Agricultural productivity and price volatility in France: a dynamic stochastic partial equilibrium approach

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Abstract

In this paper, we estimate the link between output price risks and TFP in a dynamic stochastic farm decision model, with controlling the measurement issues from the unobserved capital data and the simultaneously problem. A representative producer makes production, consumption, capital investment, and financial borrowing decisions and faces production (climate), output price and interest rate risks. We allow for structural changes in the drift term and the standard deviation of the shocks in the output price processes before and after the CAP reform.

Based a generalized maximum entropy (GME) approach, econometric estimation is performed on data for farms specialized in COP (cereals, oilseed and protein crops) production in three French regions (Centre, Picardie and Pays de la Loire), covering the period 1988-2015. We show that the estimated TFP grows steadily with small fluctuations in the first regime when prices were declining. The growth pattern becomes much more volatile, and the upward trend in TFP growth become insignificant following the increase in price volatility.

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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 were introduced. Accordingly, European agricultural prices become more volatile, in line with the volatility of world prices. While this new context generates many debates on the optimal EU farm policy, critical questions remain on 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 are 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 fluctuation and productivity growth. More recently, Liu et al. (2013) model quantitatively the co-movement between land price fluctuation and macroeconomic fluctuation. Cavalcanti et al. (2015) show that commodity price volatility impacts negatively on productivity growth, but this effect is counterbalanced by the positive effect of increased price levels. In the agricultural economic literature, Hu and Antle (1993) indirectly analyze this linkage by assessing the impact of farm policy price supports on the total factor productivity. They find that price support only has a negative impact on TFP 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), Lien et al. (2017) find, respectively, a positive relationship while focusing 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 exchange rate volatility has a negative impact on productivity growth, especially in the 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 tightening credit constraints leads to a lower productivity growth rate. Regarding the sources of linkage that are explored in the agricultural economic 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, etc.), the different econometric strategies (endogeneity solved with instrumental variables or fully structural estimation, etc.), datasets (periods, type of farming, etc.).

This paper originally 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 ensured the accuracy of the capital data series.

Indeed, from the data perspective, Griliches (1960) points out the agricultural input data measurement errors such as quality change among the inputs and heterogeneity products. Griliches and Jorgenson (1966) emphasize the major difficulty in measuring the capital time series because it 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, not to say to be recorded accurately in the account. Consequently, the capital input measure relies heavily on assumptions. Economists devote efforts in improving 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., they 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. (2012) show that different measures on capital yield different Cobb-Douglas elasticities. Above all, all this literature highlights the capital measurement problem, indicating that the available capital data, which are approximated by calibrated assumptions, can be inaccurate to retrieve TFP. As is explained, this problem is, however, treated property in our paper.

Second, from the 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 1998). That is, the producers choose the inputs knowing their level of productivity, while productivity is not observed by econometricians. 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 is raised from the modeling process. Another well-known approach in solving the endogeneity problem is Olley and Pakes (1996) approach. They correct the simultaneity issue by proxing productivity as an inverted function of investment, and estimate TFP in a two-step approach. Levinsohn and Petrin (2003) extend this approach by using intermediate inputs as a proxy for productivity. However, they do not treat the capital measurement problem in this approach. Other productivity measurement methods include, the nonparametric indexes such as Fisher index, Tornqvist index, etc., 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, Ball et al. 2013). It is convenient to use them to gain a general view on TFP, but they are limited by the static property and the calibrated elasticities (Van Biesebroeck 2007).

Third, we model quantitatively the dynamic link between TFP and price volatility, with potential risks arise from output price, productivity and 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 highly developed in macroeconomics (e.g., Smets and Wouters 2007). To apply similar estimation technique in the agricultural sector, we need to first deal with the less aggregate and more volatile agricultural data series. In particular, the agricultural producers may experience significant production risks from the weather, pesticide use, etc.. The increasing agricultural price fluctuations also results 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, nonlinear estimation techniques are indeed required. Moreover, the time series data in the agricultural are usually not sufficiently long, especially for the investment data. This requires us to do the estimation on 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 this 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 small 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 are recovered by the maximum entropy method. Performing the Monte-Carlo experiments, Zheng and Gohin (2018) show that the GME approach recovers accurately all the structural parameters in a neoclassical growth model with large shocks.

The structure of the paper is organized as follows. Section 2 contains a sketch of the model and the specification of expectations. Section 3 describes the GME method. Section 4 presents the estimation results. Section 6 concludes.

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 S_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,

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

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 elasticity of intertemporal substitution. We call γ the preference parameter in this paper, as it captures a mixture of risk preference and time preference under the power utility function. The farmer's budget constraint is

$$p_t Y_t + S_t + D_{t+1} = I_t + w_t X_t + C_t + (1 + r_t) D_t \tag{2}$$

where p_t is the potentially risky real price for output, w_t is the variable input price, and r_t is the borrowing rate. The consumption good is used as the numeraire, and capital has the same price as the consumption good. Importantly, our underlying assumption is that capital investment decision I_t, financial borrowing decisions of acquiring new debt D_{t+1}[1], and the action of paying back current debt D_t, are made at the end of the production year when the production income has been achieved. These two dynamic decisions are impacted by future production, price and interest rate risks. On the other hand, variable inputs decision is made at earlier stage of the year. We assume 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 not concerned for this decision. Finally, the budget constraint is balanced for the production (fiscal equivalent) year.

The production function follows a Cobb-Douglas production process,

$$Y_t = A_t K_t^{\alpha_k} X_t^{\alpha_x} \tag{3}$$

where α_k and α_k is 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 capital stock K_t and investment I_t. So that the law of motion for capital is,

$$K_{t+1} = (1 - \delta) K_t + I_t \tag{4}$$

where δ is the depreciation rate.

In each period, the farmer chooses strategy $\{I_t, X_t, C_t, D_{t+1}\}_{t=0}^{t=\infty}$ to maximize the ex-

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

pected lifetime utility subject to the intertemporal budget constraint (Eq.(2)), production function (Eq.(3)), and the capital evolution function (Eq.(4)). The first order conditions are given as,

$$p_t \alpha_x A_t K_t^{\alpha_k} X_t^{\alpha_x - 1} = w_{xt} \tag{5}$$

$$C_t^{-\gamma} = \beta E_t \left[C_{t+1}^{-\gamma} \left(1 - \delta + \alpha_k p_{t+1} A_{t+1} K_{t+1}^{\alpha_k - 1} X_{t+1}^{\alpha_x} \right) \right] \tag{6}$$

$$C_t^{-\gamma} = \beta E_t [C_{t+1}^{\gamma} (1 + r_{t+1})] \tag{7}$$

Eq.(5) is the variable input demand function which shows that the marginal product of variable input equals the marginal cost. Eq.(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. Eq.(7) is the debt Euler equation, and is also a standard asset pricing equation.

Price and interest rate evolution We assume that output price is exogenous at the farm level, and 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.

$$ln(p_{t+1}) = \mu_p(s_t) + ln(p_t) + \sigma_p(s_t)\epsilon_{p_{t+1}} \tag{8}$$

where μ_p is the drift parameter, σ_p is the standard deviation of output price volatility. $\mu_p(s_t), \sigma_p(s_t)$ varies with the regime s_t. s_1 represents the regime of low price volatility, and s_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 to match the decreasing trend in agricultural prices (at least a decreasing trend before 2000).

We model the interest rate in a similar way. Considering that the interest rate in France is decreasing in the last decades, and there is no observable strucural break, we model it as a random walk with drift process for the modeling period,

$$r_{t+1} = \mu_r + r_t + \sigma_r \epsilon_{r_{t+1}} \;\; \epsilon_{r_t} \sim N(0,1) \tag{9}$$

with μ_r the drift term and σ_r the standard deviation of the interest rate shock.

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

$$\ln(A_{t+1}) = \mu_a + \ln(A_t) + \rho_{ap}\sigma_p \epsilon_{p_{t+1}} + \sigma_a \epsilon_{a_{t+1}} \tag{10}$$

where μ_a is the drift term, $\epsilon_{a_{t+1}}$ is the productivity shock which is i.i.d. and normal distributed, $\epsilon_{a_t} \sim N(0,1)$, and σ_a denotes the standard deviation of productivity shock, $\epsilon_{p_{t+1}}$ is the price shock specified in the stochastic price process (Eq.8), 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 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 TFP evolution process,

$$ln(A_{t+1}) = \mu_a(s_t) + ln(A_t) + \rho_{ap}\sigma_p \epsilon_{p_{t+1}} + \sigma_a(s_t)\epsilon_{a_{t+1}} \tag{11}$$

where s_1 is the regime of low price volatility, and s_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 the economic growth in agriculture and to capture the trend in the real data. There are several ways to fit the non-stationary real data into the theoretical model. The most used approach is to remove the trend from the real data by the filters (Hodrick-Prescott filter, first difference filter), and estimate the model with the transformed data. This approach, in particular, the Hodrick-Prescott filter, is criticized because it apply univariate technique to data series with different characters, and it comes with a cost that we loss relevant information in the data series. Canova (2014) show that the parameters estimates depend on the filter chosen, and the choice of the filters are arbitrary. Moreover, the objective of the paper is to estimate productivity and evaluate the growth pattern, detrending the data would lead to a stationary productivity process. As a result, we use an alternative approach, which models the trend directly into the model. This approach is applied by An and Schorfheide (2007) and Fernández-Villaverde and Rubio-Ramírez (2007), where the technology process is modeled as a random walk with drift process.

State space representation The entire model described above can be considered as a state space model, with $\mathbf{X_t}$ the vector of decision variables, $\mathbf{S_t}$ the vector of state variables, and Θ the structural parameter set:

$$\begin{aligned}
\mathbf{X_t} &= [Y_t, I_t, C_t, X_t, D_{t+1}]^T, \\
\mathbf{S_t} &= [K_t, A_t, p_t, r_t, D_t]^T, \\
\mathbf{\Theta} &= [\beta, \gamma, \alpha_x, \alpha_k, \delta, \mu_p, \mu_a, \mu_r, \sigma_p, \sigma_a, \sigma_r, \rho_{ap}]^T.
\end{aligned}$$

In a general form, the model can be presented as,

$$\mathbf{X_t} = f(\mathbf{S_t}, \mathbf{V_t}; \mathbf{\Theta}) \tag{12}$$

$$\mathbf{S_t} = g(\mathbf{S_{t-1}}, \mathbf{W_t}; \mathbf{\Theta}) \tag{13}$$

where f and g are nonlinear functions with the vector of structural parameters $\mathbf{\Theta}$. Equation (12) is the observation equation in which the observable decisions variables $\mathbf{X_t}$ are derived from the unobservable state variables $\mathbf{S_t}$. $\mathbf{V_t}$ are the exogenous shocks such as measurement errors (to avoid singularity). Equation (13) is the state equation which describes the intertemporal evolution of state variables $\mathbf{S_t}$. $\mathbf{W_t}$ are exogenous shocks such as innovations. The underlying idea is that $\mathbf{S_t}$ is not directly observable, but we could estimate these unobservable states from the observable data $\mathbf{X_t}$, given the function form and the structural parameter set. Meanwhile, the structural parameters can also be estimated from the observable data $\mathbf{X_t}$.

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. We focus on three regions in France: Centre, Picardie and Pays de la Loire, as the main agricultural activity in the three regions is crop production. It also allows us to compare if 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). We use seven data series: output volume per farm, investment per farm, consumption per farm, variable inputs per farm, debt per farm, output price, interest rate, and the subsidies.

The price of soft wheat is used as output price, as the price movement and price level are highly similar among the crop products (soft wheat, barley and maize). The price is computed by dividing the gross production of soft wheat (in euro) by the volume of soft wheat (in kilo), while the volume of soft wheat is yield multiplied by the area of soft wheat production. Output volume is the difference between total crop production and the variation in stock, divided by output price. Variation in stock is the variation of crop products stocked by the farmer. According to the FADN variable definition, final consumption is obtained by deducting the capacity of self-financing by self-financing. Variable costs are used as variable inputs, they are the sum of intermediate consumption, personnel expense for hired labor, rent, and insurance expense. Subsidies are total subsidies net of tax.

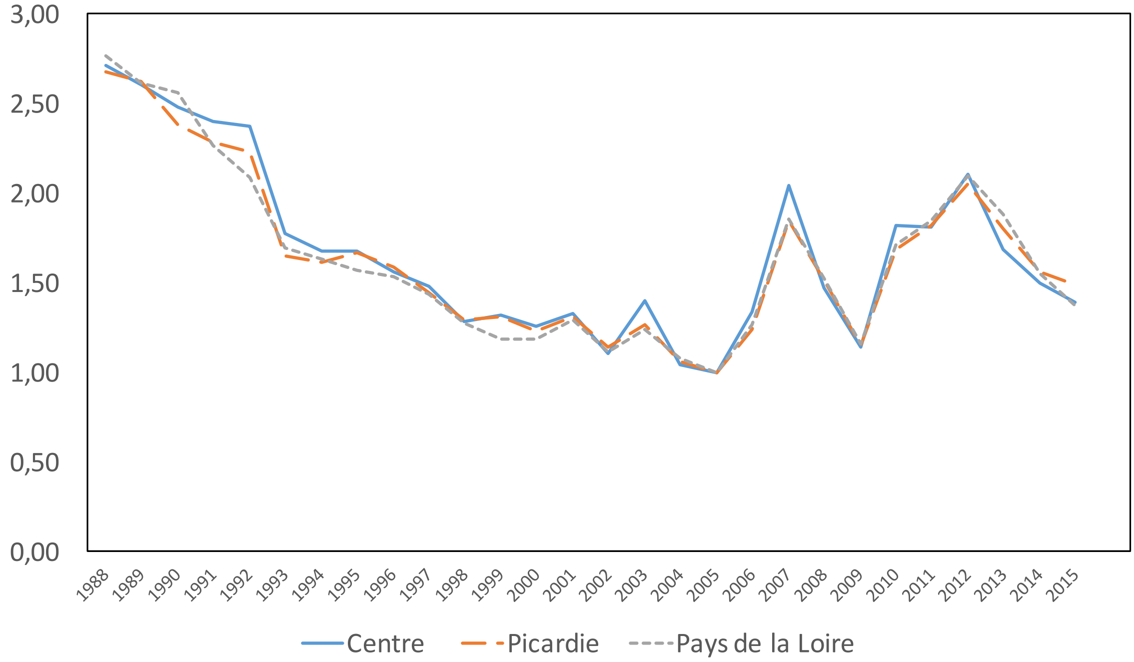

Figure 1: Evolution of real output price in Centre, Picardie and Pays de la Loire (base year 2005=1)

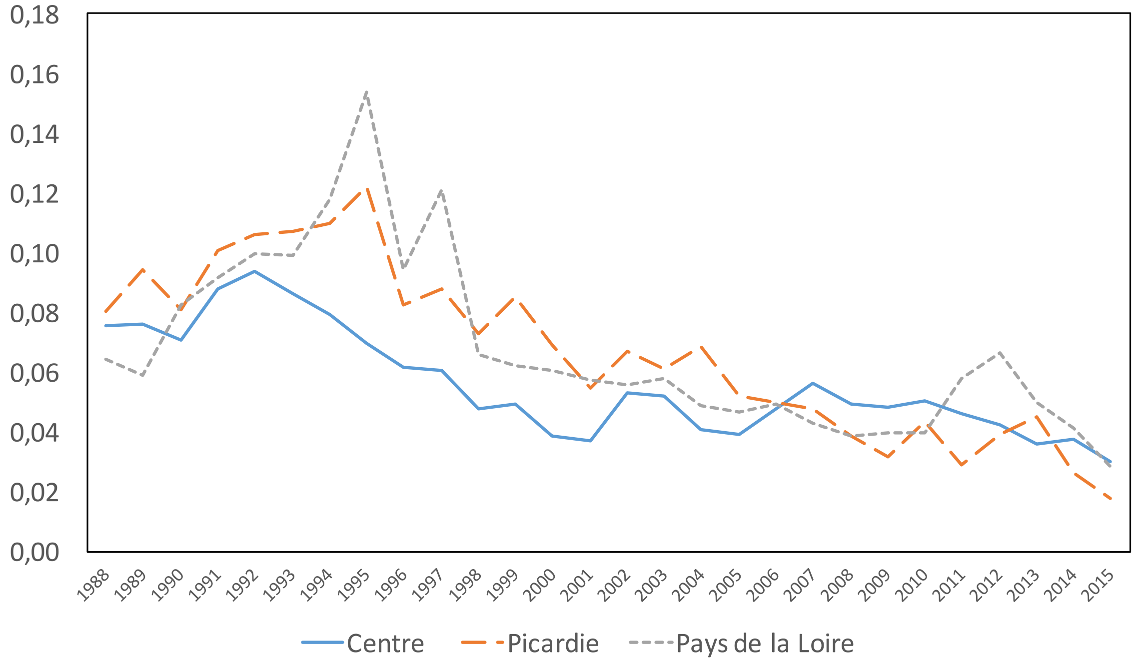

Figure 2: Evolution of interest rate in Centre, Picardie and Pays de la Loire

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

$$p_tY_t + S_t - r_tD_t - X_t - C_t = I_t + \Delta Stock_{t+1} - \Delta D_{t+1} \tag{14}$$

where $\Delta D_{t+1} = D_{t+1} - D_t$ is the variation in debt, and debt is the sum of long-term, mid-term and short-term debt. $\Delta Stock_{t+1}$ is the variation in stock. I_t is total investment. The left hand of Eq. (14), according to the FADN variable definition, equals the self-financing data series. We check the series we computed to make sure Eq.(14) holds. Interest rate 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 with time - 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 such size effect, we rescale the data by the total farm number. Finally, we deflate the investment, consumption, variable inputs, debt, subsidies, output price, and interest rate data series with the national consumption index. It is worth mentioning that the data construction shows that the individual level choice data are noisy at certain level, which infers the necessary of introducing measurement errors.

Figure 1 and 2 depict the evolution process of output price and interest rate. The price dynamics are similar across regions: it decreases steadily during the period $1988 - 2002$. Follows with a low level fluctuation in $2002 - 2005$, the real output price becomes highly volatile after 2005. The borrowing rate shows a decreasing trend over the years for the three regions, which is consistent with the decreasing market interest rate in France. However, the borrowing rate in the Centre region is generally lower than that of the other two regions before 2006. Besides, in Pays de la Loire, the borrowing rate is more volatile than the other two regions.

4 Estimation Methods

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, technical process, etc.. The dynamic model of Golan et al. (1996) matches explicitly the state space representation so they do not need to solve the model. The advantages of the GME approach in estimating DSGE or DSGE-like models are that, it evaluates the equilibrium conditions directly, so that the estimation applies to nonlinear systems. Besides, it recovers the unknown parameters and the unknown states simultaneously given the prior support values, which results in a higher computational efficiency compared to other sampling based methods. 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, the statistical inference of this method is not well developed, and the results can be sensitivity to the choices of the prior information of the parameters and the error terms.

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

$$H(\mathbf{p}) = -\sum_n p_n ln(p_n) \tag{15}$$

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 $\epsilon_{at,pt,rt}$ which represent the productivity shocks, price shocks and interest rate shocks, and ϵ_{mea} which represent the measurement errors and other approximation 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 $\theta_i (i = 1, 2, \ldots, I)$ and the errors $\epsilon_{jt} (j = 1, 2, \ldots, J; t = 1, 2, \ldots, T)$. Here i is the index for the parameters, j is the index for the errors, t is the time index. Given the prior information, suppose that the value of each parameter θ_i lies within the interval $[z_{i1}, z_{iK}]$. We define a set of discrete points (support values) $z_i = [z_{i1}, z_{i2}, \ldots, z_{iK}]'$, with associated probability weights $p_i = [p_{i1}, p_{i2}, ..., p_{iK}]'$. The unknown $\boldsymbol{\Theta}$, which is a I-vector is,

$$\boldsymbol{\Theta} = \mathbf{Zp} = \begin{bmatrix} \mathbf{z_1'} & 0 & \ldots & 0 \\ 0 & \mathbf{z_2'} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \mathbf{z_I'} \end{bmatrix} \begin{bmatrix} \mathbf{p_1} \\ \mathbf{p_2} \\ \vdots \\ \mathbf{p_I} \end{bmatrix} \tag{16}$$

where $\mathbf{Z}$ is an $I \times IK$ matrix and $\mathbf{p}$ is an IK vector. For each parameter θ_i,

$$\mathbf{z_i'p_i} = \sum_k z_{ik}p_{ik} = \theta_i \; for \; i = 1, 2, \ldots, I \tag{17}$$

Similarly, suppose the error terms $\epsilon_{\mathbf{jt}}$ lies within the interval $[v_{jt1}, v_{jtD}]$. Note here we have one more dimension, time t. We define a set of discrete points $v_{jt} = [v_{jt1}, v_{jt2}, \ldots, v_{jtD}]'$, with associated probability weights $w_{jt} = [w_{jt1}, w_{jt2}, ..., w_{jtD}]'$. The unknown shocks ϵ_t at time t, which is a J-vector, is,

$$\epsilon_{\mathbf{t}} = \mathbf{V_t w_t} = \begin{bmatrix} \mathbf{v_{t1}'} & 0 & \ldots & 0 \\ 0 & \mathbf{v_{t2}'} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \mathbf{v_{tD}'} \end{bmatrix} \begin{bmatrix} \mathbf{w_{t1}} \\ \mathbf{w_{t2}} \\ \vdots \\ \mathbf{w_{tD}} \end{bmatrix} \tag{18}$$

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

$$\mathbf{v_{jt}'w_{jt}} = \sum_d v_{jtd}w_{jtd} = \epsilon_{jt} \; for \; j = 1, 2, \ldots, J; \; t = 1, 2, \ldots, T \tag{19}$$

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

The empirical program is,

$$\max_{\mathbf{p},\mathbf{w}} -\sum_i\sum_k p_{ik}ln(p_{ik}) - \sum_j\sum_t\sum_d w_{jtd}ln(w_{jtd}) \tag{20a}$$

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

$$C_t^{-\gamma} = \beta E_t\left[C_{t+1}^{-\gamma}\left(1-\delta+\alpha_k A_{t+1}p_{t+1}K_{t+1}^{\alpha_k-1}X_{t+1}^{\alpha_x}\right)\right] \tag{20b}$$

$$C_t^{-\gamma} = \beta E_t[C_{t+1}^{\gamma}(1+r_{t+1})] \tag{20c}$$

$$p_t\alpha_x A_t K_t^{\alpha_k}X_t^{\alpha_x-1} = 1 \tag{20d}$$

$$K_{t+1} = (1-\delta)K_t + p_tY_t + S_y + D_{t+1} - X_t - C_t - (1+r_t)D_t \tag{20e}$$

$$Y_t = A_tK_t^{\alpha_k}L_t^{\alpha_l} \tag{20f}$$

$$\ln(p_{t+1}) = \mu_p + \ln(p_t) + \sigma_p\tilde{\epsilon}_{p_{t+1}}, \quad \tilde{\epsilon}_{p_t}\sim N(0,1) \tag{20g}$$

$$r_{t+1} = \mu_r + r_t + \sigma_r\tilde{\epsilon}_{r_{t+1}}, \quad \tilde{\epsilon}_{r_t}\sim N(0,1) \tag{20h}$$

$$\ln(A_{t+1}) = \rho_A\ln(A_t) + \sigma_A\tilde{\epsilon}_{A_{t+1}}, \quad \tilde{\epsilon}_{A_t}\sim N(0,1) \tag{20i}$$

$$\sum_k p_{ik} = 1 \quad for\ i = 1,2,\ldots,I \tag{20j}$$

$$\sum_d w_{jtd} = 1 \quad for\ j = 1,J; \quad t = 1,2,...T-1 \tag{20k}$$

$$p_{ik} > 0, w_{jtd} > 0 \quad for\ \ \forall i,j,t,k,d \tag{20l}$$

where p_{ik} and w_{jtd} are the probability weights of the supporting values which we have specified in the reparameterization part, and Eq.(20d) - (20f) correspond to the equilibrium conditions in Eq.(2) - (6).

The expectation operator

To bring the above program, especially the Euler equation Eq.(20d) and Eq.(20b) to the data, one important assumption is rational expectation. The central idea is that the expectation is in accordance with the model prediction. The farmer cannot precisely predict the point values of the next period shocks, but he or she knows the distribution of the shocks. In reality, while the CAP reform in 2003 induces high price fluctuation, the EU farmers are able to form their expectations on price volatility based on the historical world price fluctuation.

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 (Eq.(20g) and Eq. (20h)) outside of the structural model, based on the observed price and interest rate data. Meanwhile, the latent TFP evolution (Eq. (20i)) 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 evolves modeling the error terms as a random variable with Gaussian Quadrature nodes and the corresponding Gaussian Quadrature weights. For shocks that follow a normal distribution with zero mean and standard deviation 1, $\epsilon \sim N(0,1)$, we use a 5-point Gaussian Quadrature grid with the nodes and weights specified in Table 1 to describe the anticipated shocks:

Table 1: Gauss-Hermite approximation

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

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

$$ln(p_{t+1}^{ip}) = \mu_p + ln(p_t^{obs}) + \sigma_p \epsilon^{ip} \tag{21}$$

$$r_{t+1}^{ir} = \mu_r + r_t^{obs} + \sigma_r \epsilon^{ir} \tag{22}$$

$$ln(A_{t+1}^{ia,ip}) = \mu_A + ln(A_t) + \rho_{ap}\sigma_p \epsilon^{ip} + \sigma_A \epsilon^{ia} \tag{23}$$

where ip, ir, ia denote the nodes index for price, interest rate and TFP shocks, which correspond to i in table 1.

Regarding the decision variables, at time t, we observe 4 decision variables, consumption C_t^{obs}, production Y_t^{obs}, variable inputs X_t^{obs}, and debt D_t^{obs}. The entrepreneur cannot precisely predict the point value of next period consumption. However, under rational expectation, 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,

$$\begin{aligned} C_t^{obs} =& \sum_{m_K=0}^{M_K} \sum_{m_D=0}^{M_d} \sum_{m_A=0}^{M_A} \sum_{m_p=0}^{M_p} \sum_{m_r=0}^{M_r} b_{m_K,m_D,m_A,m_p,m_r} \\ & \psi_{m_K}(\phi(K_t))\psi_{m_D}(\phi(D_t))\psi_{m_A}(\phi(A_t))\psi_{m_p}(\phi(p_t^{obs}))\psi_{m_r}(\phi(r_t^{obs})) + \epsilon_{cs_t} \end{aligned} \tag{24}$$

$$\begin{aligned} C_{t+1}^{ia,ip,ir} =& \sum_{m_K=0}^{M_K} \sum_{m_D=0}^{M_d} \sum_{m_A=0}^{M_A} \sum_{m_p=0}^{M_p} \sum_{m_r=0}^{M_r} b_{m_K,m_D,m_A,m_p,m_r} \\ & \psi_{m_K}(\phi(K_{t+1}))\psi_{m_D}(\phi(D_{t+1}))\psi_{m_A}(\phi(A_{t+1}^{ia}))\psi_{m_p}(\phi(p_{t+1}^{ip}))\psi_{m_r}(\phi(r_{t+1}^{ir})) + \epsilon_{cne_t} \end{aligned} \tag{25}$$

$$X_{t+1}^{ia,ip} = (\alpha_x p_{t+1}^{ip} A_{t+1}^{ia} K_{t+1}^{\alpha_k})^{\frac{1}{1-\alpha_x}} \tag{26}$$

In Eq.(24), The Chebyshev coefficients b_{d_K,d_A,d_p,d_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. Adding one measurement errors series ϵ_{cs_t} avoids the singularity problem because we need to have the same number of shocks as the number of observable data series (detailed singularity problem is discussed in Fernández-Villaverde and Rubio-Ramírez 2005, Ruge-Murcia 2007).

In Eq.(25), the next period consumption is obtained using the anticipated next period states, and the estimated Chebyshev policy function in Eq. (24). Eq.(26) shows the next period variable inputs are obtained using the anticipated next period price and TFP.

Based on Eq.(21) - (26) and Gaussian Quadrature points in table 1, the empirical Euler conditions are rewritten as,

$$(C_t^{obs})^{-\gamma} = \sum_{ia}\sum_{ip}\sum_{ir} w^{ia}w^{ip}w^{ir}\beta \left[(C_{t+1}^{ia,ip,ir})^{-\gamma}\left(1-\delta+\alpha p_{t+1}^{ip}A_{t+1}^{ia}(K_{t+1})^{\alpha_k-1}(X_{t+1}^{ia,ip})^{\alpha_x}\right)\right] \tag{27}$$

$$(C_t^{obs})^{-\gamma} = \sum_{ia}\sum_{ip}\sum_{ir} w^{ia}w^{ip}w^{ir}\beta \left[(C_{t+1}^{ia,ip,ir})^{-\gamma}(1+r_{t+1}^{ir})\right] \tag{28}$$

Finally, the objective entropy (Eq.(20a)) is maximized subjective to the constraints Eq.(20d) - (28). The time-constant parameters dimension $I = 7 + 243 = 250$ (with 7 the number of the structural parameters, $243 = 3^5$ the number of Chebyshev coefficients), and the time-varying shocks dimension $J = 4$. By forming Lagrange, the first order conditions provide the basis for the solution p_{ik} and w_{jtd}. By the reparameterization definition, the estimated parameter and shocks are,

$$\sum_k \hat{p}_{ik} z_{ik} = \hat{\theta}_i \tag{29}$$

$$\sum_d \hat{w}_{jtd} v_{ktj}^{\epsilon} = \hat{\epsilon}_{jt} \tag{30}$$

Given the recovered shocks in Eq(30), the estimates of the TFP evolution process are determined by Eq.(20i).

5 Results

For the GME estimation, it is important to give prior information to the parameters. Table 2 shows the prior (support values) for the parameters and the shocks. We choose relatively loose prior to make sure that the results are not manipulated by the prior information. The probability of each support point is assigned equal initially. 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 in agricultural can be as high as to 0.1 considering the intensive use of the agricultural capital, the value 0.2 makes sure that the estimation will not hit the bounds. The drift terms for the price, TFP and interest rate evolution are all set between -0.2 and 0.2, so that we do not fix the direction of the trend in price, TFP and interest rate, and 20% is a loose level for annual growth rate. 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 a very low level, 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 well identified[2].

Estimate price and interest rate with structural change

Before estimating the structural model, we estimate first the exogenous price and interest rate evolution process - followed which the farm entrepreneur form expectations on the future output price and borrowing rate. Based on the real price evolution in Figure 1, we observe a possible structural change during the period $2002 - 2005$. This is the period when the price starts to fluctuate, and afterward, the price volatility becomes extremely high. To capture the volatility change in price, we estimate the price evolution by allowing for a structural change in the drift term and the volatility.

$$ln(p_t) = \mu_p(s_t) + ln(p_{t-1}) + \sigma_p(s_t)\epsilon_{p_t} \tag{31}$$

where $\mu_p(s_t), \sigma_p(s_t)$ varies with the regime s_t. s_1 represents the regime of low price volatility, and s_2 represents the regime of high volatility. To detect the actual year of structural change, we test the model with structural change in 2002 and 2003. The

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

Table 2: Prior information for the parameters

Parameters	Description	Support values (priors)		
		Low	Centre	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
μ_r	drift term in interest rate evolution	-0.2	0	0.2
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^{-4}	0	10^{-4}
ϵ_{cne_t}	expectation errors	-10^{-4}	0	10^{-4}
ϵ_{xne_t}	expectation errors	-1	0	1

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 $s_1 = [1988 - 2002]$, and the high price volatility regime $s_2 = [2003 - 2015]$. 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. So that we don't include a structural change in the interest rate.

Table 3 shows the GME estimates of the price and interest rate evolution process for the region Centre, Picardie and Pays de la Loire. The price evolutions for the three regions are similar: for the period $1988 - 2002$, the price has a decreasing trend $(-0.064, -0.061, -0.065)$ with a low-level volatility at 0.018, 0.021 and 0.017. For the

Table 3: GME estimation of price and interest rate evolution

	Centre	Picardie	Pays de la Loire
$\mu_p(s_1)$	-0.064	-0.061	-0.065
$\sigma_p(s_1)$	0.085	0.086	0.070
$\mu_p(s_2)$	0.018	0.021	0.017
$\sigma_p(s_2)$	0.260	0.209	0.212
Entropy	6080.74	6104.94	6106.20
μ_r	-0.002	-0.002	-0.003
σ_r	0.007	0.013	0.021
Entropy	3030.61	2923.99	1736.74

period $2003-2015$, the price volatility rises to as high as 0.260, 0.209 and 0.212, following with a small increasing trend $(0.018, 0.021, 0.017)$. Regarding the residuals of the price evolution before and after the structural change, the Durbin-Watson test statistics accept the null hypothesis that the serial correlation is zero, and the Shapiro-Wilk test statistics cannot reject the null hypothesis that the samples come from a population which has a normal distribution. For the whole period, the interest rate offering for the farms, in general, has a small decreasing trend with volatility level at 0.007, 0.013 and 0.021. This decreasing trend is in accordance with the French market interest rate.

Estimate the structural model

Table 4 shows the estimation results of two test models. For both models, output price follows the estimated random walk with drift process with structural change in 2002 (Table 3). Similarly, for TFP evolution, we assume that there is a structural change before and after 2002,

$$ln(A_t) = \mu_a(s_t) + ln(A_{t-1}) + \rho_{ap}\sigma_p\epsilon_{p_t} + \sigma_a(s_t)\epsilon_{a_t} \tag{32}$$

where $s_t = 1988 - 2002$ is the regime of low price volatility, $s_t = 2003 - 2015$ is the regime of high price volatility. The remaining structural parameters such as preference and input elasticity are constant. For Model 1, there is no correlation between price shocks and TFP ($\rho_{ap} = 0$). For Model 2, the cross-correlation is not zero ($\rho_{ap} \neq 0$).

Table 4: GME estimation of the structural model

	Centre	Picardie	Pays de la Loire
	Model 1: $\rho_{zp} = 0$		
β	0.943	0.944	0.945
γ	2.325	2.668	2.997
α_k	0.461	0.473	0.372
α_x	0.770	0.791	0.773
δ	0.120	0.127	0.080
$\mu_a(s_1)$	0.062	0.080	0.047
$\sigma_a(s_1)$	0.029	0.054	0.049
$\mu_a(s_2)$	-0.029	-0.031	-0.029
$\sigma_a(s_2)$	0.061	0.075	0.066
Entropy	1239.352	1236.651	1254.842
	Model 2: $\rho_{zp} \neq 0$ (Selected model)		
β	0.946**	0.945**	0.946**
γ	3.064**	2.519**	3.161**
α_k	0.333**	0.319**	0.348**
α_x	0.770**	0.791**	0.773**
δ	0.098*	0.091$^{\bullet}$	0.094*
$\mu_a(s_1)$	0.052*	0.055*	0.045*
$\mu_a(s_2)$	0	-0.008	0.007
$\sigma_a(s_1)$	0.028*	0.062**	0.043**
$\sigma_a(s_2)$	0.054**	0.079**	0.045**
ρ_{zp}	-0.807*	-0.876*	-0.809*
Entropy	1256.080	1257.959	1263.153

Note: ** denote rejection of the null hypothesis because of infeasible.$^{\bullet}$ 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.

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 parameter estimation, all the estimated values are changed from the priors, which indicates all the parameters are identified from the data information. Test using the entropy ratio statistic (Judge and Mittelhammer 2011) find 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 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 infeasible. The infeasibility may indicate 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 feasible solution exits under the null hypothesis but the routine cannot find it. However, consider that these structural parameters have receptively their economic meanings, they are not possible to 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 have their differences. The discount factor is overall around 0.94, this is in line with the average borrowing rate of $5-6\%$ across regions. The variable-inputs elasticity is rather constant across the regions at the level of 77%. This factor contributes to the most part of the crop production because we have included intermediate inputs, rented land and hired labor into the variable inputs. On the other hand, capital contributes to $30-35\%$ to the production across the regions. Overall, the agricultural production in the three regions exits increasing return to scale. As expected, the estimated depreciation rate is around $9-9.8\%$, which is higher than the macroeconomic depreciation rate $(2-3\%)$. The high depreciation rate is reasonable for the agricultural capital if we consider the intense use of machines and equipment for agricultural production. Last, when we allow for the Chebyshev approximation errors at a low level (lies within the range [0.0001, 0.0001] as the support values), we obtain the estimation of the preference parameters. The average level of risk-aversion is relatively high in Pays de la Loire and in Centre (3.064 and 3.161), and is 2.519 in Picardie. It indicates that instead of risk neutral, the agricultural entrepreneurs in these region prohibits a median-level risk aversion.

The structural shocks parameters which describe the TFP evolution are jointly estimated with the structural parameters, and are also depicted in Table 4. To better illustrate the estimated latent TFP evolution process, we plot in Figure 3 - 5 the estimated TFP series, along with real output price and yield (land productivity). First, regarding the first-order relationship between price and TFP, we find a significant negative correlation between price shocks and TFP. The values are $-0.807, -0.876, -0.809$ respectively for the three regions. This can be explained from a general equilibrium point of view that, a negative price shock is possibly a result of an increase in supply, which corresponds to a positive productivity shock such as weather conditions. In addition, this negative correlation can be a transaction channel for price volatility and TFP.

Second, regarding the second-order relationship - price volatility and TFP, the increasing price volatility has a negative impact on the TFP growth. In the regime of low price volatility (year $1988 - 2002$), TFP grows steadily with increasing trend $(0.052, 0.055, 0.045)$ and small fluctuations $(0.028, 0.062, 0.043)$. 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 the three regions. The pure TFP shock volatility level has increased to 0.054 for Centre, 0.079 for Picardie, and remains stable at 0.045 for Pays de la Lore. 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 Figure 3 - 5. The plotted estimated TFP 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 stop growing) and fluctuate more in the regime of high price volatility.

Being considered as the Solow residual of the production function, productivity has always been considered as exogenous and is mostly influenced by the technology change, and in agricultural, influenced by pure exogenous shocks such as weather condition. Except learning, how the individual behavior influences productivity remains ambiguous. Our estimation results show that price risk is also a factor that influences productivity growth. Based on our model assumption, the producers make expectations on future

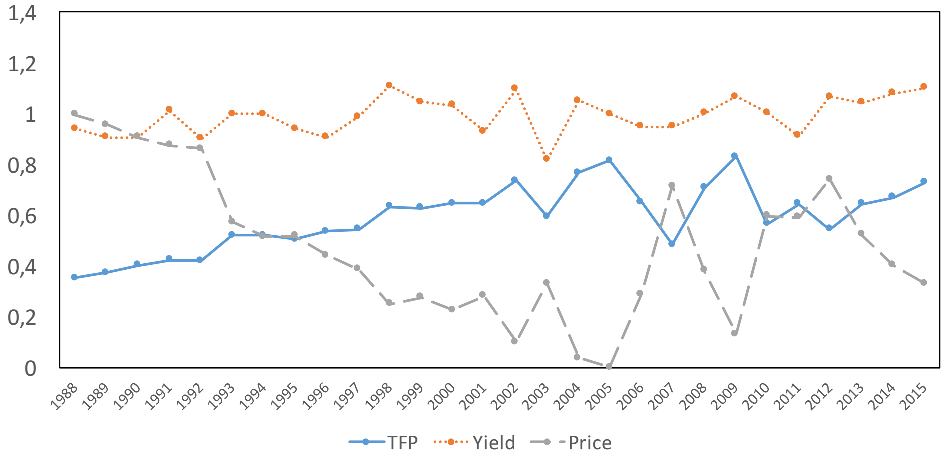

Figure 3: Centre: comparing the estimated TFP with price and yield

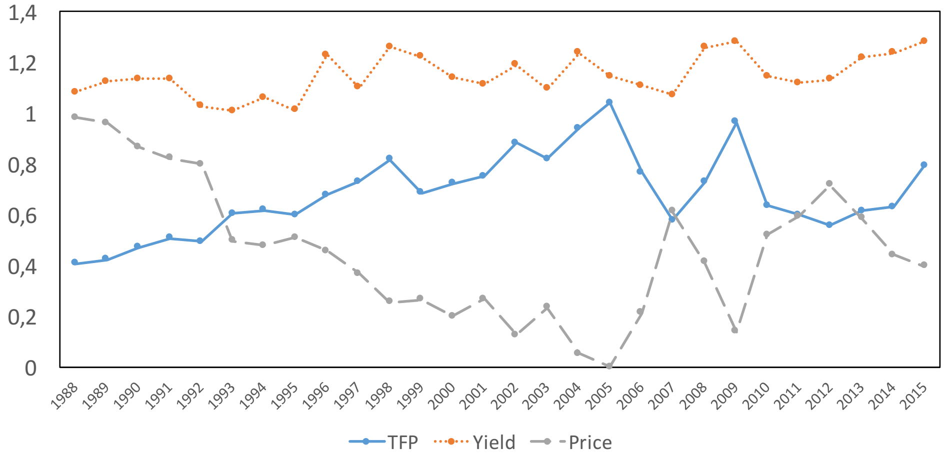

Figure 4: Picardie: comparing the estimated TFP with price and yield

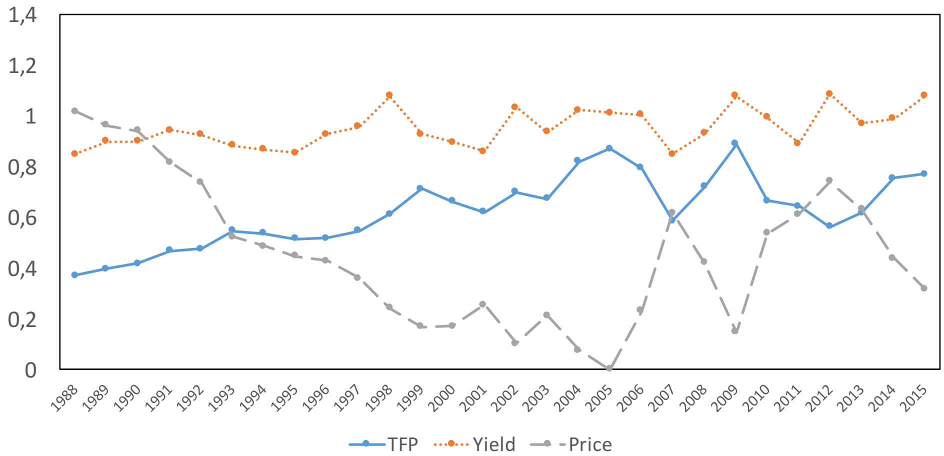

Figure 5: Pays de la Loire: comparing the estimated TFP with price and yield

prices and know the distribution of the price risks. Consequently, in the regime where price volatility is high, the producers know they are exposed to high risks, and they may have less incentive for production. This can be a channel with which the price risk is linked to productivity.

Last, compare the estimated TFP with yield in Figure 3 - 5, we can 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 fluctuation in yield is also reflected in TFP. We can learn from the figure that, instead of the intensity use of land, the source of TFP growth more comes from the intensity use of capital, the knowledge of labor, and the technology change. It also proves in a way that TFP is more important than single factor productivity.

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, etc., which can be very critical (Andersen et al. 2012). Moreover, direct econometric TFP estimation suffers from the endogeneity problem caused by simultaneity. This paper tries to solve these two problems, and estimate 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 agricultural.

Based on the FADN survey data in the region 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 extremely high. 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 become 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 alter their decisions and production incentives which in term impact negatively on the realized productivity.

As further extensions, this paper does not model, however, through which channel productivity is linked with output price fluctuation. 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 fluctuation. We have also introduced the financial debt into the model, but credit constraint is only modeled implicitly through the interest rate. It will certainly be interesting to enrich the model by introducing the structural equations for credit constraint. 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, are to be explored. In addition, policy implications for enhancing agricultural productivity in the aspect of controlling price risks is also to be discussed.

References

Aghion, Philippe, Bacchetta, Philippe, Ranciere, Romain, and Rogoff, Kenneth. Exchange rate volatility and productivity growth: The role of financial development. *Journal of monetary economics*, 56(4):494–513, 2009.

Aghion, Philippe, Angeletos, George-Marios, Banerjee, Abhijit, and Manova, Kalina. Volatility and growth: Credit constraints and the composition of investment. *Journal of Monetary Economics*, 57(3):246–265, 2010.

An, Sungbae and Schorfheide, Frank. Bayesian analysis of dsge models. *Econometric reviews*, 26(2-4):113–172, 2007.

Andersen, Matt A, Alston, Julian M, and Pardey, Philip G. Capital services in us agriculture: concepts, comparisons, and the treatment of interest rates. *American Journal of Agricultural Economics*, 93(3):714–734, 2011.

Andersen, Matthew A, Alston, Julian M, and Pardey, Philip G. Capital use intensity and productivity biases. *Journal of Productivity Analysis*, 37(1):59–71, 2012.

Arndt, Channing. Demand for herbicide in corn: An entropy approach using micro-level data. *Journal of Agricultural and Resource Economics*, pages 204–221, 1999.

Ball, Eldon, Schimmelpfennig, David, and Wang, Sun Ling. Is us agricultural productivity growth slowing? *Applied Economic Perspectives and Policy*, 35(3):435–450, 2013.

Ball, Eldon V, Wang, Sun L, Nehring, Richard, and Mosheim, Roberto. Productivity and economic growth in us agriculture: A new look. *Applied Economic Perspectives and Policy*, page 031, 2015.

Ball, V Eldon, Bureau, Jean-Christophe, Nehring, Richard, and Somwaru, Agapi. Agricultural productivity revisited. *American Journal of Agricultural Economics*, 79(4): 1045–1063, 1997.

Butzer, Rita, Mundlak, Yair, and Larson, Donald F. 15 measures of fixed capital in agriculture. *Productivity Growth in Agriculture: An International Perspective*, page 313, 2012.

Canova, Fabio. Bridging dsge models and the raw data. *Journal of Monetary Economics*, 67:1–15, 2014.

Cavalcanti, De V, Tiago, V, Mohaddes, Kamiar, and Raissi, Mehdi. Commodity price volatility and the sources of growth. *Journal of Applied Econometrics*, 30(6):857–873, 2015.

European Commission. EU agricultural market briefs. *Brussels: EC*, 2016.

Fernández-Villaverde, Jesús and Rubio-Ramírez, Juan F. Estimating dynamic equilibrium economies: linear versus nonlinear likelihood. *Journal of Applied Econometrics*, 20(7):891–910, 2005.

Fernández-Villaverde, Jesús and Rubio-Ramírez, Juan F. Estimating macroeconomic models: A likelihood approach. *Review of Economic Studies*, 74(4):1059–1087, 2007.

Frick, Fabian and Sauer, Johannes. Deregulation and productivity: Empirical evidence on dairy production. *American Journal of Agricultural Economics*, 100(1):354–378, 2017.

Golan, Amos, Judge, George, and Karp, Larry. A maximum entropy approach to estimation and inference in dynamic models or counting fish in the sea using maximum entropy. *Journal of Economic Dynamics and Control*, 20(4):559–582, 1996.

Griliches, Zvi. Measuring inputs in agriculture: a critical survey. *Journal of farm Economics*, 42(5):1411–1427, 1960.

Griliches, Zvi and Jorgenson, Dale W. Sources of measured productivity change: Capital input. *The American Economic Review*, pages 50–61, 1966.

Griliches, Zvi and Mairesse, Jacques. Production functions: The search for identification. In *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, number 31, page 169. Cambridge University Press, 1998.

Hu, Fan and Antle, John M. Agricultural policy and productivity: International evidence. *Review of Agricultural Economics*, 15(3):495–505, 1993.

Jaynes, Edwin T. Information theory and statistical mechanics. *Physical review*, 106(4): 620, 1957.

Judge, George G and Mittelhammer, Ron C. *An information theoretic approach to econometrics*. Cambridge University Press, 2011.

Kazukauskas, Andrius, Newman, Carol F, Thorne, Fiona S, et al. Analysing the effect of decoupling on agricultural production: Evidence from irish dairy farms using the olley and pakes approach. *Journal of International Agricultural Trade and Development*, 59 (3), 2010.

Levinsohn, James and Petrin, Amil. Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, 70(2):317–341, 2003.

Lien, Gudbrand, Kumbhakar, Subal C, and Hardaker, J Brian. Accounting for risk in productivity analysis: an application to norwegian dairy farming. *Journal of Productivity Analysis*, 47(3):247–257, 2017.

Liu, Zheng, Wang, Pengfei, and Zha, Tao. Land-price dynamics and macroeconomic fluctuations. *Econometrica*, 81(3):1147–1184, 2013.

Olley, G Steven and Pakes, Ariel. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297, 1996.

Ramey, Garey and Ramey, Valerie A. Cross-country evidence on the link between volatility and growth. *The American Economic Review*, 85(5):1138–1151, 1995.

Ruge-Murcia, Francisco J. Methods to estimate dynamic stochastic general equilibrium models. *Journal of Economic Dynamics and Control*, 31(8):2599–2636, 2007.

Shannon, CE. A mathematical theory of communication. *The Bell System Technical Journal*, 27(3):379–423, 1948.

Shumway, C Richard, Fraumeni, Barbara M, Fulginiti, Lilyan E, Samuels, Jon D, Stefanou, Spiro E, et al. Us agricultural productivity: A review of usda economic research service methods. *Applied Economic Perspectives and Policy*, 38(1):1–29, 2016.

Smets, Frank and Wouters, Rafael. Shocks and frictions in us business cycles: A bayesian dsge approach. *The American Economic Review*, 97(3):586–606, 2007.

Van Biesebroeck, Johannes. Robustness of productivity estimates*. *The Journal of Industrial Economics*, 55(3):529–569, 2007.

Zheng, Yu and Gohin, Alexandre. Estimating dynamic stochastic decision models: explore the generalized maximum entropy alternative. *working paper*, 2018.

Appendix

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, $L(\hat{\Theta}^c)$ is the 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,

$$\lambda = 2n\left(L(\hat{\Theta}) - L(\hat{\Theta}^c)\right) \tag{33}$$

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