the priors and data information. Finding the optimal state corresponds to finding the posterior conditioned probability of the hidden state variable at the current time, given all past observed data. These two steps can be done simultaneously or sequentially.

Statistical learning From a methodological point of view, the estimation strategy discussed in this dissertation belongs to a broader subject, namely statistical learning. Put plainly, it is to fit a parameterized model to the data.

Statistical learning has been popularized by the machine learning community in recent years due to the revival of convolution-based deep neural network (LeCun et al. 1998, Krizhevsky et al. 2012). The deep neural network, also known as deep learning, has achieved incomparable performance in tasks such as classification, and face/voice recognition. Although it may seem promising, the usefulness of deep learning techniques for economic problems is still an open question. The success of deep learning is largely associated with the depth-related feature learning procedure, in which the features are automatically extracted from data. This is the reason why the deep learning works well on rich data sets such as image or sound.

The feature extraction procedure roughly corresponds to our economic modeling procedure. *A priori*, it is unclear how the auto-generated feature can compete with our sophisticated economic model given that the economic data is sparse in general, and that the human behaviors are harder to learn compared to physical features.

1.3 Thesis Outline

The dissertation is structured in four chapters.

Chapter 2 Productivity and Price Volatility: A Literature Review This chapter surveys the literature on productivity and price risks. Total factor productivity (TFP) is usually considered as an exogenous process and is related only to innovations. We argue in this review that, as a residual in the production function, productivity captures not only the technology change, but also other unmeasured factors, such as the rate of adopting technology, efficiency, labor efforts, and other misspecification in the data. As a result, prices and price risks influence productivity through the channels of long-term research and development (R&D) related investment decisions and efficiency-related decisions. Linked to this point, the recovery of productivity dynamics depends heavily on data accuracy and the estimation method. Consequently, we review the measurement problems of inputs and output, and compare the pros and cons of different estimation methods. In particular, we emphasize the measurement issues from the unobserved capital data series and the simultaneity problem from the primal estimation. The estimation methods we propose in Chapter 3 will deal with these two problems.

Chapter 3 Estimating Nonlinear Dynamic Stochastic Decision Models: A Generalized Maximum Entropy Approach This chapter studies the numerical optimization methods to solve and estimate dynamic stochastic decision models, and proposes a new method for the estimation. We estimate an optimal growth model which can also be interpreted as a farm decision model. In addition to the likelihood-based method with the filters, we propose a generalized maximum entropy (GME) approach to estimate the model. Based on Monte-Carlo experiments with simulated data, we perform estimations with the particle filter and with the GME method. We show that the GME approach yields a precise estimation of the unknown structural parameters and the structural shocks. In particular, the preference parameter which captures the risk preference and the intertemporal preference is also relatively precisely estimated. Compared to the more widely used filtering methods, the GME approach provides a similar accuracy level but has a much higher computational efficiency for nonlinear models. Moreover, the proposed approach shows favorable properties for small sample size data.

The motivations of investigating different methods are several. Indeed, with Dynare (Adjemian et al. 2011) as an excellent tool for DSGE solution and estimation, why spend time studying the methods and developing new algorithms? Our first motivation comes from the fact that agricultural data series are volatile, price risk is a second-order term, and that we are interested in high-order risk attitudes.[2] For these reasons, linear solution and estimation are not sufficient. For second-order estimation, the particle filter is implemented in Dynare, but the performance of the particle filter (sampling-based) is not as stable as the Kalman filter (analytical), and it is time consuming. The GME method has been used to estimate state-space models, it is straight-forward to program in GAMS, it has no requirement on the linearity of the state space, and it is efficient regarding the computing time. However, to our knowledge, the GME approach has not been used to estimate DSGE models. As a result, this chapter performs experiments to discover the validity of this new method. The second motivation is with regard to the solution. Perturbation methods are not accurate with the existence of large shocks (Aruoba et al. 2006) and are only accurate around the steady states. We prefer to use projection methods to solve the model. Indeed, policy functions obtained from projection methods are more usually used for agricultural policy analysis. However, projection as solution is not implemented in Dynare. We suppose it is because it is not necessary for linear estimation and the computation burden is too heavy for second order estimation. As a result, we implement the GME approach with Chebyshev projection method in this chapter. The third motivation is more general. The solution methods, the Bayesian estimation with the filters, and the GME method are statistical learning methods still in-developing. Studying these methods makes a contribution to computational economics.

[2]Although high-order risk attitudes are not discussed in this dissertation.

Chapter 4 Productivity and Price Volatility in French Agriculture: A Dynamic Stochastic Structural Estimation Based on the GME approach developed in the last chapter, this chapter estimates productivity and the dynamic link between output-price fluctuation and productivity in a two-period dynamic stochastic farm decision model based on French data. We contribute to the capital measurement issues by treating capital and total factor productivity (TFP) as latent variables. To account for the change in price volatility, we allow for structural changes in the drift term and the standard deviation of the shocks in the output price and productivity evolution processes before and after 2003. We estimate the model based on annual survey data of the crop producers in the Centre region from the Farm Accountancy Data Network (FADN), covering the period 1988-2015. To fit the estimation to the less aggregate and very volatile agricultural data series, we approximate, first, the policy function using a third-order Chebyshev polynomial method. Second, we estimate the structural parameters using a GME approach. Our estimation shows that the productivity growth in French agriculture has slowed down and become much more volatile following the increase in price volatility. Overall, price risk has an impact on productivity in the way that when exposed to high risks, farmers change their production, consumption, investment and financial borrowing decisions, which in turn affects the realized productivity negatively.

Chapter 5 Assessing the Common Agricultural Policy (CAP) Reforms: Does Farmer Risk Attitude Matter? This chapter simulates the impacts of public policy instruments. We integrate the risk and dynamic dimension into a static CGE model, more specifically, the GTAP-AGR model, in which productivity and price risks are linked. This is realized by modifying the supply side of the GTAP-AGR model by adding farmer risk attitudes. In the growing season, farmers make optimal decisions in this modified supply model based on expectations of prices and price volatility. In the harvest season, we introduce stochastic productivity shocks in the CGE model, and the final equilibrium price jointly determined by the supply and demand side in the CGE model is not necessarily in accordance with the price expectations. The farmer receives a capital return based on the true market price. The model dynamics pass on through the expectations the farmers newly form from the succession of short-term market equilibria. We show that in addition to the price expectations, the expectations of price volatility become one of the key factors for farmer decisions through its influence on the risk premium. Under the endogenous modeling of the CAP instruments, risk aversion matters by leading to much larger production and price effects. The impacts of policy instruments are even larger if the wealth effect is taken into consideration. Risk aversion also matters by dampening the dynamics induced by endogenous price risks.

Chapter 2

Agricultural Productivity and Price Volatility: A Literature Review

2.1 Introduction

It was not until the 1950 that the economists introduced the idea of productivity as a “residual". Schultz (1953, 1956) is the first to mention that in agricultural production, and in the rest of the economy, the additional conventional inputs account little for the increase in output. As such, Schultz views the technology change as a particular input which contributes to the output as an other type of inputs. In the same vein, Solow (1957) uses the term “residual" to describe the portion of output growth that cannot be explained by input growth. This residual is called total factor productivity (TFP).

As a “residual", productivity is closely linked to the core subjects of agricultural economics: product supply, factor demand, income distribution, the relationship between output and input prices, return to scale, and capital accumulation. In economic models, it is always considered as an exogenous process. Indeed, if considered as pure technological change, productivity is only related to the development of science and technologies that increase outputs and save inputs. However, as discussed in Schultz (1953) and the subsequent work of Jorgenson and Griliches (1967), the rate at which the producers adopt technological changes, and the quality of inputs, are also of great importance to productivity growth. These factors introduce the pertinence of the individuals' decisions and public policies on productivity. Moreover, the analysis of productivity depends on the measurement of inputs and outputs, the omitted factors which would constitute a part of the residual if not being controlled, the magnitudes of parameters, the econometric methods, and the market structure assumptions. As a result, to study productivity and its relationship with price volatility, *"the measurement problems are pertinent even if on the surface it seems the subject matter is not technical"* (Mundlak 2001).

This review aims at providing an understanding of productivity, its measurement, and their drivers. We investigate the role of price and price volatility on productivity. The price formation process and the sources of price volatility are not the focus of this review, they are discussed in detail in Gouel (2011). The structure of the chapter is as follows. In the first section, we present the facts on productivity growth and productivity differences, so as to understand the importance of agricultural productivity. As a supplement, we review the recent research issues in productivity in different economic fields. In the second section, we revisit the important measurement issues in estimating the production function and productivity. In the third section, we discuss the determinants of productivity. We discuss productivity and price volatility in the fourth section, and this is linked to the previous three sections. In part, this chapter builds on the previous reviews from Mundlak (2001), Bartelsman and Doms (2000), and Syverson (2011).

2.1.1 Some Evidence on Productivity Growth and Productivity Differences

In a simple manner, productivity measures how much output is obtained from a given set of inputs. Productivity is important because, with higher productivity, firms are able to enhance their profitability, households may enjoy more products, and the well-being of the economy increases with the same resources (Shumway et al. 2016). There has been productivity growth in most industries and throughout most of the world over decades. This productivity growth is mainly achieved through the development of technologies that increase output and save inputs.

Productivity growth is the principal contributor to economic growth. This is the same in agriculture. Ball et al. (1997) find that over the period 1948 – 1994, despite the decline in labor input and modest growth in capital input, the US agricultural output growth realized nearly a 2% annual growth rate. This confirms that productivity growth is the main factor responsible for economic growth in agriculture. Jorgenson et al. (2005) find that agricultural productivity growth contributes nearly 80% output growth in the US agriculture over the period 1977 – 2000. More recently, Ball et al. (2015) revisit agricultural productivity using USDA Economic Research Service (ERS)'s production accounts. Consistent with previous literature, they find that productivity growth constitutes 91% of economic growth in agriculture over 1948 – 2013, and the quality change in labor, capital, and intermediate inputs contributes of 0.12% to economic growth.

However, there are growing concerns that agricultural productivity growth has been slowing down during the last decades. In the EU, based on the TFP index computed by European Commission (2016), productivity keeps on growing, but the growth rate is slower in recent years. Figure 2.1 and 2.2 show the productivity evolution path for the EU-15 and EU-28. The average TFP annual growth rate for EU15 is 1.38% for the period 1995 – 2005, and is 0.6% for 2005 – 2015. With a higher growth rate for the EU-N13 at 1.6% for 2005 – 2015, the EU-28 average growth is 0.8% for this period. However, the positive growth rate in the EU-15 and EU-13 are realized by the positive growth in labor productivity, which is related to the decreasing number of labor involved in agriculture. Capital productivity grows negatively. Regarding France, agricultural productivity grows in line with the EU-15 average (Figure 2.3).

For the US and the rest of the world, Alston et al. (2009) document a global slow-down in grain yield, land productivity, and labor productivity growth after 1990, and the global productivity growth rates are even substantially lower if China is left out. Ball et al. (2013) revisit the slowdown hypothesis adopting econometric techniques that allow for structural breaks. They show that the productivity growth rate has been slowing down persistently after 1974 and after 1985. Based on the results of different data and methods, Andersen et al. (2018) confirm a slowdown in agricultural productivity in all the results from different data and methods. On the contrary, Fuglie (2010) presents a comprehensive global and regional picture of agricultural total factor productivity (TFP) growth over 1961 – 2007. He finds no evidence of the agricultural productivity slowing down. The accelerating TFP growth, and decelerating input growth have offset each other and keep the real output of agriculture growing at slightly more than 2% per year since the 1970s. The different results are due to different measurement methods and focuses.

Agricultural productivity gaps across countries have long been observed by economists. They play a key role in understanding international income differences. It is a fact that poor countries have much lower agricultural productivity

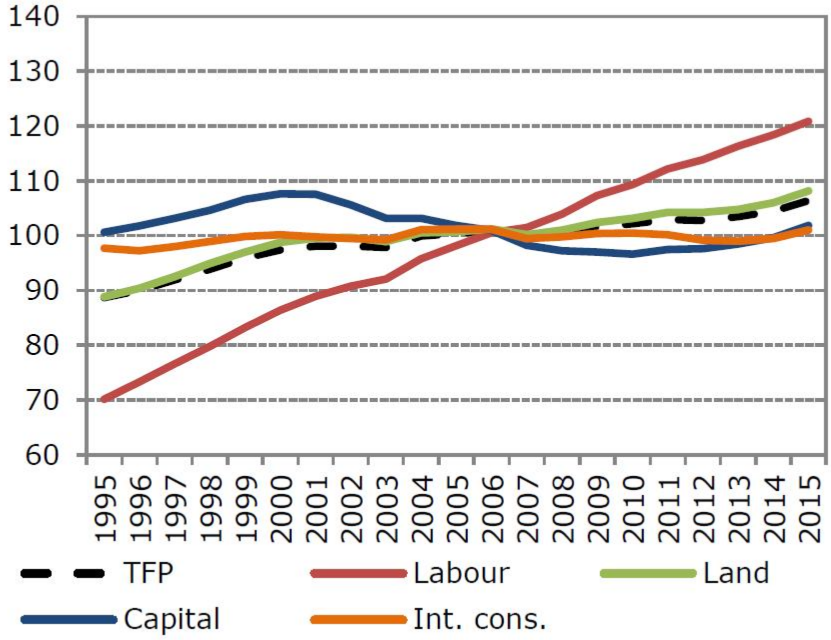


Figure 2.1: Evolution of total and partial factor productivity in the EU-15 (3-year moving average) (Source: European Commission 2016)

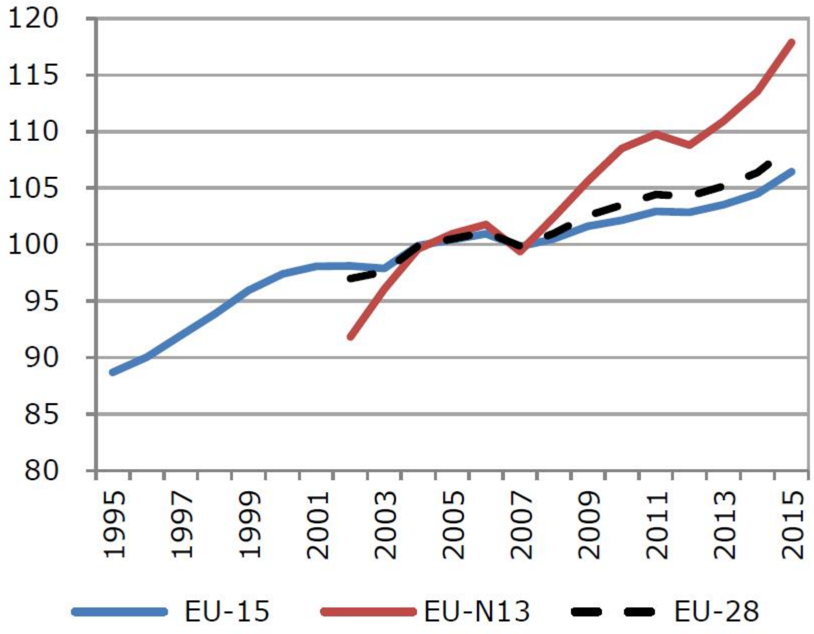


Figure 2.2: TFP-index grows faster in the EU-N13 compared to EU-15 (2005=100) (Source: European Commission 2016)

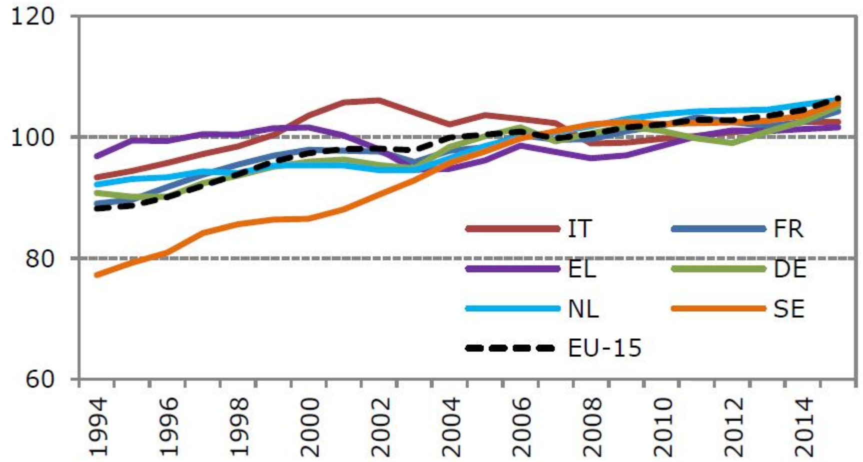


Figure 2.3: TFP growth path for the EU-15 Member States which grow in line with EU-15 (Source: European Commission 2016)

than rich countries. A number of macroeconomic studies investigate the productivity problem in poor countries quantitatively. For example, Adamopoulos and Restuccia (2014) relate aggregate agricultural productivity to farm size and the misallocation of resources from high-productive large farms to low-productive small farms. Similarly, from the perspective of firm-level productivity heterogeneity, Bartelsman et al. (2013) develop a theoretical model in which firm-level productivity heterogeneity negatively impacts aggregate productivity due to misallocation of resources across firms. Tombe (2015) relates the productivity differences to international trade: trade costs are large for agricultural products in poor countries, which amplifies the productivity difference. Moreover, there is a large puzzling gap between agricultural productivity and non-agricultural productivity in developing countries, even after improving the data measurement (Gollin et al. 2014). Most literature explains it from the labor allocation aspect, as in poor countries a much higher percentage of labor is engaged in the agricultural sector only to satisfy the basic food requirement (Schultz 1953).

The above evidence reveals the economists' concerns about agricultural productivity growth and agricultural productivity gaps. Indeed, sustained agricultural growth is crucial with more and more constrained natural resources. In this sense, developing a better measurement of productivity and understanding the sources of productivity to sustain agricultural growth becomes particularly important.

2.1.2 Recent Research Issues in Productivity

Productivity is of interest to economists in different fields. Recent research devotes effort to revisit productivity by dealing with the omitted price problem (outputs and inputs are measured in currency instead of physical units), the simultaneity problem between productivity and input choices, firm-level heterogeneity, and industrial dynamics. The central research questions are always how to obtain less biased productivity measures, and what factor impacts productivity through which mechanism.

Agricultural economists face universal issues like heterogeneous farms and dynamic decisions. Particular measurement problems exists in agriculture due to the simultaneous presence of hired and family labor, heterogeneous land and specific capital (machines and buildings). Lots of efforts have been given on improving data and providing accurate agricultural productivity measures (e.g. Shumway et al. 2016). In view of production economics, econometricians in this field have much contributed to the search for possibilities to identify the production function (see, e.g., Griliches and Mairesse 1995).

The Industrial Organization (IO) literature has provided pioneering works in modeling firm-level industrial dynamics and estimating productivity. Ericson and Pakes (1995) are the first to provide a theoretical model of industry dynamics with firm entry, exit, and investment decisions. This model has been widely used afterwards for empirical research on industry productivity. Recent IO literature also focuses on product differentiation, market power, and estimating productivity from both the supply and the demand side (see, e.g. De Loecker 2011).

Economic growth is a major topic in macroeconomics. Models such as the real business cycle model in which the economic fluctuations are driven by productivity shocks are studied with more varied assumptions and enriched by micro-components. As suggested by Colander et al. (2008), more varied behavioral assumptions than rational expectations, as well as interaction among heterogeneous agents rather than aggregate decisions are taken into consideration. Furthermore, thanks to the development of numerical computation techniques, modern macro models can be studied in a dynamic stochastic framework, which allows for a more empirically based analysis, also of policy implications (see, e.g. Fernández-Villaverde and Rubio-Ramírez 2005, Caldara et al. 2012b, Van Binsbergen et al. 2012).

2.2 Measuring Productivity

We need to first define total factor productivity (TFP), and distinguish it from partial factor productivity. Consider in a production function,

$$Y_t = A_t F(L_t, T_t, K_t, X_t) \tag{2.1}$$

where Y_t is output, L_t is labor, T_t is land, K_t is capital, X_t is intermediate inputs, and t is the time subscript. The residual of the production function, A_t, is the total factor productivity (TFP). Partial factor productivity, which is usually the ratio of output over one single input, is also used as a productivity indicator in some parts of the literature. However, partial factor productivity can be easily impacted by the usage intensity of other inputs - one firm may have higher labor productivity than the other firm only because it uses capital more intensively. Consequently, TFP is the more commonly used productivity measure. As the problem is presented, estimating productivity amounts to estimating the production function. The identification and estimation of the production function and the data measurement issues are discussed in a broad literature including but not limited to Griliches and Jorgenson (1966), Griliches (1994), Griliches and Mairesse (1995), Mundlak and Hoch (1965), Mundlak (1996, 2001), and Van Biesebroeck (2007, 2008).

2.2.1 Data Issues: Measuring Inputs and Outputs

In order to measure productivity, the first step is to obtain data on outputs and inputs. In agriculture, this concerns mostly land, labor, capital, such as machinery and buildings, and other variable inputs, including seeds and the use of fertilizers and chemicals. It is obvious that the accurate measure of the inputs and outputs affects directly the productivity measures. However, instead of presenting the facts, the data are rather quantitative proxies of the facts. Moreover, particular inputs, like land quality, and efforts made by the family labors, are difficult to measure. These unmeasured inputs will eventually enter into the residual and become part of productivity.

Capital stock and capital flow

We start with the most problematic input, capital. Measuring capital is difficult because instead of being a decision taken at each point of time which can be accurately retrieved, the capital service is a flow. Indeed, capital accumulation is a dynamic process, the investment goods purchased in one period contribute to the capital stock in the future periods. However, what amount of investment contributes to the capital stock in which future period is unobservable, and not necessarily recorded accurately in the account. Consequently, if we want to compute the capital stock from investment, it relies heavily on assumptions about depreciation, obsolescence, replacement, and it is sensitive to these assumptions. Moreover, there are different types of capital,and how to aggregate them into one is another question (usually index numbers are used). Besides, Griliches and Jorgenson (1966) point out that the consumer of capital services is often also the supplier, this entire transaction occurs in the internal account and is not observable. This is particularly true for agricultural capital. As a result, information is usually obtained from indirect inference, and assumptions on ex-post usages of capital must be made.

Approximating the capital goods from the past investment flows is called the perpetual inventory method. This is a most commonly used method for capital inputs. A simple example of such a capital series approximation is:

$$K_t = I_t + (1-\delta)I_{t-1} + (1-\delta)^2 I_{t-2} + ... + (1-\delta)^L I_{t-L} \tag{2.2}$$

where K_t denotes the capital stock in period t, I_t denotes the investment in period t, δ denotes the depreciation rate, and L is the economic life time of an asset. Further assumptions on capital adjustment costs can be added, too.

Andersen et al. (2011) show that the perpetual inventory method depends heavily on assumptions of depreciation, economic life time, and the interest rate. They compare the state-level capital measures from two major agricultural productivity databases in the U.S., the U.S. Department of Agriculture - Economic Research Service (USDA-ERS) and the International Science and Technology Practice and Policy (InSTePP) in University of Minnesota. Despite adopting similar methods and data sources, the approximated capital series can, however, be different. Andersen et al. find that these differences largely come from the different assumptions on the interest rate, which in turn affect the investment price. The importance of the interest rate assumption leads us to another universal problem: which price should be used to convert the value of capital into the physical unit of capital? Alston (2018) highlights again that how to measure the price and quantity of the capital is still a problem to be resolved.

Another capital measurement method is the physical inventory method. It measures capital directly from the data of the current capital stock. The limitation of this method is that the data on capital goods is usually unavailable, or it is only in book values. If the data is in book values, we need to choose a price deflator to deflate the book value into physical units. Again, the book value of investment is also the problem of the perpetual inventory method. Moreover, the book value of capital may be optimized to fulfill fiscal purposes.

Last, even if we can observe, or have accurately measured the capital stock, how much of the stock is used as the flow of the capital in a given period remains a question - the capital in-place is not the capital in-use. Griliches (1960) points out that it is hard to know at which rate the entrepreneur converts the capital stock into capital service for each year because it is rather an internal rate. A common approach is to assume a ratio. A consequence of such wrong capital measurement is the spurious cyclical movement in productivity. More recently, Andersen et al. (2012) also find that the assumption that the capital service flows are a constant proportional to the capital stocks gives rise to cyclical errors in the capital measure, and leads to biased pro-cyclical patterns of productivity growth.

Labor

Regarding labor, whether to use numbers of employees or working hours is a question. In agriculture, part of labor is usually self-employed, and thus puts some difficulty in measuring the working hours and the wages. Mostly obtained from surveys, the agricultural working hours can be more subjective compared to the industry working hours, which may lead to certain measurement errors. Besides, as agricultural labor quality can be different regarding education level, age, sex, family labor, and hired labor, it is important to classify labor according to these categories.

While it will relate to another strand of literature, the learning process of labor also plays an important role in augmenting production, but it is difficult to quantify these processes. Nevertheless, learning-by-doing is an area with a growing literature aimed at explaining the productivity drivers.

Land

Land is a particular input for agricultural production. Acreage is a common measurement unit for land, which usually has much smaller measurement errors compared to other inputs. The main caveat for land measurement is the land quality. It is common that land quality is different across regions and for different crops, it is thus important to adjust land measurement according to heterogeneous land quality. Besides, how to account for land quality change across years is another question. For productivity measures where prices are needed, the formulation of a land price is quite different from other goods, and there are more complex regulations regarding land.

Goods (output & intermediate inputs)

Agricultural intermediate inputs comprise animal feed, seed, livestock, chemicals, fuels, and other purchased inputs. The issue of using revenue instead of physical unit as output raises for intermediate inputs and output, or in all, for goods that should be measured in physical quantities.

Output sales or revenues deflated by an industrial level price index are often used as output measures, because physical quantities are unavailable or cannot be aggregated. This output measurement is acceptable if the market is under perfect competition, so that the homogeneous product price equals marginal cost. It is even desirable if price fully reflects quality. However, perfect competition is an assumption. If the firm-level price variation is a result of market power, the sales-based output measure would be biased. The corresponding productivity measure could not reflect fully the firm efficiency but would also include the price mark up effects. To elicit such measurement problems, Klette and Griliches (1996) show that the omitted price variable bias rises when the prices are correlated with other variables, using deflated sales as output measure leads to a downward bias in productivity estimates. De Loecker (2011) extends Klette and Griliches's work to multiple products and factor price variation, and shows again that the omitted prices result in productivity estimation bias. Based on physical output and price data, which is extremely rare as a data set, Foster et al. (2008) show that revenue productivity is positively correlated with price while physical productivity is the inverse, and the productivity-survival is actually profit-survival. In the agricultural sector, farms usually possess much less market power than industrial firms. Agricultural prices tend to be homogeneous across farms, so that this problem may be less severe for agriculture. The problem may still exist for special products, like milk. Besides, although the above caveats are causing concerns in recent studies, in most of the empirical productivity literature, deflated sales or revenues are still commonly used as an output measure.

2.2.2 Econometric Estimation: Endogeneity Problem

The basic criticism for direct econometric estimation of the production function is the endogeneity problem caused by simultaneity (first pointed out by Marschak and Andrews 1944). That is, the producers choose their inputs by partly knowing their productivity level, while their productivity level is unobserved by the econometrician. Consequently, the input choices are correlated with the residual productivity and cannot be treated as independent variables, and the ordinary least squares (OLS) method will lead to a biased estimation. Take the Cobb-Douglas production function as an example,

$$y_t = \alpha_k k_t + \alpha_l l_t + \alpha_m m_t + \alpha_x x_t + \mu_t \tag{2.3}$$

where y_t, k_t, l_t, m_t, x_t are the logs of output, capital, labor, land and intermediate inputs at time t, $\beta_k, \alpha_l, \alpha_m, \alpha_m$ are the estimates of elasticity of the respective inputs, and μ_t is the residual and represents the estimate of productivity.

If every input used for production is included in the estimation and they are all well measured, the residual TFP represents solely technology and other “purely" unexpected exogenous shocks, such as weather shocks. However, except the conventional inputs, capital, labor, land and intermediate inputs, which already have certain measurement issues, there are still a lot of left-out “unconventional" inputs, such as the quality of inputs, the efficiency of using the inputs and adopting the technology, the subjective effort made by the producers. These left-out inputs constitute also part of the residual productivity.

Anatomy of the residual To demonstrate the above view more clearly, we present the anatomy of the residual following Griliches and Mairesse (1995). The residual μ_t in Eq. (2.3) can be written as:

$$\mu_t = \omega_t + e_t + \epsilon_t \tag{2.4}$$

where ω_t is the component known by the producer but not observed by the econometrician, e_t is the component not known by both, and ϵ_t is the measurement error.

More specifically, ω_t is the component known by the producer at the point of decision making. It can be decomposed again as

$$\omega_t = a_t + z_t \tag{2.5}$$

where a_t represents the technology level, and z_t represents other left-out factors or the misspecifications in describing the production process, which may include the efficiency of adopting the technology, unmeasured land quality, unmeasured labor quality (skill, education, learning), management efficiency, the producers' effort, and even the misspecified part of the capital service flow. In addition, due to the character of a_t and z_t, the two time series also have potential serial correlation issues.

e_t is the component not known by the producer at the point of decision making, but there is a possibility that it realizes in the future and will influence the producer's future decisions. For a forward-looking producer, e_t also affects the current decisions through the channel that the distribution of e_t has an impact on the producer's expectations. This would include the unpredictable weather shocks, the environmental shocks, the unanticipated regulation changes, and the changes in producer effort in response to unanticipated market conditions. e_t, on the other hand, is serially uncorrelated.

Over all, ω_t and e_t affect the input choices for the current period and for the future, which results in the endogeneity problem. Several approaches are proposed to solve this issue.

2.2.3 How to Deal with the Endogeneity Problem?

Dual approach

A usual way to deal with the endogeneity problem is to use price as an instrumental variable. This is actually the dual approach in which profit maximization and cost minimization assumptions are adopted. Besides, a widely used non-parametric measure of productivity, the index numbers, is based on the idea of the dual approach.

Index Numbers Index numbers assume perfect competition in output and input markets and optimization behavior of firms. Based on the profit maximization and cost minimization framework, the output elasticity of the inputs are their respective cost share. If assuming constant return to scale, the value shares add up to one. As a result, the inputs' elasticities can be calibrated by imposing theoretical assumptions and the estimation can be skipped.

The index number then provides an aggregation for outputs and inputs. The TFP index is usually constructed as the ratio between an output index and an input index, where the input index is the weighted aggregation of the factor inputs quantities, with inputs' elasticity as weights, and the output index is the weighted aggregation of the outputs if there are multiple outputs. The most used indexes are the Laspeyres index, the Paasche index, and the Fisher index (geometric average of Laspeyres index and Paasche index). Other than those, the Malmquist index and the Tornqvist index (geometric average of two Malmquist indexes), the divisia index, and the Hicks-Moorsteen TFP indexes are also widely used. In the U.S., the USDA-ERS has long been improving the inputs and outputs data, and providing state-level, national, and international productivity growth using the index numbers. Ball et al. (1997) describe the calculating procedure in detail. In Europe, the European Commission also provides national-level productivity briefs using index numbers, based on Economic Accounts for Agriculture (EAA) from Eurostat.

The main advantage of the index numbers is that it is a straightforward computation, it handles multiple outputs and many inputs, and it is flexible enough to deal with heterogeneous production technology. Moreover, it proves to be robust unless the data is subject to much measurement error (Van Biesebroeck 2007). However, although it avoids the endogeneity issue from the production function estimation, it requires strong assumptions on firm behaviors and market structure, which turns out to be the main disadvantage. Another important potential bias is that the index approach assumes away factor adjustment costs. With the presence of adjustment costs, the linkage between first-order conditions and observed factor shares need not hold (Syverson 2011).

To improve the static nonparametric productivity measures to dynamic ones and to consider the adjustment costs, Luh and Stefanou (1991) develop a dynamic model with intertemporal production and investment decisions. Since the collected data are not necessarily in static or long-run equilibrium, the dynamic productivity growth measure is adjusted from the deviation from long-run equilibrium.

Applied to the U.S. data, the dynamic productivity index exceeds the conventional Tornqvist-Theil index over the period $1950 - 70$. More recently, Silva and Stefanou (2003) have developed a theoretical nonparametric dynamic framework in which costs are minimized intertemporally and adjustment cost is considered. Based on this model, Silva and Stefanou (2007) develop a nonparametric dynamic measurement of agricultural technical, allocative and economic efficiency. A possible future research direction proposed by them is to develop stochastic dynamic non-parametric measures on productivity.

The Olley and Pakes (OP) approach

Olley and Pakes (1996) estimate a dynamic structural model with heterogeneous firms producing a homogeneous good. They develop a two-stage estimation technique to overcome the simultaneity problem. The idea is to run a two-stage regression, using an investment equation as a proxy for productivity. Based on this idea, Levinsohn and Petrin (2003) use intermediate inputs as a proxy for productivity to overcome the simultaneity problem.

The strongest assumption of the OP approach is that the unobserved productivity is a strictly monotone function of an observed character of the firm. It involves a two-stage regression, first, under the condition that investment is strictly increasing under the unobserved productivity a_{it} for every state variable k_{it}, $i_{it} = i_{it}(a_{it}, k_{it})$. So we could write a_{it} as an inverted function of investment,

$$a_{it} = h_{it}(i_{it}, k_{it}) \tag{2.6}$$

The first-stage regression is thus

$$y_{it} = \beta_l l_{it} + \phi_{it}(i_{it}, k_{it}) + \epsilon_{it} \tag{2.7}$$

where $\phi_{it}(i_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + h_{it}(i_{it}, k_{it})$. This first-stage regression allows us to identify the labor elasticity β_l.

The second-stage regression is

$$y_{it+1} - \beta_l l_{it+1} = \beta_k k_{t+1} + \psi(\hat{\phi}_{it} - \beta_k k_{it}) + \epsilon_{it+1} \tag{2.8}$$

The functions ϕ_{it} and ψ_{it} are approximated by polynomials. Since capital k_{it+1} is a state variable and decided by the last period investment i_{it}, k_{it+1} is independent of the error term ϵ_{it+1}, so there is no endogeneity problem. The second stage regression allows us to identify the capital input elasticity β_k.

The estimated productivity A_{it} is thus,

$$A_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{2.9}$$

Efficiency approaches

Stochastic Frontier The stochastic frontier method falls into the family of parametric estimation. The method was first proposed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). The general idea of this method is that the unobserved productivity difference is a negative error term representing the inefficiency of firm i at time t. This error term is assumed to follow a certain distribution. Productivity is a random draw from the negative of the distribution, in this way the unobserved productivity is not correlated with input choices. The parameters are usually estimated with maximum likelihood from Monte Carlo simulation.

Data Envelopment Analysis (DEA) Data envelopment analysis (DEA) is a non-parametric method used for efficiency measures. It was first proposed by Farrell (1957). It does not require a detailed functional form and behavioral assumptions, and it is applied to each firm which allows for firm-level technology variations. In the DEA method, efficiency is defined as the ratio of a linear combination of outputs divided by a linear combination of inputs. First, weights on inputs and outputs are chosen to maximize efficiency. Second, the efficiency parameter θ_i is interpreted as the productivity differences between firm i and the most efficient firm.

2.2.4 Why is the Measuring Problem Important?

Van Biesebroeck (2007) compares the performance of the estimation methodologies in the presence of firm-level heterogeneity. He simulates samples by introducing heterogeneity in three ways: factor price heterogeneity, measurement error, and differences in production technology. The results show that an approach with the index numbers produces robust estimates unless the data is subject to much measurement error. DEA is the preferred estimator if technology varies across firms. Stochastic frontier is accurate when the productivity differences are constant over time, output is measured accurately and the firms share the same technology. OP approach allows exploring the firms' knowledge about the stochastic productivity shocks. It is accurate in the absence of fixed effects, and it also performs well in the presence of measurement error.

The problems we discuss above are to some extent technical. The measurement issue is important because when the unmeasured factors enter the residual, they become pertinent with regard to the productivity determinants. A straightforward example is to consider technology as a special production factor not measured in the input data, then the determinants related to technology will have an impact on the residual productivity. This point is demonstrated more clearly in the next section in Table 2.1. Another issue is with regard to the misspecifications in the data, which in the end will be reflected in the residual. The example is that using the capital service data as a constant proportion of the capital stock measure possibly leads to a pro-cyclical pattern of productivity growth; the revenue-based productivity measure is positively related to price while the physical based productivity measure is the inverse. As a result, it is important to take these misspecifications into consideration when performing the empirical analysis. Last, regarding the estimation, as each estimation technology has its pros and cons (Van Biesebroeck 2007), choosing a preferred unbiased estimation method given the research objective and the character of data set is important for the empirical analysis.

2.3 Determinants of Productivity

Empirical research on the determinants of productivity can be classified into two types. The first type is to measure productivity empirically with the methods described in the last section, and then to apply reduced-form econometric methods to examine the relationship between the measured productivity and the potential drivers. The second type is to measure productivity and investigate its drivers simultaneously in a structural model.

2.3.1 Decomposition of Productivity

In section 2.2, we discuss the decomposition of the residual in equations (2.3) - (2.5). The component ω_t, which is known by the producer but unobserved by the econometrician, can be decomposed further to technology and all the other left-out

Table 2.1: Decomposition of TFP (Econometric & Theory) and the Corresponding Potential Drivers

TFP (residual)	Unobserved by econometrican, known by producer (ω_t)		Unobserved by econometrican, unknown by producer (currently)	Measure-ment errors
Anatomy of residual	a_t	z_t	e_t	ϵ_t
Decompo-sition	technological change	efficiency (management, effort, ...);land, labor, capital quality; misspecification in inputs (capital);	weather shocks; environmental shocks; unanticipated market conditions	-
Potential determinants	R&D; productivity spillover	firm structure; market structure; learning by doing;	exogenous	-
Related to price & risks?	Yes (e.g. long-term investment)	Yes (e.g. efficiency related decisions)	Yes, if assumed expectations affect current decisions	No

Note: $a_t, z_t, e_t, \epsilon_t$ as used in equations (2.4) - (2.5)

factors which are not specified for the production process. The econometric error decomposition shares the same idea with a subsequent literature where TFP is decomposed into technical change measures and efficiency measures (Farrell 1957, O'Donnell 2010, 2012). O'Donnell (2012) decomposes TFP change into technical change, input- and output-oriented measures of technical, scale and mix efficiency change. He shows that before 1990 technical change was the main driver of TFP growth in U.S. agriculture, and after 1990 output-oriented scale efficiency change became the most important driver. Plastina and Lence (2018) decompose TFP change into technical change, technical and allocative efficiency change, a markup effect, and an input price effect. They show that at the state level for U.S. agriculture, technical change is the major driver for TFP growth in the long run, although the technical progress has been slowing down compared to the 1970s. Examining the TFP components and their contributions to TFP growth lead us to the further questions: what are the internal determinants for these components that result in the final TFP growth? If policy suggestions or management decisions are to be made, what would be the concrete content and policy focus? In Table 2.1 we list the connection of these questions.

2.3.2 Determinants of Productivity

Research and Development (R&D)

The most widely mentioned determinant of agricultural productivity growth is R&D. A series of studies of Griliches (1963, 1994) has emphasized the important role of R&D investment in improving productivity. This view is echoed in a subsequent literature (Pardey et al. 2010, 2013), showing that the development in technology contributes to a large part of agricultural productivity growth, and thus that the investment in public R&D is an indicator for productivity growth. Wang et al. (2013) find that public R&D and private R&D are complementary, and the accumulation of the R&D stock contributes to long-run agricultural productivity growth. Alston et al. (2011) find high benefit-cost ratios with regard to investment in agricultural research, which indicates an underinvestment in R&D. Besides, the R&D lags are much longer than the previous studies indicated. Alston (2018) shows again the high social return to agricultural R&D and the government fails to provide sufficient provision for R&D.

Sabasi and Shumway (2014) examine the factors driving the productivity growth in more detail. They show that, in addition to public R&D investment and its spillovers, health care access, education are the main factors influencing technical change, which in turn is the dominant component of productivity growth. Private R&D has mixed effects on technical change. Technical efficiency changes little over the data period, it is primarily driven by the farm size and the ratio of family to total labor. Scale and mixed efficiency also change little over the data period, it is mostly affected by agro-climate conditions, weather, and farm size.

Firm structure

Firm structure is another important determinant for agricultural productivity. Much research relates to farm efficiency, which in turn contributes to productivity, with farm structure characteristics such as size, specialization, and organization. Regarding farm size, the simplest characteristic for farm structure as an example, Sabasi and Shumway (2014) show that technical efficiency is primarily driven by the farm size and the ratio of family to total labor. Adamopoulos and Restuccia (2014) develop a heterogeneous farm model to show that farm size is an important factor for the low productivity problem in poor countries. The reason is that poor countries tend to have small farms with low productivity, which leads to a problem of resource misallocation. In this vein, public policies such as land policies (which influence farm size) have an impact on productivity.

Learning by doing

Arrow (1962) is the first to suggest learning as a potential driver for productivity growth. Learning-by-doing needs to be analyzed in a dynamic context. Luh and Stefanou (1993) treat the acquisition of knowledge as a firm-specific capital in the dynamic adjustment-cost model, they show that learning-by-doing is an important unmeasured source of agricultural productivity growth. Moreover, there are other important internal drivers such as market structure, management, and innovations.

Market structure

Regarding external drivers, a large literature finds that competition enhances productivity (e.g., Holmes and Schmitz 2010). First, competition may increase the minimum productivity threshold for survivors. It forces less efficient or less productive firms to exit the market, and increases the productivity entry level for new firms. Second, competition increases efficiency, and thus productivity within firms. It forces the existing firms to take action to increase their productivity, for example, by adopting new technologies, optimizing organizational structure, and enhancing managerial power.

Productivity spillovers

Productivity spillovers are another important external driver for productivity growth. For example, Ball et al. (2010) show that Spain had the second lowest in agricultural productivity in Europe in 1973 while it is the second highest in 2002. One of the reasons is the knowledge transfers. Lower-productivity producers are likely to imitate the productivity leaders, and it is less expensive than innovation.

2.3.3 The Role of Public Policy

Public policy affects on productivity through various channels mentioned above. Much trade literature investigates the impacts and the channel of trade reform on productivity. Theoretical and empirical evidence shows that firm-level productivity increases with firm exporting (De Loecker 2007, Aw et al. 2011). On the one hand, most research relates trade liberalization to international competition from the output price aspect. In particular, trade reform induces a reduction in domestic output prices, and increases international competition, which in turn increases firm efficiency and productivity. On the other hand, a growing literature investigates trade reform from the input side. For example, Amiti and Konings (2007) find that trade liberalization leads to a decrease in domestic input prices, and lower input price raises productivity significantly, and the decrease of input price has a higher impact on productivity than the decrease of output price.

Domestic policy also has an impact on productivity. As is mentioned above, land policy may impact productivity through farm size (Adamopoulos and Restuccia 2014). Regarding output subsidies, Rizov et al. (2013) propose a model following the OP approach, in which they model the unobserved productivity and the effects of subsidies into a structural semi-parametric estimation procedure. They find that there is a positive correlation between subsidies and productivity after the CAP reform in 2003 which decouples the subsidies from production. This result suggests that the decoupled payments are less distortive and enhance productivity. Similarly, Kazukauskas et al. (2014) test the impacts of the decoupling policy on farm productivity following the LP approach (Levinsohn and Petrin 2003). The difference is that they use the farmers' choices of intermediate inputs to control the unobserved farm productivity. Based on Irish, Danish and Dutch farm-level data, they find evidence that the decoupling policy has significant positive effects on farm productivity and behavioral changes related to farm specialization.

2.4 Price and Productivity

Regarding the literature exploring the link between price and productivity, the price-induced innovation theory (Hicks 1963) states that changes in relative prices of factors are expected to induce innovations to economize the use of relatively more expensive inputs. Liu and Shumway (2009) test the induced innovation hypothesis for US agriculture using three testing techniques but reject the hypothesis in most cases. The intuition is that the marginal cost of developing a new technology for the relatively expensive inputs is higher than the cost of using relatively cheap inputs. More recently, Cowan et al. (2015) test this theory from the supply side and the hypothesis is supported for several pairs of inputs. Nevertheless, the empirical findings are generally against the policies based on the theories that price signals alone induce technical change.

Compared to the price-induced innovation theory which indicates that relatively expensive inputs induce innovation, more studies find that input price reduction generates the productivity gain. Amiti and Konings (2007) find that trade liberalization which reduces input tariffs raises productivity significantly in Indonesia, and the decrease of input prices has a higher impact on productivity than the decrease of output prices. This productivity effect could arise from the channel of higher-quality foreign inputs which are not accessible before the trade liberalization, variety, and learning, but these channels have not been examined in the paper due to the lack of data. De Loecker et al. (2016) use detailed price and quantity data to estimate a quantity-based production function. Their structural estimation results capture the effect that trade liberalization reduces input and output prices, and increases productivity. The possible channel is that firms can take advantage of previously unavailable inputs to improve productivity. Another important finding is that the price reduction is much smaller than the marginal cost reduction through trade reform, which indicates that the firms increase the markups to offset the decline in marginal cost. Gaigné and Le Mener (2013) develop a theoretical general equilibrium model based on the empirical fact that agricultural prices fell between 1900 and 2006, and there is a trend of higher concentration in the food industry and an increase in productivity. They show that low input prices lead to a high exit rate of low-productivity firms and high industry concentration, resulting in higher productivity in the agrifood industry.

However, there is scant literature on the relationship between productivity and price volatility, or productivity under risk. Reduced-form econometric studies find mixed results regarding price volatility and productivity, but with a larger tendency of findings for a negative relationship. Ramey and Ramey (1995) find empirical evidence of the negative relationship between the volatility of economic fluctuations and economic growth. One of the possible explanations is that volatility discourages the demand for investment, and this effect exceeds the encouragement of precautionary saving, the sum of the effects in the end decelerates the economic growth (Aghion et al. 2010). Further negative impacts of price volatility on productivity are supported by Cavalcanti et al. (2015) and Kazukauskas et al. (2010). On the contrary, Frick and Sauer (2017) and Lien et al. (2017) find a positive relationship focusing, respectively, on the German and Norwegian dairy sectors. The positive effect is realized from the fact the inefficient firms are forced to exit the market because of high price risks.

While the empirical findings are evident, how do theory and structural models explain the linkage between price volatility and productivity? In the first place, the endogenous productivity theory provides some interpretation. Aghion et al. (2010) develop a theoretical growth model in which the exogenous liquidity shocks generate endogenous productivity movements through the interaction with financial markets. They decompose productivity into an endogenous and an exogenous component. The endogenous one depends on the accumulation of knowledge, long-term investment, and liquidity risk. The risk-neutral entrepreneurs maximize the expected wealth with respect to short-run investment (capital investment), long-term investment (R&D investment) and risk-free investment (bonds). They find that in the incomplete financial market, the tighten credit constraint indicates a higher risk for long-term investment when facing liquidity shocks, thus amplifying the TFP volatility and lowering the economic growth.

Based on the propagation role of the financial market, Aghion et al. (2009) find empirical evidence that exchange rate volatility has a negative impact on productivity growth, especially in countries with a low level of financial development. To support the empirical findings, they develop a two-period monetary growth model of overlapping generations with entrepreneurs and workers. At the beginning of the first period, the entrepreneurs decide the optimal labor given sticky wages. At the end of the first period, the entrepreneurs decide whether to innovate in the second period or not, in order to survive from a liquidity shock. The entrepreneurs' ability to cover the liquidity cost and to innovate is constrained by the credit market, and the productivity process depends on last period's productivity and the decision to innovate or not. They show that exchange rate appreciation decreases the firms' current earnings, and in turn reduces their ability of borrowing when facing a liquidity risk. The depreciation does the opposite. However, in a more constrained financial market, the negative effect of appreciation exceeds the positive effect of depreciation. In the end, exchange-rate volatility leads to negative productivity growth.

In the above two papers, the transmission channel is mostly through the constrained financial market, through which liquidity risks impact the decision of long-term investment or innovation. In a similar vein, Liu et al. (2013) investigate the dynamic link between land price and macroeconomic fluctuation in a DSGE model where firms' borrowing ability is constrained by the land value. The model shows that through the amplifying effect of credit constraint, the housing demand shock drives both the fluctuations in land price and the fluctuations in the decision variables including investment and production. The mechanism thus explains the co-movement of land price and macroeconomic fluctuation. Besides, based on a regime-switching model, they show that the housing demand shock accounts less for the fluctuations in the low-volatility regime, and more in the high-volatility regime.

Further structural estimations include, for example, Dhawan et al. (2010), who find empirical evidence that before 1982 energy price shocks have significant and negative spillover effects on productivity. Constructing a DSGE model in which firms use capital, labor, and energy for production, they show that the high productivity volatility before 1980 is due to the spillover effects from energy price fluctuation. Schmitt-Grohé and Uribe (2011) find empirically that the TFP and the relative price of investment series share a common stochastic trend. In a real business cycle (RBC) model, they show that the common stochastic trend in TFP and investment-specific productivities as the drivers for short-term economic fluctuations.

Based on the above intuitions, productivity and risk can be modeled structurally based on the following steps. First, we assume that the productivity process is endogenous to the determinants such as investment (R&D investment), labor effort, and learning spillovers. Second, we introduce exogenous shocks (for example, liquidity shock, demand shock) that lead to price fluctuations and impacts the decisions, which in turn affect productivity.

The measurement of data and productivity will play an important role when fitting the model to data. As demonstrated in the previous sections, productivity is a residual which captures the factors that are not included in the conventional inputs. When unconventional inputs such as input quality, learning by doing, and other unobserved components are not included in the inputs or the structural model, the residual will capture them. In the end, price and risk affect productivity through these unmeasured factors. Last, the omitted price bias should be paid special attention to when eliciting the price effects on productivity. If prices are already included in the productivity measures, the econometric estimation between price and productivity is then biased.

2.5 Conclusion

The first message from this literature review is that productivity is a residual. Econometrically, this residual can be decomposed into three parts. First, the components known by the producers and not observed by the econometrician, which are technology level and other left-out factors in describing the production process, including unmeasured inputs' quality, efficiency, and learning processes. Second, the components not known by the producers at the decision-making stage, including weather shocks, unexpected environmental shocks, and unanticipated market shocks. Third, measurement errors. The productivity decomposition theory is in line with the econometric error decomposition. Correspondingly, the drivers of productivity are R&D (which contributes to technology), firm structural and management efforts (which is related to efficiency), learning by doing (which relates to labor quality), and other external drivers such as productivity spillovers.

Price and price risks affect the productivity components, and in the end affect productivity. Regarding technology, for example, the price-induced innovation theory indicates that input price signals induce innovations. Price volatility discourages long-term R&D investment and affects negatively productivity. In terms of efficiency, the transmission channels include price signals with entry and exit of firms of different efficiency which impact productivity. Producers take advantage of previously unavailable expensive inputs to improve productivity. Producers change their effort made for producing, and coordinate the learning process or management in response to a risky environment. Last, regarding the productivity components not observed by the econometrician and the producers, the unanticipated market shocks in the future impact the current decision when producers form the expectations according to different market conditions.

The second message from this review is the importance of measurement issues. As the problem is essentially the estimation of the production function, three points are to be emphasized. The first point concerns the unbiased measurement of productivity in relation to the endogeneity problem. We have reviewed the primal and the dual approaches in dealing with this problem. Second, the capital series is particularly difficult to measure because it is not directly observable and is obtained mostly based on parameter assumptions. The capital measurement problem would lead to bias on pro-cyclical pattern of productivity growth. As a result, more effort should be made to improve the measurement of capital. Third, special attention should be paid to measuring output in values instead of physical units. The omitted price bias concerns to the growing literature on investigating the firm-level productivity in view of heterogenous firms, market power, and market structure. In particular, we will contribute to the first two problems (unbiased productivity estimation and capital measurement) by using a dynamic structural approach in the following chapters.

Chapter 3

Estimating Nonlinear Dynamic Stochastic Decision Models: A Generalized Maximum Entropy Approach[1]

3.1 Introduction

Dynamic stochastic decision models allow the economist to study intertemporal decision choices under risk. They are widely used in macroeconomics, known as dynamic stochastic general equilibrium (DSGE) models, for optimal policy analysis under various structural shocks. There have been many advances in the recent literature in solving and estimating dynamic stochastic decision models. These advances have important implications for agricultural economics because these models can be used to model farmers' dynamic decisions such as investment and consumption decisions under risks. Estimating the model parameters allows us to depict the production techniques, the farmers' preferences, and other dynamic features for agricultural production, which are essential for agricultural policy analysis.

Estimating dynamic programming models conventionally requires first to solve the model numerically, and second, to estimate the model. Solving the model with perturbation methods (Judd and Guu 1993; Schmitt-Grohé and Uribe 2004) has

[1]This chapter, co-written with Alexandre Gohin, was presented as a selected paper at 2018 CEF (Computing in Economics and Finance) Annual Meeting in Milan, and 2018 ICAE (International Conference for Agricultural Economists) Congress in Vancouver.

the highest computational efficiency. The disadvantage of this method is that it is only accurate around the steady state. Projection methods (Judd 1992) provide a highly accurate solution over the whole range of state values (Aruoba et al. 2006), but the computation burden is heavy. Especially with the increase of the number of state variables and the approximation order, projection methods suffer from the curse of dimensionality issue. Recent developments in dealing with such issues includes applying Smolyak's algorithm and developing the library of sparse grid (e.g. Stoyanov 2015).

After solving the model and obtaining a state-space representation, we can use the filters to estimate the latent state variables and obtain the likelihood function (An and Schorfheide 2007; Fernández-Villaverde and Rubio-Ramírez 2007). If the solution space is linear, the Kalman filter yields the optimal estimation. The Kalman filter is commonly used to estimate large DSGE models where the shocks are smooth and the solution space is considered close to linear.

However, with the increasing interest in high-order risk preferences, non-standard utility functions such as recursive utility (Epstein and Zin 1989), time-varying volatility (Caldara et al. 2012a), and the potentially large shocks in less aggregate models such as agricultural models, linear models are not sufficient to meet the research goals. For nonlinear estimation, the available methods include the extended Kalman filter (first-order optimality), the unscented Kalman filter (second-order optimality), and the sequential Monte-Carlo filter (also called the particle filter). Nonlinear estimation with the nonlinear filters, especially the particle filter, is, however, numerically more complicated and very time-consuming. Because it is a sampling-based method, we need to apply a further algorithm (e.g. Bayesian technique with Metropolis-Hasting algorithm, expectation maximization algorithm) to maximize the numerical likelihood, and we need to perform the solution and estimation steps sequentially in each loop. As a result, when estimating nonlinear DSGE models with filtering techniques, projection methods are seldomly used.

From the perspective of variance minimization, Ruge-Murcia (2007, 2012) proposes the simulated method of moments (SMM) to estimate the nonlinear DSGE models. It is also a sampling-based method which requires first to solve the model, and second, to generate the simulated data and evaluate the moment conditions.

With all the progress in estimating dynamic stochastic decision models, the maximum entropy method is still little mentioned. Entropy methods originate from information theory and have been developed by Jaynes (1957) to recover the probability distribution on the basis of partial information. Simply put, the central idea is that the probability distribution which best represents the known information, is the one with the maximized entropy. Golan et al. (1996) propose a generalized maximum entropy (GME) approach to estimate nonlinear state-space models. They recover the unknown structural parameters and the latent state variables in an explicit nonlinear state-space model (a dynamic stochastic decision model after nonlinear solution). Paris and Howitt (1998), Lence and Miller (1998), and Lansink (1999) use the GME approach to estimate various ill-posed production problems. Bishop (2006) discusses the use of cross-entropy in machine learning. Judge and Mittelhammer (2011) refer to the entropy criteria as an empirical exponential likelihood, and the maximum entropy method is referred to as the maximum empirical exponential likelihood (MEEL) method. Barde (2015), in an article named "back to the future", uses the maximum entropy approach as a signal restoration method to predict the equilibrium state of certain economic systems. The GME approach has several advantages in estimating dynamic stochastic decision models compared to the conventional methods. First, it evaluates directly the equilibrium conditions. As a result, the estimation is nonlinear by nature, and the nonlinear solution is only used to approximate the next period expectations in the Euler equation. Second, the GME approach recovers the unknown state and the unknown parameters simultaneously in one step, while the filtering-based approaches recover the unknown state first and then evaluate the likelihood function for each testing parameter to obtain the final parameter estimation. These two main advantages lead to a much higher computational efficiency of the GME approach. The third advantage is that the consistency of the GME estimate does not depend on the validity of assumptions on the distribution of the error terms.

In this chapter, we use the GME approach to estimate a nonlinear dynamic stochastic model, and compare it with the filtering-based approach. The test model is a neoclassical growth model, which is a standard DSGE model but can similarly be used to represent a farm decision model under risks. Based on the Monte-Carlo experiments with simulated data, we show that the GME approach provides optimal estimation between accuracy and efficiency. The contributions of the chapter are, first, to provide an alternative to estimate the nonlinear dynamic stochastic decision models apart from the conventional methods with the filters. To our knowledge, this is the first attempt to use the GME approach to estimate a DSGE model. Different from Golan et al. (1996), the model needs to be solved to obtain the state-space equations. Second, the chapter tests the GME estimator for large shocks and highly nonlinear models (5th-order projection), which describes better agricultural markets where the shocks are less smooth. Third, we show that the GME estimator possesses favorable properties for small sample size data, which is useful for economic fields with limited data.

The structure of the chapter is organized as follows. Section 2 contains a sketch of the model. Section 3 describes in detail the Bayesian estimation with the particle filter and the GME estimation. Section 4 presents the Monte-Carlo experiment and the estimation results. Section 5 concludes.

3.2 The Model

3.2.1 Economy Model Representation

We start from a neoclassical growth model. This is a core model for macroeconomic dynamics, but can also represent a farm decision model for investment, consumption and production decisions. This setting allows us to compare our results with a large number of papers in macroeconomics.

Consider a farm household who uses capital K_t to produce one good Y_t. The production income is used for personal consumption C_t and investment I_t on storable capital. The agent's goal is to maximize the discounted expected utility stream of consumption,

$$\max_{C_t, I_t} E_0 \sum_{t=0}^{\infty} \beta^t u(C_t). \tag{3.1}$$

The utility function takes the power utility form: $u(C_t) = C_t^{1-\gamma}/(1-\gamma)$, where γ determines the utility curvature and captures a mixture of risk preference and intertemporal preference. The agent's budget constraint is

$$Y_t = C_t + I_t \tag{3.2}$$

The agent has a Cobb-Douglas production process,

$$Y_t = A_t K_t^{\alpha} \tag{3.3}$$

where α is the output elasticity of capital. The total factor productivity (TFP) A_t follows a stochastic process,

$$\ln(A_{t+1}) = \rho_A \ln(A_t) + \sigma_A \tilde{\epsilon}_{A_{t+1}} \tag{3.4}$$

where ρ_A is the productivity persistence, σ_A is the standard deviation of the productivity shock, and ϵ_{A_t} is the stochastic productivity shock. $\tilde{\epsilon}_{A_t}$ is i.i.d and $\tilde{\epsilon}_{A_t} \sim N(0, 1)$.

Physical capital is owned by the agent, and is quasi-fixed in each period once installed. Its level depends on the last period capital stock K_{t-1} and investment I_{t-1}. The law of motion for capital is,

$$K_{t+1} = (1 - \delta)K_t + I_t \tag{3.5}$$

where δ is the depreciation rate.

In each period, the agent chooses strategy $\{C_t, I_t\}_{t=0}^{t=\infty}$ such as to maximize the expected lifetime utility subject to the intertemporal budget constraint (3.2), production constraint (3.3), and the capital evolution function (3.5). The Euler condition of the dynamics is given as,

$$C_t^{-\gamma} = \beta E_t \left[C_{t+1}^{-\gamma} \left(1 - \delta + \alpha A_{t+1} K_{t+1}^{\alpha-1} \right) \right] \tag{3.6}$$

It shows that consumption today is decided by the expected consumption and expected productivity in the future. Investment is implicitly determined by the Euler condition with the help of the budget constraint.

3.2.2 State-Space Representation

Since the model does not have an analytical solution, we need to solve it numerically. We use a high-order (5th-order) Chebyshev polynomials method to solve the model (Judd 1992). The nonlinear projection method provides a more accurate solution under the existence of large shocks (Aruoba et al. 2006). As our model is small, the high-order solution for this model is not severely influenced by the curse of dimensionality issue and provides accurate simulated data. We obtain the approximation of the optimal policy function through interpolation using the Chebyshev polynomial basis. The Mth-degree approximation of $C_t(A_t, K_t)$ is a complete polynomial:

$$C_t(K_t, A_t) = \sum_{m_K=0}^{M_K} \sum_{m_A=0}^{M_A} b_{m_K,m_A} \psi_{m_K}(\phi(K_t)) \psi_{m_A}(\phi(A_t)) \tag{3.7}$$

where $\psi_{d.}(.)$ are Chebyshev polynomials, $\phi(.)$ are linear mappings of the K_t, A_t collocation points to $[-1, 1]$, and b_{d_K,d_A} are the Chebyshev coefficients to be estimated. The solution is performed in GAMS with our own projection code.[2]

The solution of the dynamic model gives us a state-space representation as follows. With $\mathcal{Z}_t = [Y_t, I_t, C_t]^T$ the vector of decision variables, $\mathcal{S}_t = [K_t, A_t]^T$ the vector of state variables, and $\boldsymbol{\theta} = [\beta, \gamma, \alpha, \delta, \rho_A, \sigma_A]^T$ the structural parameter set, the state-space model is presented as,

$$\mathcal{Z}_t = f(\mathcal{S}_t, \mathcal{V}_t; \boldsymbol{\theta}) \tag{3.8}$$

$$\mathcal{S}_t = g(\mathcal{S}_{t-1}, \mathcal{W}_t; \boldsymbol{\theta}) \tag{3.9}$$

where f and g are nonlinear functions depending the vector of structural parameters $\boldsymbol{\theta}$. Equation (3.8) is the observation equation which links the observable decision variables $\mathcal{Z}_t$ and the unobservable state variables $\mathcal{S}_t$. $\mathcal{V}_t$ are the exogenous shocks such as measurement errors. Equation (3.9) is the state equation which describes the intertemporal evolution of state variables $\mathcal{S}_t$. $\mathcal{W}_t$ are the exogenous shocks, such as innovations. The object is to optimally estimate the hidden (unobservable) state $\mathcal{S}_t$ from data sequence $\mathcal{Z}_t$, the functional form, and the structural parameter set. Meanwhile, the structural parameters can also be estimated from the observable data $\mathcal{Z}_t$.

3.3 Estimation Methods

Before presenting the GME method, we briefly overview the Bayesian method combined with the particle filter, because we view it as a baseline method for comparison. The maximum entropy approach is also viewed as a derivation from the Bayesian method in Skilling (1989). As a result, it is worthwhile to begin with the Bayesian method.

[2]The detailed solution process is described in Appendix A.

Bayesian Method with the Particle Filter

Bayesian estimation Bayesian estimation is nothing but finding the posterior conditional density function of the parameters. Given a model with a parameter set $\boldsymbol{\theta}$, and observations until period T $\mathbf{z}_{1:T}$, we are interested in the posterior density $p(\boldsymbol{\theta}|\mathbf{z}_{1:T})$.

In Bayesian estimation, first, we have a prior $p(\boldsymbol{\theta})$ that contains the *a priori* knowledge of the parameters. Second, we have a likelihood function $p(\mathbf{z}_{1:T}|\boldsymbol{\theta})$ that describes the probability that the model fits the observation data given the parameter values. According to Bayes' theorem, the posterior density is,

$$p(\boldsymbol{\theta}|\mathbf{z}_{1:T}) = \frac{p(\mathbf{z}_{1:T}|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(\mathbf{z}_{1:T})} \tag{3.10}$$

where $p(\mathbf{z}_{1:T})$ is model evidence that amounts to the marginal density of observations. This term is required if we want to compute the exact posterior density in Bayesian estimation.

However, the model evidence $p(\mathbf{z}_{1:T})$ is difficult to manipulate and is independent of $\boldsymbol{\theta}$. In case we only search for the point estimation, the above formulation can be simplified. Indeed, we obtain the maximum *a posteriori* estimation by maximizing the product of the likelihood function and the prior:

$$p(\boldsymbol{\theta}|\mathbf{z}_{1:T}) \propto p(\mathbf{z}_{1:T}|\boldsymbol{\theta})p(\boldsymbol{\theta}) \tag{3.11}$$

The maximum *a posteriori* estimator is reduced to the maximum likelihood (ML) estimator if we do not consider the prior. The challenge is that the analytical solution only exists if the prior and the likelihood are Gaussian, and if the model is linear. When dealing with a non-Gaussian distribution (usually associated with nonlinear models), we will have to simulate the posterior density using a sampling-based Monte-Carlo method.

The particle filter The objective of Bayesian estimation is to find the posterior distribution of the structural parameters given the prior information, or in the case of ML estimation to find the optimum maximizing the likelihood function. For the state-space models with latent variables, the difficulty lies in computing the likelihood function. If the model is linear, the Kalman filter can be used to compute an analytical likelihood function. If the model is nonlinear, we need to use the sampling method, e.g., the particle filter, to approximate the likelihood function.

Fernández-Villaverde and Rubio-Ramírez (2005) propose to estimate parameters that maximize the likelihood function of the observations. The decomposed form of the likelihood function $p(\mathbf{z}_{1:T}|\boldsymbol{\theta})$ according to Markov property of time series data and Bayes rule is:

$$p(\mathbf{z}_{1:T}|\boldsymbol{\theta}) = p(\mathbf{z}_1|\boldsymbol{\theta}) \prod_{t=2}^{K} p(\mathbf{z}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}). \tag{3.12}$$

with

$$p(\mathbf{z}_1|\boldsymbol{\theta}) = \int p(\mathbf{z}_1|\mathbf{s}_1, \boldsymbol{\theta}) d\mathbf{s}_1 \tag{3.13}$$

and

$$p(\mathbf{z}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}) = \int p(\mathbf{z}_t|\mathbf{s}_t, \boldsymbol{\theta}) p(\mathbf{s}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}) d\mathbf{s}_t \tag{3.14}$$

and

$$p(\mathbf{s}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}) = \int p(\mathbf{s}_t|\mathbf{s}_{t-1}, \boldsymbol{\theta}) p(\mathbf{s}_{t-1}|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}) d\mathbf{s}_{t-1} \tag{3.15}$$

Using the particle filter, we can approximate $p(\mathbf{s}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta})$ through an ensemble of samples and according to the law of large numbers,

$$p(\mathbf{s}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}) = \frac{1}{N} \sum_{n=1}^{N} \delta(\mathbf{s}_t - \mathbf{s}^n_{t|t-1}) \tag{3.16}$$

Introducing the above approximation into equation (3.14), we have[3]

$$\begin{aligned} p(\mathbf{z}_t|\mathbf{z}_{1:t-1}, \boldsymbol{\theta}) &= \int p(\mathbf{z}_t|\mathbf{s}_t, \boldsymbol{\theta}) d\mathbf{s}_t \frac{1}{N} \sum_{n=1}^{N} \delta(\mathbf{s}_t - \mathbf{s}^n_{t|t-1}) \\ &= \frac{1}{N} \sum_{n=1}^{N} p(\mathbf{z}_t|\mathbf{s}^n_{t|t-1}, \boldsymbol{\theta}) \end{aligned} \tag{3.17}$$

The same approximation applied to $p(\mathbf{z}_1|\boldsymbol{\theta})$. Eventually we obtain the likelihood function as follows,

$$p(\mathbf{z}_{1:T}|\theta) = \frac{1}{N} \sum_{n=1}^{N} p\left(\mathbf{z}_1|\mathbf{s}^n_{0|0}; \theta\right) \prod_{t=2}^{T} \frac{1}{N} \sum_{n=1}^{N} p\left(\mathbf{z}_t|\mathbf{s}^n_{t|t-1}; \theta\right) \tag{3.18}$$

[3] A detailed deduction of equation (3.17) is described in Appendix B.

The algorithm of the particle filter to approximate the likelihood function is (Fernández-Villaverde and Rubio-Ramírez 2005, 2007):

1. Set $t = 1$, initialize the model probability density $p\left(\mathbf{s}_t|\mathbf{z}_{t-1};\theta\right) = p(\mathbf{s}_0;\boldsymbol{\theta})$; sample N particles $\left\{\mathbf{s}^n_{0|0}\right\}^N_{n=1}$ from $p(\mathbf{s}_0;\theta)$.

2. Sample N particles $\left\{\mathbf{s}^n_{t|t-1}\right\}^N_{n=1}$ from $\left\{\mathbf{s}^n_{t-1|t-1}\right\}^N_{n=1}$ by running the transition equation (3.9) and by using the exogenous shocks $\{\mathbf{w}^n_t\}^N_{n=1}$ (draw the shocks from the corresponding distribution function).

3. Assign the relative weights $\{\mathbf{q}^n_t\}^N_{n=1}$ for each particle $\left(\mathbf{s}^n_{t|t-1}\right)$ with the following weighting function:

$$q^n_t = \frac{p\left(\mathbf{z}_t|\mathbf{s}^n_{t|t-1};\boldsymbol{\theta}\right)}{\sum^N_{n=1} p\left(\mathbf{z}_t|\mathbf{s}^n_{t|t-1};\boldsymbol{\theta}\right)}$$

   If the particle with which the probability of the simulated output equals the observations is high, the weight assigned to the particle is high. Otherwise the weight assigned to the particle is low.

   The density $p\left(\mathbf{z}_t|\mathbf{s}^n_{t|t-1};\theta\right)$ is obtained from the measurement equation and the distribution of the exogenous shocks or the measurement errors $\mathcal{V}_t$. More specifically, the above density is the likelihood of measurement errors corresponding to the particle. The distribution of the measurement error η^n_t is:

$$\eta^n_t = \mathbf{z}^n_{t,obs} - \mathbf{z}^n_{t|t-1} \sim i.i.d.N(0, \sigma^{n2})$$

   η^n_t is the exogenous shock in the measurement equation or the measurement errors.

4. Resampling. We use the Sequential Importance Resampling (SIR) method. With this method, the particles with very low weights are abandoned, while multiple copies of particles with higher weights are kept. The number of the copies is computed based on their respective weights. The higher the weight of the particle $\left(\mathbf{s}^n_{t|t-1}\right)$, the more copies are generated, such that the total number of particles becomes N again (Van Leeuwen 2009). Call the particles from the resampling process $\left(\mathbf{s}^n_{t|t}\right)$. Then go back to step 2 until $t = T$.

The re-sampling process ensures that the particles $\left(\mathbf{s}_{t|t}^{n}\right)$ converge to the true states given the evolution of time.

By substituting the probability density $\left\{p\left(\mathbf{z}_t|\mathbf{s}_{t|t-1}^{n};\boldsymbol{\theta}\right)\right\}_{n=1}^{N}$ which we have computed in step 3 for each period into equation (3.18), we have a numerical estimation of the likelihood $p(\mathbf{z}_{1:T}|\boldsymbol{\theta})$. Once we have the likelihood function, we can use the Newton-like method to maximize the likelihood and to point-estimate the parameter set. If we adopt the Bayesian method, we can compute the posterior density $p(\boldsymbol{\theta}|\mathbf{z}_{1:T})$ by the Monte-Carlo Markov Chain (MCMC).

Maximum Entropy

The generalized maximum entropy (GME) approach we use here is described in Golan et al. (1996). In particular, their approach is used to estimate a dynamic model with unobserved data, such as land quality, unobserved shocks, and technical change. The dynamic model of Golan et al. (1996) matches explicitly the state-space representation so that they do not need to solve the model. The advantages of the GME approach in estimating DSGE or DSGE-like models have been discussed in the Introduction. In short, this approach evaluates the equilibrium conditions directly, and it recovers the unknown parameters and the unknown states simultaneously. The prior distribution of the parameters is not required to be continuous, instead, it is in form of discrete points. Moreover, the consistency of the GME estimate does not depend on the validity of assumptions on the distribution of the error terms. The disadvantages of the method are that, first, the statistical inference of this method is not well developed, and second that results can be sensitive to the choices of the prior information of the parameters and the error terms.

In a general form, Jaynes (1957) proposes to find the probability distribution that satisfies the constraints and maximizes the Shannon's entropy criterion (Shannon 1948),

$$H(\mathbf{p}) = -\sum_{n} p_n ln(p_n) \tag{3.19}$$

where $\mathbf{p} = (p_1, ..., p_N)'$ is a discrete probability distribution for discrete prior information.

For our empirical estimation, we need to recover the probability distribution of the structural parameter set $\boldsymbol{\theta}$, and the time-varying error terms, including ϵ_{At} which represent the productivity shocks, and ϵ_{c_t} which represent the measurement errors. With the recovered structural parameters and structural shocks, we are able to recover the evolution process of the latent productivity and capital.

To construct the GME framework, first, we reparameterize the structural parameters $\theta_h(h = 1, 2, \ldots, H)$ and the errors $\epsilon_{jt}(j = 1, 2, \ldots, J; t = 1, 2, \ldots, T)$. Here h is the index for the parameters, j is the index for the errors, and t is the time index. Given the prior information, suppose that the value of each parameter θ_h lies in the interval $[v^{\theta}_{h1}, v^{\theta}_{hG}]$. We define a set of discrete points (support values) $v^{\theta}_{h} = [v^{\theta}_{h1}, v^{\theta}_{h2}, \ldots, v^{\theta}_{hG}]'$, with associated probability weights $w^{\theta}_{h} = [w^{\theta}_{h1}, w^{\theta}_{h2}, ..., w^{\theta}_{hG}]'$. The unknown $\boldsymbol{\theta}$, which is a vector of length H is,

$$\boldsymbol{\Theta} = \mathbf{V}^{\theta}\mathbf{w}^{\theta} = \begin{bmatrix} \mathbf{v_1^{\theta}}' & 0 & \ldots & 0 \\ 0 & \mathbf{v_2^{\theta}}' & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \mathbf{v_H^{\theta}}' \end{bmatrix} \begin{bmatrix} \mathbf{w_1^{\theta}} \\ \mathbf{w_2^{\theta}} \\ \vdots \\ \mathbf{w_H^{\theta}} \end{bmatrix} \tag{3.20}$$

where $\mathbf{V}^{\theta}$ is an $H \times HG$ matrix and $\mathbf{w}^{\theta}$ is an HG vector. For each parameter θ_h,

$$\mathbf{v_h^{\theta}}'\mathbf{w_h^{\theta}} = \sum_{g} v^{\theta}_{hg} w^{\theta}_{hg} = \theta_h \; for \; h = 1, 2, \ldots, H \tag{3.21}$$

Similarly, suppose the error terms $\epsilon_{\mathbf{jt}}$ lie in the interval $[v^{\epsilon}_{jt1}, v^{\epsilon}_{jtL}]$. Note here that we have one more dimension, time t. We define a set of discrete points $v^{\epsilon}_{jt} = [v^{\epsilon}_{jt1}, v^{\epsilon}_{jt2}, \ldots, v^{\epsilon}_{jtL}]'$, with associated probability weights $w^{\epsilon}_{jt} = [w^{\epsilon}_{jt1}, w^{\epsilon}_{jt2}, ..., w^{\epsilon}_{jtL}]'$. The unknown shocks ϵ_t at time t, which is a vector of length J, is,

$$\epsilon_{\mathbf{t}} = \mathbf{V_t^{\epsilon}}\mathbf{w_t^{\epsilon}} = \begin{bmatrix} \mathbf{v_{t1}^{\epsilon}}' & 0 & \ldots & 0 \\ 0 & \mathbf{v_{t2}^{\epsilon}}' & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \mathbf{v_{tL}^{\epsilon}}' \end{bmatrix} \begin{bmatrix} \mathbf{w_{t1}^{\epsilon}} \\ \mathbf{w_{t2}^{\epsilon}} \\ \vdots \\ \mathbf{w_{tL}^{\epsilon}} \end{bmatrix} \tag{3.22}$$

where $\mathbf{V_t^{\epsilon}}$ is $J \times JL$ matrix and $\mathbf{w}^{\epsilon}$ is JL vector. For each shock at time t ϵ_{jt},

$$\mathbf{v_{jt}^{\epsilon}}'\mathbf{w_{jt}^{\epsilon}} = \sum_{l} v^{\epsilon}_{jtl} w^{\epsilon}_{jtl} = \epsilon_{jt} \; for \; j = 1, 2, \ldots, J; \; t = 1, 2, \ldots, T \tag{3.23}$$

Given the reparameterization, our objective is to find the optimal probability distribution $(\mathbf{w}^\theta, \mathbf{w}^\epsilon)$ of the corresponding support values which maximize the entropy objective. The empirical program is,

$$\max_{\mathbf{w}^\theta, \mathbf{w}^\epsilon} -\sum_h \sum_g w_{hg}^\theta ln(w_{hg}^\theta) - \sum_j \sum_t \sum_l w_{jtl}^\epsilon ln(w_{jtl}^\epsilon) \tag{3.24}$$

subject to the equilibrium conditions of the dynamic decision program and the adding-up constraints,

$$C_t^{-\gamma} = \beta E_t \left[C_{t+1}^{-\gamma} \left(1 - \delta + \alpha A_{t+1} K_{t+1}^{\alpha-1}\right)\right] \tag{3.25}$$

$$K_{t+1} = (1-\delta)K_t + Y_t - C_t \tag{3.26}$$

$$Y_t = A_t K_t^\alpha \tag{3.27}$$

$$\ln(A_{t+1}) = \rho_A \ln(A_t) + \sigma_A \tilde{\epsilon}_{A_{t+1}}, \quad \tilde{\epsilon}_{A_t} \sim N(0,1) \tag{3.28}$$

$$\sum_g w_{hg}^\theta = 1 \quad for\ h = 1, 2, \ldots, H \tag{3.29}$$

$$\sum_l w_{jtl}^\epsilon = 1 \quad for\ j = 1, 2, ..., J; \quad t = 1, 2, ..., T-1 \tag{3.30}$$

$$w_{hg}^\theta > 0, w_{jtl}^\epsilon > 0 \quad for \quad \forall h, j, t, g, l \tag{3.31}$$

where w_{hg}^θ and w_{jtl}^ϵ are the probability weights of the supporting values which we have specified in the reparameterization part, and equations (3.25) - (3.28) correspond to the equilibrium conditions in equations (3.2) - (3.5).

To bring the above program, especially the Euler equation (3.25), to the data, one important assumption are rational expectations. At time t, the agent observes two time series, consumption C_t^{obs} and production Y_t^{obs}. The agent cannot precisely predict the point value of the next period productivity shocks $\epsilon_{A_{t+1}}$, but he or she knows the distribution of the shocks. We model the anticipated shocks $\epsilon_{A_{t+1}}^e$ by Gaussian Quadrature according to the distribution of the real shocks. The real shocks and the distribution are to be retrieved in the GME estimation.

This process involves modeling the error terms as random variables with Gaussian Quadrature nodes and the corresponding Gaussian Quadrature weights. For shocks that follow a normal distribution with zero mean and standard deviation of 1, we use a 5-point Gaussian Quadrature grid with the nodes and weights specified in Table 3.1 to describe the anticipated shocks.[4]

[4] The Gaussian Quadrature grid is generated in Matlab with the CompEcon Toolbox developed by Miranda and Fackler (2004).

Table 3.1: Gauss-Hermite approximation

e	ϵ^e	w^e
1	-2.8570	0.0113
2	-1.3556	0.2221
3	0	0.5333
4	1.3556	0.2221
5	2.8570	0.0113

e denotes the index of the points, ϵ^e denotes the value of each point, and w^e is the associated weight.

Consequently, the anticipated next-period state A_{t+1} is decided by the anticipated shock $\epsilon^e_{A_{t+1}}$, and the anticipated consumption C^e_{t+1} is decided by the anticipated state from the policy function (3.34) with the Chebyshev polynomials. This setting adds four more constraints (3.32) - (3.35) to the GME program,

$$\ln(A^e_{t+1}) = \rho_A \ln(A_t) + \sigma_A \epsilon^e_{A_{t+1}} \tag{3.32}$$

The Chebyshev coefficients are jointly estimated in the GME program by interpolating the basis functions of the state variables K_t and A_t into the observed consumption data series,

$$C^{obs}_t = \sum_{m_K=0}^{M_K} \sum_{m_A=0}^{M_A} b_{m_K,m_A} \psi_{m_K}(\phi(K_t))\psi_{m_A}(\phi(A_t)) + \epsilon_{euler_t} \tag{3.33}$$

$$C^e_{t+1} = \sum_{m_K=0}^{M_K} \sum_{m_A=0}^{M_A} b_{m_K,m_A} \psi_{m_K}(\phi(K_{t+1}))\psi_{m_A}(\phi(A^e_{t+1})) \tag{3.34}$$

where ϵ_{euler_t} is a mixture of measurement errors and approximation errors of the consumption data series. Measurement error series ϵ_{c_t} is to avoid the singularity problem because we need to have the same number of shocks as the number of observable data series (Fernández-Villaverde and Rubio-Ramírez 2005, Ruge-Murcia 2007). Here we use two observation data series for the estimation, and there is only one structural shock. Consequently, we add one shock which represents the measurement errors. The empirical Euler condition is rewritten as,

$$(C^{obs}_t)^{-\gamma} = \sum_e w^e \beta \left[(C^e_{t+1})^{-\gamma} \left(1 - \delta + \alpha A^e_{t+1} (K_{t+1})^{\alpha-1}\right) \right] \tag{3.35}$$

Finally, the entropy objective (3.24) is maximized subject to the constraints (3.26), (3.27), and (3.29) - (3.35). The time-constant parameters dimension $H = 6 + 25 = 31$ (with 6 being the number of the structural parameters, and $25 = 5^2$ the number of Chebyshev coefficients), and the time-varying shocks dimension $J = 2$. By forming the Lagrangian, the first-order conditions provide the basis for the solution w^{θ}_{hg} and w^{ϵ}_{jtl}. By the reparameterization definition, the estimated parameters and shocks are

$$\sum_g \hat{w}^{\theta}_{hg} v^{\theta}_{hg} = \hat{\theta}_h \tag{3.36}$$

$$\sum_l \hat{w}^{\epsilon}_{jtl} v^{\epsilon}_{dtj} = \hat{\epsilon}_{jt} \tag{3.37}$$

Given the recovered shocks in (3.37), the estimates of the TFP evolution process are determined by (3.28).

3.4 Sampling Experiments

3.4.1 Experiment Design

In a general case, the GME estimator cannot be expressed in a closed form, and its finite sample properties cannot be derived from direct evaluation. In order to test the performance of the GME approach and compare it with the more widely used filtering methods, we perform the Monte-Carlo sampling experiments on simulated data. Given the parameter calibration in Table 3.2, we use a 5th-order Chebyshev polynomial approximation to generate production and consumption data series. The data are generated in GAMS (version 2017) using our own projection code.

The first parameter calibration is a benchmark-setting from the previous lit-

Table 3.2: Calibrated Parameters

Parameters	Description	Case 1 (macro)	Case 2 (agr)
β	discount factor	*0.95*	*0.95*
γ	preference parameter	*2*	*0.75*
α	output elasticity of capital	*0.36*	*0.36*
δ	depreciation rate	*0.025*	*0.05*
ρ_A	productivity persistence	*0.85*	*0.70*
σ_A	standard deviation of productivity shocks	*0.04*	*0.10*

erature (e.g., Fernández-Villaverde and Rubio-Ramírez 2005, Ruge-Murcia 2012). This setting is realistic for macro-data series and allows us to compare our results with the previous literature. The inverse elasticity-of-intertemporal-substitution parameter, or, equivalently, the preference parameter γ, which is a mixture of risk preference and time preference, is set to 2. The output elasticity of capital α is 0.36 and the depreciation rate δ is 0.025. Regarding the TFP evolution process, the standard deviation of the TFP shocks is low (0.04), but higher than 0.007 in Fernández-Villaverde and Rubio-Ramírez (2005).

For the second parameter calibration, we introduce calibrations for agricultural models. The depreciation rate is higher (0.05) considering the intensive use of agricultural capital, the level of risk aversion is lower (0.75) considering that the farmers have long been protected from policies, productivity persistence is lower (0.70), and productivity shocks are higher ($\sigma_A = 0.10$). In this way, we introduce a certain level of nonlinearity to the economy.

The objective parameter set for the estimation is $\mathbf{\Theta} = (\gamma, \alpha, \beta, \delta, \rho_{\mathbf{A}}, \sigma_{\mathbf{A}})^{\mathbf{T}}$. It is worth mentioning that different from the simulated method of moments (SMM) sampling experiments in Ruge-Murcia (2012), where two parameters (α, δ) are fixed and the other four parameters $(\beta, \gamma, \rho_A, \sigma_A)$ are to be estimated, we do not fix any parameter and we estimate the entire parameter set.

We consider a small sample with 50 observations to reflect limited availability of agricultural data. Our sample size is small compared to a sample size of 100 in Fernández-Villaverde and Rubio-Ramírez (2005), and a sample size of 200 in Ruge-Murcia (2012). We also test for sample sizes of 30 and 100.

For the GME estimation, the support values given for the parameters and the error terms are very important. On the one hand, the support values allow the economist to give prior information on the parameters. On the other hand, this introduces a possibility of manipulation, and the estimation can be sensitive to the support values. In our experiments, we choose loose priors to avoid manipulation. Table 3.3 lists the detailed support values. The discount factor β is generally known to be larger than 0.9, we set the prior between 0.9 and 0.99. The utility curvature γ has a reference value in the previous literature between 0.1 and 3. We set the prior accordingly. The output elasticity of capital is set between 0 and 1. The depreciation rate in agricultural is generally smaller than 10 percent, and we set a prior between 0.01 and 0.15. The persistence of a stationary TFP process should be smaller than 1, so our prior for the TFP persistence is

Table 3.3: GME estimation: prior information for the parameters

	Support values		
Parameters	Low	Centre	High
β	0.9	0.95	0.999
γ	0.01	1	3
α	0	0.5	1
δ	0.01	0.10	0.15
ρ_A	0.01	0.5	0.99
σ_A	0.001	0.1	0.15
ϵ_{At}	-1	0	1
ϵ_{euler_t}	-0.001	0	0.001

set between 0.01 and 0.99. To allow a large variation in volatility, the standard deviation of productivity is set between 0.001 and 0.15. The intervals of the shocks are set between -1 and 1. Furthermore, in the previous literature the optimization routine has always started from the true values (e.g. Ruge-Murcia 2007). Indeed, good starting values can largely facilitate the optimization and make the estimates more accurate. However, for real data, it is not realistic to initialize from the true values. As a result, in order to test the real-world feasibility of the method, we start the optimization routine near the center of the support values $((\beta_0, \gamma_0, \alpha_0, \delta_0, \rho_{A0}, \sigma_{A0})' = (0.9, 0.9, 0.5, 0.05, 0.5, 0.1)')$, and these values are not necessarily the true values.

The GME estimation is replicated 100 times for Case 1 and Case 2 to test the accuracy and robustness of the estimator. The empirical properties of the estimator are measured using the root mean square error (RMSE) criteria. In particular, for the estimated parameter $\hat{\theta}$, RMSE is the root of the sum of the variance and the squared bias: $RMSE = \sqrt{(\theta - \bar{\hat{\theta}}) + Var(\hat{\theta})}$. The estimation is performed in GAMS2017 for Nonlinear Program (NLP) with the Conopt solver.

For the Bayesian estimation with the particle filter, we adopt a similar prior specification and starting values as in the GME setting. The detailed prior information is reported together with the results in Table 3.5. We use $60,000$ particles to get $50,000$ draws from the posterior distribution. Since one replication takes more than 10 hours, we are not able to do the replication for 100 times. The estimation has been performed in Dynare in Matlab R2016a.

3.4.2 Results

Table 3.4 presents the GME estimation results. For the first case with small shocks, which represents the macro calibration, the GME estimator yields precise estimates of the entire parameter set. The estimation bias is small, with the lowest being 0.42% and the highest being 7.45%. In particular, the accurate estimation of the depreciation rate, the persistence and the standard deviation of the shocks indicates the latent capital evolution process, and the latent TFP evolution process are retrieved.

The second case is more realistic for the agricultural models, but the nonlinearity brought in by the large shocks may impose more difficulty for the estimation. Again, the GME estimation recovers all parameters with precision. The bias is small and most of the RMSE is explained by the standard deviation of the estimations. For both cases, according to the experiments, β and α are sharply identified regardless of the setting of parameter bounds and error bounds. The parameters describing the characteristics of the state variables (δ, ρ_A, σ_A) have on average slightly larger bias and RMSE and are theoretically more difficult to retrieve, but they are also relatively accurately recovered. Above all, the preference parameter γ is the most difficult one to be estimated in the experiments. Correspondingly, Table 3.4 shows that the bias and RMSE of γ are relatively larger than for other parameters. This is because the risk preference and the consumption smoothing preference are not easy to capture in the data - the objective function is relatively flat with the change in preference values. However, we are still able to estimate γ accurately when we allow the Euler errors to be at a low level (within the range $[-0.001, 0.001]$ as support values). This is in accordance with Attanasio and Low (2004) who state that when bringing the Euler equation to the data, the presence of measurement error can have large effects on the consistency of estimates of the relative risk aversion parameter.

As a comparison, we present the results from the Bayesian estimation with the particle filter. As expected, and as in the previous literature (Fernández-Villaverde and Rubio-Ramírez 2005), the Bayesian estimation delivers a relatively accurate estimation for the parameters. The estimation outcomes of the two methods are alike. Similarly, the preference parameter γ is the most difficult one to precisely retrieve. The Bayesian estimation tends to over-estimate γ a little more than the GME estimation. Besides, the GME estimation slightly outperforms the Bayesian estimation in terms of the unobserved TFP shocks - the bias is lower for ρ_A and

Table 3.4: GME estimation: Monte Carlo experiment results

Parameters		Mean	S.D.	Bias		RMSE
Θ	True	Case 1 (macro): Small shocks				
β	0.95	0.9460	0.0154	-0.0040	(0.42%)	0.0159
γ	2	2.1490	0.5477	0.1490	(7.45%)	0.5676
α	0.36	0.3665	0.0223	0.0065	(1.81%)	0.0233
δ	0.025	0.0261	0.0050	0.0011	(4.28%)	0.0051
ρ_A	0.85	0.8346	0.1151	-0.0154	(1.81%)	0.1162
σ_A	0.04	0.0404	0.0074	-0.0004	(1.08%)	0.0074
		Case 2 (agr): Large shocks				
β	0.95	0.9490	0.0096	-0.0010	(0.11%)	0.0100
γ	0.75	0.7876	0.4997	0.0376	(5.02%)	0.5011
α	0.36	0.3512	0.0227	-0.0088	(2.45%)	0.0244
δ	0.05	0.0499	0.0047	-0.0001	(0.26%)	0.0047
ρ_A	0.70	0.7046	0.1161	0.0046	(0.66%)	0.1162
σ_A	0.10	0.0979	0.0113	-0.0021	(2.11%)	0.0115

Note: Estimation based on 100 replications of 50 period random samples generated from a 5th-order Chebyshev approximation. Each replication takes on average 59.27 seconds in GAMS2017.

Table 3.5: Bayesian estimation with the particle filter results

Parameters		Prior distribution	Posterior distribution		
			Mean	90% HPD interval	
Θ	True		Case 1 (macro): Small shocks		
β	0.95	uni(0.8,1)	0.9495	0.9444	0.9544
γ	2	uni(0,10)	2.7757	2.7348	2.8142
α	0.36	uni(0,1)	0.3665	0.3568	0.3769
δ	0.025	uni(0,0.1)	0.0250	0.0231	0.0269
ρ_A	0.85	uni(0,1)	0.8127	0.7929	0.8346
σ_A	0.04	invg(0.1,inf)	0.0224	0.0199	0.0250
			Case 2 (agr): Large shocks		
β	0.95	uni(0.8,1)	0.9556	0.9505	0.9615
γ	0.75	uni(0,10)	0.7961	0.7550	0.8404
α	0.36	uni(0,1)	0.3440	0.3313	0.3548
δ	0.05	uni(0,0.1)	0.0487	0.0448	0.0520
ρ_A	0.70	uni(0,1)	0.6737	0.6435	0.7040
σ_A	0.10	invg(0.1,inf)	0.0499	0.0445	0.0544

Note: Estimation based on 50 period random samples generated from a 5th-order Chebyshev approximation. The computing time for Case 1 is 16h13m03s, and for Case 2 is 15h34m18s in Matlab2016a.

Table 3.6: Comparing Monte Carlo experiment results with different sample size

		T=30			T=50			T=100		
Parameters		Mean	S.D.	RMSE	Mean	S.D.	RMSE	Mean	S.D.	RMSE
Θ	True									
β	0.95	0.949	0.008	0.008	0.949	0.010	0.010	0.947	0.010	0.011
γ	0.75	0.894	0.601	0.618	0.788	0.040	0.500	0.730	0.283	0.284
α	0.36	0.355	0.016	0.017	0.351	0.023	0.024	0.358	0.019	0.019
δ	0.050	0.053	0.010	0.011	0.050	0.005	0.005	0.050	0.003	0.003
ρ_A	0.70	0.677	0.083	0.087	0.705	0.116	0.116	0.692	0.117	0.118
σ_A	0.10	0.097	0.013	0.013	0.098	0.011	0.012	0.100	0.008	0.008

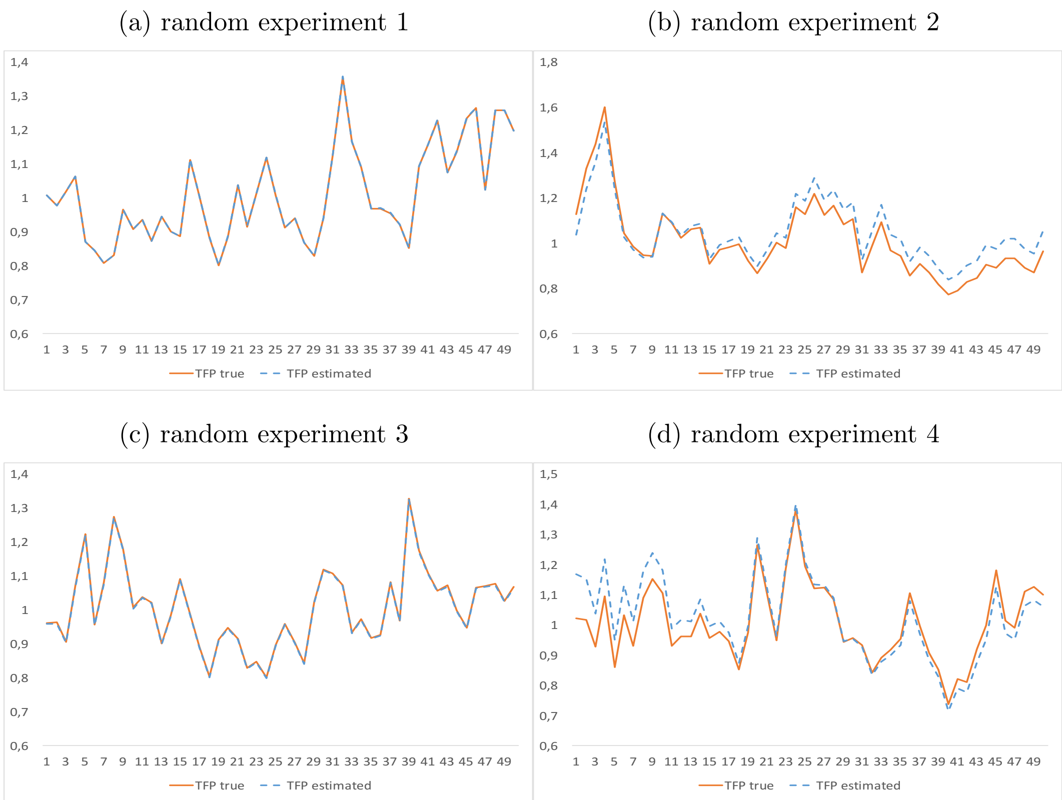
Note: Estimation based on 100 replications of 30, 50, 100 period random samples generated from a 5th order Chebyshev approximation.

σ_A under the GME estimation. Overall, both estimation methods provide relatively good estimates of the parameters. However, in terms of the computation burden, the GME estimation is much faster than the Bayesian estimation: around 60 seconds compared to more than 10 hours for one replication. We suppose the Bayesian methods with the filters is preferred in macroeconomics because they have been proven robust also with large macroeconomic models with numbers of smooth shocks and many sectors, for which we have not tested for the GME approach. Above all, our experiments show that the GME approach provides more efficient, yet solid estimates for small and highly nonlinear dynamic stochastic models.

Sensitivity to the support values and the initial values It has been mentioned in other literature that one drawback of the GME approach is that it is sensitive to the support values (Lansink 1999, Lansink and Carpentier 2001). For our estimation, this is not a serious problem because we choose large bounds for support values, as long as the economic meanings of the parameters are satisfied (see Table 3.3). Our results show that the estimations are not manipulated by the support values. This is in accordance with Lence and Miller (1998) who show that the GME estimates are not specially sensitive to the choice of parameter bounds. Regarding the initial values (the starting values), not only the GME estimation, but all the optimization problems depend more or less on them. Good initial values, sometimes the true ones, yield good estimates, while bad initial values, results in very different results. The Monte-Carlo experiments show that the GME estimation retrieves the parameters when the initial values are away from the true ones. We also test different initial values to ensure that the parameter estimates always return the true values.

Small-sample properties Table 3.6 illustrates the small-sample property of the GME estimation. The estimation of the large sample size ($T = 100$) outperforms the estimation on the small-sample size ($T = 30$), especially for the preference parameter γ. The estimation bias and RMSE of γ decrease steadily with the increase of sample size. Most parameters ($\beta, \alpha, \delta, \rho_A, \sigma_a$) can be retrieved under a smaller sample size of 30. Furthermore, with the increase in sample size, the accuracy level of δ and σ_A have largely improved, while the other parameters (β, α, ρ_A) have mixed results regarding the improvement. This may be due to the fact a sample size of 100 is still not large enough.

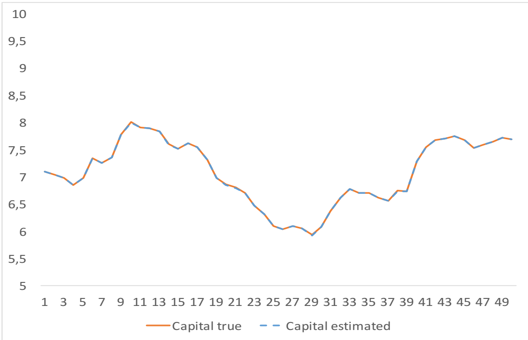
Figure 3.1: Comparing the recovered state with the true state from the GME estimation (TFP)



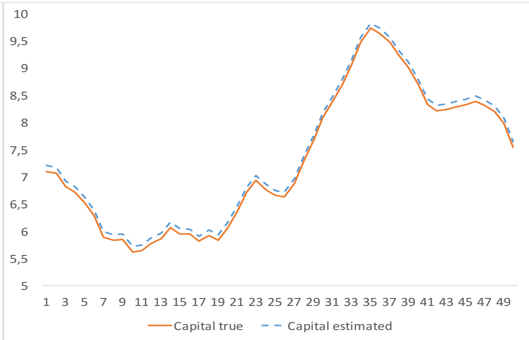
Recovering the unknown state We pick up randomly 4 estimations of the unknown state, total factor productivity (TFP), and capital from the 100 experiments to see whether the unknown state can be recovered from the GME estimation. The

Figure 3.2: Comparing the recovered state with the true state from the GME estimation (Capital)

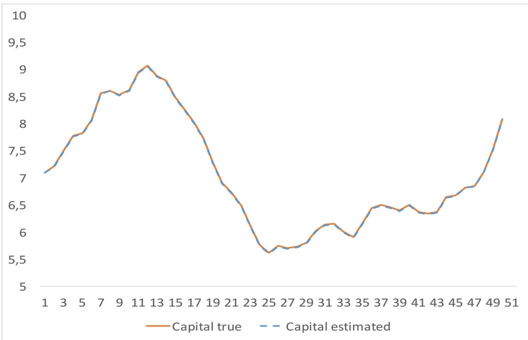
(a) random experiment 1



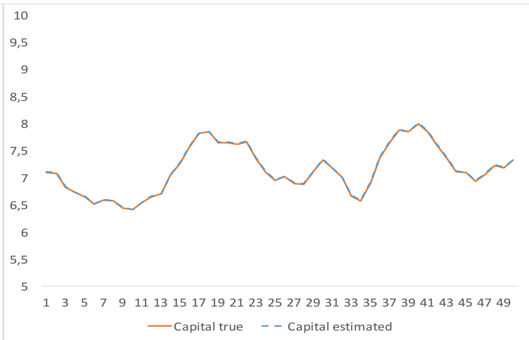
(b) random experiment 2



(c) random experiment 3



(d) random experiment 4



state variables are unobserved in real data, but in the experiment, we simulate the random shocks, so that we can access the true values of the shocks and the state. Figure 3.1 depicts the estimated TFP evolution and compares it to the true TFP evolution. We can see that in good cases (Figure 3.1a, 3.1c), the estimated TFP matches exactly the evolution of true TFP. In less good (but still satisfactory) cases (Figure 3.1b, 3.1d), the estimated TFP moves at the same direction with the true TFP, and the evolution of the TFP process is approximately recovered by the GME estimation. Figure 3.2 depicts the estimated capital and compares it to the true capital. The capital data series are also well retrieved.

3.5 Conclusion

In this chapter, we propose a GME method that can be used to estimate nonlinear dynamic stochastic decision models. For these models, the state variables such as productivity are unobserved, and a solution procedure is needed to obtain an explicit state-space representation. To our knowledge, this method has not been used to estimate DSGE or DSGE-like models before, but the filtering methods are more widely applied in this field. Based on the Monte-Carlo experiments, we show that the GME method recovers estimates of all the unknown structural parameters and the stochastic shocks. In particular, the preference parameter which captures the risk preference and the intertemporal preference is also relatively precisely estimated. Compared to the Bayesian estimation with the particle filter, we show that the GME approach provides a similar level of estimation accuracy, but much higher computational efficiency for nonlinear models. This is because the GME method does not sequentially solve and estimate the model for each testing parameter, but solves and estimates the model simultaneously given the discrete support values as the prior information. Moreover, the GME estimator shows favorable properties for small sample size data. This is useful for agricultural economics research since the agricultural data series are usually on an annual basis and are not sufficiently long.

Estimating dynamic stochastic decision models has numerous empirical applications for agricultural economics. It allows the economist to structurally model the farmers' dynamic decisions, in particular, investment and consumption decisions under risks, and depict the real values of the structural parameters from estimation instead of calibration. This has important implication for agricultural policy analysis in response to unknown shocks. Moreover, Griliches and Mairesse (1995) discuss the problems in estimating production functions, including the data measurement problem for the capital data series and the endogeneity problem to estimate the TFP as a residual. The proposed GME approach may provide a feasible solution to these problems, because it can deal with the missing data (latent state variables), and estimation of the structural equations is free from the endogeneity problem. Beyond the growth model, further work could involve fitting this classical model to agricultural decision models by adding more agricultural production factors and estimating the structural parameters and stochastic shocks using real agricultural data. From a methodological perspective, further work is to be done to compare the filtering-based approach and the entropy approach in view of Bayesian methods. Moreover, how to deal with a growing economy with trending data also remains a question.

3.6 Appendix

Appendix A: Description of the solution method

We approximate the optimal consumption policy function $C_t(A_t, K_t)$ by using the standard projection method with Chebyshev collocation (Judd 1992, Aruoba et al. 2006). After the consumption rule is approximated, production and investment can be recovered from the equilibrium conditions.

The Chebyshev polynomials are defined recursively,

$$\psi_0(x) = 1$$
$$\psi_1(x) = x$$
$$\psi_{n+1}(x) = 2x\psi_n(x) - \psi_{n-1}(x)$$

where ψ is bounded between $[-1, 1]$.

Next, we choose n collocation points for capital within the bounds $[K_{min}, K_{max}]$, with K_{min} and K_{max} being the lower and upper bounds of capital. The point $k_h \in [K_{min}, K_{max}]$, mapped to $[-1, 1]$ is,

$$\phi(K_h) = \frac{2(K_h - K_{min})}{K_{max} - K_{min}} - 1$$

Accordingly,

$$K_h = \frac{K_{max} + K_{min}}{2} + \frac{K_{max} - K_{min}}{2}\phi(K_h)$$

The h^{th} collocation point within $[-1, 1]$ is given by,

$$\phi(K_h) = \cos\left(\frac{2h - 1}{2n}\pi\right)$$

where n is the total number of points. Similar collocation points are set for A_t. Finally, the Mth-degree approximation of $C(A, K)$ is the Kronecker product of the two one-dimensional basis:

$$C_t(K_t, A_t) = \sum_{m_K=0}^{M_K} \sum_{m_A=0}^{M_A} b_{m_K,m_A} \psi_{m_K}(\phi(K_t))\psi_{m_A}(\phi(A_t)) \tag{3.38}$$

where $\psi_{m^{\cdot}}(.)$ are Chebyshev polynomials, $\phi(.)$ are linear mapping of the grid points of K, A to $[-1, 1]$, and b_{m_K,m_A,m_p} are coefficients to be estimated.

To find these coefficients, the Euler condition equation(3.5) is used as an estimating equation. Trial points

$$\{A_i, K_i\}_{i=0}^{(M_A)(M_k)}$$

are generated from the nodes of the M_A, M_k degree polynomials, by taking all possible combinations of the collocation points. Each trial point can be individually applied to the Euler condition to minimize the Euler residual, for a total number of $M_A M_k$ equations. This identified system can be solved for the coefficients by a nonlinear root-finding algorithm. The estimation is performed in GAMS2017 for Mixed Complementarity Problem (MCP) with the Conopt solver.

Appendix B: Deduction of (3.17)

In (3.17):

$$p(\mathbf{z}_t|\mathbf{z}_{1:t-1},\boldsymbol{\theta}) = \int p(\mathbf{z}_t|\mathbf{s}_t,\boldsymbol{\theta})\frac{1}{N}\sum_{n=1}^{N}\delta(\mathbf{s}_t - \mathbf{s}^n_{t|t-1})d\mathbf{s}_t$$

where $\delta(z)$ is the Dirac function which is zero for any z except when $z = 0$, $\delta(z)$ is infinite. In the following we use its characteristics

$$\int \delta(z)dz = 1$$
$$\int f(z)\delta(z)dz = f(z)\int \delta(z)dz = f(0)$$

so that,

$$\begin{aligned}
p(\mathbf{z}_t|\mathbf{z}_{1:t-1},\boldsymbol{\theta}) &= \frac{1}{N}\int\sum_{n=1}^{N}p(\mathbf{z}_t|\mathbf{s}_t + \mathbf{s}^n_{t|t-1},\boldsymbol{\theta})\delta(\mathbf{s}_t)d\mathbf{s}_t \\
&= \frac{1}{N}\sum_{n=1}^{N}\int p(\mathbf{z}_t|\mathbf{s}_t + \mathbf{s}^n_{t|t-1},\boldsymbol{\theta})\delta(\mathbf{s}_t)d\mathbf{s}_t \\
&= \frac{1}{N}\sum_{n=1}^{N}p(\mathbf{z}_t|\mathbf{s}_t + \mathbf{s}^n_{t|t-1},\boldsymbol{\theta})\int \delta(\mathbf{s}_t)d\mathbf{s}_t \\
&= \frac{1}{N}\sum_{n=1}^{N}p(\mathbf{z}_t|\mathbf{s}_t + \mathbf{s}^n_{t|t-1},\boldsymbol{\theta})_{(\mathbf{s}'_t=0)} \\
&= \frac{1}{N}\sum_{n=1}^{N}p(\mathbf{z}_t|\mathbf{s}^n_{t|t-1},\boldsymbol{\theta}) \qquad (3.39)
\end{aligned}$$

Chapter 4

Productivity and Price Volatility in French Agriculture: A Dynamic Stochastic Structural Estimation[1]

4.1 Introduction

The European Union has adopted many reforms of the Common Agricultural Policy (CAP) in the past 25 years. Price support has decreased and decoupled payments have been introduced. As a consequence, European agricultural prices have become more volatile, in line with the volatility of world prices. This new context generates many debates on the optimal EU farm policy. A critical question concerns the real impacts of the rising agricultural price volatility on farm decisions. Farmers may have modified their production (such as investment) and financial (such as borrowing) decisions while facing incomplete contingent markets for subsequent production periods. This may have contributed to the observed decline of the farm partial productivity growth (European Commission 2016).

There is currently mixed empirical evidence on the linkage between price volatility and productivity (either partial or total factor productivity (TFP)). In the macroeconomic literature, Ramey and Ramey (1995) find a negative relationship between economic fluctuations and productivity growth. More recently, Liu et al. (2013) model quantitatively the co-movement between land-price fluctuations and macroeconomic fluctuations. Cavalcanti et al. (2015) show that commodity price

[1]This chapter, co-written with Alexandre Gohin, was presented as a selected paper at 2018 AAEA (Agricultural and Applied Economics Association) Annual Meeting in Washington D.C.

volatility impacts negatively productivity growth, but this effect is counterbalanced by the positive effect of increased price levels.

In the agricultural economics literature, Hu and Antle (1993) indirectly analyze this linkage by assessing the impact of farm policy price supports on TFP. They find that price support has a negative impact on TFP only when this support is high. More recently, Kazukauskas et al. (2010) find a negative effect of price volatility on productivity in Irish dairy farms. On the other hand, Frick and Sauer (2017) and Lien et al. (2017) find a positive relationship while focusing, respectively, on the German and Norwegian dairy sectors.

The mixed results on the linkage between price volatility and TFP invite us to explore the underlying structural mechanisms. The macroeconomic literature stresses the important role of the credit market. For instance, Aghion et al. (2009) show that the exchange-rate volatility has a negative impact on productivity growth, especially in countries with highly constrained financial markets. Aghion et al. (2010) develop a growth model in which the exogenous risks generate productivity movement through the interaction with financial markets. They show that higher economic volatility induced by tighter credit constraints leads to a lower productivity growth rate. Regarding the sources of linkage that are explored in the agricultural economics literature, Frick and Sauer (2017) capture the heterogeneity of farmers, and find that the interplay of deregulation and price volatility has a positive aggregate effect by forcing inefficient farmers to exit. Furthermore, the mixed results may also come from the different economic framework (primal vs. dual, static vs. dynamic), the different econometric strategies (endogeneity solved with instrumental variables or fully structural estimation), or datasets (periods, type of farming).

This paper contributes to the literature in three main aspects. First, to assess the link between TFP and price risk, the first essential step is to estimate the production function and its residual, total factor productivity (TFP). The accuracy of the input data, especially the capital data series, impacts directly on the accuracy of the estimated TFP. We avoid the capital measurement problem by treating the capital data series as a latent variable. We use the observed decision data series to estimate the latent capital data series. The depreciation rate, instead of being assumed or calibrated, is a structural parameter to be estimated simultaneously. In this way we have improved the accuracy of the capital data series.

Indeed, from the data perspective, Griliches (1960) points out that the agricultural input and output data are measured with errors, for example, due to quality change in the inputs and the heterogeneity among the products. Griliches and Jorgenson (1966) emphasize that the major difficulty in measuring the capital time series arises from the fact that capital is not directly observable. The capital accumulation is a dynamic process, the investment goods purchased in one period contribute to the capital stock in the future periods. However, what amount of investment contributes to the capital stock in which future period is unobservable. Consequently, the capital input measure relies heavily on assumptions. Economists have devoted efforts to improve the productivity data series ever since. Ball et al. (1997), Ball et al. (2015) and Shumway et al. (2016) review the U.S. Department of Agricultural (USDA) agricultural productivity account. They describe in detail the labor, land, and intermediate inputs data selection and calculation process, as well as the measurement improvements over time. Nevertheless, the capital data series is always obtained indirectly using the investment flow by making assumptions on depreciation, replacement, and obsolescence of the assets, while not knowing if the assumed rates are the true ones. Andersen et al. (2011) compare the measurement of the annual capital services flows from two major databases in the U.S., and show that capital measurements are extremely sensitive to the assumptions such as depreciation rate and interest rate. Moreover, they show that the TFP measurement is, correspondingly, very sensitive to these assumptions. Butzer et al. (2010) show that different measures on capital yield different Cobb-Douglas elasticities. Above all, all of this literature highlights the capital measurement problem, indicating that the available capital data, which are approximated by calibrated assumptions, can be inaccurate to retrieve a reliable TFP measure. As explained earlier, this problem is properly treated here.

Second, from an estimation perspective, we eliminate the important endogeneity problem by applying a fully structural estimation approach. The basic criticism of estimating TFP as a residual of the production function is the endogeneity problem caused by simultaneity (Griliches and Mairesse 1995). That is, the producers choose the inputs knowing their level of productivity, while productivity is not observed by the econometrician. We do not suffer from this problem because we construct a full structural model in which all farm decisions, including production, consumption, investment, and financial borrowing decisions, are considered. These choices are decided by state variables such as price, productivity, interest and current capital, while the state variables are only decided by last-period states and exogenous shocks. Our model form is a state-space model, and no endogeneity issue arises from the modeling process. Another well-known approach to solve the endogeneity problem is the approach by Olley and Pakes (1996). They correct for the simultaneity issue by proxying productivity as an inverted function of investment, and estimating TFP in a two-step approach. Levinsohn and Petrin (2003) extend this approach by using intermediate inputs to proxy for productivity. However, they do not treat the capital measurement problem in this approach. Other productivity measurement methods, including the nonparametric indexes, such as, the Fisher index and the Tornqvist index, are the most straightforward measurement for TFP. These Indexes are widely used to compute the USDA agricultural productivity account (e.x., Ball et al. 1997, 2013). It is convenient to use them to gain a general view on TFP, but they are limited by this static focus and the calibrated elasticities (Van Biesebroeck 2007).

Third, we model quantitatively the dynamic link between TFP and price volatility, with potential risks arising from output price, productivity, and the interest rate. To account for the change in price volatility before and after the CAP reform, we allow for structural changes in the drift term and standard deviation of the shocks in the output price and productivity evolution process. Our model is similar to the dynamic stochastic general equilibrium (DSGE) models in macroeconomics. The estimation technique for linearized DSGE models is well developed in macroeconomics (e.g., Smets and Wouters 2007). To apply a similar estimation technique in the agricultural sector, we need to first deal with the less aggregate and more volatile agricultural data series. In particular, agricultural producers may experience significant production risks from the weather shocks or pesticide use. The increasing agricultural price fluctuations also result in larger price risks for the producers. To take the larger shocks into consideration, linear estimation is not sufficient for the application in the agricultural sector, rather nonlinear estimation techniques are required. Moreover, the time series data in the agricultural are usually not sufficiently long, especially for the investment data. This requires to conduct the estimation using small samples.

We use the generalized maximum entropy method (GME) proposed by Golan et al. (1996) to estimate simultaneously the structural parameters and the latent state variables in a dynamic farm decision model. This method is preferred because it is applicable to highly nonlinear systems. It evaluates the equilibrium conditions directly, and we only use the approximated policy functions to obtain next period expectations. As result, the computational burden is much smaller compared to the Bayesian estimation with the particle filters. Golan et al. (1996) show that the unknown parameters and the unknown states in the dynamic estimation problems can be recovered by the maximum entropy method. Performing Monte-Carlo experiments, Chapter 3 shows that the GME approach recovers accurately all the structural parameters in a neoclassical growth model with large shocks.

The structure of the chapter is as follows. Section 4.2 contains a sketch of the model. Section 4.3 describes the data. Section 4.4 presents the estimation method. Section 4.5 discusses the estimation results. Section 4.6 concludes.

4.2 The Model

Consider the following model in which a farmer uses capital K_t and variable inputs X_t to produce one good Y_t. Land owned by the farmer and family labor are considered as fixed. The farm income comes from the production sales, the subsidies SUB_t and the new debt D_{t+1}, and is used for personal consumption C_t, buying variable inputs X_t, making investment I_t on capital K_t, and paying back the matured debt D_t with interest. The farmer's goal is to maximize the expected utility stream of consumption,

$$\max_{I_t, C_t, X_t, D_{t+1}} E_0 \sum_{t=0}^{\infty} \beta^t u(C_t). \tag{4.1}$$

where β is the discount factor. The utility function takes the power utility form: $u(C_t) = C_t^{1-\gamma}/(1-\gamma)$, where γ is the inverse of the elasticity of intertemporal substitution. We call γ the preference parameter, as it captures a mixture of risk preference and time preference under the power utility function. The farmer's budget constraint is

$$p_t Y_t + SUB_t + D_{t+1} = I_t + X_t + C_t + (1 + r_t) D_t \tag{4.2}$$

where p_t is the potentially risky real price for output and r_t is the borrowing rate. The consumption good is used as the numeraire. Capital and variable inputs have the same price as the consumption good. Importantly, our underlying assumption is that the capital investment decision I_t, the financial borrowing decisions of acquiring new debt D_{t+1},[2] and the action of paying back current debt D_t with interest, are made at the end of the production year when the production income has been achieved. These two dynamic decisions are impacted by future productivity, price, and interest-rate risks. The decision on variable inputs is made at an earlier stage of the year. We assume that the farmer adjusts the variable inputs with the production and price risks during the crop growing season, so that the short-term risks within one year are of no concern for this decision. Finally, the budget constraint is balanced for the production (fiscal equivalent) year.

The production function follows a Cobb-Douglas production process,

$$Y_t = A_t K_t^{\alpha_k} X_t^{\alpha_x} \tag{4.3}$$

where α_k and α_x are the output elasticity of capital and variable inputs.

Physical capital is owned by the farmer, and is quasi-fixed in each period once installed. Its level depends on the last period's capital stock K_t and investment I_t, so that the law of motion for capital is

$$K_{t+1} = (1-\delta)K_t + I_t \tag{4.4}$$

where δ is the depreciation rate.

In each period, the farmer chooses the strategy $\{I_t, X_t, C_t, D_{t+1}\}_{t=0}^{t=\infty}$ to maximize the expected lifetime utility subject to the intertemporal budget constraint (4.2), production function (4.3), and the capital evolution function (4.4). The first-order conditions are given as,

$$p_t \alpha_x A_t K_t^{\alpha_k} X_t^{\alpha_x - 1} = 1 \tag{4.5}$$

$$C_t^{-\gamma} = \beta E_t \left[C_{t+1}^{-\gamma} \left(1 - \delta + \alpha_k p_{t+1} A_{t+1} K_{t+1}^{\alpha_k - 1} X_{t+1}^{\alpha_x} \right) \right] \tag{4.6}$$

$$C_t^{-\gamma} = \beta E_t [C_{t+1}^{-\gamma} (1 + r_{t+1})] \tag{4.7}$$

Equation (4.5) is the variable input demand function which shows that the marginal product of variable input equals the marginal cost. Equation (4.6) is the Euler condition for capital investment. It shows that the shadow price of capital equals the present value of marginal product and the resale value of depreciated capital, whereas the shadow price of capital equals marginal utility of consumption. Equa-

[2]The debt subscript $t+1$ also ensures that the time subscripts of the two flow variables, capital and debt, are in accordance.

tion (4.7) is the debt Euler equation, and is also a standard asset-pricing equation.

Price and interest-rate evolution We assume that the output price is exogenous at the farm level, and that the logarithm of output price p_t follows a random walk with drift processes. Furthermore, to capture the volatility change in price before and after the CAP reform, we estimate the price evolution by allowing for a structural change in the drift term and the volatility,

$$ln(p_{t+1}) = \mu_p(\tau_t) + ln(p_t) + \sigma_p(\tau_t)\epsilon_{p_{t+1}} \tag{4.8}$$

where μ_p is the drift parameter, and σ_p is the standard deviation of output price volatility. $\mu_p(\tau_t)$ and $\sigma_p(\tau_t)$ vary with the regime τ_t. τ_1 represents the regime of low price volatility, and τ_2 represents the regime of high volatility. ϵ_{p_t} is the price shock, it is identically and independently distributed (i.i.d) and follows a Gaussian distribution $\epsilon_{p_t} \sim N(0, 1)$. This specification allows a stochastic trend in the price evolution process, and is used to match the decreasing trend in agricultural prices (at least a decreasing trend before 2000).

Similarly, we assume that the interest rate is exogenous at the farm level, and it follows a stationary AR(1) process. There is no structural break in the interest-rate evolution process,

$$r_{t+1} = \rho_r r_t + \sigma_r \epsilon_{r_{t+1}} \ \epsilon_{r_t} \sim N(0, 1) \tag{4.9}$$

where ρ_r is the persistence parameter and σ_r is the standard deviation of the interest rate shock. Although the market interest rate in France has been decreasing during the past three decades, it is rare to include a trend in the interest rate for the long term.

TFP evolution We assume that the total factor productivity follows a random walk with drift process, and that the price shocks have a cross correlation with the productivity process,

$$\ln(A_{t+1}) = \mu_a + \ln(A_t) + \rho_{ap}\sigma_p\epsilon_{p_{t+1}} + \sigma_a\epsilon_{a_{t+1}} \tag{4.10}$$

where μ_a is the drift term, $\epsilon_{a_{t+1}}$ is the productivity shock which is i.i.d. and normally distributed, $\epsilon_{a_t} \sim N(0, 1)$, σ_a denotes the standard deviation of productivity shock, $\epsilon_{p_{t+1}}$ is the price shock specified in the stochastic price process (4.8), and ρ_{ap} is the cross correlation term which denotes the impact of price shock on the TFP process. It is not known, however, if such a cross correlation exists or not in reality. In the estimation part, we will test the models by allowing $\rho_{ap} = 0$ and $\rho_{ap} \neq 0$. Furthermore, similar to price, we allow for a structural change in the drift term and the volatility for the TFP evolution process,

$$ln(A_{t+1}) = \mu_a(\tau_t) + ln(A_t) + \rho_{ap}\sigma_p\epsilon_{p_{t+1}} + \sigma_a(\tau_t)\epsilon_{a_{t+1}} \tag{4.11}$$

where τ_1 is the regime of low price volatility, and τ_2 is the regime of high price volatility.

We introduce a stochastic trend into the productivity evolution and model it as a random walk with drift process. This is to account for productivity growth and to capture the trend in the real data. There are several ways to fit the nonstationary data into the theoretical model. The most used approach is to remove the trend from the data by the filters (the Hodrick-Prescott filter, the first difference filter), and then estimate the model with the transformed data. This approach, in particular, the Hodrick-Prescott filter, is criticized because it applies the univariate technique to data series with different characters, and it comes with the cost that we lose relevant information in the data series. Using a growth rate filter for the estimation is also widely adopted in research. In our model, since the variables are in levels, using growth rate directly as the level variables modifies the economic implications. Canova (2014) shows that the parameter estimates depend on the filter chosen, and the choice of the filters is arbitrary. Moreover, as the objective of the chapter is to estimate productivity and evaluate the growth pattern, detrending the data would lead to a stationary productivity process. Alternatively, we choose to introduce the trend directly into the model. Modeling TFP as a random walk with drift process is also adopted in An and Schorfheide (2007) and Fernández-Villaverde and Rubio-Ramírez (2007). However, for the estimation, Fernández-Villaverde and Rubio-Ramírez (2007) first rescaled the model to a stationary one with the trending TFP, such that the transformed model can be solved around the steady state. Afterwards, they add the trend back into the solved model. We suggest that the projection method provides a global solution that is valid on the whole defined state space, and a steady state is not required for the solution. As a result, we do not rescale the model but solve the model directly with the Chebyshev projection method. However, we need to ensure that the state variables are within the defined bounds such that the solution is valid in the “box". This leads to limitations for the model predictions if TFP and price grow out of the “box".

State-space representation The model described above can be solved and presented as a state-space model with $\mathcal{Z}_t$ the vector of decision variables, $\mathcal{S}_t$ the vector of state variables, and $\boldsymbol{\theta}$ the structural parameter set:

$$\mathcal{Z}_t = [Y_t, I_t, C_t, X_t, D_{t+1}]^T,$$
$$\mathcal{S}_t = [K_t, A_t, p_t, r_t, D_t]^T,$$
$$\boldsymbol{\theta} = [\beta, \gamma, \alpha_x, \alpha_k, \delta, \mu_p, \mu_a, \rho_r, \sigma_p, \sigma_a, \sigma_r, \rho_{ap}]^T.$$

In a general form, the model can be presented as

$$\mathcal{Z}_t = f(\mathcal{S}_t, \mathcal{V}_t; \boldsymbol{\theta}) \tag{4.12}$$
$$\mathcal{S}_t = g(\mathcal{S}_{t-1}, \mathcal{W}_t; \boldsymbol{\theta}) \tag{4.13}$$

where f and g are nonlinear functions with the vector of structural parameters $\boldsymbol{\theta}$. Equation (4.12) is the observation equation in which the observable decisions variables $\mathcal{Z}_t$ are derived from the unobservable state variables $\mathcal{S}_t$. $\mathcal{V}_t$ are the exogenous shocks such as measurement errors. Equation (4.13) is the state equation which describes the intertemporal evolution of the state variables $\mathcal{S}_t$. $\mathcal{W}_t$ are exogenous shocks such as innovations. $\mathcal{S}_t$ is not directly observable, but we could infer these unobservable states from the observable data $\mathcal{Z}_t$, given the functional form and the structural parameter set. Meanwhile, the structural parameters can also be estimated from the observable data $\mathcal{Z}_t$.

4.3 Data

We use the Farm Accountancy Data Network (FADN) Type of Farming (TF) data for farms specialized in COP (cereals, oilseed and protein crops) production, covering the period 1988 to 2015. The data is publicly available at Agreste website.[3] We focus on three regions in France: Centre, Picardie, and Pays de la Loire. The main agricultural activity in the three regions is crop production. Studying three

[3]The Agreste website is the official website of Ministry of Agriculture of France. (http://agreste.agriculture.gouv.fr/).

regions allows us to compare whether the policy effect on productivity is homogeneous across the regions. The data are the average annual survey data for individual farms, containing also the information on the financial statements (balance sheet, cash flow statement, and income statement). For each region, we construct seven data series: output volume per farm (Y_t), investment per farm (I_t), consumption per farm (C_t), variable inputs per farm (X_t), debt per farm (D_t), output price (p_t), interest rate (r_t), and the subsidies per farm (SUB_t).

The price of soft wheat is used as output price (p_t), as the price movement and price level are highly similar among the crop products (soft wheat, barley, and maize).[4] The wheat price is computed by dividing the gross production of soft wheat (in €) by the volume of soft wheat (in kilogram), while the volume of soft wheat is yield multiplied by the area of soft wheat production. The Output volume series (Y_t) is the difference between total crop production and the inventory variation, divided by output price. The inventory variation is a factor we did not include in the model, but it exists in the farm account data. It represents the variation of the crop inventory that the farmer holding reserves. The value of inventory variation is in general $1\% - 5\%$ of the total production value. The consumption series (C_t) used is private withdrawals per farm holding. According to the FADN variable definition, the private withdrawals is the farm holding's capacity of self-financing less the realized self-financing. The holding's capacity of self-financing, by definition, is the sum of profit before tax (available in data), depreciation charge (available in data), and exceptional expenses and income. The self-financing series is available in the data. The variable costs are used as variable inputs (X_t). They are the sum of intermediate consumption, expenses for hired labor, rent payments, and insurance expenses. Subsidies (SUB_t) are total subsidies net of tax.

Regarding the financial data series, according to the budget constraint in the data,

$$p_t Y_t + SUB_t - r_t D_t - X_t - C_t = I_t + \Delta Stock_{t+1} - \Delta D_{t+1} \tag{4.14}$$

where $\Delta D_{t+1} = D_{t+1} - D_t$ is the change in debt. The debt series (D_t) is calculated using the sum of mid-term and short-term debt. $\Delta Stock_{t+1}$ is the inventory variation. The investment series (I_t) is obtained using total investment data. The left-hand side of Eq.(4.14), according to the FADN variable definition, equals the

[4]See Figure (4.9) in Appendix C. The oilseeds price does not move in line with the crop price, but its weight is low compared to the crop products.

self-financing data series. We check the series we have computed to make sure Eq.(4.14) holds. Last, the interest-rate series (r_t) is computed as the financial charge divided by initial debt.

Consider that the sample size is decreasing in the survey because the total farm number is decreasing. In the meantime, the farm size is growing over time. It indicates that the sample contains more large farms in recent years. As a result, the average of the sample cannot represent a farm with a constant size. To control for such size effect, we rescale the data by the total farm number. Finally, we deflate the investment, consumption, variable inputs, debt, subsidies, and output price series with the national consumption index. The real interest series is obtained by deducting the inflation rate from the borrowing rate.

Figures 4.1 and 4.2 describe the evolution of output price and interest rate, and Figures 4.3 - 4.5 describe the evolution of the decision variables, including production, consumption, investment and debt. The price dynamics are similar across regions: the price decreases steadily during the period $1988-2002$. Following low-level fluctuations in $2002-2005$, the real output price becomes highly volatile after 2005. The movement of the interest rate in the three regions is generally in line with the market long-term interest rate in France. The borrowing rates offered to the farm holding are higher than the long-term interest rate in the years $1990-2000$, but the gap becomes smaller after 2005. The borrowing rate in Centre is lower than in the other two regions before 2006. In the years $1993-1998$, the borrowing rate in Pays de la Loire is much higher and more volatile than in the other two regions. Regarding the decision variables, we do not observe explicit trends except for the production series in Picardie and Pays de la Loire.

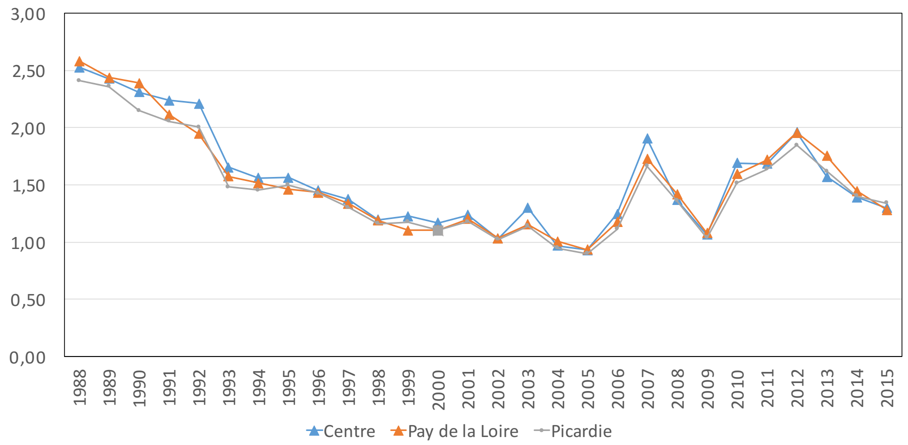


Figure 4.1: Evolution of real output price in Centre, Picardie and Pays de la Loire (100€/tonne, CPI 2005=1)

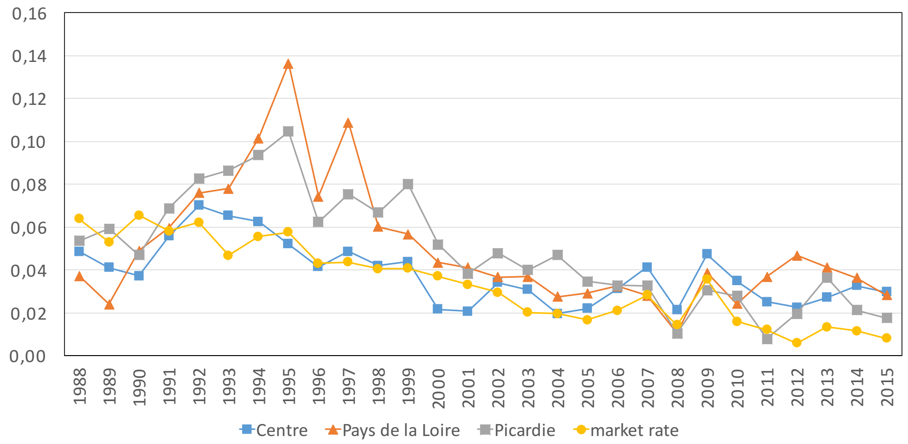


Figure 4.2: Evolution of real interest rate in Centre, Picardie and Pays de la Loire

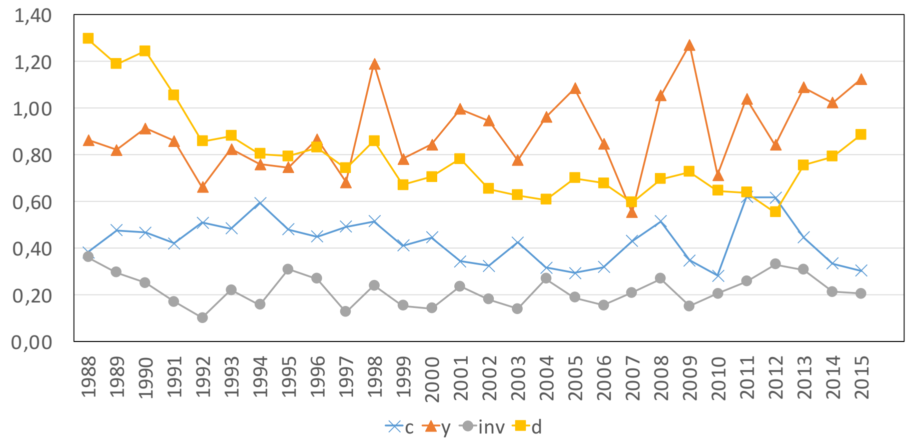


Figure 4.3: Evolution of production (k tonne), consumption (100 k€), investment (100 k€) and debt (100 k€) in Centre

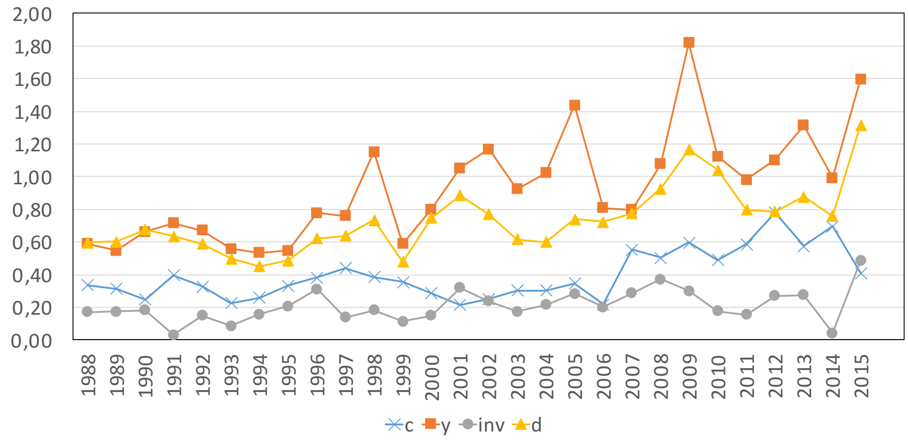


Figure 4.4: Evolution of production (k tonne), consumption (100 k€), investment (100 k€) and debt (100 k€) in Picardie

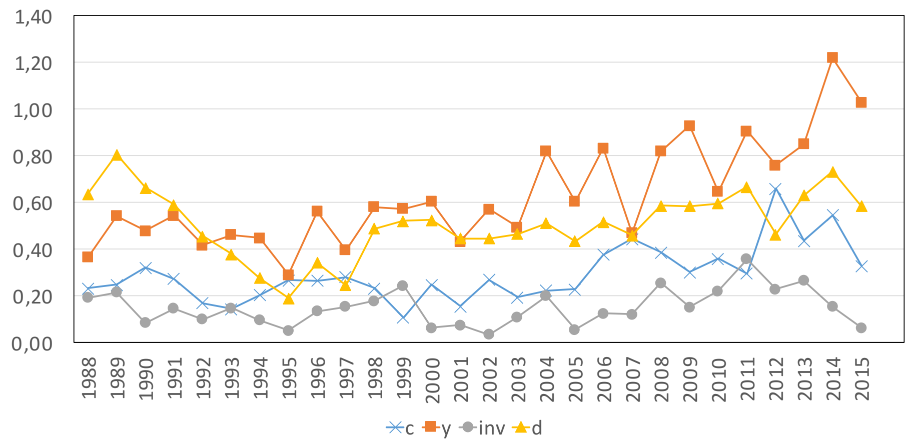


Figure 4.5: Evolution of production (k tonne), consumption (100 k€), investment (100 k€) and debt (100 k€) in Pays de la Loire

4.4 Estimation Methods

We use the generalized entropy (GME) approach for the estimation. We first reparameterize the parameters and the shocks. For the structural parameters θ_h, we define a set of discrete support values for the parameters $v^{\theta}_{h} = [v^{\theta}_{h1}, v^{\theta}_{h2}, ..., v^{\theta}_{hG}]'$, with associated probability weights $w^{\theta} = [w^{\theta}_{h1}, w^{\theta}_{h2}, ...w^{\theta}_{hG}]$. The parameter value is given by $\theta_h = \sum_g v^{\theta}_{hg} w^{\theta}_{hg}$. Here, h is the index for the parameters with $h = 1, 2, ..., H$, and g is the index for the discrete support values for the parameters with $g = 1, 2, ..., G$. Similarly, for the shocks $\epsilon_j t$, we define a set of discrete points $v^{\epsilon}_{j} = [v^{\epsilon}_{jt1}, v^{\epsilon}_{jt2}, \ldots, v^{\epsilon}_{jtL}]'$, with associated probability weights $w^{\epsilon}_{jt} = [w^{\epsilon}_{jt1}, w^{\epsilon}_{jt2}, ..., w^{\epsilon}_{jtL}]'$. The value of each point of the shocks is given by $\epsilon_{jt} = \sum_l v^{\epsilon}_{jtl} w^{\epsilon}_{jtl}$. Here, j is the index for the shocks with $j = 1, 2, ..., J$, t is the time index, and l is the index for the discrete support values for the shocks with $l = 1, 2, ..., L$.

Given the reparameterization definition, our objective is to find the optimal probability distribution $(\mathbf{w}^{\theta}, \mathbf{w}^{\epsilon})$ of the corresponding support values, which maximizes the entropy objective. The empirical program is

$$\max_{\mathbf{w}^{\theta}, \mathbf{w}^{\epsilon}} - \sum_h \sum_g w^{\theta}_{hg} ln(w^{\theta}_{hg}) - \sum_j \sum_t \sum_l w^{\epsilon}_{jtl} ln(w^{\epsilon}_{jtl}) \tag{4.15}$$

where $\mathbf{w}^{\theta}, \mathbf{w}^{\epsilon}$ are, respectively, the probability distribution of the time-constant parameters and time-varying the shocks. The entropy objective is maximized subject to the equilibrium conditions of the dynamic decision program and the adding up constraints,

$$C_t^{-\gamma} = \beta E_t \left[C_{t+1}^{-\gamma} \left(1 - \delta + \alpha_k A_{t+1} p_{t+1} K_{t+1}^{\alpha_k - 1} X_{t+1}^{\alpha_x} \right) \right] \tag{4.16}$$

$$C_t^{-\gamma} = \beta E_t [C_{t+1}^{-\gamma} (1 + r_{t+1})] \tag{4.17}$$

$$p_t \alpha_x A_t K_t^{\alpha_k} X_t^{\alpha_x - 1} = 1 \tag{4.18}$$

$$K_{t+1} = (1 - \delta) K_t + p_t Y_t + SUB_t + D_{t+1} - X_t - C_t - (1 + r_t) D_t \tag{4.19}$$

$$Y_t = A_t K_t^{\alpha_k} X_t^{\alpha_x} \tag{4.20}$$

$$\ln(p_{t+1}) = \mu_p + \ln(p_t) + \sigma_p \tilde{\epsilon}_{p_{t+1}}, \quad \tilde{\epsilon}_{p_t} \sim N(0, 1) \tag{4.21}$$

$$r_{t+1} = \rho r_t + \sigma_r \tilde{\epsilon}_{r_{t+1}}, \quad \tilde{\epsilon}_{r_t} \sim N(0, 1) \tag{4.22}$$

$$\ln(A_{t+1}) = \mu_A + \ln(A_t) + \sigma_A \tilde{\epsilon}_{A_{t+1}}, \quad \tilde{\epsilon}_{A_t} \sim N(0, 1) \tag{4.23}$$

$$\sum_g w^{\theta}_{hg} = 1 \quad for\ h = 1, 2, \ldots, H \tag{4.24}$$

$$\sum_{l} w_{jtl}^{\epsilon} = 1 \quad for \ j = 1, J; \quad t = 1, 2, ...T - 1 \tag{4.25}$$

$$w_{hg}^{\theta} > 0, w_{jtl}^{\epsilon} > 0 \quad for \quad \forall h, j, t, g, l \tag{4.26}$$

The expectation operator

To bring the above program, especially the Euler equations (4.16) and (4.17) to the data, one important assumption is rational expectations. The central idea of the rational-expectations hypothesis is that the expectations are in accordance with the model prediction. The farmer cannot precisely predict the point values of the next period's shocks, but he or she knows the distribution of the shocks. In reality, while the CAP reform in 2003 induces high price fluctuations, the French farmers are able to form the expectations on price volatility based on the historical world price fluctuations.

To evaluate the conditional expectation operator, regarding the state variables, we observe price and interest rate, and we do not observe capital and TFP. First, we estimate the exogenous price and interest rate evolution processes (4.21) and (4.22) outside of the structural model, based on the observed price and interest rate data. Meanwhile, the latent TFP evolution (4.23) is to be retrieved in the GME program of the structural model. Second, we evaluate the TFP shocks, price shocks, and interest-rate shocks via Gaussian Quadrature.

This involves modeling the error terms as a random variable with Gaussian Quadrature nodes and the corresponding weights. For shocks that follow a normal distribution with zero mean and standard deviation 1, $\epsilon \sim N(0, 1)$, we use a 3-point Gaussian Quadrature grid with the nodes and weights specified in Table 4.1 to describe the anticipated shocks.

Accordingly, the nodes for the anticipated next period price, interest and TFP

Table 4.1: Gauss-Hermite approximation

e	ϵ^e	w^e
1	-1.7321	0.1667
2	0	0.6667
3	1.7321	0.1667

e denotes the index of the points, ϵ^e denotes the value of each point, and w^e is the associated weight.

are,

$$ln(p_{t+1}^{ip}) = \mu_p + ln(p_t^{obs}) + \sigma_p \epsilon^{ip} \tag{4.27}$$

$$r_{t+1}^{ir} = \rho_r r_t^{obs} + \sigma_r \epsilon^{ir} \tag{4.28}$$

$$ln(A_{t+1}^{ia,ip}) = \mu_A + ln(A_t) + \rho_{ap}\sigma_p \epsilon^{ip} + \sigma_A \epsilon^{ia} \tag{4.29}$$

where ip, ir, ia denote the nodes index for price, interest-rate and TFP shocks, which correspond to e in Table 4.1.

Regarding the decision variables, at time t, we observe five decision variables, consumption C_t^{obs}, production Y_t^{obs}, investment I_t, variable inputs X_t^{obs}, and debt D_t^{obs}. The agent cannot precisely predict the point value of next-period consumption. However, under rational expectations, the nodes of the anticipated consumption can be decided by the nodes of anticipated state from the policy functions. The policy functions are approximated based on the current period t policy variables and states by Chebyshev polynomials. Mathematically, the M^{th}-degree approximation of the policy function is

$$\begin{aligned} C_t^{obs} = & \sum_{m_K=0}^{M_K} \sum_{m_D=0}^{M_d} \sum_{m_A=0}^{M_A} \sum_{m_p=0}^{M_p} \sum_{m_r=0}^{M_r} b_{m_K,m_D,m_A,m_p,m_r} \\ & \psi_{m_K}(\phi(K_t))\psi_{m_D}(\phi(D_t))\psi_{m_A}(\phi(A_t))\psi_{m_p}(\phi(p_t^{obs}))\psi_{m_r}(\phi(r_t^{obs})) + \epsilon_{cs_t} \end{aligned} \tag{4.30}$$

$$\begin{aligned} C_{t+1}^{ia,ip,ir} = & \sum_{m_K=0}^{M_K} \sum_{m_D=0}^{M_d} \sum_{m_A=0}^{M_A} \sum_{m_p=0}^{M_p} \sum_{m_r=0}^{M_r} b_{m_K,m_D,m_A,m_p,m_r} \\ & \psi_{m_K}(\phi(K_{t+1}))\psi_{m_D}(\phi(D_{t+1}))\psi_{m_A}(\phi(A_{t+1}^{ia}))\psi_{m_p}(\phi(p_{t+1}^{ip}))\psi_{m_r}(\phi(r_{t+1}^{ir})) + \epsilon_{cne_t} \end{aligned} \tag{4.31}$$

$$X_{t+1}^{ia,ip} = (\alpha_x p_{t+1}^{ip} A_{t+1}^{ia} K_{t+1}^{\alpha_k})^{\frac{1}{1-\alpha_x}} \tag{4.32}$$

In equation (4.30), The Chebyshev coefficients b_{m_K,m_A,m_p,m_r} are jointly estimated in the GME program by interpolating the basis functions of the state variables K_t, A_t, p_t D_t and r_t into the observed consumption data series. m is the degree of approximation, $\psi_{d}.(.)$ are Chebyshev polynomials, $\phi(.)$ are linear mapping of state variables to $[-1, 1]$. ϵ_{cs_t} is the approximation error of the policy function from consumption data series, and ϵ_{cne_t} is the error of expectations.

In equation (4.31), the next period consumption is obtained using the anticipated next-period states, and the estimated Chebyshev policy function in (4.30). Equation (4.32) shows the next-period variable inputs are obtained using the anticipated next-period price and TFP.

Based on equations (4.27) - (4.32) and Gaussian Quadrature points in Table 4.1, the empirical Euler conditions are rewritten as

$$(C_t^{obs})^{-\gamma} = \sum_{ia}\sum_{ip}\sum_{ir} w^{ia}w^{ip}w^{ir}\beta\left[(C_{t+1}^{ia,ip,ir})^{-\gamma}\left(1-\delta+\alpha p_{t+1}^{ip}A_{t+1}^{ia}(K_{t+1})^{\alpha_k-1}(X_{t+1}^{ia,ip})^{\alpha_x}\right)\right] \tag{4.33}$$

$$(C_t^{obs})^{-\gamma} = \sum_{ia}\sum_{ip}\sum_{ir} w^{ia}w^{ip}w^{ir}\beta\left[(C_{t+1}^{ia,ip,ir})^{-\gamma}(1+r_{t+1}^{ir})\right] \tag{4.34}$$

Finally, the entropy objective (4.15) is maximized subjective to the constraints (4.16) - (4.34). The time-constant parameters dimension $H = 12 + 243 = 255$ (with 7 the number of the structural parameters, and $243 = 3^5$ the number of Chebyshev coefficients), and the time-varying shocks dimension $J = 4$. By forming the Lagrangian, the first-order conditions provide the basis for the solution w_{hg}^{θ} and w_{jtl}^{ϵ}. By the reparameterization definition, the estimated parameter and shocks are

$$\sum_g \hat{w}_{hg}^{\theta}v_{hg}^{\theta} = \hat{\theta}_h \tag{4.35}$$

$$\sum_l \hat{w}_{jtl}^{\epsilon}v_{jtl}^{\epsilon} = \hat{\epsilon}_{jt} \tag{4.36}$$

where $v_{hg}^{\theta}, v_{jtl}^{\epsilon}$ are, respectively, the discrete support values for the parameters and the shocks. Given the recovered shocks in equation (4.36), the estimates of the TFP evolution process are determined by equation (4.23).

4.5 Results

Table 4.2 shows the priors (support values) for the parameters and the shocks. We choose relatively loose priors to make sure that the results are not manipulated by the prior information. The probability of each support point is initially assigned equal. The output elasticity of the inputs is set between 0 and 1, because by the economic meaning, the elasticity of one input is smaller than 1. The depreciation rate is set between 0 and 0.2. The depreciation rate in agriculture can be as high as 0.1, considering the intensive use of the capital. The value 0.2 makes sure that the

Table 4.2: Prior information for the parameters

		Support values		
Parameters	Description	Low	Center	High
β	discount factor	0.9	0.95	0.99
γ	preference	0	3	7
α_k	output elasticity of capital	0	0.3	0.7
α_x	output elasticity of variable inputs	0	0.5	1
δ	depreciation rate	0	0.1	0.2
μ_p	drift term in price evolution	-0.2	0	0.2
μ_a	drift term in TFP evolution	-0.2	0	0.2
ρ_r	persistence in interest rate evolution	0	0.5	1
ρ_{ap}	correlation between price shock and TFP	-1	0	1
σ_p	standard deviation of price shocks	0	0.1	0.3
σ_a	standard deviation of TFP shocks	0	0.1	0.3
σ_r	standard deviation of interest rate shocks	0	0.1	0.3
b_{d_K,d_A,d_p,d_r}	Chebyshev coefficients	-1	0	1
ϵ_{pt}	price shocks	-1	0	1
ϵ_{at}	TFP shocks	-1	0	1
ϵ_{rt}	interest rate shocks	-1	0	1
$\epsilon_{xt(mea)}$	measurement errors	-1	0	1
$\epsilon_{yt(mea)}$	measurement errors	-1	0	1
ϵ_{cs_t}	Chebyshev approximation errors	-10^{-3}	0	10^{-3}
ϵ_{cne_t}	expectation errors	-10^{-3}	0	10^{-3}
ϵ_{xne_t}	expectation errors	-1	0	1

estimation will not hit the bounds. The drift terms for the price and TFP evolution are set between -0.2 and 0.2, so that we do not fix the direction of the trend in price and TFP evolution. The support values for all the shocks and factor inputs measurement errors are set between -1 and 1. Importantly, the policy approximation errors are set at very low levels, which indicates that the approximated policy function is very close to the true one. Consequently, it indicates a small Chebyshev approximation error such that the preference parameter can be identified.[5]

[5]Based on the Monte-Carlo experiment on simulated data in Chapter 2, the preference parameter is accurately estimated only when the policy approximation error is small.

Table 4.3: GME estimation of price and interest rate evolution

	Center	Picardie	Pays de la Loire
$\mu_p(\tau_1)$	-0.064	-0.061	-0.065
$\sigma_p(\tau_1)$	0.085	0.086	0.070
$\mu_p(\tau_2)$	0.018	0.021	0.017
$\sigma_p(\tau_2)$	0.260	0.209	0.212
Entropy	6080.74	6104.94	6106.20
ρ_r	0.980	0.972	0.990
σ_r	0.011	0.015	0.021
Entropy	30511.988	30277.463	29804.113

Estimation of price and interest rate with structural change

Before estimating the structural model, we estimate the exogenous price and interest-rate evolution processes (4.8) and (4.9), according to which the farmer forms expectations on the future output price and borrowing rate.

Based on the real price evolution in Figure 4.1, we observe a possible structural change during the period $2002-2005$. This is the period when the price starts to fluctuate. Afterwards, the price volatility becomes much higher. To detect the actual year of structural change, we test the model with structural change in 2002 and 2003. The Shapiro-Wilk normality test on the residuals shows that a structural change in 2002 best describes the exogenous price. Consequently, we split the whole period into two, with the low price volatility regime $\tau_1 = [1988-2002]$, and the high price volatility regime $\tau_2 = [2003-2015]$. The Chow test on the first difference real price data confirms that there is a structural change in 2002. Similar to price, we estimate the exogenous interest-rate evolution outside the structural model. The Chow test rejects the structural change in 2002 for the interest rate data. Therefore, we do not include a structural change in the interest rate.

Table 4.3 shows the GME estimates of the price and interest-rate evolution for the regions Centre, Picardie, and Pays de la Loire. The price evolution for the three regions is similar: for the period $1988-2002$, the price has a decreasing trend $(-6.4\%, -6.1\%, -6.5\%)$ with a low-level volatility at $8.5\%, 8.6\%$, and 7.0%. For the period $2003-2015$, the price volatility rises to as high as $26.0\%, 20.9\%$, and 21.2%, following with a small increasing trend $(1.8\%, 2.1\%, 1.7\%)$. For the whole period, the interest rate offering for the farms, in general, has a high persistence level of 0.980, 0.972, and 0.990. The evolution processes of the interest rate in the three regions are smooth with low volatility.

Estimation of the structural model

Table 4.4 shows the estimation results of two test models. For both models, the output price follows the estimated random walk with drift process with structural change in 2002 (Table 4.3). As specified, TFP follows a random walk with drift process with a structural change before and after 2002,

$$ln(A_t) = \mu_a(\tau_t) + ln(A_{t-1}) + \rho_{ap}\sigma_p\epsilon_{p_t} + \sigma_a(\tau_t)\epsilon_{a_t} \tag{4.37}$$

where $\tau_t = 1988 - 2002$ is the regime of low price volatility, and $\tau_t = 2003 - 2015$ is the regime of high price volatility. For Model 1, there is no correlation between price shocks and TFP ($\rho_{ap} = 0$). For Model 2, the cross-correlation is not zero ($\rho_{ap} \neq 0$).

The entropy values show that Model 2 better describes the data and it is the selected model. The significance of ρ_{ap} also confirms the existence of the cross-correlation between TFP and price shock.

Regarding the structural parameters, all the estimated values are changed from the prior, which indicates that all the parameters are identified from the data. The test using the entropy ratio statistic (Judge and Mittelhammer 2011) finds the depreciation rate, the trend in TFP for the period $2003 - 2015$ for Picardie and Pays de la Loire to be significantly different from zero. In addition, imposing a zero discount factor, zero input elasticity, zero preference, zero volatility, zero trend for the period $1988-2002$, and zero correlation with price shocks lead to infeasibilities. The infeasibility indicates that the data are not compatible with the null hypothesis, so that we can reject the null hypothesis that these structural parameters are zero (Arndt 1999). Since the constraints for the optimization are nonlinear, it is also possible that a feasible solution exits under the null hypothesis but the routine cannot find it. However, if we consider that these structural parameters have economic meaning, they cannot be zero under the chosen economic framework. As a result, infeasibility is taken as a rejection of the null hypothesis.

The estimated structural parameters share some similarity across the three regions, but also exhibit differences. The discount factor is overall around 0.94, this is in line with the average interest rate of $5 - 6\%$ across the regions. The variable-input elasticity is rather constant across the regions, at about 77%. This factor contributes the most to the crop production because we have included intermediate inputs, rented land, and hired labor into the variable inputs. On the other

Table 4.4: GME estimation of the structural model

	Centre	Picardie	Pays de la Loire
	Model 1: $\rho_{zp} = 0$		
β	0.944	0.942	0.938
γ	2.574	2.816	2.069
α_k	0.431	0.463	0.494
α_x	0.770	0.791	0.773
δ	0.115	0.115	0.078
$\mu_a(\tau_1)$	0.058	0.075	0.027
$\sigma_a(\tau_1)$	0.044	0.076	0.083
$\mu_a(\tau_2)$	-0.026	-0.033	0.007
$\sigma_a(\tau_2)$	0.078	0.071	0.074
Entropy	1241.675	1237.892	1254.842
	Model 2: $\rho_{zp} \neq 0$ (Selected model)		
β	0.947**	0.946**	0.946**
γ	3.310**	2.596**	2.901**
α_k	0.313**	0.303**	0.338**
α_x	0.770**	0.791**	0.773**
δ	0.096*	0.092$^\bullet$	0.097*
$\mu_a(\tau_1)$	0.047*	0.056*	0.044*
$\sigma_a(\tau_1)$	0.036*	0.062**	0.043**
$\mu_a(\tau_2)$	0.002	-0.012	0.007
$\sigma_a(\tau_2)$	0.051**	0.088**	0.046**
ρ_{zp}	-0.805*	-0.884*	-0.833*
Entropy	1256.242	1257.814	1263.059

Note: ** denote rejection of the null hypothesis because of infeasibility.$^\bullet$ and * denote rejection of the null hypothesis at the 90% and 95% confidence level respectively. The critical values for the individual test at 90% confidence level is 2.71, and at 95% confidence level is 3.84.

hand, capital contributes to $30-34\%$ to the production across the regions. Overall, agricultural production in the three regions shows increasing return to scale. The estimated depreciation rate is around $9.0-9.7\%$, which is higher than the macroeconomic depreciation rate $(2-3\%)$. The high depreciation rate is reasonable for agricultural capital if we consider the intense use of machines and equipment for agricultural production. Last, when we allow for Chebyshev approximation errors at a low level (the range $[-0.001, 0.001]$ as the support values), we obtain the estimation of the preference parameters. The average level of risk-aversion are respectively $3.31, 2.60$ and 2.90 for Centre, Picardie, and Pays de la Loire. This indicates that instead of being risk neutral, the farmers in these regions exhibit a medium-level risk aversion.

The structural shock parameters which describe the TFP evolution are jointly estimated with the structural parameters, and are also shown in Table 4.4. To better illustrate the estimated TFP evolution process, we plot in Figures 4.6 - 4.8 the estimated TFP series, along with real output price and yield (land productivity). Regarding the first-order relationship between price and TFP, we find a significant negative correlation between price shocks and TFP. The values are $-0.805, -0.884, -0.833$ respectively for the three regions. From a general equilibrium point of view, a negative price shock is partly a result of an increase in supply, which corresponds to a positive productivity shock as from weather conditions. In addition, this negative correlation can be a transmission channel for price volatility and TFP.

Regarding the second-order relationship, price volatility, and TFP, the increasing price volatility has a negative impact on TFP growth. In the regime of low price volatility (year $1988 - 2002$), TFP grows steadily with an increasing trend $(0.047, 0.056, 0.044)$ and small fluctuations $(0.036, 0.062, 0.043)$. In the regime with high price volatility (year $2003 - 2015$), the TFP growth has slowed down and the growth pattern becomes much more difficult to predict. Indeed, the increasing trend becomes not significant in the three regions. The pure TFP shock volatility level has increased to 0.051 for Centre, 0.088 for Picardie, and remains stable at 0.046 for Pays de la Loire. It indicates that instead of coming from the pure TFP shock such as weather conditions, the increasing TFP fluctuation is mostly a result of increased price fluctuation. The estimated parameters are shown more intuitively in Figures 4.6 - 4.8. The plotted estimated TFP series imply that, during the period $2002-2005$, TFP still grows with a little larger fluctuation compared to the previous period. It is after 2005 that TFP drops sharply and then follows with a big rebound during the period $2007-2009$. After 2009, agricultural productivity falls again. It rebounds and keeps on growing after 2013. Overall, the estimation results imply that TFP grows slower (or stops growing) and fluctuates more in the regime of high price volatility.

Comparing the estimated TFP with yield in Figures 4.6 - 4.8, we see that TFP is different from single factor productivity. On the one hand, there is no growing trend in land productivity, while TFP keeps on growing in the first period. On the other hand, the fluctuations in yield are also reflected in TFP. This indicates that instead of the intensity use of land, the source of TFP growth comes more from

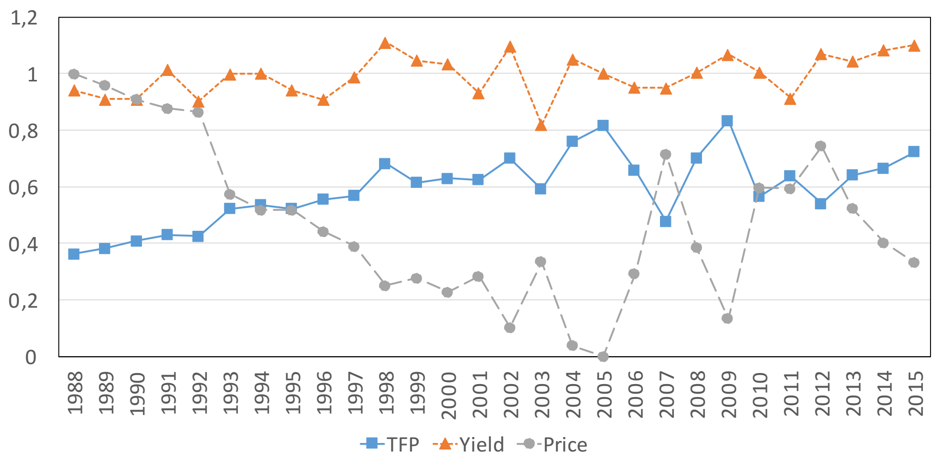


Figure 4.6: Centre: comparing the estimated TFP with price and yield

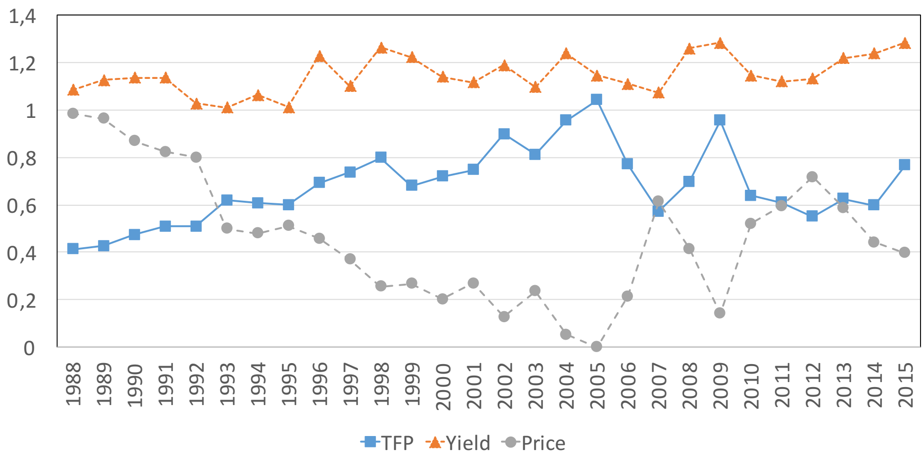


Figure 4.7: Picardie: comparing the estimated TFP with price and yield

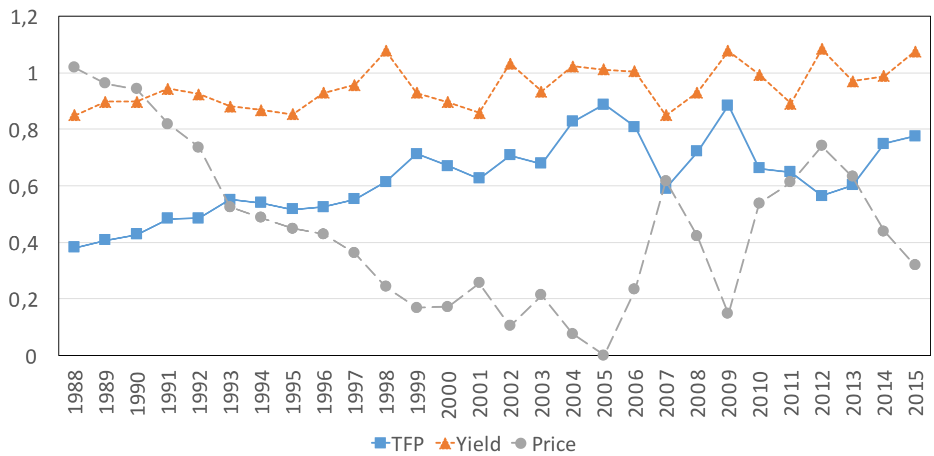


Figure 4.8: Pays de la Loire: comparing the estimated TFP with price and yield

the intensity use of capital, the knowledge of labor, and the technological change.

As the residual of a production function, TFP has always been considered as exogenous and is mostly influenced by the technological change, and in agriculture, influenced by exogenous shocks such as weather conditions, rainfall and other environmental shocks. Our estimation results show that the price risk is also a factor that influences the TFP growth, whereas the increasing price risks decelerate TFP growth.

The negative impact of price risks on productivity passes through various channels. In general, following our model assumptions, the producers make expectations on future prices and know the distribution of the price risks. Consequently, in the regime where price volatility is high, the producers know that they are exposed to high risks, and they change their decisions to deal with the risks, which in turn affects the realized productivity.

A most important transmission channel in our model is the financial borrowing decision. We do not model explicitly the credit constraints in the model, but the rate at which the farmers can borrow from the bank is closely linked to price risks. As a result, the farmers' capacity of borrowing is implicitly constrained by the interest rate. Indeed, on the one hand, thanks to the CAP reforms, the farmers receive direct payments with certainty regardless of the price and productivity risks, which contributes positively to their borrowing capacities. On the other hand, the increasing price risks bring large uncertainty to the production incomes, which affects negatively the farmers' borrowing capacities. In all, the negative impacts surpass the positives ones, because despite the decreasing trend in the market interest rate, the borrowing rate offered to the farmers stopped decreasing with the increased price volatility. Furthermore, except for the influences from the borrowing rate, a risk-averse agent tends to consume less and save more, in our case, borrow less, when facing higher risks. Consequently, the farmers have less money to engage in productivity-enhancing activities. In particular, investing in new machines and purchasing high-quality but more expensive inputs.

Except for insurance which is not modeled in this chapter, there are many ways in which the farmers deal with the increasing risks. One way is production diversification. The farm managers turn to low-productivity activities with lower risks, or they diversify the crop varieties to diversify the risks. In each manner, it comes with a cost and results in lower productivity.

Labor contributes to TFP in terms of learning and labor management efficiency.

The production effort made by the labor is yet a behavior which is ambiguous to analyze. Considered as part of the labor quality, the effort made by labor is captured in the TFP residual. We can infer from the result that the farmers put less effort in production which negatively affects labor efficiency. This is because when the farmers expect large uncertainty in the production outcome, they have less incentive to produce with effort because the production revenue is influenced more by the large exogenous price risks than the production quantity. However, we do not draw a definite conclusion with regard to the labor effort channel because it is too ambiguous to measure.

Besides, we do not consider heterogeneous farms in our model, even though the market structure is known to be an important channel for aggregate productivity growth (Syverson 2011). Indeed, with the increase in market risks, low-productivity farms exit the market and high-productivity farms survive, which in turn positively affects the aggregate agricultural productivity. In our analysis, this effect is not captured because we have scaled the data from farm size to retain the homogeneous farm assumption.

The slowed-down productivity growth results also partly because there has been no major technology innovation in agricultural production in the last two decades. Technology growth is related to the long-term R&D investment. While the impacts we assess here are more short-term, we do not discuss much the impacts of increasing price risk on R&D investment at farm level. However, it is worth mentioning that, while introducing higher price fluctuations, the CAP reforms have also led to increase the budget for R&D investment for technology innovations. The long-term impact from the increasing R&D investment should show gradually in productivity assessments.

Another positive influence the CAP reforms bring to productivity concerns the environmental aspect, but it is also a long-term impact. Because the new CAP ties the direct payments to many environmental constraints, in the short-term, it negatively affects productivity as the farms turn to lower-productivity production activities which avoid the environmental constraints, or the TFP of the recent production activities reduces because of the constrains. However, in the long-term, TFP will benefit from higher quality inputs and other positive environmental externalities.

Last, we argue that the model solution with nonstationary state variables is valid if the state variables fall into the defined bounds, and thus the estimation is valid within the bound. Further work remains to be done to find a robust estimation with nonstationary state variables with the GME approach which is globally valid.

4.6 Conclusion

Measuring agricultural productivity from the observed data series has always been a challenge for economists. Traditional productivity measurements approximate the unobservable capital data series from the investment data and by assuming the depreciation rate, interest rate, which can be very critical (Andersen et al. 2012). Moreover, direct econometric TFP estimation suffers from the endogeneity problem caused by simultaneity. This chapter tries to solve these two problems, and estimates the dynamic link between price risk and productivity in a dynamic stochastic farm decision model. We investigate how the increasing price volatility in France after the CAP reform impact on total factor productivity (TFP) in agriculture.

Based on the FADN survey data for the regions Centre, Picardie, and Pays de la Loire in France from 1988 to 2015, we estimate simultaneously the structural parameters and the TFP series using the generalized maximum entropy (GME) approach. To assess the impact of the increasing price volatility, we impose a structural change in the drift term and volatility in the price and TFP evolution process. Our estimation results confirm that there are two regimes for output price: one regime, $1988-2002$, where the price volatility is low, and the other regime, $2003-2015$, where the price volatility is much higher. We show that the estimated TFP grows steadily with small fluctuations in the first regime before the CAP reform. The growth pattern becomes much more volatile following the increase in price volatility, and the upward trend in TFP growth becomes insignificant. In addition, we find a negative correlation between the price shocks and TFP evolution. Regarding the structural parameter estimation, we find a relatively higher level depreciation rate in agriculture compared to that in macroeconomics. Our estimation also shows evidence on the existence of a medium level risk aversion for the farmers in these three regions. Overall, price risk does have an impact on productivity in the way that when farmers are exposed to high risks, they modify their decisions and production incentives which in term impact negatively on the realized productivity.

For further extensions, this chapter does not model, however, through which channel productivity is linked with output price fluctuations. For example, Liu et al. (2013) study the link between land price and macroeconomic fluctuations in a DSGE model. They introduce land as a collateral asset in the credit constraint, and the credit constraint and housing demand shock jointly amplify the macroeconomic fluctuations. We have also introduced financial debt into the model, but credit constraints are only modeled implicitly through the interest rate. It will certainly be interesting to enrich the model by introducing structural equations for credit constraints. Further applications of the GME approach method on more flexible production function forms, such as the quadratic function, more flexible utility function form, such as recursive utility, can be also explored.

4.7 Appendix

Appendix A: The entropy ratio test

We construct the entropy statistics following Judge and Mittelhammer (2011) and Arndt (1999). The test is similar to the likelihood ratio test. Denote $L(\hat{\Theta})$ the objective value of the GME problem, and $L(\hat{\Theta}^c)$ is objective value for the GME problem when a constraint hypothesis is added to the constraint set (e.g., the capital elasticity is 0). The test statistics is

$$\lambda = 2n\left(L(\hat{\Theta}) - L(\hat{\Theta}^c)\right) \tag{4.38}$$

which follows the usual central Chi-square distribution. n denotes the degree of freedom which is the number of constraints imposed.

Appendix B: Derivation of the equilibrium conditions

Direct FOCs

We consider the problem from the interior choices X_t, K_{t+1}, C_t, and D_{t+1}. We can eliminate C_t through direct substitution,

$$C_t = p_t Y_t + SUB_t + D_t - (K_{t+1} - (1-\delta)K_t) - w_{xt}X_t - (1+r_t)D_t \tag{4.39}$$

leaving us with the first-order conditions:

$$\begin{aligned} E_0\left[\beta^t u'(C_t)\frac{\partial C_t}{\partial X_t}\right] &= 0 \\ E_0\left[\beta^t u'(C_t)\frac{\partial C_t}{\partial K_{t+1}} + \beta^{t+1}u'(C_{t+1})\frac{\partial C_{t+1}}{\partial K_{t+1}}\right] &= 0 \\ E_0\left[\beta^t u'(C_t)\frac{\partial C_t}{\partial D_{t+1}} + \beta^{t+1}u'(C_{t+1})\frac{\partial C_{t+1}}{\partial D_{t+1}}\right] &= 0 \end{aligned} \tag{4.40}$$

Taking C_t derivatives and cleaning up discount factors, this system of equations reduces to:

$$E_0\left[u'(C_t)\left(p_t\alpha_x\frac{Y_t}{X_t}-w_{x_t}\right)\right]=0$$
$$E_0\left[u'(C_t)(-1)+\beta u'\left(C_{t+1}\right)\left(p_{t+1}\alpha_k\frac{Y_{t+1}}{K_{t+1}}+(1-\delta)\right)\right]=0$$
$$E_0\left[u'\left(C_t\right)+\beta u'\left(C_{t+1}\right)\left(-(1+r_{t+1})\right)\right]=0 \tag{4.41}$$

From the perspective of period t, the system of equations reduces to:

$$\alpha_x p_t\frac{Y_t}{X_t}=w_{xt}$$
$$C_t^{-\gamma}=\beta E_t\left[C_{t+1}^{-\gamma}\left(1-\delta+\alpha_k p_{t+1}\frac{Y_{t+1}}{K_{t+1}}\right)\right]$$
$$C_t^{-\gamma}=\beta E_t[C_{t+1}^{-\gamma}(1+r_{t+1})] \tag{4.42}$$

Using Lagrangian multiplier or value-function maximization yield to the same equilibrium conditions.

Value-function approach

The equilibrium conditions can also be derived from value-function iterations. The Bellman equation of the dynamic programming problem writes as,

$$V(A_t,K_t,D_t)=\max_{C_t,X_t,L_t,N_t,D_{t+1},K_{t+1}}\{u(C_t)+\beta E_t V(A_{t+1},K_{t+1},D_{t+1})\} \tag{4.43}$$

s.t.

$$C_t=p_tY_t+SUB_t+D_{t+1}-(K_{t+1}-(1-\delta)K_t)-w_{xt}X_t-(1+r_t)D_t$$

Assume the value function V(.) is differentiable. The first-order condition with respect to K_{t+1} and D_{t+1} is,

$$(-1)u'(C_t)+\beta E_t\frac{\partial V(A_{t+1},K_{t+1},D_{t+1})}{\partial K_{t+1}}=0 \tag{4.44}$$
$$u'(C_t)+\beta E_t\frac{\partial V(A_{t+1},K_{t+1},D_{t+1})}{\partial D_{t+1}}=0 \tag{4.45}$$

Suppose that the sequence of future capital stocks and future debts have been chosen optimally (the value function is maximized). Take the derivatives of V(.) with respect to K_t and D_t:

$$\frac{\partial V(A_t, K_t, D_t)}{\partial K_t} = u'(C_t)(p_t\alpha_k\frac{Y_t}{K_t} + 1 - \delta) + \beta E_t\frac{\partial V(A_{t+1}, K_{t+1}, D_{t+1})}{\partial K_{t+1}}\frac{dK^*_{t+1}}{dK_t}$$
$$\frac{\partial V(A_t, K_t, D_t)}{\partial D_t} = u'(C_t)(-(1 + r_t)) + \beta E_t\frac{\partial V(A_{t+1}, K_{t+1}, D_{t+1})}{\partial D_{t+1}}\frac{dD^*_{t+1}}{dD_t} \qquad (4.46)$$

According to the Envelope theorem, as K_{t+1} and D_{t+1} are at the optimal values such that the value function is maximized, it indicates that $\partial V(A_{t+1}, K_{t+1}, D_{t+1})/\partial K_{t+1} = 0$, $\partial V(A_{t+1}, K_{t+1}, D_{t+1})/\partial D_{t+1} = 0$. The derivatives of the value function are,

$$\frac{\partial V(A_t, K_t, D_t)}{\partial K_t} = u'(C_t)(p_t\alpha_k\frac{Y_t}{K_t} + 1 - \delta) \qquad (4.47)$$
$$\frac{\partial V(A_t, K_t, D_t)}{\partial D_t} = u'(C_t)(-(1 + r_t)) \qquad (4.48)$$

This is the derivative of the value function with respect of its augments. Advance the period to $t + 1$,

$$\frac{\partial V(A_{t+1}, K_{t+1}, D_{t+1})}{\partial K_{t+1}} = u'(C_{t+1})(p_t\alpha_k\frac{Y_{t+1}}{K_{t+1}} + 1 - \delta) \qquad (4.49)$$
$$\frac{\partial V(A_{t+1}, K_{t+1}, D_{t+1})}{\partial D_{t+1}} = u'(C_{t+1})(-(1 + r_{t+1})) \qquad (4.50)$$

Substitute (4.49) and (4.50) into first order condition (4.44) and(4.45):

$$u'(C_t) = \beta E_t u'(C_{t+1})(p_t\alpha_k\frac{Y_{t+1}}{K_{t+1}} + 1 - \delta) \qquad (4.51)$$
$$u'(C_t) = \beta E_t u'(C_{t+1})(1 + r_{t+1})] \qquad (4.52)$$

Appendix C: Comparing the prices of wheat, barley and maize

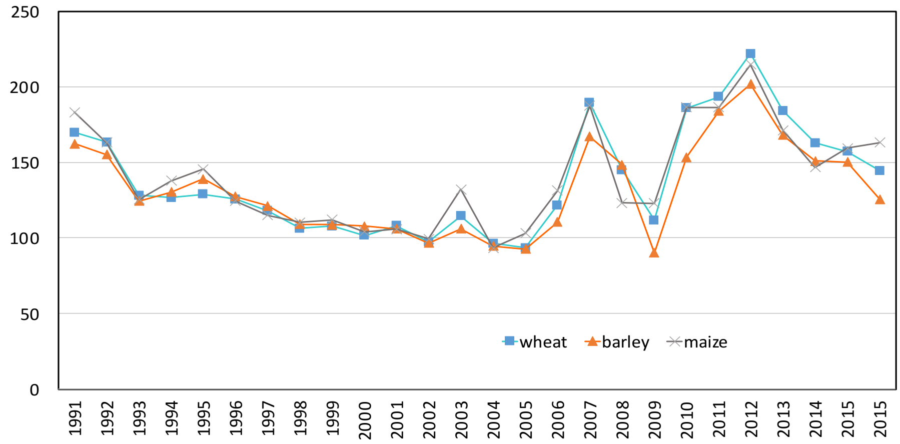


Figure 4.9: Comparing the prices of wheat, barley and maize in France (€/tonne). Source: FAOSTATS

Chapter 5

Assessing the Market Impacts of the Common Agricultural Policy: Does Farmer Risk Attitude Matter?[1]

5.1 Introduction

The Common Agricultural Policy (CAP) of the European Union (EU) is a complex public policy pursuing different objectives with many instruments. This policy has a long history and has been reformed several times in the last two decades. These reforms gradually reduce the initial market price support system and introduce payments intended to deal directly with potential market failures (public goods and bads, missing contingent markets, and unfair competition) and to directly support farm income. The CAP instruments are now classified in two pillars. The first pillar includes mostly market-price instruments and direct payments, whereas the second pillar includes mostly agri-environmental, rural development and risk-management instruments.

Many ex-ante assessments of the economic and physical impacts of these reforms (or proposals) have been performed at the farm and/or market levels. This paper focuses on the modeling frameworks that have been recently developed to assess the market impacts of the CAP. We can distinguish between Computable General Equilibrium (CGE) frameworks, Partial Equilibrium (PE) frameworks, and some studies combining both frameworks. Recent assessments using GE frameworks

[1]This chapter, co-written with Alexandre Gohin, was presented as a selected paper at the 2017 EAAE (European Association of Agricultural Economists) Congress in Parma.

include Boulanger and Philippidis (2015), who analyze scenarios of reductions of all CAP payments, Urban et al. (2014), who explore a complete removal of first-pillar payments, Boysen et al. (2016), who simulate a complete removal of first-pillar instruments, and Espinosa et al. (2014), who concentrate on second-pillar rural development instruments. Recent assessments using PE frameworks include Mittenzwei et al. (2014), who remove WTO green box payments, Deppermann et al. (2014), who analyze separately price instruments and direct payments, and Renwick et al. (2013), who remove all first-pillar instruments. CAP assessments performed with both CGE and PE models include Pelikan et al. (2014), who focus on the greening conditions attached to first-pillar direct payments, and Schroeder et al. (2014), who focus on the second-pillar instruments. Generally, these studies conclude that the market impacts of the price instruments are, in absolute terms, more important than those induced by the direct payments of the first pillar, when the latter are linked to the land factor. On the other hand, there is less confidence in the relative impacts of the more recent second-pillar instruments.

All of the aforementioned studies recognize the challenges to model accurately the way CAP instruments really operate. These market CGE/PE models are well designed to capture the working of the price instruments. However, they rely on more disputed assumptions for the other CAP instruments. In particular, the important direct payments of the first pillar are often modeled through so called coupling factors. These factors intend to measure the impacts of payments which occur through economic mechanisms that are not explicitly considered in these market models. Mostly cited is the wealth effect provided by direct payments to risk-averse farmers (Hennessy 1998). In fact, these models are generally static and non-stochastic, preventing the explicit modeling of such economic mechanisms. This leads for instance Moro and Sckokai (2013) to call for the revision of these market models routinely run for policy analysis because the impact of direct payments is analyzed by means of arbitrary coupling factors. In the same vein, Heckelei (2014) argues that these models are weak on the dynamic and stochastic dimensions and that they need to be improved to remain policy relevant.

To our knowledge, there have been limited efforts to improve the PE/CGE models devoted to analyze agricultural policy issues in these two dimensions. Regarding the stochastic dimension, while there are numerous studies assessing impacts under different market conditions (for instance on the CAP, Nolte et al. 2012), there are few studies that take into account the attitude of economic agents towards risks.

Burfisher et al. (2000) assess with a static CGE model the impacts of direct payments in the Canada, US and Mexico. They specify exogenous risk premiums that act like a production tax. They find a very limited impact of their policy scenarios. Gohin and Tréguer (2010) assess with a stochastic static PE model the market impacts of the U.S. biofuel programs. They assume first that farmers are risk-neutral, second that they are risk-averse. In that second case, the risk premium is endogenous to market conditions. These authors find that the market impacts of the U.S. biofuel programs at the stochastic steady state are similar across the two versions, unless the downside risk aversion of farmers and the price skewness induced by the U.S. farm policy are taken into account. Regarding the dynamic dimension, Féménia and Gohin (2011) develop a dynamic version of the static GTAP-AGR CGE model (Keeney and Hertel 2005) to assess the market impacts of agricultural trade liberalization. These authors find for this policy scenario that the available static results are quite robust to most expectation assumptions that are required in a dynamic framework. When the price expectations are rational, then the dynamic results converge to the static ones. On the other hand, when the price expectations greatly depart from rationality due to informational constraints, they are much different, with possible chaotic dynamic results. In the same vein, Boussard et al. (2006) compare two dynamic CGE models and also find major impacts of the expectation assumptions in a trade liberalization scenario. These two studies focus on the so-called endogenous risks arising from informational issues but ignore the exogenous production risks (not directly linked to human actions such as yield risks from stochastic climate events).

The objectives of this chapter are, first, to integrate the risk and dynamic dimension into a static CGE model. This is realized by modifying the supply side of the GTAP-AGR model by adding risk attitude. In the planting season, farmers make optimal decisions in this modified supply model based on expectations of price and price volatility. In the harvest season, we introduce stochastic productivity shocks in the CGE model, and the final equilibrium price jointly determined by the supply and demand side in the CGE model is not necessarily in accordance with the price expectations. The farmer receives a capital return based on the true market price. The model dynamics pass on through the expectations the farmers newly form from the succession of short-term market equilibria.

Second, we investigate to what extent the introduction of risks and farmer risk attitude matter when assessing the market impact of CAP. We show that in addition to the price expectations, expectations of price volatility become one of the key factors for farmer decisions through its influence on the risk premium. Under the endogenous modeling of the CAP instruments, risk aversion matters by leading to much larger production and price effects. The impacts of policy instruments are even larger if the wealth effect is taken into consideration.

The structure of the chapter is as follows. Section 2 explains how we develop a dynamic stochastic version of the GTP-AGR model. We start from a standard static GTAP-AGR model, and explain the supply side we will modify. Next, we present the development of a dynamic version without risks, in which the dynamics passes through expectation schemes. Last, we present a modified PE model with risk attitudes, and demonstrate the development of a dynamic stochastic version with exogenous production risks. Section 3 performs policy simulations in different versions of the model. Section 4 concludes.

5.2 Modeling Frameworks

The different CAP reforms adopted in the last two decades have progressively changed the nature of policy instruments, with less emphasis on agricultural market price instruments and more emphasis on instruments targeting agricultural production factors and/or technologies (such as land payments and organic production). In order to assess the market impacts of this shift, the modeling frameworks offering an explicit representations of these factors and technologies become a priori more and more relevant. We indeed observe that the CGE framework, which naturally encompasses these features, is more and more prevalent for the assessment of the CAP. In fact, many global CGE models have been developed in recent years to perform policy assessments (such as the GTAP, GTAP-AGR, GTAPEM, LEITAP-MAGNET, MIRAGE-AGRI). None of them explicitly introduces the stochastic dimension, and are they generally based on the predominant global GTAP database. With respect to the CAP assessment, these different models mostly differ in their elasticity calibration (with more or less complex production, utility and factor mobility specifications) and their CAP instrument representation (in particular with the shares of direct payments linked to different primary factors of production).

We start from the publicly available static GTAPinGAMS model developed by Rutherford (2006) that we modify to introduce the GTAP-AGR elasticities. The CAP instrument representation is directly given by the latest GTAP database, in particular the allocation of direct payments to the different primary factor returns. We briefly document the production part of this static CGE model before explaining our subsequent modifications to introduce the dynamic and stochastic dimensions.

5.2.1 The Static GTAP-AGR CGE Model

The GTAP-AGR model is a static CGE model derived from the GTAP model, designed to better capture certain structural features of world agricultural markets and policies (essentially through better calibration of elasticities). The GTAP model is a relatively standard multi-region CGE model where consumers are assumed to maximize their utility, and factor owners their revenue. This model employs the simplistic assumptions of perfect competition in all commodity and factor markets, that flexible prices ensure market equilibrium, and that investment are saving driven. Commodities are differentiated by origin, allowing the modeling of bilateral international trade flows. This GTAP framework is implemented using data organized in Social Accounting Matrices (SAM) per region capturing economic flows during a given year and exogenous substitution/price/income elasticities.

On the farm supply side, the modeled agent is not one farmer who may own different primary factors (capital and land in addition to his own human capital and labor force) and decide production variables. Rather, the approach is activity-based with a distinction made between the different primary factor owners. More precisely, it is assumed that there is a representative land owner in each region who allocates each year his land asset over different farm and non-farm activities. This allocation depends on the land return provided by each activity and is technically implemented by (nested) Constant Elasticity of Transformation (CET) mobility functions which capture in a synthetic way the heterogeneity of the land asset. In the same vein, there is a representative labor supplier (for both skilled and unskilled) in each region who allocates each year his labor force and human capital to different activities in response to their labor returns. This is the same logic for the representative physical capital owner, who can be a domestic or foreign household. The primary factor returns generated by the different activities are constrained by the market and policy environment, and the technological relationships that link outputs to inputs and primary factors of production. These technologies are usually mono-product, exhibit constant returns to scale and are specified through nested Constant Elasticity of Substitution (CES) technologies defined over variable inputs (chemicals for instance) and primary factors of production.

This agricultural supply modeling based on activity is not specific to the CGE approach, it is also implemented in some PE models (for instance the CAPRI model developed at the University of Bonn). It exhibits desirable features, such as the use of activity-based input-output matrices that are compiled by national statistical institutions and incorporated in the SAM. It also exhibits some weaknesses, such as the requirements to measure all commodity uses and primary factor returns by all activities. This can be problematic when activities are highly detailed (such as the distinction between wheat and coarse grains in the cereal sector). Indeed, this has long been recognized when trying to assess the market impacts of CAP direct payments (Jensen and Frandsen 2004).

More than these measurement issues, our main point here is that this static activity-based supply modeling does not allow the explicit modeling of farmers' attitude towards risk. Farmers, and other producers as well, are not explicitly identified. They are indeed aggregated with other households and eventually only the aggregated attitude toward risks can be contemplated. Moreover, this static approach assumes that the regional households (more precisely primary factor owners) know the true market prices of commodities and the true primary factor returns when they decide their factor allocation. The lag between production decisions and commodity selling on market is not recognized, preventing the real modeling of the dynamic and stochastic dimensions. In order to integrate the later analysis of farmers' attitude towards risk on CAP assessments, we thus need to model farmers even in the static approach. The simplest way to do this is to assume that the physical capital initially allocated to each activity is specific to that activity and is owned by a representative producer who maximizes his primary factor return. This return will contribute to the income of the regional representative household. Indeed, this assumption is also adopted by recursive dynamic models (such as Linkage or Mirage) and static CGE models as well, when they want to compute short term effects (Keeney and Hertel 2009 for instance).

The interpretation of the static CGE model is then the following. There is a representative producer in each activity who is the owner of the physical capital installed in that activity. This producer (farmer for an agricultural activity) maximizes his profit by choosing the optimal level of production, input use and factor use (possibly hiring labor and renting land) subject to his CES-based production technology. This profit will be added to the income of the regional household. Hence, it is assumed that farmers have the same structure of preferences over consumption goods as other economic agents.

Mathematically, the following producer program is implemented for all farm activities in all regions:

$$\begin{aligned}&\text{Max} \quad \pi(K_{ir}) = P_{y_{ir}} Y_{ir} - WT_{ir} T_{ir} - WS_{ir} SL_{ir} - WU_{ir} UL_{ir} - \sum_j WX_{jir} X_{jir} \\ &s.t. \quad Y = f(X_{jir}, T_{ir}, SL_{ir}, UL_{ir}, K_{ir}) \end{aligned} \tag{5.1}$$

where the indexes i and r stand for the activity i in region r, $\pi(K_{ir})$ is the profit, Y_{ir} is the output level, $P_{y_{ir}}$ is the output price, T_{ir} is the land use, WT_{ir} is the land rental price, SL_{ir} is the skilled labor input and WS_{ir} the respective price, UL_{ir} is the unskilled labor input and WU_{ir} the respective price, and X_{jir} is the intermediate use of commodity j for activity i with WX_{jir} the corresponding prices. All prices are net of subsidies.

In order to clarify the latter implementation with the version with risk aversion and its more intricate calibration/resolution below, it is useful to detail the production technology and the calibration of specified parameters. It takes the following nested CES form:

$$Y_{ir} = \alpha_{y_{ir}} \left(\delta_{y_{ir}} Q_{va_{ir}}^{-\rho_{y_{ir}}} + (1 - \delta_{y_{ir}}) Q_{nva_{ir}}^{-\rho_{y_{ir}}} \right)^{-1/\rho_{y_{ir}}}$$

where $Q_{va_{ir}}$ is the quantity of the value added bundle and $Q_{nva_{ir}}$ is the quantity of the non value added bundle. These two aggregates are also defined by CES functions:

$$\begin{aligned}Q_{va_{ir}} &= \alpha_{q_{ir}} (\delta_{T_{ir}} T_{ir}^{-\rho_{qva_{ir}}} + \delta_{sl_{ir}} SL_{ir}^{-\rho_{qva_{ir}}} + \delta_{ul_{ir}} UL_{ir}^{-\rho_{qva_{ir}}} + \delta_{k_{ir}} K_{ir}^{-\rho_{qva_{ir}}})^{-1/\rho_{qva_{ir}}} \\ Q_{nva_{ir}} &= \alpha_{q_{nva_{ir}}} (\sum_j \delta_{x_{jir}} X_{jir}^{-\rho_{qnva_{ir}}})^{-1/\rho_{qnva_{ir}}}\end{aligned}$$

with $\quad \delta_{t_{ir}} + \delta_{sl_{ir}} + \delta_{ul_{ir}} + \delta_{k_{ir}} = 1, \quad \sum_j \delta_{x_{jir}} = 1$

The constant return to scale assumption greatly facilitates the resolution of this program and its implementation. This assumption ensures that the profit is given by the product between the capital stock and the unitary capital return, the latter being independent of the former:

$$\pi(K_{ir}) = WK_{ir} K_{ir}$$

It is thus possible to solve this program and calibrate the numerous CES parameters as if the capital stock were endogenous and the unitary capital return were exogenous. When the optimal Hicksian demand functions are introduced in the full CGE model, the capital stock is turned exogenous and the unitary capital return becomes endogenous and activity-specific. The optimal Hicksian levels of variable inputs and primary factor uses are given by the following cost minimization program:

$$\begin{aligned} &\text{Min} \quad C(Y_{ir}, K_{ir}) = WT_{ir}T_{ir} + WS_{ir}SL_{ir} + WU_{ir}UL_{ir} + \sum_j WX_{jir}X_{jir} \\ &s.t. \quad Y_{ir} = f(X_{jir}, T_{ir}, SL_{ir}, UL_{ir}, K_{ir}) \end{aligned} \tag{5.2}$$

The Hicksian demands are:

$$\begin{aligned} X_{jir} &= Q_{nva_{ir}} \alpha_{q_{nva_{ir}}}^{\sigma_{q_{nva_{ir}}}-1} \left(\frac{\delta_{x_{jir}} P_{nva_{ir}}}{WX_{jir}} \right)^{\sigma_{q_{nva_{ir}}}} \\ SL_{ir} &= Q_{va_{ir}} \alpha_{q_{va_{ir}}}^{\sigma_{q_{va_{ir}}}-1} \left(\frac{\delta_{sl_{ir}} P_{va_{ir}}}{WS_{ir}} \right)^{\sigma_{q_{va_{ir}}}} \\ UL_{ir} &= Q_{va_{ir}} \alpha_{q_{va_{ir}}}^{\sigma_{q_{va_{ir}}}-1} \left(\frac{\delta_{ul_{ir}} P_{va_{ir}}}{WU_{ir}} \right)^{\sigma_{q_{va_{ir}}}} \\ T_{ir} &= Q_{va_{ir}} \alpha_{q_{va_{ir}}}^{\sigma_{q_{va_{ir}}}-1} \left(\frac{\delta_{t_{ir}} P_{va_{ir}}}{WT_{ir}} \right)^{\sigma_{q_{va_{ir}}}} \\ K_{ir} &= Q_{va_{ir}} \alpha_{q_{va_{ir}}}^{\sigma_{q_{va_{ir}}}-1} \left(\frac{\delta_{k_{ir}} P_{va_{ir}}}{WK_{ir}} \right)^{\sigma_{q_{va_{ir}}}} \end{aligned}$$

with

$$\begin{aligned} Q_{va_{ir}} &= Y_{ir} \alpha_{y_{ir}}^{\sigma_{y_{ir}}-1} \left(\frac{\delta_{y_{ir}} P_{y_{ir}}}{P_{va_{ir}}} \right)^{\sigma_{y_{ir}}} \\ Q_{nva_{ir}} &= Y_{ir} \alpha_{y_{ir}}^{\sigma_{y_{ir}}-1} \left(\frac{(1-\delta_{y_{ir}}) P_{y_{ir}}}{P_{nva_{ir}}} \right)^{\sigma_{y_{ir}}} \\ P_{nva_{ir}} Q_{nva_{ir}} &= \sum_j WX_{jir} X_{jir} \\ P_{va_{ir}} Q_{va_{ir}} &= WT_{ir}T_{ir} + WS_{ir}SL_{ir} + WU_{ir}UL_{ir} + WK_{ir}K_{ir} \end{aligned} \tag{5.3}$$

The optimal output level is implicitly determined by the introduction of the zero profit condition in the full CGE model. The concrete implementation of these functions requires knowledge of substitution elasticities. The values of δ, the CES parameters, are then determined using initial economic flows registered in the

SAMs. For instance, we have:

$$\delta_{t_{ir}} = \frac{WT_{ir}T_{ir}{}^{1/\sigma_{qva_{ir}}}}{WT_{ir}T_{ir}{}^{1/\sigma_{qva_{ir}}} + WS_{ir}SL_{ir}{}^{1/\sigma_{qva_{ir}}} + WU_{ir}UL_{ir}{}^{1/\sigma_{qva_{ir}}} + WK_{ir}K_{ir}{}^{1/\sigma_{qva_{ir}}}} \tag{5.4}$$

We also clarify for later versions the program of the representative land owner in each region. It is given by:

$$\begin{aligned} &\text{Max} \quad R(T_r) = \sum_i WT_{ir}T_{ir} \\ &s.t. \quad T_r = CET(T_{ir}) \end{aligned} \tag{5.5}$$

We obtain the optimal land supply function in terms of market returns

$$T_{ir} = T_{ir}^S(T_r, WT_{ir})$$

The equilibrium between this land supply function and the previously land demand function determined by the farmer is obtained by the endogenous land rental price. It should be recognized here that the land market regulations are not explicitly represented (eventually very implicitly by the choice of the CET transformation elasticity).

5.2.2 The Development of a Dynamic Version

In most productive activities, inputs and/or primary factors of production are engaged before the production is realized. This is particularly true in farming where arable crop producers for instance first decide their land use and seed application, then apply variable inputs over the plant growing period such as fertilizers and pesticides, and finally harvest the crop and market it (possibly directly selling on the market or storing before selling). This time lag between production decisions and production marketing implies that the farmers must base their decisions on expected prices, which can be different from true ones. By nature, this issue is neglected in static analyse while dynamic analyses generally conclude that the price expectations are critical.

There have been many debates about the precise nature of farmers' price expectations and more generally on expectations by economic agents (Manski 2004). This is a difficult empirical task, possibly more complicated in agriculture than in other productive sectors due to the existence of pervasive agricultural policies. The endogenous modeling of price expectations is in fact highly challenging. For instance, future markets provide some information about the market expectations at a given point of time about future prices, both their mean level and their volatility (option prices). These contingent markets exist for some commodities in some regions. Svaleryd and Vlachos (2002) find that there is a positive interdependence between the development of financial markets and trade liberalization. This finding is especially relevant in the EU agricultural context, where some futures markets have emerged following the CAP reforms and the decrease of market price support system. This suggests that the micro-structure of markets needs to be endogenous to the contemplated policy scenarios. To our knowledge, this idea has never been introduced in dynamic models used for ex-ante simulations. One possible reason is the predominant use of the rational expectations assumption which poses that economic agents, in the aggregate, do not suffer from informational issues. This assumption is highly convenient as it avoids identifying the information gathered and processed by each economic agent. Just and Rausser (2002) develop a theoretical analysis showing that the relevance of the rational expectations assumption depends on the costs of information collection and process relative to their benefits. If the costs are high relative to the benefits, simple expectation schemes such as myopic, naïve one can be optimal.

Hence, the modeling of dynamic behavior is a tricky issue involving unobservable expectations and information used by economic agents. In this chapter, we adopt backward price expectation schemes. That is, we assume that farmers form their price expectations using past observations, with different weights attached to recent versus old observations. Two main arguments support our assumption. The first argument is computational. The alternative rational expectations assumption implies a forward looking behavior where economic agents, including farmers, are assumed to solve the full CGE model for all future years. Even when we ignore the volatility dimension, the resolution of a highly detailed forward-looking CGE model with endogenous regime (active versus non active market price support regime) is a computational challenge. To our knowledge, available software to solve dynamic stochastic general equilibrium (DSGE) models (such as the Dynare) are more and more powerful allowing richer specifications and many state variables. However, they presently remain highly sensitive to discontinuities in the models. The second argument is that we want to assess the market impacts of the CAP not only at the stochastic steady states, but also during the transition period between two stochastic steady states. It is generally more accepted that the rational expectations assumption fits better in the long run than the short run. In other words, there may exist some learning periods where economic agents progressively update their beliefs/expectations before reaching a new stochastic steady state induced by the policy scenario.

In addition to the expectations assumptions, for the implementation of the dynamic version, we also need to decide the number of periods we consider during a given year (such as the planting period, the application periods of fertilizers and pesticides, the harvesting period) and the predetermined versus endogenous variables in each period. We again adopt the simplest assumptions by dividing a year in two periods. In the first period that can be labeled the production period in which farmers equipped with their physical capital decide their production, input and primary factor levels given their commodity price expectations and also the labor price expectations (labor is used all along the production campaign, such as during harvesting). On the other hand, the land use is negotiated at the beginning of the production campaign with the land owner. This economic agent needs to form land return expectations for other potential activities when deciding to allocate some land to one farming activity. Hence, in the first period of a given year, we determine the output level, input use, primary factor use (land and labor) by the farmers, parts of the land allocation by the land owner and the equilibrium land return for these dynamic activities. In the second period of the given year, that can be labeled the marketing period, these variables become predetermined in the static CGE model, market price will be determined, residual capital return as well. They may differ from expected values by farmers.

Mathematically, the program solved by the producer in the first period of each year (indexed by t) is:

$$\begin{aligned}
&\text{Max} \quad E(\pi(K_{irt})) = E(P_{y_{irt}})Y_{irt} - WT_{irt}T_{irt} - E(WS_{irt})SL_{irt} \\
&- E(WU_{irt})UL_{irt} - \sum_j E(WX_{jirt})X_{jirt} \\
&s.t. \quad Y_{irt} = f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt}) \qquad (5.6)
\end{aligned}$$

This program is very similar to the program (1) defined before. The only difference comes from the formulation of expected prices/returns in place of realized prices/returns. The resulting Hicksian demand functions are thus of the same nature. The program of the representative land owner is also changed in the same spirit, with expected land returns rather than realized ones for the dynamic activities. Formally, the representative land ower solves a first program in the first period of each year. This program is:

$$\begin{aligned} &\mathrm{M}ax \sum_i E(WT_{irt})T_{irt} \\ &s.t. \quad T_{rt} = CET(T_{irt}) \\ &s.t. \quad E(WT_{irt}) = WT_{irt} \end{aligned} \tag{5.7}$$

We thus define a PE model in the first period, made of the optimal decisions of farmers and land allocation by land owners. This PE model determines in particular the land returns for the dynamic farm activities and their optimal supplies, variable input and primary factor uses. In order to solve this model, we must assume the exact price expectations made by farmers (and landowners). The economic flows reported in the SAM do not indicate whether the realized capital return is exactly the anticipated one by farmers. We simplify again the analysis by assuming that the initial situation reported in the SAM is a steady state and that economic agents did not make price expectation errors in that year.

The results of this first-period PE model are fed into the full CGE model, where the relevant variables are now turned to exogenous ones and corresponding equations are removed. In this modified CGE model, the representative land owner still allocate the remaining land to the different activities.

It remains to determine the dynamics over the years. The exogenous variables in the first-period PE model are the capital stocks and the net price expectations. We need to determine the dynamics of these exogenous variables. We again make simplified assumptions by assuming that the capital stock in each farm activity is always the same. This implies that the sectoral investment in the full CGE model solved in the preceding year is assumed to equal the exogenous depreciation. We recognize that this assumption restricts our analysis by potentially excluding some risk management strategies pursued by farmers. In particular, they may delay or advance their investments following unexpected price realizations. As far as we know, available econometric studies assessing the farmers' risk aversion mostly ignore these possibilities. So our latter development of the volatility version with

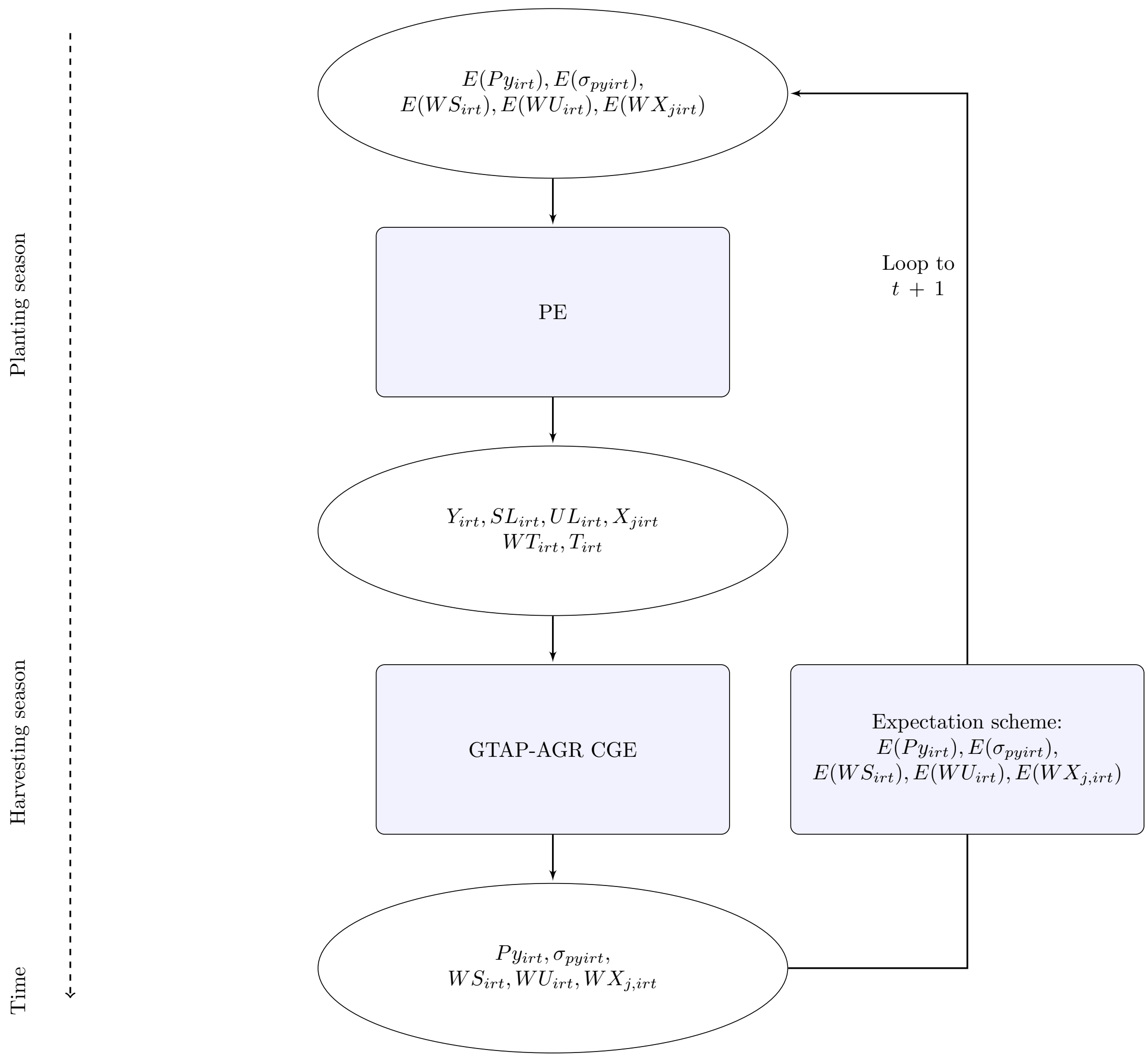


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Figure 5.1: The dynamic version

risk aversion is consistent with this assumption. The only inter-year dynamics occur in our analysis by the revision of the net price expectations. As mentioned earlier, we assume that the price expectations made by farmers for future periods take into account past observations, including the last computed one. In case of the product price, this means that:

$$E(P_{y_{ir,t+1}}) = (1 - \phi_p)E(P_{y_{irt}}) + \phi_p P_{y_{irt}}, \quad 0 < \phi_p < 1 \tag{5.8}$$

In a sensitivity analysis, we can vary the ϕ_p parameter, allowing the implementation of static, myopic and adaptive price expectations.

Figure 5.1 shows the flow of the dynamic version. To sum up, this dynamic version represents the minimal departure from the previous static CGE framework. It is made of two models, one PE focused on the dynamic activities and one full CGE. The dynamics are recursive, we obtain a succession of temporary equilibria. The dynamics over years is accomplished with only one type of variables, the expected prices/factor returns.

5.2.3 The Development of a Stochastic Version

The agricultural activity is confronted with many sources of risks, the most obvious one being the yield risk linked to climate events for crop activities. These production risks may lead to price risks, depending on the functioning of agricultural markets. Some European farmers have long been protected from these price risks with the market-price instruments of the CAP. While the presence of production/price risks is not disputed, the exact attitude of farmers towards these risks is more debated. Many efforts have been pursued in recent years with different methods to reveal their risk attitude (e.g. Roe 2015). This is challenging for instance because one must also identify their expectations. It is still rather accepted that farmers in general, and EU farmers in particular, can be risk-averse. This means that they prefer to produce a safe crop rather than a risky crop giving the same expected return. Our development of a stochastic version intends to capture these features.

We again do that in a simplified manner starting from the above dynamic version. For instance, we maintain the specification of production technologies with nested CES functions, and thus do not explicitly recognize the potential roles of some variable inputs to manage risks (fertilizers are generally considered as risk-increasing and pesticides risk-decreasing). Capturing these roles requires a new specification of the production technology, such as the "Just and Pope" one. Instead, we will follow previous examples (e.g. Van Meijl and Van Tongeren 2002) by assuming multiplicative production risks in non-EU regions. Formally, we assume that the total factor productivity parameters are stochastic and thus take different values (explained later). At the second period of each year, we solve the full CGE model with these different values, leading to different world and EU prices for agricultural commodities.

Modified PE Model with Risk Attitude

Turning to the first period (planting season) of a production year, we assume that EU farmers face only price risks, and they only adjust their production level and input uses to manage the price risks. They maximize the expected utility of their profit and that their utility function exhibits constant absolute risk aversion (CARA). Formally, the farmer's decision problem is:

$$\begin{aligned} &\text{Max} \quad EU(\pi(K_{irt})) = EU(P_{y_{irt}}Y_{irt} - WT_{irt}T_{irt} - WS_{irt}SL_{irt} \\ &- WU_{irt}UL_{irt} - \sum_j WX_{jirt}X_{jirt}) \\ &s.t. \quad Y_{irt} = f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt}) \end{aligned} \tag{5.9}$$

This expected utility program can be rewritten as a mean-variance program if we furthermore assume that the stochastic output price follows a normal law (a log normal assumption can be contemplated in an extension, while still specifying a mean-variance approach, Chavas 2004):

$$\begin{aligned} &\text{Max} \quad EU(\pi(K_{irt})) = E(P_{y_{irt}}Y_{irt} - WT_{irt}T_{irt} - WS_{irt}SL_{irt} \\ &- WU_{irt}UL_{irt} - \sum_j WX_{jirt}X_{jirt} - \frac{1}{2}\rho\sigma^2_{p_{y_{irt}}}Y^2_{irt}) \\ &s.t. \quad Y_{irt} = f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt}) \end{aligned} \tag{5.10}$$

The farm objective function now includes the risk premium, which represents the amount of money that farmers are ready to forget in order to avoid risk. This risk premium is given by the product of the absolute risk aversion parameter (ρ), the expected variance of output prices, and the square of the production level. As expected, the higher the level of risk aversion and the higher the price volatility, the higher is the amount of money the farmer is ready to give up in order to avoid the price risk.

This new farm program involves the expected variance of output price. That is, we now need to define the average output prices expected by farmers as well as their variance. An exceptional price last year may lead farmers to revise their price expectations and to consider that they will be more volatile in the future years. Or they may simply disregard it and consider that the volatility of output price is constant.

The resolution of the farm program can be decomposed in two steps. In the first step, the production costs are minimized, leading to the optimal Hicksian demand and the optimal cost function. This is similar to the static case. In the second step, the expected utility (the weighted mean-variance) is then maximized by choosing the optimal production level. The corresponding program is:

$$\text{Max} \quad EU(\pi(K_{irt})) = E(P_{y_{irt}} Y_{irt} - C(Y_{irt}, K_{irt}) - \frac{1}{2}\rho\sigma^2_{p_{y_{irt}}} Y^2_{irt}) \tag{5.11}$$

The first-order condition implicitly determines the optimal output level:

$$CM(Y_{irt}, K_{irt}) = E(P_{y_{irt}}) - \rho E(\sigma_{p_{y_{irt}}})^2 Y_{irt} \tag{5.12}$$

where CM denotes marginal cost. This equation states that the marginal cost at the optimal output level is equal to the expected price minus the marginal risk premium. Even if we maintain the constant return to scale assumption, the profit computed as the difference between receipt and variable expenditures does not equate the return to capital services. It also includes the risk premium. It should be acknowledged that the risk premium is not paid to a third party and does not appear in the SAMs because we do not consider contingent markets. We thus need to assume this value and will consider different initial values based on a literature review. More precisely, we will assume different risk premiums in percentage of the market receipt:

$$\beta_{ir} = \frac{0.5\rho E(\sigma_{p_{y_{irt}}})^2 Y_{irt}}{E(P_{y_{irt}}) Y_{irt}} \tag{5.13}$$

In other words, we will assume in the calibration part the value of the product of the risk-aversion parameter and the expected price variances by farmers and thus the initial marginal cost level. In order to solve and calibrate the cost minimization program, it is no longer possible to use the previous trick, that is the exogenous unitary capital return. The profit is no longer a simple expression of the capital stock multiplied by an unitary and exogenous capital return. The resolution/calibration of this cost minimization program leads to a system of first-order conditions that is nonlinear in the parameters and the variables. It is no longer possible to get closed-form solutions for the optimal input/factor demands. It is equally impossible to get closed-form expressions to calibrate the technological parameters. Accordingly, we will need to solve a system of first-order conditions to calibrate the technological parameters and can not simply compute them as in equation. (5.4) before. This system is:

$$\begin{aligned}
&\text{Min} \quad EC(Y_{irt}, K_{irt}) = WT_{irt}T_{irt} + E(WS_{irt})SL_{irt} + E(WU_{irt})UL_{irt} + \sum_j E(WX_{jirt})X_{jirt} \\
&s.t. \quad Y_{irt} = f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt}) \qquad (5.14)
\end{aligned}$$

The Lagrangian of this system is,

$$\begin{aligned}
L(T_{irt}, SL_{irt}, UL_{irt}, X_{jirt}, \lambda) &= WT_{irt}T_{irt} + E(WS_{irt})SL_{irt} + E(WU_{irt})UL_{irt} \\
&+ \sum_j E(WX_{jirt})X_{jirt} + \lambda(Y_{irt} - f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt})) \qquad (5.15)
\end{aligned}$$

The first-order conditions of the Lagrangian are given as:

$$WT_{irt} - \lambda\frac{\partial Y_{irt}}{\partial T_{irt}} = 0 \qquad (5.16)$$

$$E(WS_{irt}) - \lambda\frac{\partial Y_{irt}}{\partial SL_{irt}} = 0 \qquad (5.17)$$

$$E(WU_{irt}) - \lambda\frac{\partial Y_{irt}}{\partial UL_{irt}} = 0 \qquad (5.18)$$

$$E(WX_{jirt}) - \lambda\frac{\partial Y_{irt}}{\partial X_{jirt}} = 0 \qquad (5.19)$$

$$Y_{irt} - f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt}) = 0 \qquad (5.20)$$

The Lagrange multiplier λ is the marginal cost when the minimization program is optimized. Taking into account condition (5.12), λ equals the expected price minus the marginal risk premium at the optimal output level:

$$\lambda = \frac{\partial C}{\partial Y} = E(P_{y_{irt}}) - \rho\sigma^2_{p_{y_{irt}}}Y_{irt} \qquad (5.21)$$

By substituting (5.21) into the first-order condition set (5.16) - (5.19), the explicit first-order conditions are finally presented as

$$WT_{irt} - (E(P_{y_{irt}}) - \rho\sigma^2_{p_{y_{irt}}} Y_{irt}) \cdot A \cdot \delta_{t_{irt}} T_{irt}^{-\rho_{qva_{irt}}-1} = 0 \tag{5.22}$$
$$E(WS_{irt}) - (E(P_{y_{irt}}) - \rho\sigma^2_{p_{y_{irt}}} Y_{irt}) \cdot A \cdot \delta_{sl_{irt}} SL_{irt}^{-\rho_{qva_{irt}}-1} = 0 \tag{5.23}$$
$$E(WU_{irt}) - (E(P_{y_{irt}}) - \rho\sigma^2_{p_{y_{irt}}} Y_{irt}) \cdot A \cdot \delta_{ul_{irt}} UL_{irt}^{-\rho_{qva_{irt}}-1} = 0 \tag{5.24}$$
$$E(WX_{jirt}) - (E(P_{y_{irt}}) - \rho\sigma^2_{p_{y_{irt}}} Y_{irt}) \cdot B \cdot \delta_{x_{jirt}} X_{jirt}^{-\rho_{qnva_{irt}}-1} = 0 \tag{5.25}$$
$$Y_{irt} - f(X_{jirt}, T_{irt}, SL_{irt}, UL_{irt}, K_{irt}) = 0 \tag{5.26}$$

where

$$A = \alpha_{y_{irt}} \delta_{y_{irt}} (\frac{Y_{irt}}{\alpha_{y_{irt}}})^{1+\rho_{y_{irt}}} Q_{va_{irt}}^{-\rho_{y_{irt}}-1} \cdot \alpha_{qva_{irt}} (\frac{Q_{va_{irt}}}{\alpha_{qva_{irt}}})^{1+\rho_{qva_{irt}}} \tag{5.27}$$
$$B = \alpha_{y_{irt}} \delta_{y_{irt}} (\frac{Y_{irt}}{\alpha_{y_{irt}}})^{1+\rho_{y_{irt}}} Q_{nva_{irt}}^{-\rho_{y_{irt}}-1} \cdot \alpha_{qnva_{irt}} (\frac{Q_{nva_{irt}}}{\alpha_{qnva_{irt}}})^{1+\rho_{qnva_{irt}}} \tag{5.28}$$

The Hicksian demand and optimal output levels are obtained from the above equilibrium conditions based on expected factor returns, expected output price/output price volatility, and the risk-aversion coefficient of the producer. Different from the analytical Hicksian demands and the analytical elasticity calibration in the static GTAP-AGR model (see equations (5.3) and (5.4)), Hicksian demand, output supply, and elasticity calibrations are obtained by solving the first-order condition set (5.22) - (5.28) in GAMS. In addition, the land owner's program is the same as in the dynamic version in equation (5.7). Jointly with equations (5.22) - (5.28), land return WT_{irt} and land use are determined in the PE model.

Stochastic Version and its Dynamics

Figure 5.2 describes the flow of the stochastic version. To introduce exogenous risks in the CGE model, we assume in each year there are productivity shocks ϵ_{irt} outside the EU that follow a Gaussian distribution with mean zero and a standard deviation of $\sigma_{y_{irt}}$. The productivity shocks lead to world-price fluctuations in the full CGE model. They are implemented in the GTAP-AGR model through the production parameter $\alpha_{y_{irt}}$,

$$\alpha_{y_{irt}} = \alpha_{y_{irt0}} e^{\epsilon_{irt}}, \quad with \quad \epsilon_{irt} \sim N(0, \sigma_{y_{irt}}) \tag{5.29}$$

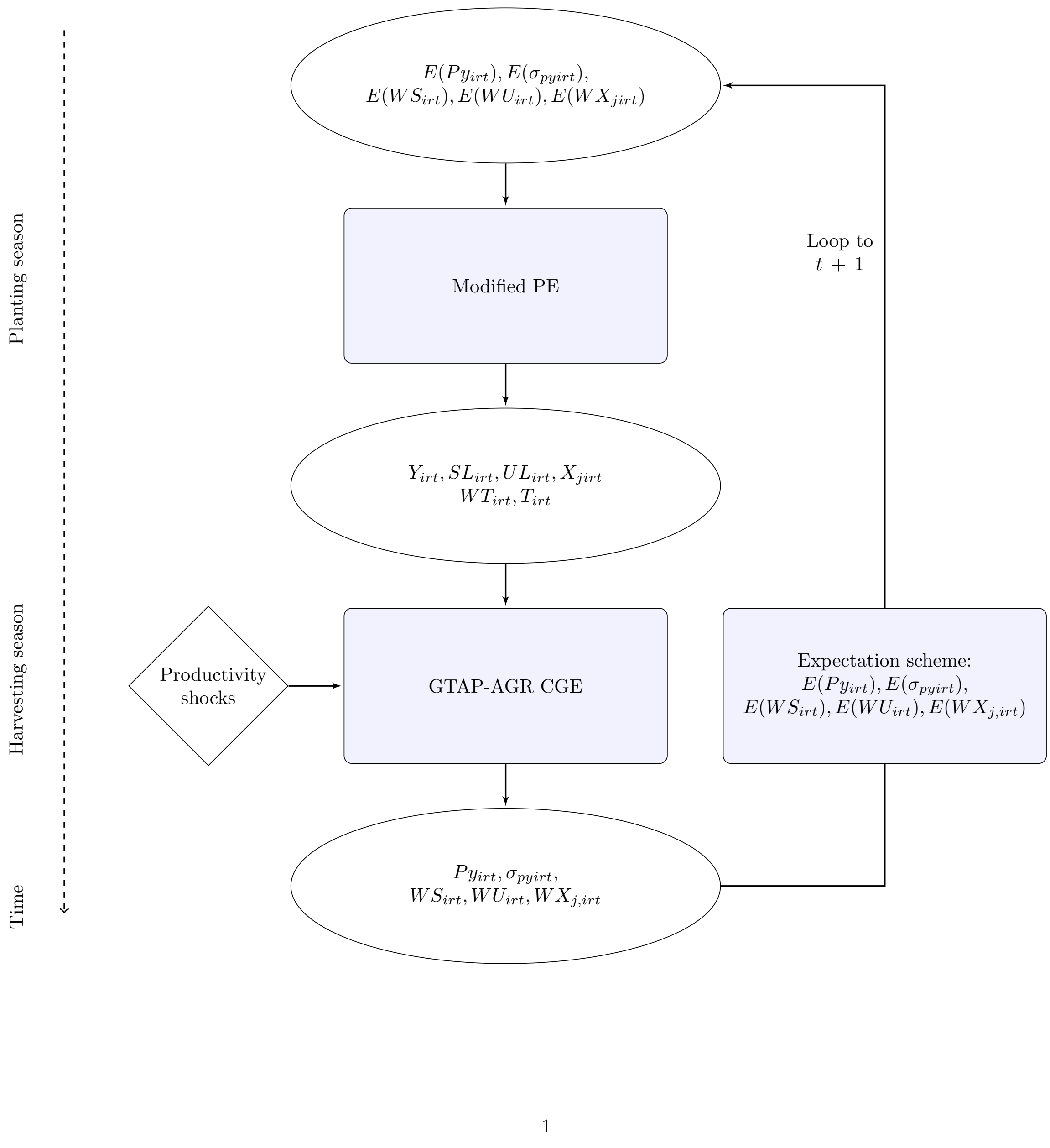

Figure 5.2: The stochastic version

where $\alpha_{y_{irt0}}$ is the production parameter calibrated at the initial point for product i and region r.

In the second period (harvesting season) of a production year, the market equilibrium is reached in the GTAP-AGR model by taking account the product supply/factor demand from the modified PE and the productivity shocks. Factor return, output price, and output price volatility are obtained correspondingly. However, because of the productivity shocks in the non-EU regions, the equilibrium price in EU is not necessarily equal to the price expectation ($p_{irt} \neq E(p_{irt})$), and this is the origin of price risks for EU farmers.[2]

Turning to the planting season of next year, the farmers form expectations on factor return (except land), output price and output price volatility based on the realized ones in this year. These expectations are fed into the modified PE, and the PE/CGE loops pass on. Adaptive expectations are formed based on the realized price and price volatility. Similarly for factor returns.

$$E(P_{y_{ir,t+1}}) = (1-\phi_p)E(P_{y_{irt}}) + \phi_p P_{y_{irt}}, \quad 0 < \phi_p < 1 \tag{5.30}$$

$$E(\sigma_{y_{ir,t+1}}) = (1-\phi_\sigma)E(\sigma_{y_{irt}}) + \phi_\sigma \sigma_{y_{irt}}, \quad 0 < \phi_\sigma < 1 \tag{5.31}$$

The dynamics passes to next year though the expectations, and passes over the years with the loops of inter-year short-term equilibira.

To sum up this stochastic version, it again represents the minimum departure from the previous dynamic PE/CGE framework. We only introduce risk aversion for EU farmers who only adjust their production level and input uses to manage their price risks. These price risks originate from productivity shocks in non EU regions. We now simulate a succession of stochastic temporary equilibria. The dynamics over years is accomplished with two types of variables, the expected prices/factor returns and the expected volatility of output prices.

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[2] Productivity risk is not modeled in the EU region because it is more complex to simultaneously consider two risks. Above all, productivity risk and price risk play a similar role in affecting the EU farm income. As a first extension, we consider only one risk.

5.3 Simulations

5.3.1 Empirical Assumption

We implement the different versions of GTAP-AGR model described above using the latest GTAP database, version 9 GTAP, of which the data is calibrated from 2011 economic flows. We aggregate the data to 26 commodities including 17 agricultural products, 5 regions including EU28, China, US, Argentina-Brazil-Uruguay(ABU) and Rest of the World (RoW). In both the dynamic and stochastic versions, we have the opportunity to choose the number of dynamic activities. We start by focusing on one crop (wheat), and later extend to other activities. In these two versions, the expectation schemes need to be determined.

The price expectations of the producers are formed based on past observed prices and past price expectations by the historical weighting parameter α, similarly, the volatility expectations are based on past volatilities and past volatility expectations. We start with the naïve expectation scheme by assuming $\alpha = 1$, that is, the price expectations of the producers are equal to the observed prices of last year, and the volatility expectations equal the average price volatility of last year. In the sensitivity analysis, the weighting parameter α is extended to other values. It should be noted that in the stochastic version, it is not possible to obtain one certain price because the prices are stochastic. We simulate different prices via Gaussian Quadrature approximation, given the distribution of the productivity shocks. Accordingly, the standard deviation of the price is obtained from the distribution of the stochastic output price.

When implementing the stochastic version, we also need to make assumptions on the risk premium and the productivity shocks. For the calibration of the risk premium, we fix the baseline risk premium at 2% of the production value ($\beta = 2\%$), which implies an absolute risk aversion coefficient of 1.25 with regard to the baseline price volatility. Our choice of β is in accordance with Femenia et al. (2010) who

Table 5.1: Percentage impacts of a 1% decrease of the expected price and of the expected volatility on EU wheat production.

	Risk neutrality	Risk aversion
Expected price	-1.30	-1.42
Expected volatility (σ)	0	0.11

use a risk premium at 2.1% of the market receipt.

We assume that the total factor productivity shocks follow a stochastic Gaussian process with mean zero and a standard deviation of 0.1. The shocks apply in US, China, ABU and RoW every year.

To test the relevance of our calibration assumptions, we simulate with the first-period PE model the effects of a 1% expected price decrease and a 1% price volatility decrease on EU wheat production. We use the standard deviation of prices (σ) as the indicator for volatility. As is reported in Table 5.1, risk aversion leads to a higher price elasticity (1.4) compared to that without risk aversion (1.3). The intuition is that when we account for the farmers' risk attitude, the return on fixed capital is lower while the risk premium is price sensitive (as it depends on the output volume).

As expected, the wheat supply is not sensitive to price volatility in the risk-neutral case, and is sensitive to price volatility when the producer is risk-averse. The estimated supply elasticity with respect to price volatility is -0.1. This is because when the producer exhibits constant absolute risk aversion (CARA), a decrease in price volatility results in a lower risk premium, and thus a lower share of profit corresponding to the risk premium compared to that corresponding to the return on fixed capital. To put it in another way, risk-averse producers allocate a lower proportion of the profit to avoid the risk when the price volatility decreases, in this way they produce more.

5.3.2 Policy Scenarios

We are now ready to analyze the market impacts of the CAP using our different versions of GTAP-AGR model. First, we explain the modeling of CAP instruments shown in Table 5.2. In most CGE applications, the price instruments which act through ad valorem export subsidies and import tariffs are usually assumed to

Table 5.2: Policy scenarios

	Exogenous policy representation
Price instrument	Exogenous export subsidies and import tariffs
Direct payments	Ad-valorem land payment
	Endogenous policy representation
Price instrument	Export subsidies and import tariffs in protecting domestic price
Direct payments	Per hectare land payment

be exogenous. In reality, the levels of these price instruments can be adapted to protect the domestic price from dropping below a price floor (the so-called intervention price) when the world price is low. Accordingly, we will consider below two alternative modeling of the price instruments: either an exogenous representation where the unitary levels are fixed, either an endogenous representation where they adjust to ensure minimum intervention/entry prices.

The modeling of direct payments is also challenging with the decoupling of farm payments introduced in 2003. These direct payments are perceived by farmers provided that they have a corresponding land use. Accordingly, they are often modeled as an ad valorem subsidy to the land factor, while remaining coupled subsidies are linked to the production. Below we adopt the allocation of subsidies provided in the GTAP9 database and again consider two modeling approaches. The standard exogenous one assumes that the unitary land payment is ad valorem (and thus change with the land return) while the endogenous one assumes that the unitary land payment are fixed per hectare. These two alternative models of CAP instruments are indeed worth differentiating with our stochastic framework.

We successively simulate two radical policy scenarios: first, the EU removes the price instruments on wheat, and second, the EU removes the direct payments on wheat. In both scenarios, the policy instruments in other regions and on other farm products stay at their initial level. Importantly, the impacts are assessed compared to a baseline. It should be understood that the baseline may change depending on the representation of the CAP and our modeling framework. More specifically, in both the static version and the dynamic version, we assume that the economy is initially at the steady state, and the initial point is used as the baseline. In the stochastic version, the introduction of productivity shocks requires us to first compute a stochastic steady state for the baseline.

5.3.3 Simulation Results

5.3.3.1 Results from the Static GTAP-AGR Model

We concentrate our analysis on price and production in EU and RoW. Table 5.3 shows the impacts of the policy scenarios in the static GTAP-AGR model. We find that the EU wheat production declines by 2.0% in response to the removal of price instruments. This is because removing the trade barriers puts a downward pressure on domestic EU wheat prices, which induces a 1.7% reduction in EU wheat price.

On the contrary, the wheat production and price in rest of the world increase by 0.5% and 0.3% respectively since they benefit from smaller supply coming from Europe.

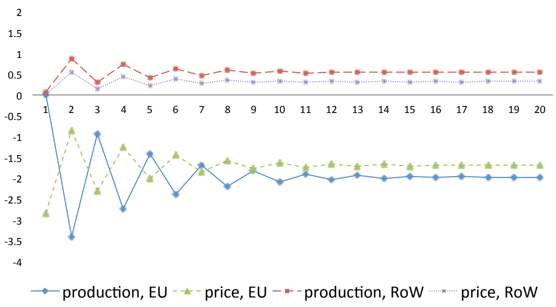
We also find that removing the direct payments induces a 1.3% decline in EU wheat production. As the direct payments are linked to the factor land, more acreage is thus allocated to other activities with higher land returns and less acreage is used for wheat production. Accordingly, the EU wheat production declines and the EU wheat price increases. Again, the rest of the world faces less competition from Europe, as witnessed by the expanding of wheat production by 0.3% and the increase of wheat price by 0.2% in RoW. All these results are quite standard and constitute our benchmark results before dealing with the dynamic and stochastic dimensions.

5.3.3.2 Results from the Dynamic Version

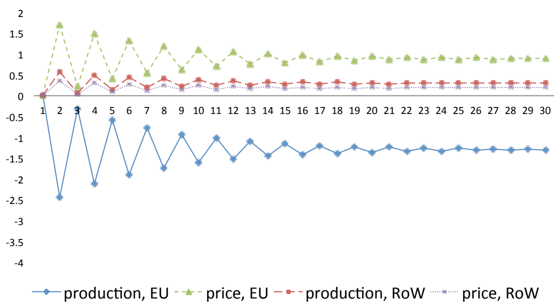
Figure 5.3a and 5.3b depict the evolution of EU wheat production and price after implementing the two policy scenarios in 2011. After 20 and 30 years' evolution respectively, the EU wheat production and price converge to a steady state, and the converged market impacts in the dynamic model are almost the same with the impacts in the static model (Table 5.3). We find that even when the expectation scheme is naïve, this radical scenario applied to wheat does not lead in the long run to diverging series. This is partly explained by the fact that the price elasticity of total demand of EU is quite large in absolute terms, at least according to the GTAP-AGR choice of elasticities. In other words, this does not lead to a cobweb diverging dynamic system.

Table 5.3: Simulated impacts of the removal of price instruments and direct payment on EU wheat with the static and the dynamic versions (in percent with respect to the initial baseline)

	European Union		**Rest of the world**	
Removal of price instruments	Production	Price	Production	Price
Static model	-1.98	-1.69	0.54	0.32
Dynamic model (steady state)	-1.98	-1.69	0.54	0.32
Removal of direct payments	Production	Price	Production	Price
Static model	-1.29	0.90	0.30	0.19
Dynamic model (steady state)	-1.31	0.91	0.31	0.19



(a) Removal of price instruments



(b) Removal of direct payments

Figure 5.3: Simulated evolution of the EU wheat production and price under the naïve expectation assumption with the dynamic version (in percent compared to the initial baseline)

5.3.3.3 Results from the Stochastic Version with Exogenous Representation of the CAP

We now use our stochastic version with the exogenous policy representation. Before assessing the policy impacts, it is important to explain the new stochastic baseline. We perform first-stage simulations by including only the productivity shocks. We reach the new stochastic steady state after 50 years in the stochastic model without risk aversion and after 70 years in the stochastic model with risk aversion, as it takes longer time for the expected volatility (σ) converge to the steady state with risk aversion. The first part of table 5.4 presents the new baseline values with respect to the calibration of risk preferences' parameters.

The productivity shocks outside Europe leads to a price volatility of 0.17 in the RoW and of 0.15 in the EU at the stochastic steady state. The level of world volatility is consistent with the measured volatility while the EU one is not (European Commission 2010). As will be shown below, this is due to policy representation where there is a perfect price transmission (modulo the Armington product differentiation assumption). Compared to the initial point used in the static and dynamic versions, the EU wheat production increases slightly under both risk neutrality and risk aversion. Overall, the productivity shocks in other regions bring positive effects on the EU and RoW production. These positive effects are due to the nonlinearity in the model, in particular, the convexity of the demand function.

Having obtained the new baseline, we implement the policy shocks at the 51^{st} year for the risk-neutrality case and at the 71^{st} year for the risk-aversion case.

Table 5.4: Simulated impacts of the removal of CAP instruments with the stochastic version and the exogenous policy representation (production and price in percent with respect to the baseline)

	European Union				**Rest of the world**		
	Production	Price	Volatility(σ)	β	Production	Price	Volatility(σ)
New baseline with productivity shocks							
Risk neutral	1.08	0.93	0.15	-	1.45	1.64	0.17
Risk aversion	1.14	0.89	0.15	2%	1.44	1.63	0.17
Impacts of the policy shocks							
Removal of price instruments							
Risk neutral	-1.88	-1.62	0.15	-	0.52	0.31	0.17
Risk aversion	-2.03	-1.52	0.16	2.03%	0.56	0.34	0.17
Removal of direct payments							
Risk neutral	-1.30	0.90	0.16	-	0.30	0.20	0.17
Risk aversion	-1.37	0.95	0.16	2.04%	0.31	0.21	0.17

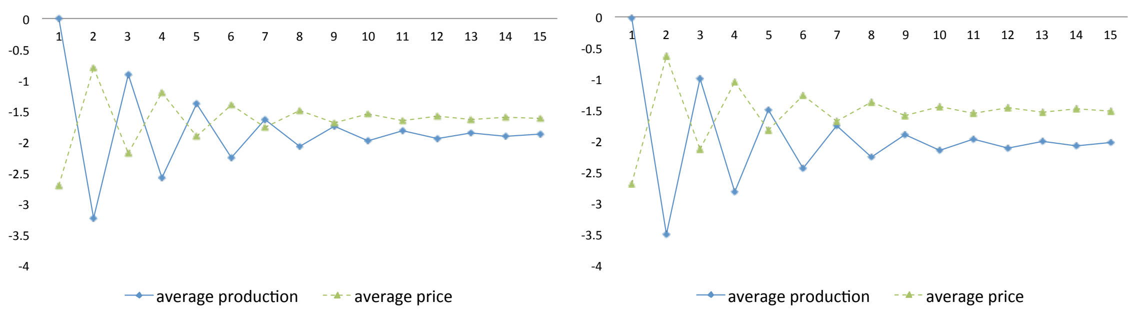
Table 5.4 presents the converged values, and Figure 5.4 and Figure 5.5 show the evolution of European production and price for both policy scenarios.

With the removal of price instruments, the economy converges to a new stochastic steady state in around 25 years. We observe similar evolution paths and modest differences between the impacts with or without risk aversion. The price volatility in Europe increases slightly to 0.16 with risk aversion, while it remains the same at 0.15 for the risk neutral case. As a result, the risk premium of the EU farmers increases by a very small amount.

Although the price volatility does not change much from the baseline, we find that the risk-averse wheat producers in Europe reduce their production slightly more (by 2.0%) compared to risk-neutral producers (by 1.9%). As discussed before in Table 5.1, the risk-averse producers have higher price elasticities than risk-neutral farmers. The trade liberalization puts a downward pressure on the EU domestic price, the risk-averse farmers produce less than the risk-neutral farmers. With regard to the impacts on price, we find that at the converged steady state, the EU wheat price decreases by 1.5% with risk aversion and by 1.6% without risk aversion.

With the removal of direct payments, the economy reaches the steady state after 30 years. Again, there is no obvious difference between the evolution paths with and without risk aversion (Figure 5.5a and Figure 5.5b). The results in Table 5.4 show first that this policy shock has a limited impact on the price volatility, which increases slightly from 0.15 to 0.16 in EU for both risk attitudes. The reason for this small impact is that the price volatility is mainly induced by the productivity shocks in other regions, on which the European policy reform has very limited influence. Second, we find as expected that the risk-averse producers in Europe reduce their wheat supply a little more (by 1.4%) compared to the risk-neutral producers in Europe (by 1.3%). Accordingly, the wheat price in Europe increases more under risk aversion (by 1.0%) than under risk neutrality (by 0.9%). The intuitions behind these results are the same as mentioned before with the static version.

In sum, under the exogenous policy representation, the market impacts of price instruments are larger than those induced by direct payments. The results obtained from the stochastic models do not deviate much from the static and dynamic results in Table 5.3. This indicates that adding the risk attitude and the stochastic productivity has not brought a significant impact. Although there are differences between the market impacts with or without risk aversion, the differences are quite modest. Our finding is consistent with previous findings that the impacts of considering the economic agents' risk aversion are limited. In this particular case, we conclude that risk aversion does not matter much for the assessment of market impacts of CAP reforms.

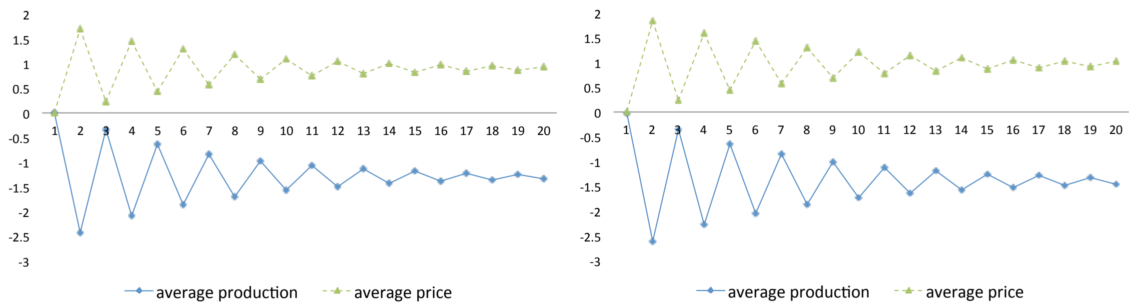


(a) Risk neutral (b) Risk aversion

Figure 5.4: Simulated evolution of the EU wheat production and price following the removal of price instruments, with the stochastic version and the exogenous policy representation (in percent compared to the baseline)

5.3.3.4 Results from the Stochastic Version with Endogenous Representation of the CAP

Although the exogenous policy assumption is widely adopted, agricultural producers in Europe have been protected from price risks, thanks to the policy which



(a) Risk neutral (b) Risk aversion

Figure 5.5: Simulated evolution of the EU wheat production and price following the removal of direct payments, with the stochastic version and the exogenous policy representation (in percent compared to the baseline)

prevents the domestic price from fluctuating severely with the world price. Under this consideration, we now turn to the stochastic version with an endogenous representation of policy.

As usual, we first simulate the new baseline brought by the productivity shocks (Table 5.5). Different from the previous stochastic baseline, the economy converges to the new stochastic steady state much faster (around 6 years) both with and without risk aversion. On the one hand, the price volatility in the EU is much lower, which is at the value of 0.09, compared to a volatility of 0.15 with exogenous policy, and it remains at 0.17 in the RoW for both policy representations. This is much more consistent with historical volatilities on both EU and world market prices (European Commission 2010). On the other hand, the average EU wheat price raises as much as 4.4% under risk neutrality and 4.3% under risk aversion. Accordingly, the EU wheat production raises by 5.0% and by 5.5% respectively. The low price volatility and the high price increase are due to the endogenous policy representation: when the positive productivity shocks induce an expansion of wheat production outside Europe and a decline in wheat world price, the endogenous import tariffs and export subsidies in Europe increase to protect the EU price from dropping below a price floor. It erases the negative fluctuation below the price floor and leads to a price stabilization effect. As a result, the EU wheat price is less volatile and converges faster to a higher steady state price. With regards to the rest of the world, the EU price stabilization policy has limited effect on the world price volatility, since the EU market is not large enough to significantly influence the world price fluctuation (according to the GTAP database). Nevertheless, the

Table 5.5: Simulated impacts of the removal of CAP instruments with the stochastic version and the endogenous policy representation (production and price in percent with respect to the baseline)

	European Union				Rest of the world		
	Production	Price	Volatility(σ)	β	Production	Price	Volatility(σ)
New baseline with productivity shocks							
Risk neutral	5.04	4.40	0.09	-	-0.09	0.78	0.17
Risk aversion	5.47	4.33	0.09	2%	-0.21	0.70	0.17
Impacts of the policy shocks							
Removal of price instruments							
Risk neutral	-5.57	-4.89	0.15	-	2.07	1.17	0.17
Risk aversion	-12.83	-0.59	0.16	7.11%	3.88	2.42	0.18
Removal of direct payments							
Risk neutral	-1.83	0.29	0.09	-	0.52	0.33	0.17
Risk aversion	-2.79	0.45	0.09	2.39%	0.79	0.51	0.17

increase in EU wheat production leads to a decrease in RoW wheat production and a different baseline for the RoW.

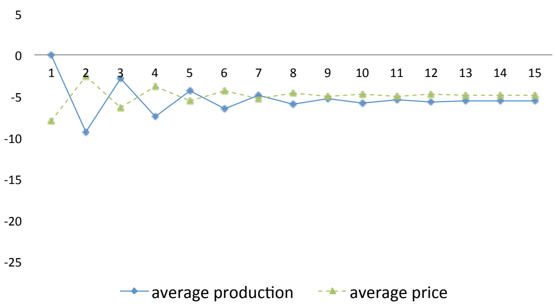
Next, we perform the policy shocks in 2021 (10 years after the initial year). The second part of Table 5.5 presents the converged results, Figure 5.6 and Figure 5.7 show the evolution of production and price in both policy scenarios.

After the removal of price instruments, the economy moves to the stochastic steady state in 20 years in the risk neutrality case and in 15 years in the risk aversion case. The difference between the impacts with and without risk aversion is no longer negligible: the risk-averse wheat producers in Europe reduce their production much more (by 12.8%) than the risk-neutral ones (by 5.6%), and the EU wheat price decreases much less (by 0.6%) in the risk-averse case than that of the risk-neutral case (by 4.9%). To explain this important difference, we know first that the removal of price instruments puts a downward pressure on the EU wheat price. Since the risk-averse EU farmers have higher price elasticities than the risk-neutral ones, they reduce their production more when they expect the wheat price to decrease. We've discussed this mechanism in the exogenous policy part, this effect exists but is not big enough if the farmers' risk premium stays around the baseline of 2%. Then additionally, removing price instruments eliminates the endogenous policy and its price stabilization effects. As a result, the price volatility in Europe rises to a considerable large level (0.16) compared to the baseline (0.09). Under the assumption of $CARA$, the risk premium parameter β depends on the price volatility, and it increases from 2% to 7%. With this great increase in risk premium, the price elasticities of the risk averse producers rise to a much higher level than that at the baseline. With the combined effects of the decrease in expected price and the increase in expected volatility, the risk averse EU farmers reduce their production much more sharply than the risk-neutral farmers.

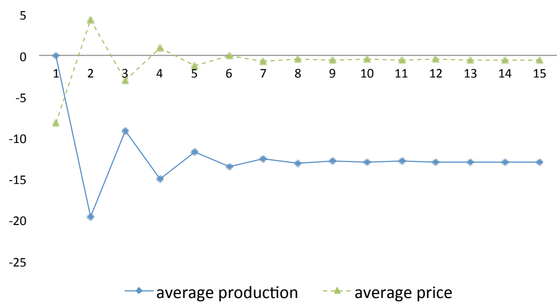
We also find that risk aversion leads to different impacts after the removal of direct payments. Under the endogenous policy, it takes only around 5 years to converge to the steady state for both cases. Figures 5.7a and 5.7b show the evolution paths with and without risk aversion: the discrepancy lies especially between the second year and the third year after the policy shock. In the risk aversion case, the production continues to fall despite the increase in the output price expectations, while in the risk-neutral case, production rebounds a little with the increase in output price expectations. We also find in Table 5.5 that the final converged wheat production in Europe declines more (by 2.8%) in the risk aversion case compared to the risk neutrality case (by 1.8%), and the EU wheat price increases more (by 0.5%) with risk aversion than without risk aversion (by 0.3%). This is because under the endogenous policy representation, removing direct payments leads to an increase in price volatility in Europe from 0.086 to 0.094, so that the risk premium of the risk averse producers rises from 2% to 2.4%. As a result, the risk-averse producer becomes more sensitive to the increase in land price expectations, and they reduce their supply more following the removal of land subsidies.

Moreover, risk aversion has a smoothing effect following the removal of price instruments. The production and price converge to the steady state faster under risk aversion (15 years) than under risk neutrality (20 years). This effect could also be seen in Figures 5.6a and 5.6b, where the dynamics is smoother in the risk-averse case. This is because the removal of endogenous price instruments induces volatility change. While the change in volatility has no effect on the supply in the risk neutrality case, it affects the slope of the supply curve in the risk aversion case and leads to a converging effect. This effect is even more obvious in the coarse grain case.

In sum, under the endogenous representation of the CAP instruments, the results from the stochastic version are no longer similar to the static and dynamic results. This indicates the importance of adding the stochastic dimension in the modeling frameworks. First, including risk aversion leads to much larger market impacts following the removal of CAP instruments: the risk-averse farmers reduce their production much more than the risk-neutral ones. Second, risk aversion brings a converging effect for the dynamics with the removal of price instruments. In this case, risk aversion matters for farmers' decisions and it has a large influence on farm production and market prices.

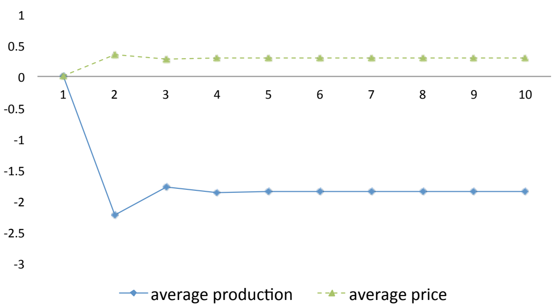


(a) Risk neutral

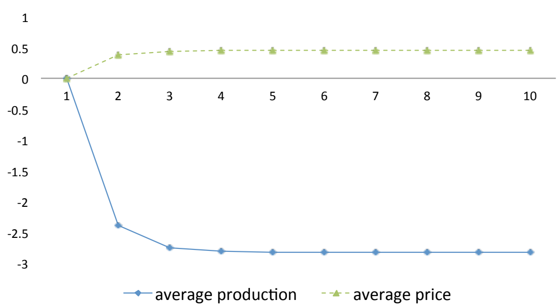


(b) Risk aversion

Figure 5.6: Simulated evolution of the EU wheat production and price following the removal of price instruments, with the stochastic version and the endogenous policy representation (in percent compared to the baseline)



(a) Risk neutral



(b) Risk aversion

Figure 5.7: Simulated evolution of the EU wheat production and price following the removal of direct payments, with the stochastic version and the exogenous policy representation (in percent compared to the baseline)

5.3.4 Sensitivity Analysis

5.3.4.1 Wealth Effect: Sensitivity to the Risk Aversion Parameter

One assumption of our previous simulations is that the producers exhibit constant absolute risk aversion (CARA). A large literature assesses the impact of farm payments on production through the so-called wealth effects. They assume that farmers exhibit decreasing absolute risk aversion (DARA). To approximate this effect in our stochastic version where farmers' wealth has not been explicated, we increase the EU farmers' absolute risk aversion parameter ρ by 50% from the initial estimate, so that the risk premium represents 3% of the receipts. At the same time, we simulate the policy scenarios in the stochastic model. Table 5.6 reports the simulation results at the stochastic steady state for both the exogenous and the endogenous policy representations.

Although risk aversion does not matter under exogenous policy with CARA, including the wealth effect reveals a relatively larger production effect. Wheat production decreases by 3.7% following the removal of price instruments and decreases by 2.9% following the removal of direct payments. The level of production decrease is much higher than that under CARA due to the wealth effect.

As risk aversion already matters under endogenous policy with CARA, it plays an even more important role if the wealth effect is considered. The sensitivity results show that EU farmers reduce their production by 17.7% with the removal of price instruments and by 6.4% with the removal of direct payments. This production cut effect is much more intense than that in the CARA case due to our approximation of the wealth effect.

Table 5.6: Wealth effect: simulated impacts of the removal CAP instruments under decreasing absolute risk aversion (production and price in percent with respect to the baseline)

	European Union				**Rest of the World**		
	Production	Price	Volatility(σ)	β	Production	Price	Volatility(σ)
Stochastic version with exogenous policy							
Removal of price Instruments	-3.69	-0.56	0.16	3.11%	0.94	0.60	0.17
Removal of direct Payments	-2.91	-2.03	0.16	3.12%	0.66	0.45	0.17
Stochastic version with endogenous policy							
Removal of price Instruments	-17.70	2.75	0.17	11.45%	5.11	3.29	0.18
Removal of direct payments	-6.37	1.44	0.10	4.29%	1.81	1.17	0.17

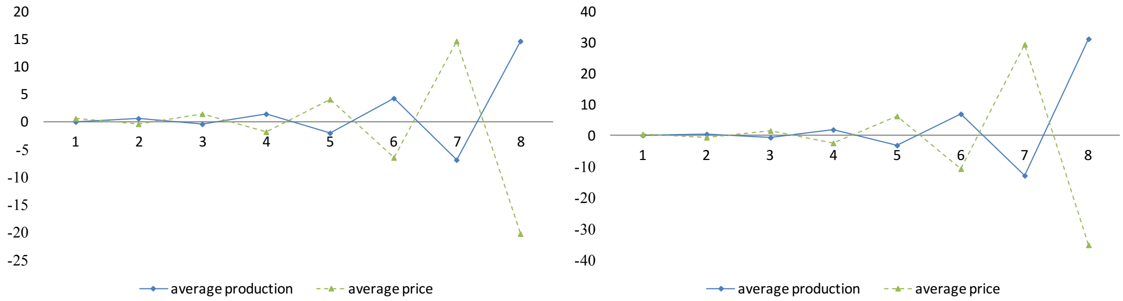
5.3.4.2 The Case of Coarse Grains

In the previous section, we focus our analysis on wheat, now we turn to coarse grains. We repeat all the simulations by replacing the assumptions on wheat to the assumptions on coarse grains, for example, we assume now that the EU coarse grains farmers are risk averse, while other parameters and policy scenarios remain the same.

Figures 5.8 to 5.10 present the simulation results. We start with the exogenous policy representation. Again, we first need to obtain the new stochastic steady state after introducing the productivity shocks. However, Figure 5.8 suggests that the evolution of production and price diverges and there is no stochastic steady state for this dynamics with or without risk aversion. This divergence is not surprising, because, first, without the endogenous policy which stabilizes the price, the shocks cause more severe market fluctuations especially under naïve expectations. More importantly, compared to wheat, the Armington elasticity for coarse grains used in the GTAP database is lower, hence the price elasticity of total demand is lower in absolute terms. Consequently, the dynamic system is more likely to diverge due to a steeper demand curve of coarse grains.

Under the endogenous policy representation, the economy reaches the stochastic steady state with the productivity shocks after 10 years. On the one hand, Figure 5.9 shows that with the removal of price instruments, the dynamics diverges quickly at the 4^{th} year under risk neutrality. As explained above, this divergence is caused by the relatively lower Armington elasticity for coarse grains. However, the system is more and more likely to converge with the increase of risk premium, and it reaches convergence when the initial calibrated risk premium raises to 3%. This confirms the converging effect of risk aversion with the removal of price instruments. The intuition is explained in the wheat case.

On the other hand, with the removal of direct payments and in the case without risk aversion, the EU corn production and price converges to the new stochastic steady state after 15 years. The EU corn production decreases by 1.6% and the EU corn price increases by 0.7%. In the case of risk aversion, the dynamics could not reach the convergence, but loops around a certain production and price level (Figures 5.10b and 5.10c). This is because risk aversion increases the elasticity of supply on coarse grains, while the presence of endogenous price instruments keeps the volatility relatively stable. When the elasticity of supply increases to a similar value as the elasticity of demand, the dynamics could not converge but ends in a loop.



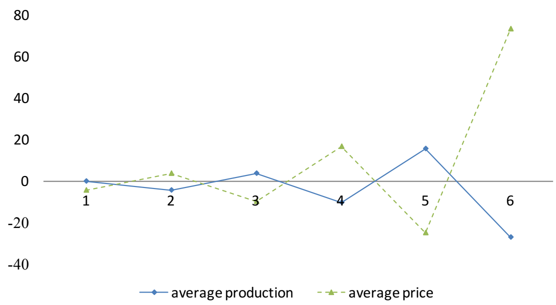
(a) Risk neutral (b) Risk aversion

Figure 5.8: Simulated evolution of the EU coarse grains production and price with productivity shocks, with the stochastic version and the exogenous policy representation (in percent compared to the initial baseline)

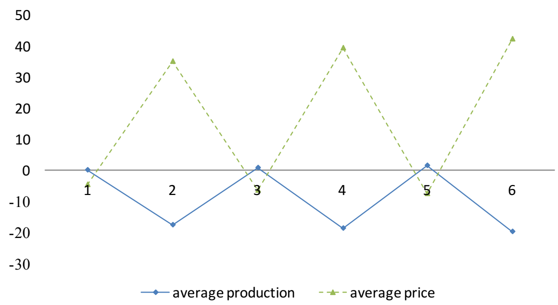
5.3.4.3 Sensitivity to the Historical Weighting Parameter

In our previous simulations, we assumed that the historical weighting parameter α equals 1. It indicates that the agents react immediately to the market price change. It is well known that the expectation schemes have a significant impact on market dynamics. More precisely, the system is more likely to diverge when α gets close to one. This is an important reason why we encountered divergence in the coarse grains case. In the case of wheat, the dynamics converges despite of naïve expectations because the Armington elasticity for wheat is relatively higher, so that the total demand curve is relatively flatter. In order to attain convergence for every situation and to verify the role of different expectation schemes, we decrease α from one (completely naïve) to 0.1 (nearly myopic) on both price and volatility expectations in our stochastic model with risk aversion.

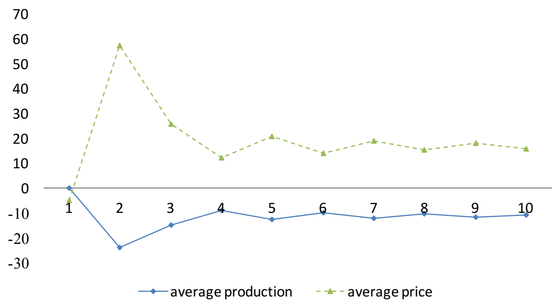
Figures 5.11 and 5.12 show the simulated evolution paths of production and price regarding different α after removing the CAP instruments under endogenous policy in the case of wheat. First, the dynamics is much smoother with the lower α. This is because when the agents react slowly to the price news, the fluctuations in the dynamics become less intense. It solves the divergence problem we encounter in the coarse grains case: if we use a historical weighting parameter of 1/5, we obtain converged corn production and price with productivity shocks and policy shocks. Second, although the smooth levels are different, the converged dynamic systems



(a) Risk neutral

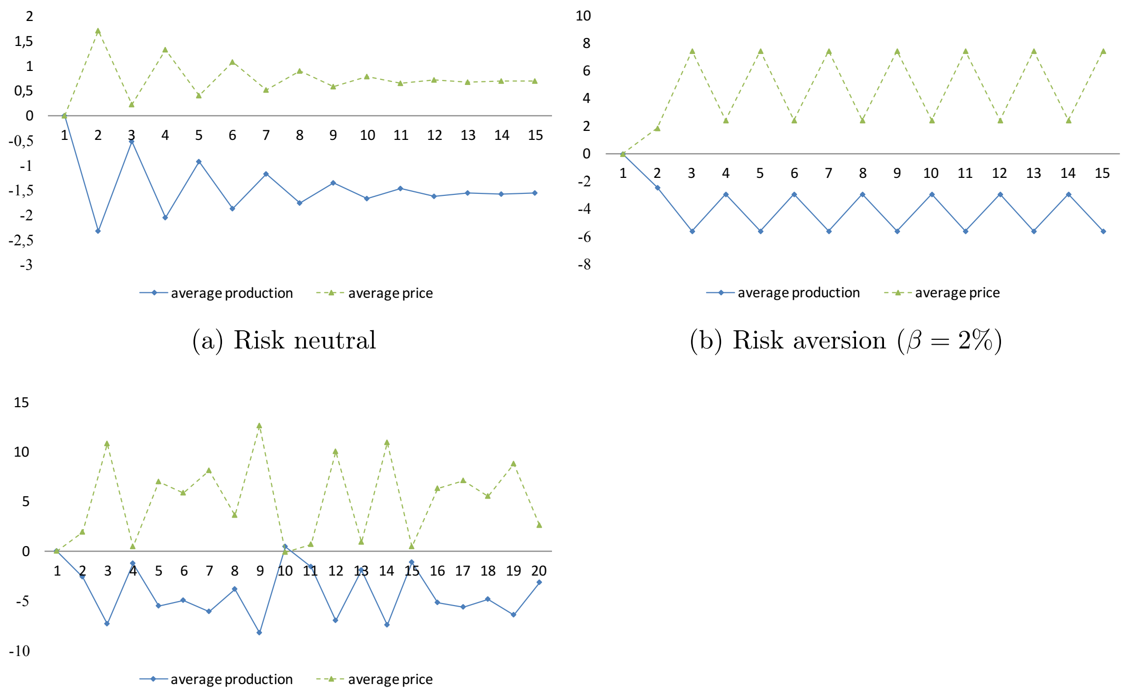


(b) Risk aversion ($\beta = 2\%$)



(c) Risk aversion ($\beta = 3\%$)

Figure 5.9: Simulated evolution of the EU coarse grains production and price following the removal of price instruments, with the stochastic version and the endogenous policy representation (in percent compared to the baseline)

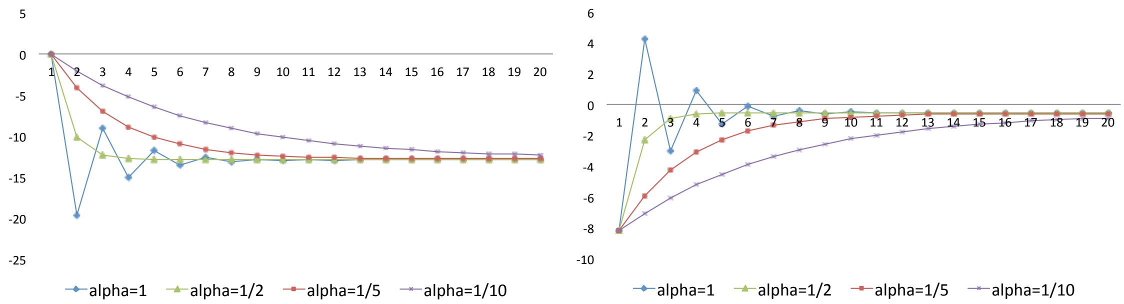


(a) Risk neutral

(b) Risk aversion ($\beta = 2\%$)

(c) Risk aversion ($\beta = 3\%$)

Figure 5.10: Simulated evolution of the EU coarse grains production and price following the removal of direct payments, with the stochastic version and the endogenous policy representation (in percent compared to the baseline)



(a) Production (b) Price

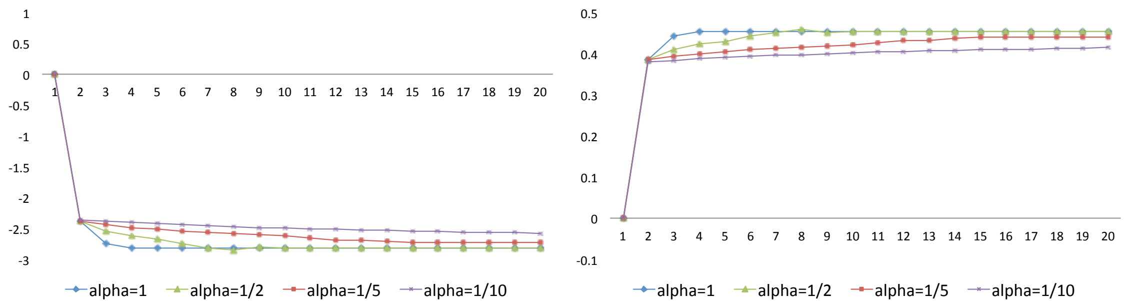
Figure 5.11: Simulated evolution of the EU wheat production and price following the removal of price instruments, with the stochastic version and the endogenous policy representation, sensitivity to the expectation schemes (in percent compared to the baseline)

get to the same stochastic steady state regarding different values of α. Except that the lower the α, the more periods are needed to reach the stochastic steady state. For example, in the stochastic model with risk aversion, endogenous policy and simulating the removal of price instruments, it takes 8 years to reach the steady state when α is 1, 15 years when α is 1/5, and more than 20 years when α is 1/10. This is reasonable because the slower the agents react to market price news, the slower the dynamics reaches the final equilibrium.

This sensitivity analysis implies thus that α influences the smooth level of the dynamics, the length of period needed to reach the stochastic steady state. As long as the system converges, it converges to the same stochastic steady state whatever values of α.

5.4 Conclusion

The Common Agricultural Policy (CAP) has been reformed several times with shifts from initial market price support to decoupled payments. Many models have been developed to assess the market impacts of these reforms, but without explicitly introducing the stochastic dimension. In this paper, based on the standard static GTAP-AGR model and a dynamic version of GTAP-AGR model, we propose a stochastic PE/CGE modeling framework in which we introduce exogenous productivity shocks and farmers' attitude towards risks. We investigate to what extent the farmers' risk attitude matters in assessing the market impacts of CAP



(a) Production (b) Price

Figure 5.12: Simulated evolution of the EU wheat production and price following the removal of direct payments, with the stochastic version and the endogenous policy representation, sensitivity to the expectation schemes (in percent compared to the baseline)

instruments.

We show that risk attitude matters mostly when we allow an endogenous representation of CAP instruments. In particular, risk aversion does alter the farmers' production decisions in the way that risk-averse farmers have higher price elasticities of supply. With the introduction of risk aversion, price volatility becomes important to the producers' decisions through its influence on the risk premium. As the CAP reforms under the endogenous policy increase considerably the market fluctuations, the farmers' risk premium increases with the price volatility and leads to larger market impacts. Moreover, if the farmers exhibit decreasing absolute risk aversion, the additional wealth effects will bring even larger market impacts. With regard to the evolution of dynamics, risk aversion also leads to a converging effect after the removal of the endogenous price instruments. On the other hand, if we adopt the exogenous policy representation, we find that including farmers' risk attitude brings limited difference in assessing market impacts of the CAP instruments. This is because with exogenous policy, the CAP reforms bring limited influences on price volatility, consequently, the risk premium which remains at the initial level is not large enough to make a difference. In sum, our findings imply that risk aversion matters in assessing the CAP instruments particularly when the policy aims at stabilizing prices.

As usual, our modeling framework is subject to some limiting assumptions. For example, we assume that capital is fixed, so that the investment equals the capital depreciation for each period. In fact, risks and risk aversion exist not only in production decisions, but also in inter temporal saving and investment decisions. It is thus worthwhile to extend the recent model to a stochastic model with investment, while risk aversion is implemented in production, investment and saving decisions. More generally, our modeling framework may be fruitfully used to assess different risk management solutions.

5.5 Appendix

An Alternative solution of the supply model with risk premium

The risk-averse farmer's program is,[3]

$$Max\left[p_y y - (p_1x_1 + p_2x_2 + p_3x_3 + p_{nva}q_{nva}) - \frac{1}{2}\rho\sigma_{p_y}^2 y^2\right] \tag{5.32}$$

where y is the farm's output, p_y is the output price, x_1, x_2, x_3 represent the land input, unskilled labor input and skilled labor input, and p_1, p_2, p_3 are their prices, respectively. Note that the capital input is not included in the cost because we consider it fixed. q_{nva} is the quantity of non value added input, more specifically, it is the sum of the intermediate inputs nested by a CES function. p_{nva} is the price of non value added input. $\frac{1}{2}\rho\sigma_{p_y}^2 y^2$ is the Arrow-Pratt approximation of the risk premium, where ρ is the farmer's absolute risk aversion coefficient, σ_{p_y} is the volatility of output price.

The farmer has a production function,

$$y = \alpha_y\left(\delta_y q_{va}^{-\rho_y} + (1-\delta_y)q_{nva}^{-\rho_y}\right)^{-1/\rho_y} \tag{5.33}$$

where q_{va} is the quantity of value added, and it is constituted by Land, unskilled labor, skilled labor and fixed capital (x_4) through a CES function,

$$q_{va} = (\alpha_q(\delta_1 x_1^{-\rho_q} + \delta_2 x_2^{-\rho_q} + \delta_3 x_3^{-\rho_q} + \delta_4 x_4^{-\rho_q}), \quad \delta_1+\delta_2+\delta_3+\delta_4 = 1 \tag{5.34}$$

Combining equations (5.33) and (5.34) together, we have the output in a nested CES form,

$$y = \alpha_y\left(\delta_y(\alpha_q(\delta_1 x_1^{-\rho_q} + \delta_2 x_2^{-\rho_q} + \delta_3 x_3^{-\rho_q} + \delta_4 x_4^{-\rho_q})^{-1/\rho_q})^{-\rho_y} + (1-\delta_y)q_{nva}^{-\rho_y}\right)^{-1/\rho_y} \tag{5.35}$$

This maximization program could be analyzed in two steps, the first step consisting of minimizing the cost given a production quantity, and the second step consisting of maximizing the objective function given the optimal minimum cost.

[3]We use simplified notations here for clarity. Time index t is dropped because the analysis is within one period.

For the first step,

$$Min_{(x.,q_{nva})}(p_1x_1 + p_2x_2 + p_3x_3 + p_{nva}q_{nva})$$

subject to equation (5.35)

This system is very straight-forward to be solved by Lagrange multipliers, and it gives us the optimal q_{nva} and factor inputs under the expression of x_1,

$$x_i^* = x_1 \frac{(\delta_i/p_i)}{(\delta_1/p_1)}^{\frac{1}{1+\rho_q}}, i = 2, 3 \tag{5.36}$$

$$q_{nva}^* = \left(\frac{p_1(1-\delta_y)}{p_{nva}\delta_y} \alpha_q^{\rho_q} \delta_1^{-1} x_1^{1+\rho_q} q_{va}^{\rho_y-\rho_q} \right)^{\frac{1}{\rho_y+1}} \tag{5.37}$$

The second step is to maximize the profit,

$$Max \left[p_y y - (p_1x_1 + p_2x_2 + p_3x_3 + p_{nva}q_{nva}) - \frac{1}{2}\rho\sigma^2 y^2 \right]$$

Taking the first order derivative with respect to y, we have,

$$p_y - \rho\sigma^2 y^* = \left(p_1 + p_2 \frac{\partial x_2}{\partial x_1} + p_3 \frac{\partial x_3}{\partial x_1} + p_{nva} \frac{\partial q_{nva}}{\partial x_1} \right) \frac{\partial x_1}{\partial y} \tag{5.38}$$

The partial derivatives of $x_2, x_3, q_{nva}, q_{va}$ and y with repect to x_1 are:

$$\frac{\partial x_i}{\partial x_1} = \left(\frac{\delta_i/p_i}{\delta_1/p_1} \right)^{\frac{1}{1+\rho_q}}, \quad i = 2, 3$$

$$\frac{\partial q_{nva}}{\partial x_1} = \frac{1}{\rho_y+1} \cdot q_{nva}^{-\rho_y} \cdot \frac{(1-\delta_y)p_1}{\delta_y p_{nva}} \cdot \alpha_q^{\rho_q} \cdot \delta_1^{-1} \cdot \left[q_{va}^{\rho_y-\rho_q}(1+\rho_q)x_1^{\rho_q} + x_1^{1+\rho_q}(\rho_y-\rho_q) q_{va}^{\rho_y-\rho_q-1} \cdot \frac{\partial q_{va}}{\partial x_1} \right]$$

$$\frac{\partial q_{va}}{\partial x_1} = \alpha_q \left(\frac{q_{va}}{\alpha_q} \right)^{1+\rho_q} \cdot \left(\delta_1 + \delta_2 (\frac{\delta_2/p_2}{\delta_1/p_1})^{-\frac{\rho_q}{1+\rho_q}} + \delta_3 (\frac{\delta_3/p_3}{\delta_1/p_1})^{-\frac{\rho_q}{1+\rho_q}} \right) \cdot x_1^{-\rho_q-1}$$

$$\frac{\partial y}{\partial x_1} = \alpha_y \cdot (\frac{y}{\alpha_y})^{1+\rho_y} \cdot \left[\delta_y \cdot q_{va}^{-\rho_y-1} \cdot \frac{\partial q_{va}}{\partial x_1} + (1-\delta_y) \cdot q_{nva}^{-\rho_y-1} \cdot \frac{\partial q_{nva}}{\partial x_1} \right]$$

Equations (5.34), (5.35), (5.36), (5.37) and (5.38) together constitute an equilibrium system from which we could obtain the optimal output, the land input, unskilled labor input, skilled labor input and intermediate inputs, as well as naturally, the quantity of value added and the quantity of non value added.

Chapter 6

General Conclusion

6.1 General Conclusion

While physicists model the natural world based on physical laws, economists model the economic agents' behavior based on economic principles and assumptions. As the interaction of the agents' activities constitutes the market, we expect that the economic model can describe the "economy" to some extent. The economic agents' behaviors, however, are more sophisticated to model compared to the physical elements, and the principles and assumptions based on which the models are built keep on being challenged and improved. After all, there is no perfect model, but we hope some of models are useful for the research questions of interest.

This dissertation is developed in the context that the EU has adopted a succession of policy reforms which remove price supports and introduce direct payments. Accordingly, EU agricultural prices have become much more volatile, in line with the world prices. French farmers face increasing risks from the market fluctuations: how would they modify their decision choices, which may in turn influence productivity, remains in question. In this context, we model the dynamic behaviors of the agricultural producers under risks based on partial equilibrium and general equilibrium frameworks. The research objectives are, first, to estimate the evolution of productivity and the deep parameters in the dynamic farm decision model. Second, we study the quantitative link of price risk, farmers' dynamic decisions under risk, and productivity in this structural estimation framework. Third, we assess the market impact of the policy instruments in a context where prices are risky.

Our first contribution is with regard to the measurement problems in estimating the production function. The accuracy of the input data, especially the problematic measurement of capital, has severe impacts on the TFP estimation in agriculture. We treat the capital data series as a latent state variable and infer it from the observed decision variables. The depreciation rate, instead of being assumed or calibrated, is a structural parameter to be simultaneously estimated with capital. In this way, we have improved the accuracy of the capital data series. Besides, we avoid the standard endogeneity problem in the production function estimation by applying a fully structural estimation approach.

Our second contribution is methodological. We borrow the solution and estimation technique from the DSGE estimation in macroeconomics and explore the nonlinear estimation given that the agricultural producers experience large production and price risks. Except for larger shocks, nonlinear estimation is useful for all economic fields since more economic properties can be captured in the nonlinear terms. The generalized maximum entropy (GME) approach that we proposed is a forgotten but powerful approach. Different from the filtering approach, it integrates the unknown parameters and the states in one entropy objective, and the prior distribution is discrete instead of being continuous. We are not the first to use the GME approach to estimate a state-space model. However, to our knowledge, we are the first to integrate the solution process into the estimation before a state-space representation is available. We show that the GME approach can accurately estimate a growth model with high computational efficiency. This is meaningful not only for the farm decision models, but also for the estimation of DSGE models and more generally the state-space models.

Our third contribution is from the modeling perspective. We integrate the dynamic and risk dimensions for agricultural models. On the one hand, inspired by the DSGE models, we develop a farm decision model in which a representative farmer makes production, consumption, investment and financial borrowing decisions with implicit credit constraints. In this way, output-price fluctuations and productivity are studied in one structural framework. An important feature of the model is the consistency of the model structure and the deep parameters. This feature allows us to study the policy reforms, because the agents' optimal behaviors stay independent from the policy changes. Besides, while the DSGE models are macro models with micro foundations, the farm decision model can be considered to apply at the firm level. We do not give a general equilibrium closure to the farm decision model because the agriculture sector alone is too small to set equilibrium prices. On the other hand, based on the CGE literature, we develop a dynamic stochastic GTAP-AGR CGE model. It is an attempt to introduce risk and risk attitude into a general equilibrium model which is widely used for agriculture policy analysis.

Regarding the research questions posed at the beginning of the dissertation: how does productivity evolve with the new structural changes? What are the dynamic links between productivity, farm decisions, and price risks? The empirical estimation shows that agricultural productivity in the French regions grows steadily before the CAP reform when the prices fluctuate less. The growth pattern has slowed down and becomes much more volatile following the increase in price volatility. Overall, price risk does have an impact on productivity in the way that when farmers are exposed to high risks, they alter their decisions and production incentives, which in turn affect negatively on the realized productivity.

The policy simulation in the dynamic stochastic GTAP-AGR CGE model, in which we assume that the exogenous productivity shocks influence the endogenous EU prices, shows that accounting for risk and risk attitude is important in assessing the CAP instruments. In addition to the price expectations, price volatility expectations are also a factor affecting risk-averse farmers' decisions, and in the end affect the market outcome.

Sustaining and stimulating the EU agricultural productivity growth is a key objective of the CAP agenda 2014-2020. Previous literature (Alston 2018) shows that agricultural R&D generates a high economic return and contributes to TFP growth from the aspect of technology change. Consequently, the fact that productivity is endogenous to R&D is valued by the policymakers, and the amount of R&D budget has increased largely in the 2003 CAP reform. However, the CAP reforms since 2003 have led to much higher market risk for French agriculture. Different risk management tools, public and private, are also constructed in the new CAP, but the baseline is that these instruments manage risks but do not interfere market prices (except market safety net for excessive price risks). We argue that the current CAP policy assessment tools have not caught up with the increasing market fluctuations. First, risk and risk attitudes are still largely missing in the available policy assessment tools. As is shown in this dissertation, risk and preference are important factors for farm decisions in both dynamic stochastic decision models and the dynamic CGE model. As a result, we emphasize here the importance of accounting dynamic and risk dimensions for policy analysis in the new market condition with increasing risks. Second, the aspect that productivity is endogenous to price and price risk is mostly ignored in the policy-making process. It should be recognized by the policymakers that the farmers' decisions in response to the increasing risks negatively impact productivity. Above all, market conditions need to be considered for policy goals with regard to productivity enhancement.

6.2 Perspectives

We conclude with some perspectives for future research based on our current work:

Estimation without consumption This proposition is to simplify the research question. We focus on estimating capital and the production techniques (elasticities), and leave out the preference parameter. Indeed, the agent's optimized behavior is based on the consumption-based utility function. In order to recover preferences, we need to have accurate consumption data. However, consumption data are difficult to collect. First, if the consumption data are the true consumption, while insurance is not included in the model, the true consumption by the farmers tends to be smoother than that given by the model. For example, in years with negative productivity shocks, the representative farmer receives a lower farm income, but he or she may maintain the consumption level with insurance or other external help. Second, if the consumption used for estimation purpose is not the true consumption, then the estimated revealed preference is not the true preference. On the contrary, if we assume linear utility function, which indicates risk neutrality, consumption will be canceled out in the Euler equation. Consequently, we no longer need the consumption observations to estimate the structural parameters (except for preferences). The preferences captured in the data enter into the Euler errors, which will greatly simplify the estimation. We will perform sampling experiments to see if we can obtain accurate estimation on capital and elasticities without using the consumption data. In other words, the research question is: does the accuracy of the preference parameter matter for the recovery of other structural parameters?

A growing economy Our estimation in Chapter 4 is performed keeping the state variables within the bounds, such that to deal with the TFP trend. How to develop a robust GME approach to estimate the nonstationary model, which describes a growing economy, remains under investigation. At the current stage of our investigation, first, we reformulate the GME model so that the function approximations are based on stationary variables. Second, we simulate data from a nonstationary model, and perform Monte-Carlo experiments to test the estimation results.

Structural change in capital evolution? One important feature for the structural models is that the deep parameters in the model stay unchanged with the policy changes. However, for example, the behavioral economics literature studies a different assumption that the preference parameter can change over time. We propose a further study by assuming that the capital evolution pattern, for example, the depreciation rate, may change with structural changes in market conditions. The intuition is that the farmers are more reluctant to invest in capital with higher market risks. Instead, they use more intensively the available capital, which may lead to a higher capital depreciation rate. This proposition, still, will contribute to the debate over the accurate measurement of the capital formation process.

Integrating risk-management tools In the current modeling, the representative farmer only coordinates the intertemporal decisions to manage the risks. The French farmers are increasingly adopting risk-management tools. Public and private instruments, like insurance, futures, options, or product diversifications, are more and more used. While both production risk and price risk are included in the dynamic stochastic decision model, a natural extension is to include some risk management tools into the model. This extension can be used to evaluate the effectiveness of the risk-management tools, the optimized implementation of the tools (futures or options), and farmers' intertemporal decisions with insurance.

Assessing other TFP drivers By enriching the farm decision model, we can assess the effect of other TFP drivers on TFP in one structural estimation framework. These drivers can include R&D investments, climate change, environmental constraints, and farm structural factors. This can be accomplished by adding the factor explicitly into the TFP evolution function, while in our current modeling framework, these factors are captured in the exogenous productivity shocks.

Expectation Maximization In addition to the ML approach proposed by Fernández-Villaverde and Rubio-Ramírez (2005) and implemented in Dynare, Expectation-Maximization (EM) also provides a viable approach to estimate the model parameters. A notable difference of EM compared to the ML approach is that in EM we consider the hidden state from the very beginning of the formulation by considering the likelihood function as the marginal full joint distribution over the hidden state. EM consists of two dependent coordinate ascent procedures. In the expectation step (E-step), we evaluate the posterior conditional distribution $p(\mathbf{s}_{0:T}|\mathbf{z}_{1:T}, \boldsymbol{\theta}_l)$, where l denotes the EM iteration. Here we need the smoothed state conditioned on the whole data span and the prior parameter $\boldsymbol{\theta}_l$, whereas in the ML approach, we only need to compute the filtered state. In the maximization step (M-step), we search for $\boldsymbol{\theta}_{l+1}$ maximizing the function $\mathcal{Q}$ that is related to the lower bound of the likelihood function, $\boldsymbol{\theta}_{l+1} = \arg\max_{\boldsymbol{\theta}_{l+1}} \mathcal{Q}(\boldsymbol{\theta}_{l+1}, \boldsymbol{\theta}_l)$.

A great advantage of EM is that in the M-step, only the full joint distribution is a function of $\boldsymbol{\theta}_{l+1}$. This has profound implications. Indeed, in most cases, the gradient of the full joint distribution with regard to the parameters is much easier to manipulate than the likelihood function in the ML approach. Even for complex models where the closed-forms for the parameters do not exist, we can still find the parameters through sampling-based iterative searching strategy as shown by Yang and Mémin (2018).

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Résumé Substantiel en Français

Motivation

L'agriculture française fait face à plusieurs défis économiques, environnementaux et sociaux, Les défis d'ordre économique sont liés à une concurrence accrue des productions agricoles des pays tiers, en partie suite aux réformes de la Politique Agricole Commune (PAC) et aux accords bilatéraux. La concurrence vient aussi des autres pays européens, tout particulièrement des pays du Nord de l'Europe. Les agriculteurs français font également face à une volatilité accrue des prix des produits et intrants agricoles. Ceci est en partie dû aux réformes de la PAC qui réduisent les soutiens de prix et introduisent des paiements directs qui imposent moins d'interventions de marché. D'un point de vue environnemental, l'agriculture française fait face à des ressources naturelles plus limitées, ainsi qu'à des contraintes réglementaires, visant à ce qu'elle génère de moindres impacts négatifs sur les ressources naturelles tout en augmentant ses externalités positives.

Comme tous les autres secteurs productifs, la capacité de l'agriculture française à relever ses différents défis va en partie dépendre de sa capacité à améliorer sa productivité traditionnellement définie comme le rapport entre les productions et les utilisations d'intrants. En effet, l'augmentation de la productivité est le principal moteur de la croissance, et constitue un facteur important pour la compétitivité de l'économie (Ball et al. 2015, Andersen et al. 2018). Une croissance continue de la productivité a été observée dans toutes les industries, dont l'agriculture, grâce aux innovations majeures dans les technologies de l'information et l'automatisation. Toutefois, selon l'indice de la Productivité Totale des Facteurs (PTF) calculée par European Commission (2016), conformément aux États membres de l'UE-15, la croissance de la productivité de l'agriculture française s'est ralentie au cours des dernières décennies.

La productivité et sa dynamique ne sont pas seulement les reflets de la croissance technologique, mais aussi les choix en matière d'adoption de technologies, d'allocation de ressources, d'incitations, et d'ajustements structurels. Du point de vue des décideurs, ces choix, ainsi que les innovations, sont liés aux politiques qui influent sur les conditions du marché et aux investissements dans la recherche et l'éducation. Comme la productivité n'est pas directement observable, une tâche des économistes est de comprendre la productivité, d'identifier les sources de sa croissance et de la mesurer sans biais.

Cette thèse vise, d'une part, à mesurer l'évolution récente de la productivité de l'agriculture française dans un modèle dynamique structurel, en considérant les années récentes marquées par une volatilité plus importante des prix des produits et intrants agricoles. Cela devrait nous permettre de mieux identifier le rôle respectif des facteurs exogènes comme le climat, endogènes comme les facteurs économiques, et règlementaires comme les mesures politiques. Deuxièmement, nous étudions le lien dynamique entre la volatilité des prix, les décisions des agriculteurs et la productivité dans le cadre d'estimation structurelle. Ces deux objectifs sont atteints en développant des modèles dynamiques structurels dans lesquels les incitations économiques et les prix ont explicitement un rôle potentiel sur les décisions des agents économiques, tout en prenant en compte les modifications structurelles de la volatilité des prix. Nous estimons la productivité et les paramètres comportementaux dans le modèle dynamique structurel. Les méthodes d'estimation sont bien développées pour estimer les modèles espaces-états et les modèles d'équilibre général stochastique dynamique (DSGE). L'estimation contribue aux problèmes de mesure liés au capital non observé et au problème d'endogénéité lié à l'estimation d'une fonction de production.

Le troisième objectif consiste à évaluer les effets sur le marché des instruments de politique dans le contexte de prix instables. Ceci est fait grâce au développement d'une version dynamique stochastique d'un modèle d'équilibre général calculable (EGC). Les preuves économétriques de l'effet des risques de prix sur la production agricole, et en particulier sur la productivité, constituent la base empirique de l'analyse des politiques.

Dans ce qui suit, nous motivons les objectifs de recherche.

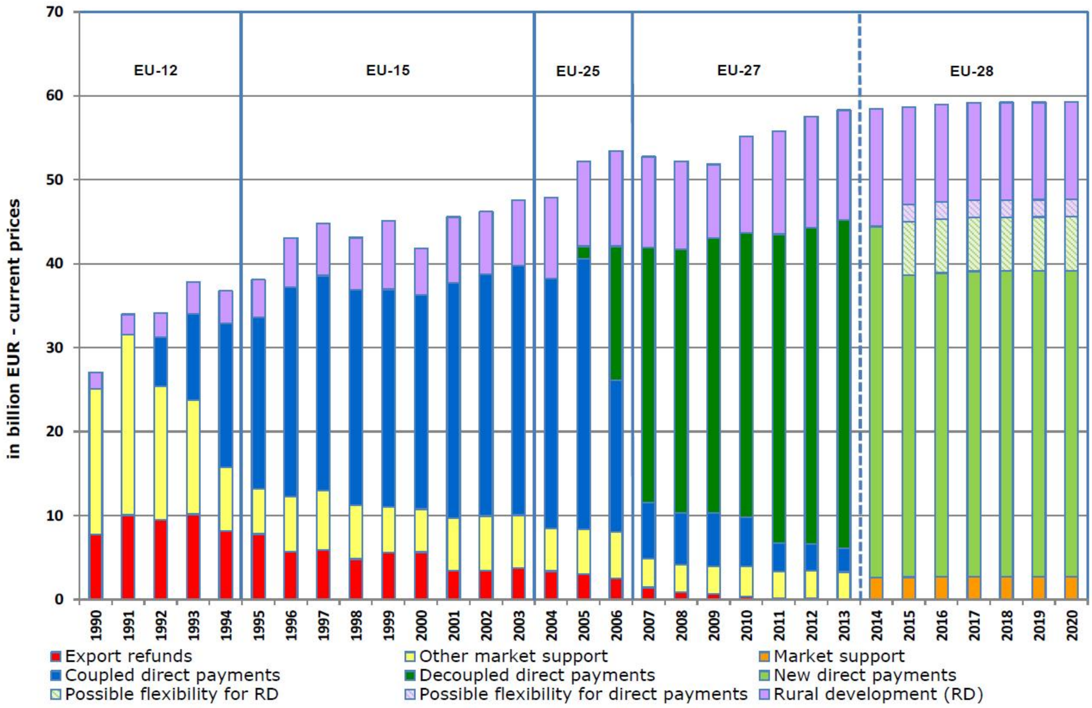
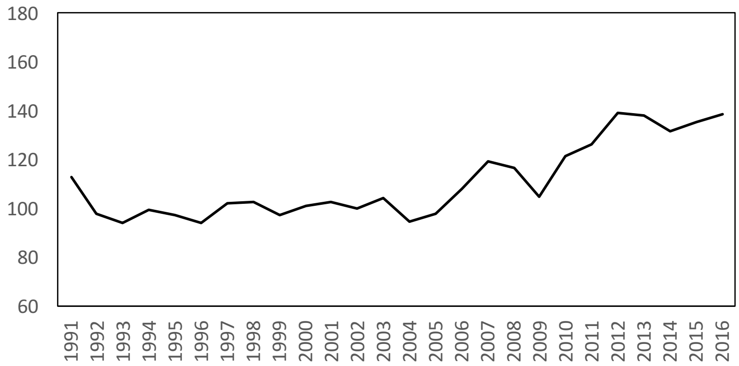


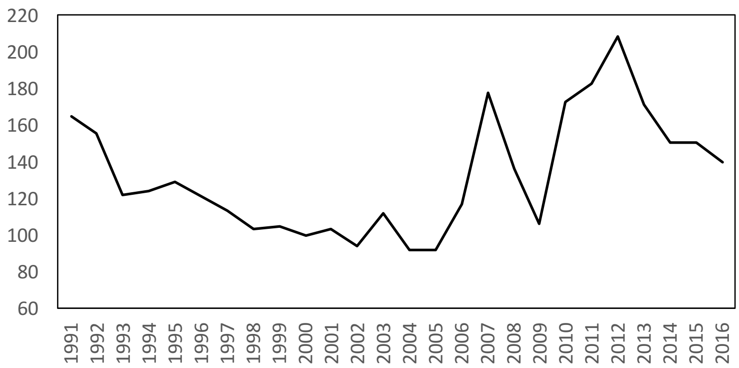
Figure 6.1: Les dépenses de la PAC par année civile (en prix courants) (Source: European Commission 2013)

Réformes Politiques et Nouveau Contexte de Volatilité des Prix

Afin de garantir un revenu stable aux agriculteurs, une offre stable d'aliments abordables pour les consommateurs et de renforcer la compétitivité de l'agriculture de l'UE, de nombreux réformes de la PAC ont eu lieu au cours des dernières décennies. La figure 6.1 montre l'évolution des dépenses de la PAC depuis 1990. Globalement les soutiens publics européens par des prix nominaux constants ont diminué au profit de soutiens directs aux revenus agricoles de plus en plus conditionnés par des critères environnementaux, et plus récemment par quelques mesures de gestion des risques et des crises. La réforme majeure de 2003 a découplé les subventions de la production, et les paiements directs sont principalement liés à l'utilisation des terres. La nouvelle PAC 2014-2020 met davantage l'accent sur les questions d'environnement et de risque et est mieux ciblée en limitant l'aide aux agriculteurs actifs dans la production. Les subventions foncières passent progressivement à de nouveaux paiements directs destinés aux exploitations en activité, encourageant les jeunes agriculteurs et les petites exploitations, et assortie de conditions croissantes pour des critères environnementaux et des mesures de gestion des risques.



(a) Indices des prix à la production français: agriculture (Source: FAOSTAT)



(b) Indices des prix à la production français: céréales (Source: FAOSTAT)

Figure 6.2: Indices de prix annuels des producteurs (Source: FAOSTAT)

De plus, une part croissante du budget est consacrée au développement rural et à la Recherche/Développement (R & D), dans le but de favoriser le transfert de connaissances et les innovations technologiques afin d'améliorer la productivité.

Au niveau national, une volonté politique de plus en plus affirmée vise le changement de pratiques agricoles avec une réduction de certaines externalités négatives, comme par exemple, une réduction des usages de produits phytosanitaires et d'antibiotiques.

La succession des réformes de la PAC, en particulier la réforme majeure de 2003, a entraîné une exposition plus grande des agricultures européennes, et donc française, à la volatilité potentielle des prix agricoles mondiaux. Le niveau et la volatilité des prix mondiaux ont sensiblement augmenté après 2000. Les prix agricoles en France ont longtemps été stables et la tendance à la baisse des produits céréaliers a commencé à augmenter et à fluctuer beaucoup plus après 2003 (la Figure

6.2).

Ce nouveau contexte économique et règlementaire dans lequel opère l'agriculture française n'a pas été pleinement intégré dans les précédentes analyses sur l'évolution de sa productivité. Or certains travaux (Pietola and Myers 2000, Odening et al. 2013) ont pu déjà mesurer, dans d'autres contextes, qu'une plus grande volatilité des prix avait un impact négatif sur les investissements et/ou les productivités. Effectivement, les mesures de productivité ont assez fortement changé ces dernières années à la suite des réformes successives de la PAC et des différentes réformes des politiques nationales touchant l'agriculture.

Ce nouveau contexte de marché conduit aux deux premières questions de la thèse de recherche: quelle est la trajectoire d'évolution de la productivité avec les changements structurels du marché? Comment la volatilité croissante des prix et les nouveaux risques liés aux prix ont-ils un impact sur les décisions agricoles et la productivité? Les deux questions correspondent aux deux premiers objectifs de la recherche. Pour y répondre, nous devons développer des mesures de productivité non biaisées permettant de prendre en compte les réformes politiques et les risques de variation des prix. De plus, nous devons développer un modèle structurel nous permettant d'étudier le lien entre les risques de prix, les décisions des agriculteurs et la productivité.

Mesurer la Productivité

Les différences de résultats susmentionnés sur la productivité de l'agriculture française peuvent en partie s'expliquer par les données et les méthodes utilisées. En fait, différentes méthodes ont été développées depuis de nombreuses années pour mesurer la productivité relative d'une firme/secteur/région et/ou de son évolution dans le temps. Comme l'explique Van Biesebroeck (2007), ces différentes méthodes ont été élaborées à cause de deux difficultés principales rencontrées dans toutes les applications. D'une part, les fonctions de production des firmes, et donc les arbitrages opérés par les producteurs, ne sont pas directement observables à partir de données traditionnellement disponibles. D'autre part, les productions, marchandes et encore plus non marchandes, et les intrants sont mesurés avec erreur. C'est tout spécialement le cas pour les facteurs quasi-fixes qui comprennent le travail familial et le capital en agriculture. Andersen et al. (2011) soulignent dans le cas de l'agriculture américaine les difficultés à mesurer les flux de services des différents capitaux et les rentabilités associées qui sont nécessaires dans toutes les méthodes de mesure de la productivité. Pour contourner ces deux difficultés, l'idéal qui est constamment suggéré dans la littérature économique consiste à obtenir de meilleures données. De nouvelles approches ont également été proposées pour de meilleures estimations de la productivité (De Loecker et al. 2016, Plastina and Lence 2018).

Nous proposons une nouvelle approche pour mesurer la productivité agricole, dans laquelle la productivité est modélisée et estimée conjointement avec les paramètres comportementaux. Cette approche repose sur les méthodes d'estimation basées sur le principe d'entropie maximale et au filtre à particules. Les méthodes de filtres sont bien développées pour estimer les modèles DSGE dans la littérature macroéconomique moderne. Les deux méthodes sont appliquées pour récupérer les états cachés dans l'estimation du modèle espaces-états. Dans notre cas, la productivité et le capital sont les états cachés. Ces techniques d'estimation nous permettent de mesurer la productivité et ses déterminants dans des cadres stochastiques et dynamiques, et donc prendre en compte la volatilité des prix et les instruments de gestion des risques, tout en reconnaissant que nous n'avons pas de mesure exacte de ces facteurs quasi fixes.

Évaluation de la Politique

Notre troisième objectif est d'évaluer l'impact des instruments de politique sur les marchés dans un contexte de volatilité des prix. Dans les modèles économiques récents d'analyse de la politique agricole, comme les modèles d'équilibre général calculable (EGC), les comportements statiques des agents sont modélisés à l'aide de cadres de maximisation des bénéfices et de minimisation des coûts. Néanmoins, les dimensions de dynamique et de risque sont largement ignorées. Malgré la puissance des modèles EGC à grande échelle pour la modélisation complète de l'ensemble du marché, il est impossible d'analyser les réponses dynamiques des agriculteurs à l'environnement de plus en plus risqué dans de tels modèles statiques. Alternativement, basés sur les principes microéconomiques, les modèles DSGE sont largement utilisés pour comprendre la croissance économique et les cycles. Cela ouvre des possibilités d'intégration de dimensions dynamiques et de risque pour les modèles agricoles. En effet, dans cette thèse, la productivité et son lien avec la volatilité des prix sont modélisés et estimés sur la base du concept de modélisation DSGE, tandis que l'évaluation des politiques est effectuée dans le cadre EGC.

Approche

Nous développons des modèles structurels dynamiques pour atteindre les objectifs de recherche. En effet, la productivité et l'évolution des prix sont des processus dynamiques et les événements à risque se situent dans le futur. Comparés aux modèles sous forme réduite, les modèles structurels sont développés sur la base des principes comportementaux des agents. Ils nous permettent d'intégrer les décisions des agents, la volatilité des prix et la productivité dans un seul et même cadre, et sont mieux adaptés pour évaluer les réformes politiques.

Modélisation Dynamique

Deux types de modèles dynamiques sont construits dans la thèse. Premièrement, un modèle de décision agricole similaire à un modèle DSGE, dans lequel un agriculteur tourné vers l'avenir prend des décisions en matière de production, de consommation, d'investissement en capital et d'emprunt financier, afin de maximiser l'utilité actualisée de la consommation. Ce modèle fait partie de la famille des modèles de programmation dynamique. Comparé aux modèles DSGE, ce modèle est axé sur les producteurs, de sorte que les prix sont exogènes. En outre, c'est à un niveau moins agrégé. Deuxièmement, nous développons un modèle EGC dynamique récursif avec une succession d'équilibres à court terme. Ce modèle étend les modèles EGC récents en intégrant les dimensions de risque et dynamique.

La dynamique du modèle passe par le canal de l'accumulation de capital et des évolutions prix et productivité. En agriculture, les sources de risque incluent le prix et la productivité dans les périodes futures. Ils ont une incidence sur les décisions d'investissement actuelles dans la façon dont l'agent fait des prévisions sur les rendements futurs. En outre, une des particularités de l'agriculture est que les risques jouent également un rôle dans une période donnée, entre la saison de croissance et la saison de récolte. Ce risque est modélisé dans le modèle EGC dynamique récursif.

Changement Structurel Par-dessus tout, les modèles structurels dynamiques décrivent le comportement des agents à travers des principes économiques. Bien que les interactions des agents constituent le marché, nous nous attendons à ce que les modèles structurels décrivent dans une certaine mesure les résultats du marché. Un trait important des modèles structurels est la cohérence mathématique de la structure du modèle et des paramètres « profonds » ou « fondamentaux ». Les changements de politique affectent les conditions du marché, mais les comportements optimaux des agents restent indépendants des changements de politique. Ainsi, les modèles structurels sont robustes à la critique de Lucas (Lucas 1976) et peuvent être utiles pour l'analyse des politiques. Pour cette raison, le modèle de décision agricole est éligible pour analyser le nouveau contexte de marché avec les réformes de la PAC. Les changements structurels sont imposés dans les paramètres décrivant l'évolution des prix et de la productivité, mais pas les paramètres profonds qui déterminent les règles de décision des agents.

Estimation Structurelle

Étant donné que le modèle structurel décrit le marché, l'objectif de l'estimation économétrique est de trouver l'ensemble des paramètres optimaux avec les résultats du modèle correspondant et qui peuvent le mieux expliquer les données historiques. L'estimation permet de décrire les techniques de production, les préférences des agriculteurs, ainsi que l'accumulation de capital latent et le processus d'évolution de la productivité. L'estimation de ces modèles est techniquement difficile, car un processus de résolution numérique est nécessaire pour obtenir un modèle d'espace d'état explicite. Les paramètres structurels et les états latents du modèle espaces-états doivent donc être estimés à l'aide des données observées.

Les techniques bayésiennes sont appliquées à l'estimation à la fois des paramètres et de l'état caché. En ce qui concerne les paramètres, nous possédons des informations préalables sur les paramètres profonds car ils ont une signification économique correspondante. Les paramètres postérieurs sont estimés en fonction des a-priori et des informations. La recherche de l'état optimal correspond à la recherche de la probabilité conditionnée postérieure de la variable d'état cachée à l'heure actuelle, compte tenu de toutes les données observées dans le passé. Ces deux étapes peuvent être effectuées simultanément ou séquentiellement.

Apprentissage Statistique D'un point de vue méthodologique, la stratégie d'estimation abordée dans cette thèse appartient à un sujet plus vaste, à savoir l'apprentissage statistique. En clair, il s'agit d'ajuster un modèle paramètré aux données.

L'apprentissage statistique a été popularisé par la communauté de l'apprentissage automatique au cours des dernières années en raison de la renaissance du réseau de neurones profonds (LeCun et al. 1998, Krizhevsky et al. 2012). L'apprentissage profond a réalisé des performances incomparables dans des tâches telles que la classification, et la reconnaissance faciale/vocale. Bien que cela puisse semble prometteur, l'utilité des techniques de l'apprentissage profond à résoudre les problèmes économiques reste une question ouverte. Le succès de l'apprentissage profond est largement associé à la procédure d'apprentissage des fonctions des descriptions liées à la profondeur du réseau, dans laquelle les fonctions des descriptions sont automatiquement extraites des données. C'est la raison pourquoi l'apprentissage profond fonctionne bien sur des riches ensembles de données tels que l'image ou le son. La procédure d'extraction de caractéristiques correspond à notre procédure de modélisation économique. A priori, il est difficile de savoir comment les fonctions des descriptions peut concurrencer notre modèle économique sophistiqué, étant donné que les données économiques sont clairsemées en général et que les comportements humains sont plus difficiles à apprendre, comparés aux caractéristiques physiques.

Plan de la thèse

Cette thèse se divise en quatre chapitres.

Chapitre 2 Productivité et Volatilité des Prix: une Revue de Littérature Ce chapitre examine la littérature sur la productivité et les risques de prix. La productivité totale des facteurs (PTF) est généralement considérée comme un processus exogène et concerne uniquement les innovations. Dans cette revue, nous soutenons que, en tant que résidu de la fonction de production, la productivité saisit non seulement le changement technologique, mais également d'autres facteurs non mesurés tels que le taux d'adoption de la technologie, l'efficacité, les efforts de main-d'œuvre et les autres spécifications manquantes dans les données. En conséquence, les prix et les risques de prix influent sur la productivité par le biais des canaux de décisions d'investissement à long terme liées à la R & D et de décisions liées à l'efficacité. Associé à cela, la reprise de la dynamique de la productivité dépend fortement de la précision des données et de la méthode d'estimation. En conséquence, nous passons en revue les problèmes de mesure des entrées et des sorties et comparons les avantages et les inconvénients de différentes méthodes d'estimation. Nous soulignons en particulier les problèmes de mesure liés aux séries de données sur le capital non observées et le problème de simultanéité issu de l'estimation primale. La méthode d'estimation que nous proposons traitera ces deux problèmes.

Chapitre 3 Estimation des Modèles de Décision Dynamiques Stochastiques non linéaires: une Approche d'Entropie Maximale Généralisée Ce chapitre étudie les méthodes d'optimisation numérique permettant de résoudre et d'estimer des modèles de décision stochastiques dynamiques. Le modèle de base de cette thèse est un modèle de décision de ferme de type DSGE, dans lequel la productivité et le capital sont des variables latentes, et où un processus de résolution est nécessaire pour obtenir le modèle espaces- états. En plus de la méthode basée sur la vraisemblance avec les filtres, nous proposons une approche de maximum d'entropie généralisée (MEG) pour estimer le modèle. À notre connaissance, cette méthode n'a pas encore été utilisée pour estimer ces modèles. Sur la base d'expériences de Monte-Carlo avec des données simulées, nous effectuons des estimations avec le filtre à particules et avec la méthode MEG. Nous montrons que l'approche MEG fournit une estimation précise des paramètres structurels inconnus et des chocs structurels. En particulier, le paramètre de préférence qui rend compte de la préférence de risque et de la préférence inter temporelle est également estimé avec une précision relative. Comparée aux méthodes de filtrage les plus largement utilisées, l'approche MEG fournit un niveau de précision similaire mais offre une efficacité de calcul beaucoup plus élevée pour les modèles non linéaires. De plus, l'approche proposée montre des propriétés favorables pour les données de petite taille.

Les motivations d'étudier des méthodes différentes sont plusieurs. En effet, Dynare (Adjemian et al. 2011) constitue un excellent outil de solution et d'estimation de DSGE. Alors pourquoi perdre du temps à la recherche de nouveaux méthodes et à développer de nouveaux algorithmes? Notre première motivation provient du fait que les séries de données agricoles sont volatiles, que les risque de prix est un terme de second ordre et que on s'intéresse aux propension au risque d'ordre élevé. Pour ces raisons, la solution et l'estimation linéaire ne sont plus suffisantes. Pour une estimation de second ordre, le filtre particulaire est déjà implémenté dans Dynare, mais ses performances (basées sur l'échantillonnage) ne sont pas aussi stables que le filtre de Kalman (analytique) et prennent beaucoup de temps de calcul. La méthode de MEG a été utilisée pour estimer les modèles espaces-états, elle est simple à implémenter dans GAMS, elle n'exige aucune linéarité, et elle est efficace en ce qui concerne le temps de calcul. Cependant, à notre connaissance, l'approche MEG n'a pas été utilisée pour estimer les modèles de DSGE. En conséquence, dans ce chapitre, on effectue des expériences pour découvrir la validité de cette nouvelle méthode. La seconde motivation concerne la solution de DSGE. Les méthodes de perturbation ne sont pas précises avec l'existence de chocs importants (Aruoba et al. 2006) et ne sont précises qu'autour de l'état stationnaire. On préfère utiliser des méthodes de projection à résoudre le modèle. En effet, les fonctions de politique obtenues à partir de méthodes de projection sont plus couramment utilisées pour l'analyse des politiques agricoles. Cependant, la projection en tant que solution n'est pas implémentée dans Dynare. On suppose que c'est parce que cela n'est pas nécessaire pour un problème d'estimation linéaire et que la tâche de calcul est trop lourde pour une estimation de second ordre. En conséquence, on mit en oeuvre l'approche de MEG avec la méthode de projection de Chebyshev dans ce chapitre. La troisième motivation est plus générale. Les méthodes de solution, l'estimation bayésienne avec les filtres et la méthode de MEG sont des méthodes d'apprentissage statistique en cours de développement. L'étude de ces méthodes contribue à l'économie de calcul numérique.

Chapitre 4 : Productivité de l'Agriculture française et Volatilité des Prix : une Estimation Dynamique Stochastique Structurelle Ce chapitre estime le lien entre la fluctuation des prix des produits et la productivité dans un modèle de décision agricole stochastique dynamique à deux périodes fondé sur des données françaises. Pour tenir compte de la variation de la volatilité des prix, nous intégrons les modifications structurelles du terme de dérive et d'écart type des chocs dans les processus d'évolution du prix à la production et de la productivité avant et après 2003. Nous estimons le modèle sur la base des données d'enquêtes annuelles des producteurs de cultures de la région Centre issues du réseau d'information comptable agricole (FADN) couvrant la période 1988-2015. Pour adapter l'estimation aux séries de données agricoles moins globales et très volatiles, nous approximons d'abord la fonction de politique en utilisant une méthode polynomiale de Chebyshev du troisième ordre. Deuxièmement, nous estimons les paramètres structurels en utilisant une approche de maximum d'entropie généralisée. Notre estimation montre que la PTF augmente régulièrement avant 2003, que le taux de croissance a ralenti et que la structure de la croissance devient beaucoup plus volatile à la suite de la hausse de la volatilité des prix après 2003. Selon le modèle à deux périodes, les chocs de productivité purs sont stables avant et après 2003. Les fluctuations croissantes de la PTF sont principalement dues à la hausse des chocs en terme de prix.

Chapitre 5 : Évaluation de la Réforme de la Politique Agricole Commune (PAC): l'Attitude des Agriculteurs en Matière de Risque est-elle Importante? Ce chapitre simule les impacts des instruments de politique publique. Nous intégrons la dimension risque et dynamique dans un modèle EGC statique, plus précisément le modèle GTAP-AGR, dans lequel les risques de productivité et de prix sont liés. Ceci est réalisé en modifiant le côté « offre » du modèle GTAP-AGR en ajoutant des attitudes de risque des agriculteurs. Pendant la saison de croissance, les agriculteurs prennent les décisions optimales dans ce modèle d'approvisionnement modifié en fonction des attentes en matière de prix et de volatilité des prix. Pendant la saison des récoltes, nous introduisons des chocs de productivité stochastiques dans le modèle EGC. De plus, le prix d'équilibre final, déterminé conjointement par l'offre et la demande dans le modèle EGC, n'est pas nécessairement conforme aux attentes de prix. L'agriculteur reçoit un rendement du capital basé sur le prix réel du marché. La dynamique du modèle transmet les attentes que les agriculteurs ont récemment formées de la succession des équilibres de marché à court terme. Nous montrons qu'outre les anticipations de prix, les anticipations de volatilité des prix deviennent l'un des facteurs clés de la décision des agriculteurs par le biais de leur influence sur la prime de risque. Nous montrons que, dans le cadre de la modélisation endogène des instruments de la PAC, l'aversion pour le risque est importante car elle entraîne des effets de production et de prix beaucoup plus importants. Les effets des instruments politiques sont encore plus importants si l'effet de richesse est pris en compte. L'aversion au risque est également importante en atténuant la dynamique induite par les risques de prix endogènes.

Conclusion Générale

Alors que les physiciens modélisent le monde naturel à l'aide de lois physiques, les économistes modèlent le comportement des agents économiques en fonction de principes et d'hypothèses économiques. Etant donné que l'interaction des activités des agents constitue le marché, nous nous attendons à ce que le modèle économique puisse décrire dans une certaine mesure "l'économie". Les comportements des agents économiques sont toutefois plus sophistiqués à modéliser que les éléments physiques, et les comportements des agents économiques sont plus sophistiqués. Les principes et les hypothèses sur lesquels sont fondés les modèles continuent à être remis en question et améliorés. Après tout, il n'existe pas de modèle parfait, mais nous espérons que certains modèles seront utiles pour les questions de recherche qui les intéressent.

Cette thèse est développée dans le contexte où l'UE a adopté une succession de réformes de la PAC qui suppriment les soutiens de prix et introduisent des paiements directs. En conséquence, les prix agricoles de l'UE sont devenus beaucoup plus volatils, parallèlement aux prix mondiaux. Les agriculteurs français sont confrontés à des risques croissants liés aux fluctuations du marché: la manière dont ils modifieraient leurs décisions, qui pourraient à leur tour influencer la productivité, reste en question. Dans ce contexte, nous modélisons les comportements dynamiques des producteurs agricoles sous des risques basés sur des cadres d'équilibre partiel et d'équilibre général. Les objectifs de la recherche sont, premièrement, d'estimer l'évolution de la productivité et les paramètres profonds dans le modèle de décision de ferme dynamique. Deuxièmement, nous étudions le lien quantitatif du risque de prix, les décisions dynamiques des agriculteurs en matière de risque et la productivité dans ce cadre d'estimation structurelle. Troisièmement, nous évaluons l'impact des instruments de politique sur le marché dans un contexte où les prix sont risqués.

Notre première contribution concerne les problèmes de mesure liés à l'estimation de la fonction de production. La précision des données, en particulier la mesure problématique du capital, a de graves répercussions sur l'estimation de la PTF en agriculture. Nous traitons la série de données de capital comme une variable d'état latente et l'inférons des variables de décision observées. Le taux d'amortissement, au lieu d'être supposé ou calibré, est un paramètre structurel à évaluer simultanément avec le capital. De cette manière, nous avons amélioré la précision des séries de données sur les immobilisations. En outre, nous évitons le problème d'endogénéité standard dans l'estimation de la fonction de production en appliquant une approche d'estimation entièrement structurelle.

Notre deuxième contribution est méthodologique. Nous empruntons la solution et la technique d'estimation à l'estimation DSGE en macroéconomie et explorons l'estimation non linéaire étant donné que les producteurs agricoles sont exposés à des risques de production et de prix importants. À l'exception des chocs plus importants, l'estimation non linéaire est utile pour tous les domaines économiques, car il est possible de capturer davantage de propriétés économiques en termes non linéaires. L'approche de maximum d'entropie généralisée (MEG) que nous avons proposée est une approche oubliée mais puissante. Différente de l'approche de filtrage, elle intègre les paramètres inconnus et les états dans un objectif d'entropie, et la distribution antérieure est discrète au lieu d'être continue. Nous ne sommes pas les premiers à utiliser l'approche MEG pour estimer un modèle espaces-états. Cependant, à notre connaissance, nous sommes les premiers à intégrer le processus de résolution dans l'estimation avant qu'une représentation d'espace-état ne soit disponible. Nous montrons que l'approche MEG peut estimer avec précision un modèle de croissance avec une efficacité de calcul élevée..

Notre troisième contribution est celle de la modélisation. Nous intégrons les dimensions dynamique et risque des modèles agricoles. D'une part, inspirés des modèles DSGE, nous développons un modèle de décision agricole dans lequel un agriculteur représentatif prend des décisions en matière de production, de consommation, d'investissement et d'emprunt financier avec des contraintes de crédit implicites. De cette manière, les fluctuations du prix de la production et la productivité sont étudiées dans un cadre structurel. Une caractéristique importante du modèle est la cohérence de la structure du modèle et des paramètres profonds. Cette fonctionnalité nous permet d'étudier les réformes de la politique, car les comportements optimaux des agents restent indépendants des changements de politique. En outre, alors que les modèles DSGE sont des modèles macro avec des fondements micro, le modèle de décision agricole peut être considéré comme s'appliquant au niveau de l'entreprise. Nous ne donnons pas de fermeture d'équilibre général au modèle de décision agricole car le secteur agricole seul est trop petit pour fixer des prix d'équilibre. D'autre part, sur la base de la littérature CGE, nous développons un modèle GTAP-AGR CGE dynamique stochastique. Il s'agit d'une tentative d'introduire le risque et l'attitude de risque dans un modèle d'équilibre général qui est largement utilisé pour l'analyse des politiques agricoles.

Concernant les questions de recherche posées au début de la thèse: comment la productivité évolue-t-elle avec les nouveaux changements structurels? Quels sont les liens dynamiques entre productivité, décisions agricoles et risques de prix? L'estimation empirique montre que la productivité agricole dans les régions françaises augmente régulièrement avant la réforme de la PAC lorsque les prix fluctuent moins. La croissance a ralenti et devient beaucoup plus volatile à la suite de la hausse de la volatilité des prix. Globalement, le risque de prix a un impact sur la productivité car, lorsque les agriculteurs sont exposés à des risques élevés, ils modifient leurs décisions et leurs incitations à la production, ce qui, à son tour, affecte négativement la productivité réalisée.

La simulation politique du modèle stochastique dynamique GTAP-AGR CGE, dans laquelle nous supposons que les chocs de productivité exogènes influent sur les prix endogènes de l'UE, montre que la prise en compte du risque et l'attitude de risque sont importantes pour l'évaluation des instruments de la PAC. Outre les anticipations de prix, les anticipations de volatilité des prix sont également un facteur influant sur les décisions des agriculteurs peu enclins à prendre des risques et, en définitive, sur les résultats du marché.

Soutenir et stimuler la croissance de la productivité agricole de l'UE est un objectif clé de l'agenda de la PAC pour 2014-2020. La littérature précédente (Alston 2018) montre que la R & D agricole génère un rendement économique élevé et contribue à la croissance de la PTF du point de vue du changement technologique. Par conséquent, le fait que le montant de son budget de R & D a augmenté considérablement avec la réforme de la PAC de 2003 est efficace. Cependant, les réformes de la PAC depuis 2003 ont entraîné un risque de marché beaucoup plus élevé pour l'agriculture française. Différents outils de gestion des risques, publics et privés, sont également construits dans la nouvelle PAC, mais le principe de base est que ces instruments gèrent les risques mais n'interfèrent pas avec les prix du marché (sauf le filet de sécurité du marché pour les risques de prix excessifs). Nous soutenons que les outils actuels d'évaluation de la politique de la PAC n'ont pas été à la hauteur des fluctuations croissantes du marché. Premièrement, les outils d'évaluation des politiques disponibles font encore largement défaut. Comme le montre cette thèse, le risque et la préférence sont des facteurs importants pour les décisions agricoles dans les modèles de décision stochastiques dynamiques et le modèle CGE dynamique. Par conséquent, nous soulignons ici l'importance de la dynamique comptable et des dimensions du risque pour l'analyse des politiques dans la nouvelle situation de marché à risques croissants. Deuxièmement, le processus d'élaboration des politiques ne tient généralement pas compte du fait que la productivité est endogène au prix. Les décideurs devraient reconnaître que les décisions des agriculteurs en réponse aux risques croissants ont un impact négatif sur la productivité. Il faut tenir compte des conditions du marché pour atteindre les objectifs stratégiques en matière d'amélioration de la productivité.