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Supply response of corn farmers in Quebec: Analyzing the impact of prices volatility

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Abstract

This study examines the supply response and the effect of price predictability of corn in the province of Quebec. A generalized autoregressive conditional heteroskedasticity (GARCH) process is used to model output price expectations and its volatility. The empirical results show that price predictability has a positive effect on producers' decisions. Estimation of supply elasticity illustrates that expected output price is the most important risk factor for corn producers in Quebec. As expected, we found that the Farm Income Stabilization Insurance (ASRA) in Quebec leads producers to be more sensitive to effective prices than to market prices. Our results also show that application of this program causes less sensitivity to input prices than to output prices. Reducing producers' risk aversion is another implication of this program.

Cette étude examine la fonction de réponse de l'offre du maïs ainsi que l'effet de la prévisibilité de son prix dans la province de Québec. Une procédure hétéroscédasticité conditionnelle autorégressive généralisée (GARCH) est utilisé afin de modéliser les anticipations de prix d'output et sa volatilité. Les résultats empiriques montrent que la prévisibilité des prix a un effet positif sur la décision du producteur. En outre l'estimation de l'élasticité de l'offre révèle que le prix anticipé d'output est le facteur le plus important du risque pour le producteur de maïs au Québec. Comme prévu, nous avons constaté que l'assurance-stabilisation des revenus agricoles (ASRA) au Québec fait au sort que le producteur soit plus sensible aux prix effectifs qu'au prix du marché. De plus nos résultats montrent que l'application de ce programme entraîne une moindre sensibilité aux prix des intrants par rapport aux prix d'output. La diminution de l'aversion au risque de producteur est une autre conséquence de l'application de ce programme.

***Keywords**: Income insurance, price volatility, GARCH, corn supply, effective price, market price*

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INTRODUCTION

Many types of risks affect agricultural activities; they include the risk of production (including climate risk, production yield risk, and disease), the risk associated with a possible change in government policies, the risk associated with fluctuations in the exchange rate, price risk and the risk of competition in international markets (Antón, Kimura and Martini, 2011). These risk increase uncertainty for agricultural producers and affect their behavior because they make it more difficult to estimate income, cost, and agricultural profit.

Agricultural prices are very volatile and do not follow a particular trend (Rodríguez et al, 2010; Rezitis and Stavropoulos, 2010; European Commission, 2001). Given the lag between the production decision and marketing, farmers make decisions based on their expectations about prices. Therefore, price volatility leads to income fluctuations and affects farmers' welfare. Several empirical studies have focused on analyzing the effect of price volatility on production.[1] Ryan (1977) introduced a simple linear model in which price risk variables were initially constructed from the variance and covariance of pinto bean and sugar beet prices during the three preceding years. The fixed weight lag scheme proposed by Fisher is used to weight these variance terms. Holt and Aradhyula (1990), Holt (1993), Rezits and Stavropoulos (2008), and Rezits and Stavropoulos (2010) have modeled price volatilities using a GARCH model. Holt (1993) used a rational price expectation model while the others suppose that prices follow an autoregressive form. Mbaga and Coyle (2003) used the Autoregressive Distributed Lag model (ADL) to analyze the reaction of beef production to price risk. They modeled price

[1] Dalal and Alghalith (2009) and Bobtcheff and Villeneuvey (2010) theoretically analyzed the impact of two sources of uncertainty, namely uncertainty on output price and on input price. For these authors, increasing the price risks (inputs and outputs) should reduce production.

expectations and price volatility by the naive expectations model and squared errors of prediction respectively.

However, these studies assume that price volatility is a source of risk that reduces supply, but this variable cannot be presented as a measure of risk in all conditions. For example, in the presence of a constant rate of inflation, price volatility may increase. The authors argue that this increase in volatility should lead to lower production. However, in this case, the magnitude of volatility cannot affect the producer's decision. In other words, in this situation, the producer is able to predict prices and therefore does not envision any risk. Therefore, the incorporation of the price variance as a variable explaining the source of the risk is not relevant.

The objective of our study is to analyze the impact of price volatility and price prediction on corn production in the province of Quebec. This study focuses on price risk because of the high volatility of agricultural input and output prices (Huchet-Bourdon, 2012; FAO, 2011). We assume that prices follow an autoregressive process, and a generalized autoregressive conditional heteroskedasticity (GARCH) process is adapted to model the price volatility. This technique is appropriate when modeling agricultural price volatilities because it allows unconditional variance to vary over time. In Quebec's agricultural sector, an important consideration is the existence of the Farm Income Stabilization Insurance Program (*Assurance Stabilisation du Revenue Agricole*, ASRA)[2]. Under this program, the government compensates producers when the market price is less than the production cost. Consequently, ASRA reduces losses associated with price risk and therefore generates different supply responses to positive and negative shocks. This fact leads us to model price volatilities by the Asymmetric GARCH

[2] The sectors supported by ASRA, which reached their peak in 2002, comprise: fattened calves, steers, grain-fed calves, piglets, pigs, lambs, oats, wheat, corn, potatoes, milk calves, canola, barley, soybeans and apples.

model, which allows us to capture the asymmetric effects of price shocks generated by ASRA. Given that ASRA guarantees Quebec agricultural producers their production cost, the market price is different from the price received by Quebec producers. This program may thus change supply response to prices. Consequently we expect producers to be more sensitive to effective prices than to market prices. In addition, compensation of production costs by ASRA may reduce producers' risk aversion.

The rest of the paper is structured as follows. The second section presents the econometric model of corn supply and describes the data used. The third section explains the empirical results, and the final section presents the implications and conclusions of the study.

METHODOLOGICAL APPROACH AND DATA

Supply function

Following Rude and Surry (2013), we assume that producers have a constant absolute risk aversion, and that the price distribution is normal. Under these conditions the objective function of the producer is written as follows:

$$(0) \qquad MAX: P^e S \quad - C(\mathrm{S}) - \frac{\lambda}{2}\, s^2\, \mathrm{h}^{\mathrm{e}}$$

Where P^e is price expectations, h^e is price variance, S is corn supply, λ is the absolute risk aversion parameter and $\mathrm{C}(S)$ is the cost function.

Profit maximization by the producer allows us to derive the following supply function:

$$(0) \qquad S_t = \gamma_0 + \gamma_1 PC^e{}_t + \gamma_{21} PF^e{}_t + \gamma_3\, h^{\mathrm{e}}_{Ct} + \gamma_{41}\, h^{\mathrm{e}}_{Ft} + \gamma_5 \mathrm{D_t} *\ h^{\mathrm{e}}_{Ct} + +\gamma_6 \mathrm{G_t} + \gamma_7 \mathrm{T_t} +\ \varepsilon_{1t}$$

Where $PC^e{}_t$ is the expected price of corn (as output), $PF^e{}_t$ the expected price of fertilizer[3] (as input), h^{e}_{Ct} the effective volatility of corn prices, h^{e}_{Ft} the fertilizer price volatility and ε_{1t} the error term. The variable D_t is set to 1 when the difference between the absolute value of price growth between two consecutive periods is negligible.[4] This variable distinguishes the price volatility in the case of predictability and unpredictability of prices. As mentioned, if the producer is able to predict prices, it does not foresee any risk and therefore the incorporation of volatility as a source of risk is no longer relevant. To compare the importance of effective volatility of output and volatility of predictable prices, we add a variable defined by interaction between volatility (h_t) and predictability of prices (D_t). We anticipate that the coefficient of this variable is lower than those of effective volatility. We assume that, in the long run, supply adjusts to its desired level (Nerlove, 1956) and we incorporate lagged dependent variables ($\sum_i S_{t-i}$) in the model.[5] To capture the effect of technological progress, we incorporate a trend variable (T_t). The dummy variable (G_t) is introduced to capture the effect of structural changes. These structural changes generated by the oil price increase after 2006, engender the rise in

[3] Seeds and fertilizer are two principal inputs in the production of corn. The autocorrelation between the residuals of the seed price equation led us to remove this input from the model.

[4] Computing the difference in price growth rates, in which we suppose the economic situation is predictable, is a hypothesis based on empirical data. This rate corresponds to periods, including at least two years, in which the difference in growth rate is minimal. This rate is 6% for corn prices.

[5] Production lags imposed on the model are determined by the VARSOC method. This method uses information criteria such as the Hannan-Quinn criterion (HQIC), the Schwarz's Bayesian information criterion (SBIC), the Akaike information criterion (AIC), the final prediction error (FPE) and the sequential likelihood ratio (LR) to determine the optimum lag of the model. However, our tests do not suggest any lags.

agricultural prices. (Baumeister and Kilian, 2014). The study of Avalos (2014) confirms the changes in dynamic of corn price after 2006 which is related to oil price variation.

Price expectation

Following Rezitis and Stavropoulos (2010), we assume that prices follow the autoregressive process (AR):

(0)
$$P_t = \beta(L)P_t + \mathcal{E}_{2t}$$

$$\mathcal{E}_{2t}|\Omega_{t-1} \sim N(0, h_t)$$

where β(L) is a polynomial lag operator, P_t is current price, $\mathcal{E}_{2t}$ is an error term, $\Omega_{t-1}$is the information set of all past states available in period t-1 and h_t is the conditional variance of $\mathcal{E}_t$. The Bayes Information Criterion (BIC) was used to determine the appropriate order of corn market and effective price equations while using the general to specific method of selecting the appropriate order of the fertilizer price equation.[6] Consequently, price equations are as follows:

(0)
$$PC_t = b_0 + \sum_{i=1}^{3} b_i PC_{t-i} + c_1 G_t + c_2 T_t\ \mathcal{E}_{2t}$$

(0)
$$PCEF_t = b'_0 + b'_1 PCEF_{t-1} + c'_1 G_t + c'_2 T_t + \mathcal{E}_{2t}$$

[6] Using BIC to determine the order of the fertilizer price equation has caused autocorrelation between the residual of the input price equation.

(0) $$PF_t = b_0'' + b_1''PF_{t-1} + b_2''PF_{t-8} + b_3''PF_{t-9} + +c_1''G_t + c_2''T_t + \varepsilon_{3t}$$

Where $\mathrm{PC_t}$, $\mathrm{PCEF_t}$and $\mathrm{PF_t}$ represent corn market price, corn effective price and fertilizer price respectively. $\mathrm{G_t}$ and $\mathrm{T_t}$ capture respectively effect of structural changes and a trend on prices.

Variance modeling

Unlike the other time series models, generalized autoregressive conditional heteroskedasticity models (GARCH) allow the conditional variance to vary over time, which is very relevant given the dynamics of agricultural prices. This characteristic of these models led us to use GARCH models to model price volatilities.

The ASRA program in Quebec generates asymmetric effects of shocks on supply. Thus, an asymmetric GARCH model is used. In this model, the past values of the error terms ($\sum_{i=1}^{q} \gamma_i \varepsilon_{2(t-i)}$) are added to the price variance equation. These terms allow positive and negative shocks to have different effects on volatility. In this model the volatility is defined as:

(0) $$VAR(\varepsilon_t]\varepsilon_u, u < t) = h_t^e = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{2(t-i)}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{i=1}^{q} \gamma_i \varepsilon_{2(t-i)}$$

According to equation(0), the conditional variance (h_t^e) is defined as a linear function of q lagged squared residuals and p lagged past conditional variances. The following restrictions are imposed to ensure that the conditional variance is strictly positive:

$$\alpha_0 > 0, \alpha_i > 0 \; et \; \beta_i > 0$$

The stationarity of variance is guaranteed by $\sum_i \alpha_i + \sum_i \beta_i < 1$ (Bollerslev, 1986). Further, if the prices do not show the GARCH effect, we use simple moving variance to incorporate price volatility in the model.

The residual test of price equations reveals the presence of serial auto-correlations in the squared residuals of the market and effective price of corn. This is one of the implications of the GARCH effect in the model, which led us to run the Lagrange Multiplier test to ensure the presence of heteroskedasticity in these equations. The results of this test, applied to equations (0) and (0), indicate that the hypothesis of no GARCH effect can be rejected at the 1% level of significance (Table A1 and Table A2). Consequently we have modeled the volatility of the market and effective price of corn by a GARCH model. The order of the GARCH model is determined by a visual examination of the correlogram of the squared residual of the price equation (Figures A1 andA2) and the results of the Ljung-Box (1976) Q test (Bollerslev, 1988).[7] Consequently, to model market price volatility, equation (0) can be written as follows:

(0) $$h^m{}_{ct} = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \theta_1 \mathcal{E}_{t-1}$$

Where $h^m{}_{ct}$ is the volatility of the corn market price.

Nevertheless, the application of an asymmetric GARCH model to effective prices engenders a non-significant effect of risk variables ($PCEF^e{}_t$,$PF^e{}_t$,$h^e{}_{ct}$,$h^e{}_{ft}$) on production. In other words, the results of application of an asymmetric GARCH model imply the risk is not an

[7] Visual examination of the correlogram of the squared residual of the price equation (figures A1 and A2) and the results of the Ljung-Box Q test (1976) propose ARCH(1) and GARCH(2,2) model for modeling respectively market price and effective price variance.

important factor for the corn producer in Quebec, Which is not consistent with the prior studies. The empirical studies applied to agricultural sector support significant effect of factors of risk on production (Ryan,1977; Holt and Aradhyula,1990; Holt,1993; Mbaga and Coyle,2003; Rezits and Stavropoulos,2008; Rezits and Stavropoulos,2010; and Rude and Surry,2013). For this reason we use GARCH (2, 2) model to model effective price volatility:

(0) $$h^f{}_{c,t} = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \alpha_2 \varepsilon^2{}_{t-2} + \beta_1 h^f_{c,t-1} + \beta_2 h^f_{c,t-2}$$

Where $h^f{}_{c,t}$ is the volatility of the effective price of corn.

Further, the residual test of the fertilizer price equation and the Lagrange Multiplier test (Table A3) confirm the lack of a GARCH effect in the fertilizer price equation. For this reason we have incorporated simple moving variance of fertilizer price in the model.

Estimation approach

Variables $PC^e{}_t$,$PF^e{}_t$, $h^e{}_{ct}$ and $h^e{}_{ft}$ generated by the GARCH model can be used to estimate equation (0). Pagan (1984) concluded that using variables generated by stochastic models to estimate a structural equation could cause biased estimates of the parameters' standard deviations. One of the methods used to avoid this problem is the Full Information Maximum Likelihood (FIML) method. [8] This method simultaneously estimates the supply function, the price equation and the GARCH process parameters. Considering equations (0) and (0), the joint distribution of $\mathcal{E}_{1t}$ and $\mathcal{E}_{2t}$ is written as follows:

[8] Whereas Rude and Surry (2013) used a state-space model to estimate the parameters of pork supply model, we could not adopt the same approach because application of this model impairs the performance of our model.

(0) $$\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \sim N\left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & h_t \end{bmatrix}\right]$$

Where $\begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & h_t \end{bmatrix} = \prod_t$ represents the variance-covariance matrix. The log-likelihood function of the above system is given as follows:

(0) $$l_T(\Theta) = 0.5 \sum_{t=1}^{T} l_t(\Theta)$$

(0) $$l_t(\Theta) = -log\left|\prod_t\right| - \varepsilon'_t {\prod_t}^{-1} \varepsilon_t$$

Data

Our analyses cover the period of 1985 to 2013, and the supply model is based on annual data. Data on harvested area of corn (corn supply) are obtained from Statistics Canada,[9] and are expressed in Hectares.

Corn market prices[10] are monthly data and are obtained from Statistics Canada.[11] The effective prices are built by adding compensation under the Farm Income Stabilization Insurance program (ASRA) to market prices. Compensation values are from the *La Financière agricole* (provincial government agency) website. The monthly data are used to form expectations and

[9] Table 001-0010

[10] Commodity prices are collected at point of first transaction, where fees deducted before a producer is paid are excluded (for example, storage, transportation and administration costs), but any bonuses and premiums that can be attributed to specific commodities are included. Commodity-specific program payments are not included in the price.

[11] Table 002-0043

conditional variance of output price. Then we incorporated the annual weighted[12] average in our model.

Fertilizer prices are from Statistics Canada[13] and are quarterly data. Quarterly data are used to construct expectations of input price, and the annual simple average of these expectations was incorporated in the model. Following Rezitis and Stavropoulos (2010), all prices are deflated by the consumer price index[14] (2002 = 100). Table 1 presents some statistics of the data used in the analyses.

<<< Table 1 about here >>>

RESULTS

Table 2 provides the results of unit root tests. Augmented Dickney Fuller (ADF) and Philips-Perron (PP) tests were conducted. The Durbin-Watson statistic was used to determine the optimal lag of variables.

<<< Table 2 about here >>>

The corn effective price variable remains stationary in all cases. Corn harvested area and fertilizer price variables are non-stationary, while the results regarding corn market price are mixed.

[12] The weights are the share of monthly delivery of corn in annual delivery.

[13] The Farm Input Price Index (FIPI) measures the change through time in the prices received for agricultural commodities at the first transaction point. Much of the price information used in compiling the index is obtained from a monthly survey of farm respondents throughout Canada, tables 3280001 and 3280015.

[14] Price deflation by the industrial products price index (IPPI), as estimated by Rude and Surry (2013), generates the autocorrelation in the squared residuals of GARCH.

Supply response to market price

This section analyses the reaction of corn supply response to market prices. Incorporation of G_t and $T_t$in price equations engenders the poor performance of the final model. Consequently we have incorporated these variables in supply equation to capture the effect of structural changes and the trend on production.

The estimation results of the output price equation are presented in Table 3.[15]

<<< Table 3 about here >>>

According to the results, the coefficients of autoregressive terms of the price (b_1 and b_2) are significant at the 1% level. The coefficient of the conditional variance expressed by α_1 is significant, which indicates time-varying volatility. In addition, because $\alpha_1 > 1$, even if the variance is not conditional on past information (ε_{t-i}), but the return process to equilibrium and volatility process is stationary (Gourieroux, 2012). The coefficient of asymmetry factor of shocks (θ_1) is significant at 1%, which confirms the presence of an asymmetric effect of shocks on volatility. The positive sign of θ_1 indicates that a positive shock in price causes more volatility than a negative shock of the same magnitude. This fact is justified by the existence of the ASRA program. Finally the Ljung-Box Q statistic test was applied to the residuals (ε_{2t}) and the squared residuals (${\varepsilon^2}_{2t}$) of the market price equation to analyze the performance of the model. The results of this test on ε_{2t} and ${\varepsilon^2}_{2t}$ support the non-rejection of the hypothesis that the residuals of the market price equation are white noise, and the hypothesis for the absence

[15] The estimations of coefficients of equation (0) by the SAARCH model point to the absence of the significance of coefficient of the third lags (b_3). This led us to eliminate this variable from the estimation procedure. However, the Lagrange multiplier test confirms the presence of the ARCH effect in the market price equation (Table A4).

of the ARCH effect is rejected. These results are one of the implications of the GARCH model presented by equations (0)[16] and (0) (Bollerslev 1987). The application of an appropriate order of GARCH removes the correlation of squared residuals (Giannopoulos, (1995)). The Ljung-Box test applied to residuals and squared residuals of the SAARCH model indicates the absence of correlation between the residuals and squared residuals.

Table 4 presents the estimated parameters of fertilizer price (equation(0)).

<<< Table 4 about here >>>

According to the results of Table 4, the coefficients of autoregressive terms of fertilizer (b''_1, b''_2 and b''_3) are significant at the 1% level.

The Ljung-Box Q statistic test, applied to the residuals (ε_{3t}) and the squared residuals ($\varepsilon^2{}_{3t}$) of the fertilizer price equation, affirms the absence of correlation between the residuals and the squared residuals of the input price equation.

Table 5 presents the results of the estimation of the structural model constructed by equations (0), (0) and(0). The coefficient of determination (89%) and the test of likelihood ratio (LR) (chi2 (28) = 21.58) confirm the good specification of the model. The Ljung-Box Q test statistic, finds no correlation between the squared residuals of the model (Table 5). The same result is found for the residuals.[17]

<<< Table 5 about here >>>

[16] Coefficient b_3 (See equation (6)) has been eliminated from this equation.

[17] The autocorrelation between the residuals of the model was examined by several tests, namely Ljung-Box (Table 5), Harvey, and Guilkey (Table A5). There is concordance between the results of these tests regarding the absence of residual autocorrelation of the model.

The coefficient of the expected price of corn (γ_1) has a positive sign, as expected. However, the coefficient of the expected price of fertilizer (γ_{21}) is negative, implying a decrease in corn supply following an increase in the input price, which is also expected. The negative sign of the coefficients of corn price volatility and fertilizer price volatility (respectively γ_3 and γ_4) implies that the supply responds negatively to an increase in volatility. The coefficient γ_5 shows the corn supply response to the volatility of output prices when price predictions are possible. The negative sign of this coefficient implies that volatility is still a risk factor for the producer even when the price evolution is predictable. However, the comparison between the value of the probability (p-value) of the coefficient of effective volatility (γ_3) and that of the coefficient of volatility of predictable price (γ_5) indicates that the effect of price volatility on supply is less important if prices are predicted.[18] This scenario can be justified by the effect of price predictability on risk. The more is the price predictable, the less the bias between the anticipated price and realized price is important. This results in a lower risk for the producer.

The coefficients γ_6 and γ_7 capture the effects of structural changes and the corn supply trend respectively.

As presented in Table 5, among the variables that determine price risk (${PC^e}_t$,${PF^e}_t$, ${h^{me}}_{ct}$ and ${h^e}_{ft}$) only the coefficient of variance of fertilizer prices (γ_4) and the coefficient of the price of corn (γ_1) are significant at the 5% level.

[18] Effective volatility is significant at the 16% level, and volatility of predictable prices is significant at the 80% level.

Estimation of supply elasticity[19] relative to the expected price of corn (0.25), to the expected price of fertilizer (-0,015), to output price volatility (-0.04) and to input price volatility (-0.07) implies that corn producers are more sensitive to the output price than to the input price. Several reasons may explain this result. First, the gap between the production decision and purchase of inputs is shorter than that between production decisions and marketing (Nijs, 2014). Further, input prices are positively correlated to the price of outputs. In other words, the increase in input prices causes a rise in output prices. Therefore, production is less affected by input price variations than by that of output price.

Supply response to effective price

This section analyzes the reaction of the corn supply function to the expectations and variance of the effective price and input price. To incorporation of a characteristic variable of structural change (G_t) in the price equations excludes our model to capture direct effect of this variable on corn supply. Table 6 presents the estimated parameters of corn effective price (equations (0) and(0)).

<<< Table 6 about here >>>

According to the results, the coefficient of the autoregressive term of the price (b_1') is significant at the 1% level. The coefficients of conditional variance (α_2 and β_2) are also significant at the 10% level, which implies varying volatility over time. In addition, these coefficients sum less than unity ($\sum_{i=1}^{2} \alpha_i + \beta_i$ = 0.92), implying persistent volatility.

<<< Table 7 about here >>>

[19] We used estimated parameters of the model and the simple average of variables to estimate elasticity.

The results in Table 7 demonstrate that the coefficients of autoregressive terms of fertilizer (b_1'', b_2'' and b_3'') are significant at the 1% level.

A Maximum Likelihood method was used to estimate the equations of the structural model constructed by equations (0),(0),(0) and (0). The coefficient of determination (76%) and the result of the test of likelihood ratio (LR) (chi2 (57) = 61.18) illustrate the good specification of the model.

The results of application of the Ljung-Box Q statistic test to the residuals and squared residuals of the effective price equation (generated by GARCH), to that of the fertilizer price equation and to supply equation[20] confirms the absence of correlation in these equations. Table 8 presents the estimated parameters of the supply equation by the FIML method.

<<< Table 8 about here >>>

The coefficient of the anticipated price of corn (γ_1), expected price of fertilizer (γ_{21}) corn price volatility and fertilizer price volatility (respectively γ_3 and γ_4) have the expected signs. These results are consistent with prior studies (such as Holt and Aradhyula (1990), Holt (1993), Rezits and Stavropoulos (2008), Rezits and Stavropoulos (2010), and Rude and Surry (2013)).

Moreover, the negative value of coefficient γ_5 (less significant compared to γ_3) implies that volatility is still a risk factor for producers even if price evolution is predictable. However, it is less important than effective volatility for corn producers in Quebec.

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[20] The autocorrelation between the residuals of the model was examined by several tests, namely Ljung-Box (Table 8), Harvey, and Guilkey (Table A6). There is concordance between the results of these tests regarding the absence of residual autocorrelation of the model.

The coefficient γ_7 captures the effect of a trend on corn supply. The results illustrate the significant effect of expected output price, the variance of input price and the expected fertilizer price on corn supply. As shown in Table 8, the estimated coefficient of the price of the input is less significant than those of the output price. As mentioned, because the price of the input is included in the production cost, this result is justified by the existence of the ASRA program, which compensates producers for the difference between the production cost and the market price.

Estimation of corn supply elasticity[21] relative to expectations of corn effective price (0.65), to expectations of fertilizers price (-0.13), to corn price volatility (-0.04) and to fertilizer price volatility (-0.07) implies that the corn supply is more sensitive to output prices and input price than to volatilities. These estimates also imply that corn supply is more sensitive to the expected price of outputs than to the expected price of inputs. This is because input price, included in production cost, is compensated by ASRA. Consequently the producer envisions less risk relative to input than relative to output.

Relative marginal risk premium index

Finally, we analyzed the risk-averse behavior of corn producers in Quebec by calculating the Relative marginal Risk Premium (RRP). This index is determined by the negative of the ratio of the variance and price elasticity of supply (Holt and Moschini, 1992):

[21] We used estimated parameters of the model and the simple average of variables to estimate elasticity.

(0) $$RRP_t = -\gamma_{ab} \cdot \frac{h_t^e}{P_t^e}$$

Where $\gamma_{ab} = \left\{\frac{\gamma_3}{\gamma_1}, -\frac{\gamma_{41}}{\gamma_{21}}\right\}$; $h_t^e = h_{ct}^e$ If $\gamma_{ab} = \frac{\gamma_3}{\gamma_1}$; $h_t^e = h_{ft}^e$ If $\gamma_{ab} = -\frac{\gamma_{41}}{\gamma_{21}}$

The results indicated in Table 9 reveals positive and significantly different from zero (Appendix A7) value of this index in both models, implying risk-averse behavior of corn producers rather than risk-neutral behavior (Rezitis and Stavropoulos, 2010). In addition, the value of RRP_t shows that the producer is more risk averse relative to input than to output. This can be explained by the application of ASRA in Quebec, because corn as an output is covered by ASRA, whereas the input is not guaranteed.

Moreover, the comparison between the values of this index in the two models shows that the index is lower in the model that includes effective prices (relative to output and input prices). This implies that, as expected, the application of ASRA decreases the risk aversion of corn producers in Quebec relative to output price risk by 50%. The decrease in risk aversion coefficient is 89% when considering input price risk.

<<< Table 9 about here >>>

CONCLUSION

The impact of price fluctuations on the supply of agricultural products has been considered one of the major issues in the literature. Many theoretical and empirical studies have analyzed the effects of price risk on the supply of different agricultural products. They mainly defined price fluctuation as a source of risk that can reduce production. However, when prices are predictable, their fluctuations cannot be considered as a source of risk. In this paper we demonstrated that the more predictable the economic situation, the less price volatility affects production. In other terms the predictable economic situation decreases negative effect of risk on production and in other words reduces risk aversion of producer. Consequently this increase in production due to predictability of economic situation can impose more compensation cost (paid by ASRA) to governments.

Given that the ASRA program affects the agricultural supply response to prices, we studied the supply response of corn to market prices, along with the effective prices defined as market prices plus ASRA compensation. An asymmetric GARCH procedure and a GARCH model are used to model the market price expectations and market price volatility and effective price and its volatility respectively. However, the absence of the GARCH effect in input prices led us to model input price volatility by a simple moving variance. The model parameters were estimated by the Full Information Maximum Likelihood (FIML) method.

The results show that the anticipated output prices (the market price or effective price) and input price expectations have respectively positive and negative effects on the corn supply. Further, the results indicate that volatility of the market price and of the effective price has a negative effect on production. These results are consistent with prior studies. This decrease of production affects the revenue and the welfare of producer. Further the volatile nature of agricultural prices makes the farmers vulnerable to price volatilities. That is why the governments deduct the protective programmes such as ASRA to support agricultural producers against price risk.

In addition, we show that positive shocks cause more volatility than negative shocks of the same size. This result can be justified by the application of the ASRA program.

The estimations of supply elasticity relative to output and input price expectations, as well to price volatilities, demonstrate that corn producers in Quebec perceive output price expectations as the most important risk factor. These estimations show that supply is more elastic to effective price and its volatility than to market price and its volatility. Further, results show that the ASRA program generates lower sensitivity of supply to input prices than to output prices, because the price of the input—as a component of production cost—is compensated by the ASRA program.

Finally the risk-averse behavior of corn producers has been analyzed by estimation of the Relative marginal Risk Premium index. Although this estimation implies risk-averse behavior of corn producers in Quebec, it affirms more risk aversion relative to input than relative to output. Moreover, the comparison between the value of this index before and after application of ASRA implies that the ASRA program decreases producers' risk aversion.

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LIST OF TABLES

Table 1. Data statistics

Variable	Data period	Mean	Minimum	Maximum	variance
PC (Corn market price explained by dollars per ton)	Monthly data	1.7	0.99	3.03	0.17
PF (fertilizer price explained by dollars per ton)	Quarterly data	0.38	0.23	0.77	0.02
S (Corn supply explained by hectare)	Annual data	340350	225000	449000	4 669 933 016
PCEF(Corn effective price explained by dollars per ton)	Monthly data	2.15	1.35	3.91	0.26

Table 2. Results of unit roots tests

Variable	Model without intercept and without trend		Model with intercept and without trend		Model with intercept and trend	
Variable	augemented Dickney Fuller (ADF)	Philips-Perron (PP)	augemented Dickney Fuller (ADF)	Philips-Perron (PP)	augemented Dickney Fuller (ADF)	Philips-Perron (PP)
PC (3 lags)	-0.45	-1.242	-2.138	-3.779[c]	-1.47	-3.383[a]
PF (2 lags)	-0.142	-0.607	-1.787	-2.170	-0.87	-1.096
S(3 lags)	0.884	1. 155	-1.487	-1.503	-1.629	-2.192
PCEF (1 lag)	-1.695[a]	-1.791[a]	-4.259[c]	-3.958[c]	-4.224[b]	-4.36[b]

*a significant at 10% * b significant at 5% * c significant at 1%.

Table 3. Results of corn market price equation

Parameter	Variable	Coefficient
Conditional mean		
b_0	1	0.054(0.000)
b_1	PMG_{t-1}	1.27 (0.000)
b_2	PMG_{t-2}	-0.3(0.000)
c_1	G_t	-
c_2	T_t	-
Conditional Variance		
α_0	1	0. 004 (0.00)
α_1	$\varepsilon^2_{2(t-1)}$	1.44 (0.000)
θ_1	$\varepsilon_{2(t-1)}$	0.06 (0.006)
Test of market price equation's residual generated by the autoregressive (AR) model (ε_{2t})		
Q(6)		7.2 (0.3)
Q(12)		13.8 (0.31)
Q(18)		15.6 (0.62)
Q(24)		16.6 (0.86)
Q^2 (6)		14.2 (0.03)
Q^2 (12)		51.6 (0.000)
Q^2 (18)		58.6 (0.000)
Q^2 (24)		59 (0.000)
Test of market price equation's residual generated by the SAARCH model ($\varepsilon_{2t} * h_t^{-0.5}$)		
Q(6)		9.09 (0.17)
Q(12)		14.5 (0.27)
Q(18)		17.7 (0.47)
Q(24)		22.3 (0.56)
Q^2 (6)		1.12 (0.98)
Q^2 (12)		11.7 (0.47)
Q^2 (18)		13.4 (0.77)
Q^2 (24)		19.8 (0.71)

p-values are in parentheses

Table 4. Results of fertilizer price equation

Parameter	Variable	Coefficient
	Mean	
b''_0	1	0.008(0.49)
b''_1	PF_{t-1}	0.99 (0.000)
b''_2	PF_{t-8}	-0.48 (0.000)
b''_3	PF_{t-9}	0.48(0.000)
c''_1	G_t	-
c''_2	T_t	-
	Residual test of fertilizer price equation (ε_{3t})	
Q(6)		3.49 (0.74)
Q(12)		7.97 (0.78)
Q(18)		8.82 (0.96)
Q(24)		10.35 (0.99)
Q^2 (6)		2.2 (0.90)
Q^2 (12)		6.08 (0.91)
Q^2 (18)		7.34 (0.99)
Q^2 (24)		7.61 (0.99)

p-values are in parentheses

Table 5. Results of corn supply response versus market price

Parameter	Variable	Coefficient
γ_0	1	21800000 (0.000)
γ_1	PC_t^e	52335.8 (0.09)
γ_{21}	PF_t^e	-14606.3 (0.84)
γ_3	$h^{Me}{}_{ct}$	-364687.7 (0.16)
γ_4	$h^{e}{}_{Ft}$	-5906817 (0.000)
γ_5	$D{*}h^{Me}{}_{pct}$	-161207.7 (0.80)
γ_6	G_t	-37853.9 (0.04)
γ_7	T_t	12567.5 (0.000)
Residual test of supply equation (ε_{1t})		
Q(6)		3.95 (0. 68)
Q(12)		14.3 (0. 28)
Q(18)		17.47(0. 49)
Q(24)		19.98(0. 70)
Q^2 (6)		0.88(0. 99)
Q^2 (12)		3.54(0. 99)
Q^2 (18)		8.69(0. 97)
Q^2 (24)		10.49(0. 99)

p-values are in parentheses

Table 6. Results of corn effective price equation

Parameter	Variable	Coefficient
	Conditional mean	
b'_0	1	0.001(0.000)
b'_1	$PCEF_{t-1}$	0.9 (0.000)
c'_1	G_t	-0.04(0.05)
c'_2	T_t	-2.53e-06(0.47)
	Conditional Variance	
α_0	1	0. 004 (0.001)
β_1	$h_{(t-1)}$	0.07 (0.19)
$\beta 2$	$h_{(t-2)}$	0.7(0.000)
α_1	$\varepsilon^2_{2(t-1)}$	0.2 (0.000)
α_2	$\varepsilon^2_{2(t-2)}$	-0.05 (0.06)

Residual test of price equation generated by autoregressive model (AR) (ε_{2t})

Q(6)	5.57 (0.47)
Q(12)	15.860 (0.20)
Q(18)	20.14 (0.32)
Q(24)	31.13 (0.15)
Q^2 (6)	8.94 (0.18)
Q^2 (12)	30.64 (0.002)
Q^2 (18)	37.90 (0.004)
Q^2 (24)	48.82 (0.002)

Residual test of price equation generated by GARCH model ($\varepsilon_{2t} * h_t^{-0.5}$)

Q(6)	6.14 (0.41)
Q(12)	14.21 (0.29)
Q(18)	17.77 (0.47)
Q(24)	30.85 (0.16)
Q^2 (6)	1.64 (0.95)
Q^2 (12)	11.67 (0.47)
Q^2 (18)	13.92 (0.73)
Q^2 (24)	28.31 (0.25)

p-values are in parentheses

Table 7. Results of fertilizer price equation		
Parameter	Variable	Coefficient
	Mean	
b''_0	1	0.05(0.01)
b''_1	PF_{t-1}	0.88 (0.000)
b''_2	PF_{t-8}	-0.49(0.000)
b''_3	PF_{t-9}	0.42(0.000)
c''_1	G_t	0.04(0.013)
c''_2	T_t	0.0002(0.25)
Residual test of fertilizer price equation (ε_{2t})		
Q(6)		2.95 (0.81)
Q(12)		9.81 (0.63)
Q(18)		10.68 (0.91)
Q(24)		13.55 (0.95)
Q^2 (6)		1.22 (0.98)
Q^2 (12)		6.56 (0.88)
Q^2 (18)		7.94 (0.98)
Q^2 (24)		8.22 (0.99)

p-values are in parentheses

Table 8. Results of corn supply response versus effective price

Parameter	Variable	Coefficient
γ_0	1	-28900000 (0.000)
γ_1	$PMGEF_t^e$	104733.9 (0.06)
γ_{21}	PE_t^e	-31017.89 (0.13)
γ_3	$H^{Fe}{}_{ct}$	-682994.9 (0.34)
γ_4	$H^{e}{}_{Ft}$	-5591501 (0.000)
γ_5	$D^*h^{Fe}{}_{ct}$	-580071.6 (0. 64)
γ_6	G_t	-
γ_7	T_t	14556.07 (0.000)
Tests of residual of supply equation (ε_{1t})		
Q(6)		5.94 (0.42)
Q(12)		6.36(0.90)
Q(18)		19(0.39)
Q(24)		28.2(0.25)
Q^2 (6)		7.45(0.28)
Q^2 (12)		9.5(0.65)
Q^2 (18)		14.58(0.69)
Q^2 (24)		18.26(0.79)

p-values are in parentheses

Table 9. Estimation of Relative marginal Risk Premium index (RRP) of Quebec corn producers		
	Mean RRP in the model including the market price	Mean RRP in the model including the effective price
Output	0.12	0.06
Input	3.39	0.37

APPENDIX

Table A1. Lagrange Multiplier Test (ARCHLM) for corn market prices (AR(3))

Chi2	Degrees of freedom	Prob>chi2
38.512	1	0.000

Null hypothesis: No ARCH effect   Alternative hypothesis: ARCH(p) disturbance

Table A2. Lagrange Multiplier Test (ARCHLM) for corn effective prices (AR(3))

Chi2	Degrees of freedom	Prob>chi2
20.782	10	0.02

Null hypothesis: No ARCH effect   Alternative hypothesis: ARCH(p) disturbance

Table A3. Lagrange Multiplier Test (ARCHLM) for fertilizer price

Chi2	Degrees of freedom	Prob>chi2
	Excluding G_t and T_t	
3.523	8	0.90
	Including G_t and T_t	
3.813	8	0.87

Null hypothesis: No ARCH effect   Alternative hypothesis: ARCH(p) disturbance

Table A4. Lagrange Multiplier Test (ARCHLM) for corn market prices (AR(2))

Chi2	Degrees of freedom	Prob>chi2
51.738	1	0.000

Null hypothesis: No ARCH effect   Alternative hypothesis: ARCH(p) disturbance

Table A5. Harvey and Guilkey autocorrelation test applied to corn supply function versus market price

	Harvey LM test	Rho	Pvalue>chi2	Durbin-Watson test
Single Equation Autocorrelation Tests				
	Harvey LM test	Rho	Pvalue>chi2	Durbin-Watson test
Supply equation	1.2954	0.048	0.25	1.55
Corn market price equation	0.2642	0.0098	0.61	1.63
Corn volatility equation	0.3026	0.0112	0.58	1.65
Rho: Correlation coefficient				
Overall SEM Autocorrelation Tests				
	Harvey LM test		Pvalue>chi2	
Harvey LM test	1.8622		0.61	
Guilkey LM test	7.3919		0.60	
Null hypothesis: No Overall SEM Autocorrelation				

Table A6. Harvey and Guilkey autocorrelation test applied to corn supply function versus effective price

	Harvey LM test	Rho	Pvalue>chi2	Durbin-Watson test
Single Equation Autocorrelation Tests				
	Harvey LM test	Rho	Pvalue>chi2	Durbin-Watson test
Supply equation	1.95	0.07	0.16	1.17
Corn market price equation	2.04	0.07	0.15	1.27
Corn volatility equation	1.93	0.07	0.16	1.43
Fertilizer price equation	1.71	0.06	0.18	1.15
Rho: correlation coefficient				
Overall SEM Autocorrelation Tests				
	Harvey LM test		Pvalue>chi2	
Harvey LM test	8.2		0.14	
Guilkey LM test	21.2		0.67	

Null hypothesis: No Overall SEM Autocorrelation

Table A7. Significance test of the relative marginal risk premium index (in the model including the market price)

	Number of observations	mean	standard error	standard deviation	T statistic	Degrees of freedom
Model including the market price						
Output prices	29	0.12	0.03	0.13	4.8	28
Input prices	27	3.39	0.87	4.55	3.8	26
Model including the effective price						
Output prices	29	0.06	0.005	0.029	12.25	28
Input prices	27	0.37	0.09	0.5	3.8	26

Null hypothesis: mean=0

Alternative Hypothesis:
mean<0 Pr(T<t)=1 mean ≠0 Pr(T>t)=0.000 mean>0 Pr(T>t)=0.0000

*t statistic represents test of null hypothesis versus alternative hypothesis.

* This statistic affirms the significance of the relative marginal risk premium index.

FIGURES

Figure A1: Correlogram test of squared residual of market corn price

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	0.1267	0.1268	5.6377	0.0176		
2	0.0899	0.0517	8.4818	0.0144		
3	0.0508	0.0093	9.3943	0.0245		
4	0.0011	-0.0291	9.3948	0.0520		
5	0.0037	0.0013	9.3996	0.0941		
6	-0.0140	-0.0129	9.469	0.1489		
7	0.0050	0.0150	9.4779	0.2201		
8	0.0002	0.0036	9.4779	0.3036		
9	0.0013	0.0034	9.4785	0.3943		
10	0.2170	0.2254	26.45	0.0032		
11	0.1653	0.1251	36.33	0.0001		
12	0.1462	0.1082	44.082	0.0000		
13	0.0959	0.0460	47.426	0.0000		
14	-0.0077	-0.0352	47.448	0.0000		
15	0.0062	-0.0090	47.462	0.0000		
16	-0.0092	-0.0107	47.493	0.0001		
17	-0.0212	-0.0248	47.658	0.0001		
18	-0.0169	0.0004	47.763	0.0002		
19	-0.0131	0.0039	47.827	0.0003		
20	-0.0162	-0.0112	47.924	0.0004		
21	-0.0192	-0.0095	48.061	0.0007		
22	-0.0068	-0.0386	48.079	0.0011		
23	-0.0154	-0.0357	48.168	0.0016		
24	0.0097	0.0117	48.203	0.0024		
25	-0.0188	-0.0445	48.336	0.0034		
26	-0.0051	0.0015	48.346	0.0049		
27	0.0044	0.0232	48.353	0.0070		
28	-0.0010	0.0090	48.353	0.0098		
29	0.0186	0.0380	48.485	0.0131		
30	0.0239	0.0320	48.703	0.0168		
31	0.0425	0.0566	49.396	0.0192		
32	0.0403	0.0312	50.023	0.0222		
33	-0.0097	-0.0378	50.06	0.0288		
34	-0.0001	-0.0181	50.06	0.0373		
35	0.0027	0.0010	50.063	0.0475		
36	0.0252	0.0529	50.311	0.0570		
37	-0.0019	-0.0237	50.313	0.0709		
38	-0.0027	0.0047	50.316	0.0872		
39	-0.0094	-0.0402	50.35	0.1053		
40	-0.0075	-0.0399	50.372	0.1260		

Figure A2: Correlogram test of squared residual of effective corn price

-1 0 1 -1 0 1

LAG	AC	PAC	Q	Prob>Q	[Autocorrelation]	[Partial Autocor]
1	0.0901	0.0902	1.3875	0.2388		
2	0.0556	0.0471	1.9192	0.3830		
3	0.0326	0.0229	2.1031	0.5513		
4	-0.0276	-0.0334	2.2353	0.6926		
5	-0.1045	-0.1000	4.1489	0.5282		
6	-0.0119	0.0140	4.1738	0.6532		
7	0.0037	0.0074	4.1761	0.7593		
8	0.0432	0.0550	4.5086	0.8086		
9	0.0491	0.0334	4.9414	0.8394		
10	0.0051	-0.0181	4.9462	0.8947		
11	0.0761	0.0771	6.0001	0.8734		
12	0.0547	0.0359	6.5472	0.8860		
13	0.0772	0.0854	7.6467	0.8658		
14	-0.0877	-0.1123	9.0744	0.8263		
15	-0.0100	0.0010	9.093	0.8726		
16	0.1418	0.1525	12.872	0.6821		
17	0.0448	0.0267	13.25	0.7193		
18	0.0905	0.1011	14.81	0.6749		
19	0.0614	0.0008	15.532	0.6882		
20	0.1273	0.1230	18.661	0.5439		
21	0.0278	0.0290	18.811	0.5972		
22	-0.0124	-0.0042	18.841	0.6551		
23	0.0957	0.1437	20.644	0.6028		
24	0.0338	-0.0034	20.87	0.6464		
25	-0.0259	-0.0241	21.004	0.6924		
26	-0.0963	-0.1155	22.87	0.6403		
27	-0.0014	0.0014	22.87	0.6920		
28	-0.0104	-0.0172	22.893	0.7384		
29	0.1308	0.1490	26.408	0.6036		
30	-0.0166	-0.0174	26.465	0.6512		
31	0.0581	0.0829	27.169	0.6637		
32	0.0411	0.0224	27.523	0.6927		
33	-0.0192	-0.0139	27.602	0.7328		
34	-0.0368	0.0070	27.89	0.7607		
35	0.0299	0.0111	28.081	0.7903		
36	0.0007	-0.0484	28.081	0.8243		
37	-0.0557	-0.0438	28.757	0.8318		
38	-0.0147	0.0006	28.804	0.8591		
39	0.0057	0.0309	28.811	0.8841		
40	0.0318	0.0053	29.037	0.9003		