Induced Technological Change in Canadian Agriculture Field Crops - Canola and Wheat: 1926 - 2003

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Abstract

A tractable two-stage constant elasticity of substitution (CES) production function is applied to disaggregated western Canadian wheat and canola data for 1926-2003 to investigate the induced innovation hypothesis. Time series properties of the data are analyzed using cointegration and error correction to assess causality in differentiating between technological change and factor substitution. The results provide empirical support for the hypothesis with respect to prairie wheat and canola production.

Key words: Disaggregated data, induced innovation, stationarity, unit roots, cointegration, vector error correction model.

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1. Introduction

Canadian agriculture has been characterized by phenomenal growth since the early 1900s. Notable studies by Karagiannis and Furtan (1990, 1993), Lopez (1980), and Clark, Klein, and Kerr (2003) have tested the induced innovation hypothesis to explain the role of technological change in the development of Canadian agriculture. Some of the early work that has contributed to the understanding of induced innovation, technological change, and the diffusion of modern technologies includes Hayami and Ruttan (1971, 1985), Bingswanger (1974, 1978), Bingswanger and Ruttan (1978), Thirtle (1985a,b,c), Thirtle and Ruttan (1987), and Ahmad (1966). More recently, Ohmstead and Rhode (1991), Huffman and Evenson (1993), and Thirtle, Schimmelpfennig, and Townsend (2002) are among numerous studies that have provided further insights into induced innovation in American agriculture.

In their description, Hayami and Ruttan (1985) refer to induced innovation as technological change that facilitates the substitution of abundant (hence inexpensive) factors of production for scarce (hence expensive) factor in the economy. Frisvold (1991) elaborates further noting that the theory of induced innovation is comprehensive because it implies specific hypothesis about the causal linkages between factor prices, future price expectations, research priority setting, and the eventual development of new technologies. Hayami and Ruttan postulated that public research institutions conduct research in direct response to farm-level demands for lower unit costs by developing new technologies that enable farmers to substitute increasingly abundant factors for progressively scarce ones.

Empirical tests of this hypothesis in Canadian agriculture (Karagiannis and Furtan; Clark, Klein, and Kerr) show consistency of changes in factor prices with biases in technological change. In other words, changes in factor prices induced Canadian farmers to adopt technologies that saved the more expensive input via factor substitution. While making important contributions, studies on induced innovation in Canadian agriculture have used aggregate data to investigate productivity and develop fundamental generalizations about Canada's agricultural development. In our paper, we make a new contribution by considering potential differences between crops in terms of both biological and mechanical technological change. Rapid advances in plant breeding and genetic engineering of crop plants suggest that further insights would be provided by more explicitly incorporating disaggregated data reflecting changing cropping patterns and crop-specific biological investment to explain induced changes in the use of factors of production in Canadian agriculture.

This paper has several objectives. 1) To specify and test an induced innovation model of Canadian agriculture based on inter-crop comparisons of rates of technological change for two Canadian field crops: canola and wheat; 2) To investigate the time series properties of the Canadian data using cointegration and error correction to assess causality in differentiating between technological change and factor substitution; 3) To extend the period under study to 2003 given that previous Canadian studies used data up to 1985.

In recent years, considerable debate has emerged regarding public sector role in agricultural R&D. This study hopes to stimulate discussion and contribute to the debate regarding the importance of agricultural R&D and extension expenditures in determining observed rates and biases of technological change in Canadian agriculture.

2. Analytical Approach

In this paper, we adopt a tractable two-stage constant elasticity of substitution (CES) analytical approach used by Thirtle, Schimmelpfennig, and Townsend (2002), and Thirtle, Townsend, and van Zyl (1998). However, our application uses crop-specific data as opposed to aggregate data. The approach adopted by Thirtle, Schimmelpfennig, and Townsend (2002), and Thirtle, Townsend, and van Zyl (1998) combines approaches by de Janvry, Sadoulet, and Fafchamps (1989) and Frisvold (1991) to directly test the induced innovation hypothesis. The linearly homogenous two-stage CES with *n*-factors of production was originally developed by Sato (1967) as a generalization of the two-factor CES production function developed by Arrow, Chenery, Minhas, and Solow (1961). The first application of Sato's *n*-factor CES was by Hayami and Ruttan (1971), Shintani and Hayami (1975), and Kaneda (1982). Subsequent applications include Kawagoe, Otsuka, and Hayami (1986) to Japanese agriculture; Thirtle (1985a,b) to US agriculture; and Karagiannis and Furtan (1990) to Canadian agriculture. In these applications to agriculture, a linearly homogenous CES production function typically contains four inputs: fertilizer, F, land, A, machinery, M, and labour, L, as well as an efficiency parameter, E_i ($i=F, A, M, L$) nested into a specification shown in equation (1) which expresses the relationship between output and the two categories of inputs using separability assumptions:

$$Q=[\gamma(Z_1)^{-\rho}+(1-\gamma)(Z_2)^{-\rho}]^{-1/\rho} \qquad (1)$$

where Q is an index of output, and Z_1 and Z_2 are first-stage separable composite functions of (F,A) and (M,L) respectively as in equations (2) and (3):

$$Z_1=[\alpha(A)^{-\rho_1}+(1-\alpha)(E_F F)^{-\rho_1}]^{-1/\rho_1} \tag{2}$$

$$Z_2=[\alpha(L)^{-\rho_2}+(1-\alpha)(E_M M)^{-\rho_2}]^{-1/\rho_2} \tag{3}$$

where E_F and E_M are factor-augmenting parameters for the inputs to capture biological (land-augmenting) and mechanical (labour-augmenting) technical change respectively; α, β, and γ are distribution parameters; ρ is a substitution parameter, and the direct elasticity of substitution between fertilizer and land, and machinery and labour is given by:

$$\sigma_1 = \frac{1}{1+\rho_1}; \quad and \quad \sigma_2 = \frac{1}{1+\rho_2} \tag{4}$$

Thus, equation (1) represents stage-two while (2) and (3) are the first stage of the CES. To obtain estimating equations, the problem can be stated in terms of producer profit maximization. Following Frisvold, a producer's profit maximization problem subject to an expenditure constraint can be stated as:

$$Max\ \Pi = PQ - P_A A - P_L L - P_M M - P_F F \tag{5}$$

$$s.t.\ \ K \geq P_A A + P_L L + P_M M + P_F F$$

where P is the price of output, P_F,, P_A, P_M , and P_L are input prices for fertilizer, land, machinery, and labour., and K is a farm expenditure constraint. Estimating equations are obtained from first order conditions and expressed in terms of optimal input ratios as:

$$\ln\left(\frac{F}{A}\right)=\sigma_1\ln\left(\frac{1-\alpha}{\alpha}\right)+(\sigma_1-1)\ln E_F-\sigma_1\ln\left(\frac{P_F}{P_A}\right) \tag{6}$$

$$\ln\left(\frac{M}{L}\right)=\sigma_2\ln\left(\frac{1-\beta}{\beta}\right)+(\sigma_2-1)\ln E_M-\sigma_2\ln\left(\frac{P_M}{P_L}\right) \tag{7}$$

where (P_F,/P_A) and (P_M /P_L) are input price ratios, E_F and E_M are factor-augmenting parameters, and σ_1 and σ_2 represent the direct partial elasticity of substitution of fertilizer for land and labour for machinery, as in Kawagoe, Otsuka, and Hayami (1986).

It is clear that profit maximizing levels of inputs and the state of biological and mechanical agricultural technology as embodied in E_F and E_M respectively, both of which are functions of public and private sector research and development (R&D) investment which Frisvold defined as:

$$E_F = E_F[(\Theta B, R, t)] \tag{8}$$

$$E_M = E_M[(\Theta B, R, t)] \tag{9}$$

where B represents historical public sector R&D budgetary expenditure, R is a vector of historical private sector R&D, and Θ is a vector of parameters representing the share of biological and mechanical R&D in total R&D allocation, and hence a measure of the bias of technological change since the allocation of the R&D budget between biological and mechanical R&D activities is influenced by expected relative prices, as shown in the equation below:

$$\Theta^* = \left[\frac{P_F^e}{P_A^e}, \frac{P_M^e}{P_L^e}, \frac{P_A^e}{P_L^e}, B, R, t\right] \tag{10}$$

where Θ^* refers to the optimal bias of technical change and it is a function of expected relative prices. The derivatives of Θ^* imply

$$\frac{d\theta}{d\left(\frac{P_F^e}{P_A}\right)} > 0; \quad \frac{d\theta}{d\left(\frac{P_M^e}{P_I}\right)} < 0; \quad \frac{d\theta}{d\left(\frac{P_A^e}{P_I}\right)} > 0 \qquad (11)$$

depending on two conditions:

$0 < \sigma < \sigma_1 < 1$ and $0 < \sigma < \sigma_2 < 1$.

These conditions are empirical and must be tested. There is empirical corroboration of this condition in econometric research by, for instance, Kaneda, Hayami, and Ruttan (1985), Thirtle (1985a), Frisvold (1991), Thirtle, Townsend, and van Zyle (1998), Karagiannis and Furtan (1990), and Thirtle, Schimmelpfennig, and Townsend (2002).

Hence, a priori, short-run effects of price ratios on input ratios (as indicated by current values of price ratios) are simply factor substitution) or movements along and between fixed isoquants while long-run price effects (as indicated by lagged values of price ratios) correspond to induced development of new technology and hence the complete shift of the isoquant overtime, creating what Ahmad (1966) refers to as the innovation possibility curve (IPC).

3. Econometric Specification and Estimation

A system of equations was specified for two Canadian prairie crops: wheat and canola. The original objective to model barley, oats, and soybean was dropped due to serious data problems and high levels of multicollinearity in those variables. Our data covers the period 1926 to 2003. Data was missing for canola production between 1926 and 1940 and the estimation accounts for this. As well, data on R&D expenditure does not cover the entire period under study. Input data (expenditure and price indices) are obtained from Statistics Canada Agricultural Economic Statistics (1926-2004).

Data on R&D expenditures was based on the ICAR database.

For both wheat and canola, econometric estimation required reduced forms for equations (6) and (7) as follows:

$$\ln\left(\frac{F}{A}\right)_t = \alpha_0 + \alpha_1 \ln\left(\frac{P_F}{P_A}\right)_t + \alpha_2 \ln\left(\frac{P_F}{P_A}\right)_{t-1} + \alpha_3 \ln\left(\frac{P_M}{P_L}\right)_{t-1} + \alpha_4 \ln\left(\frac{P_A}{P_L}\right)_{t-1} + \alpha_5 \ln B_t + \alpha_6 \ln R_t + \alpha_7 t + \varepsilon_{1t} \tag{12}$$

$$\ln\left(\frac{M}{L}\right)_t = b_0 + b_1 \ln\left(\frac{P_M}{P_L}\right)_t + b_2 \ln\left(\frac{P_M}{P_L}\right)_{t-1} + b_3 \ln\left(\frac{P_F}{P_A}\right)_{t-1} + b_4 \ln\left(\frac{P_A}{P_L}\right)_{t-1} + b_5 \ln B_t + b_6 \ln R_t + b_7 t + \varepsilon_{1t} \tag{13}$$

where e_{it} ($I=1,2$) are contemporaneously correlated stochastic error terms. We run preliminary estimates using Zellner's seemingly unrelated (SUR) regression method to account for heteroskedasticity and contemporaneous correlation in the errors across equations. The results showed very high R^2 values, high t ratios, but alarmingly low Durbin-Watson (*D.W.*) statistics. In all cases, $D.W. \Rightarrow 0$ as time $T \Rightarrow \infty$; $R^2 \Rightarrow 1$ as $T \Rightarrow \infty$. We also noticed a tendency for the intercept to diverge as $T \Rightarrow \infty$ even when its true value was shown to be zero in some instances. It is well-known that this conditions is a key attribute of a spurious regression and, hence evidence of cointegration. A spurious regression is symptomatic of serious data problems, in particular when a time series contains a unit root, an indication that the series is nonstationary. Nonstationary series exhibit strong trends such that standard asymptotic analysis cannot be applied to derive the distribution of the test statistics. In order to determine if the levels of the series are non stationary and their differences stationary, we conducted three unit root tests: Augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979, 1981), the Phillips-Perron (PP) test (Phillips and Perron 1998), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski et al 1992). The ADF test basically tests the null hypothesis of a unit root (H_o: ρ $=1$) against the alternative hypothesis that the process has no unit root (H_1: ρ <1). Note that H_o is tested against the one-sided alternative H_1: ρ <1 since explosive series do not make economic sense. The test is based on the equation of the form:

$$\Delta X_t = X_t - X_{t-t} = c + (\alpha - 1) X_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta X_{t-i} + \varepsilon_t \tag{14}$$

which is simply obtained by rearranging an *AR(1)* process equation. X_t is a vector of input shares, input prices, and R&D and k is the lag order such that as k and $t \Rightarrow \infty$, the regression residuals tend toward white noise. The problem lies in the choice of k. In general, the size of the test is better when k gets larger, but this causes the test to lose power. The ADF test statistic is defined by the ratio of $1-\alpha$ to its standard error. H_o is rejected if the test statistic exceeds the critical at a given significance level. If we reject H_o, then the series is stationary and no differencing is necessary to obtain stationarity. Otherwise, the data series must be differenced and the resulting series tested until an H_o of no unit root is rejected. The deterministic part, c, can be a constant, a constant plus a linear trend, or zero. The ADF test has a weakness in that the stochastic trend is the H_o. This ensures the acceptance of a unit root unless there is strong evidence against it. To deal with this problem, the significance level is increased (type I error) leading to a decrease in type II error, in which case the power of the test (1- type II error) will increase. The other test is the PP test and it is a nonparametric test to control for higher-order autocorrelation in the data series. It differs from the ADF test by making a correction to the t-statistic of the $1-\alpha$ coefficient from the *AR(1)* regression to account for the autocorrelation in e_t. By contrast, the ADF makes the correction by adding lagged differences to the right hand side. The KPSS test simply reverses the ADF test and tests for stationarity (i.e., no unit root). But as with the ADF test, the problem is determining the reference point for k: the test is biased for values of k that are too small when there is serial correlation, and when k is too large, the test loses power. In spite of this, the reliability of either test is enhanced when the application of both ADF and KPSS tests generates consistent results (i.e., when the ADF H_o is not rejected and the KPSS H_o is rejected; or the ADF H_o is rejected and the KPSS H_o is not rejected).

The second step involves a cointegration test based on the finding from unit root tests. This is done to ascertain whether the estimated time series of the residuals from the cointegrating regression have a unit root and whether a linear combination of the variables that are integrated to the same order exists. In other words, we test for cointegrating vectors to establish the presence of non-spurious long-run relationships between the variables. We used the Johansen cointegration test to estimate a cointegrating regression where the H_o of no cointegration is tested against the H_1 of cointegration. The idea of cointegration enables us to model both short-run and long-run relationships simultaneously. Establishing the order of integration is key in implementing an error correction. Basically, a time series is said to be integrated of order d, denoted $I(d)$, if it can achieve stationarity after differencing d times. Hence, by definition, an $I(0)$ series is stationary while an $I(1)$ is referred to as a random walk and contains a unit root and hence nonstationary. Series that are nonstationary may diverge from each other in the short-run. However, their linear combination may be stationary and share a long-run equilibrium relationship. Engle and Granger (1987) refer to this property as cointegration. Thus, in general, if two series X_t and Y_t are both $I(1)$, their linear combination $Z_t = X_t - \alpha Y_t$ is also $I(1)$. However, if the value of α is such that Z_t is $I(0)$, then X_t and Y_t are said to be cointegrated, and the cointegrating relationship $X_t - \alpha Y_t = 0$ represents a long-run equilibrium relationship between the two variables while Z_t measures the divergence from this long-run relationship at some given time period t.

According to Granger representation theorem (Engle and Granger 1987), if X_t and Y_t are cointegrated, an error correction representation of the following form exists:

$$\Delta X_t = \beta_1 Z_{t-1} + \sum_{i-1}^{k} \varphi_i \Delta X_{t-i} + \sum_{j-1}^{k} \theta_j \Delta Y_{t-j} + \varepsilon_{1t} \quad (15)$$

$$\Delta Y_t = \beta_2 Z_{t-1} + \sum_{i-1}^{k} \Omega_i \Delta X_{t-i} + \sum_{j-1}^{k} \delta_j \Delta Y_{t-j} + \varepsilon_{2t} \quad (16)$$

where ϵ_{1t} and ϵ_{2t} are spherical noise terms. The series X_t and Y_t are cointegrated when at least one of the coefficients β_1 or β_2 is not equal to zero, in which case the two series will exhibit a long-run relationship. If $\beta_1 \neq 0$ or $\beta_2 = 0$, then series Y_t will cause X_t in the long-run while the opposite is true if $\beta_2 \neq 0$ or $\beta_1 = 0$. If both parameters are nonzero, then there is a feedback relationship between the two series which will adjust to each other in the long-run. There are also short-run relationships between the two series, and these are given by φ and θ such that if φ are not all zero, then Y_t will cause X_t in the short-run. If θ 's are not all zero, X_t movements will cause Y_t in the short-run.

Table 1 reports ADF and SPSS unit root test results for each of our model variables. For brevity, we do not report PP test results here because they are consistent with ADF test results. The Schwartz criterion was used to select the number of lags. For all level variables, the ADF test statistic is less than the critical values (at 1%, 5%, and 10% levels). Hence, we cannot reject the H_o that a unit root exists (i.e., the data series is nonstationary). In other both the input ratios and their corresponding price ratios are integrated *I(1)* and may be cointegrated, which implies that we are able to use an error correction model to estimate both short-run and long-run relationships simultaneously by specifying the variables in their levels and differences for short-run and long-run equilibrium effects respectively. Since we have determined that the variables are *I(1)*, we must establish the existence of non-spurious long-run relationships between the variables. Table 2 presents results from the Johansen cointegration test for cointegrating vectors. The results justify the implementation of an error ECM for this analysis.

4 Empirical Results from Error Correction Model

Empirical results from fitting the ECM for wheat and canola are presented in Table 3. As shown earlier, the economic interpretation of these estimated coefficients in based on the fact that the equations are themselves first order conditions of the two-stage CES production function. The ECM fits the data reasonably well and the signs of the estimated coefficients are generally quite consistent with a priori expectations. All the equations were estimated using SUR. We begin the discussion by looking at the wheat equations where the dependent variables are (F_w/A_w) and (M_w/L_w) expressed as first differences of the natural logarithms of the ratio of their respective inputs. The regressors in each wheat equation include these variables in first differences and levels. First differences are interpreted as short-run elasticities while the levels of the variables represent long-run equilibrium. Looking at the (F_w/A_w) equation, both the adjusted R^2 and $D.W.$ are more plausible in comparison to the values obtained from the spurious regressions. Consistent with an ECM, the adjusted R^2 is much lower. The variable $\Delta(P_F/P_A)_t$ represents the own-price and its coefficient at -0.979659 is highly significant with a *t*-statistic of -3.03416. The high value of the coefficient is interesting if we interpret the coefficient as the short-run direct partial elasticity of substitution between F_w and A_w. In other words, during the period under study, the short-run possibilities of substitution between F_w and A_w were quite high in Canadian prairie agriculture. These short-run substitution possibilities are of course to be understood as movements along the isoquant. The long-run coefficient associated with the price ratio for wheat $((P_F/P_A)_{t-1}$ is -0.849776 and highly significant, suggesting that increase in the $(P_F/P_A)_t$ price ratio with respect to wheat production induces a land-using technological change. If this coefficient had been positive, we would conclude that a land-saving technological change is induced from an increase in the $(P_F/P_A)_t$ ratio.

A key parameter in the fertilizer equation for wheat clearly is the error correction term, ξ, which is an indication of the direction of adjustment or correction toward long-run equilibrium. The sign of this error correction term must be negative in order to ensure that our ECM is stable. The estimated value for ξ is -0.407826, suggesting moderate (approximately 40%) correction or movement toward long-run equilibrium when the system is not in equilibrium. The wheat equation also includes R&D on wheat. Although the signs are positive, suggesting that wheat farmers have applied more and more fertilizer, the estimated coefficient is not significant. This could be partly due to the manner in which we derived R&D expenditure values from the ICAR database which use professional person years to arrive at a monetary value of R&D. Ideally, we would like to see a highly significant coefficient for R&D in order to corroborate the hypothesis of induced innovation in this equation. This needs further analysis.

Next, we look at the (M_w/L_w) equation for wheat. This equation fits the data well, with an adjusted R^2 of 0.41 and a $D.W.$ of 2.10. A $D.W.$ of 2.10 once again shows that the dynamic specification of our model has resolved the earlier problems associated with the first spurious regression which led to very high R^2 , highly significant coefficients, but very low $D.W.$ The variable $\Delta(P_M/P_L)_t$ associated with this equation represents the own price and its coefficient at -0.36650 is the short-run direct partial elasticity of substitution between M_w and L_w. The reasonably high value shows possibilities of substitution between M_w and L_w in the short-run. Notice how the coefficient for the differenced own price term lagged of -0.740248 suggests long-run factor substitution as opposed to induced innovation. The long-run coefficient associated with this price ratio is negative (-0.141275) implying labour-saving technological change in wheat production on the Canadian prairies due to a decrease in the M_w/L_w ratio. The estimated value for the error correction term is -0.0480884 but insignificant in this equation. The R&D terms for this equation were not significant but had the correct sign.

Next, we examine the canola equation where the dependent variables are the first differences of the log of the ratio of canola fertilizer to canola hectares (F_C/A_C) and canola machinery to canola labour (M_C/L_C). The (F_C/A_C) equation fits reasonably well , with an adjusted R^2 of 0.47 and a *D.W.* of 1.34. The intercept is highly significant and so are the own-price short-run direct partial elasticities of substitution between F_C and A_C. The value of -0.867994 shows very high short-run substitution possibilities between F_C and A_C. The error correction term, ξ, is estimated at -0.758038, which is quite a high correction (76%) toward long-run equilibrium. This equation also includes canola R&D whose long-run value is significant and positive.

In the (M_C/L_C) equation, we have an adjusted R^2 of 0.43 and a *D.W.* of 1.79. The short-run direct partial elasticity of substitution is -0.827957 while the error correction term is -0.174 which is a slow adjustment toward long-run equilibrium. The long-run own price coefficient $(P_M/P_L)_{t-1}$ is -0.266 and shows that canola production on the prairies is characterized by labour-saving technological change.

Table 4, we have computed long-run elasticities for each of the four equations. These are movements along the IPC (in the sense used by Ahmad) incorporating all possible technologies that researchers can develop. The relative size of these long-run elasticities is obviously affected by the size of the error correction term. In this specific calculation, both the (M_C/L_C) and (M_w/L_w) equations show much slower adjustment along the innovation possibility curve relative to the (F_C/A_C) and (F_w/F_w) equations.

We also examine the loading matrix from Johansen's cointegration equations to assess the direction of causation between factor inputs and factor prices for western Canada for both wheat and canola. And it is quite evident from the reported *F*-statistics that we cannot reject the hypothesis that factor ratios do not Granger cause factor prices - causality seems to run from own inputs price ratios.

Conclusion

A key objective of this study was to provide some crop specific empirical evidence of induced innovation in the production of wheat and canola on the Canadian prairies. There appears to be support for the hypothesis given the fact that the signs on our estimated own-price variables had correct had signs, consistent with our a priori expectations. An issue that is very relevant and of particular interest in our study would be the role of R&D in stimulating the development of technologies along the IPC, especially the development of new canola varieties developed through biotechnology with enhanced traits such as herbicide tolerance. This is particularly the case given the massive growth of private sector R&D investment in canola which is now widely recognized as an indicator of successful research in canola breeding and genetic engineering. Unfortunately, we were not able to disaggregate wheat and canola R&D into private sector R&D components. As well, our wheat R&D coefficients were not significant although they had the correct signs. Granted that wheat continues to be Canada's largest crop, this crop is also characterized by R&D under-investment relative to canola (Figure 1). These issues entail a need for further analysis.

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Table 1 ADF and SPSS Unit Root Tests

	ADF TEST				KPSS TEST			
	Test Stat	Critical Value			Test Statistic	Critical Value		
Variable		**1%**	5%	10%		**1%**	5%	10%
Log of ratio of F:A for wheat (F_W/A_W)	-1.775011	-3.517847	-2.899619	-2.587134	1.166563	0.739000	0.463000	0.347000
Δ log of ratio of (F_W/A_W)	-8.872325	-3.519050	-2.900037	-2.587409	0.245164	0.739000	0.463000	0.347000
Log of ratio of F:A for canola (F_C/A_C)	-1.776517	-3.517847	-2.899619	-2.587134	1.666190	0.739000	0.463000	0.347000
Δ log of (F_C/A_C)	-8.862709	-3.519050	-2.900137	-2.587409	0.245533	0.739000	0.463000	0.347000
Log of ratio of M:L for wheat (M_W/L_W)	-1.348916	-3.519050	-2.900137	-2.587409	0.931882	0.739000	0.463000	0.347000
Δ log of (M_W/L_W)	-4.063746	-3.519050	-2.900137	-2.587409	0.342460	0.739000	0.463000	0.347000
Log of (M_C/L_C)	-1.348912	-3.519050	-2.900137	-2.587409	0.931882	0.739000	0.463000	0.347000
Δ log of (M_C/L_C)	-4.063761	-3.519050	-2.900137	-2.587409	0.342460	0.739000	0.463000	0.347000
Log of ratio of F price: A price ($P_F/P_{A)}$	-0.257548	-3.517847	-2.899619	-2.587134	1.110940	0.739000	0.463000	0.347000
Δ log of P_F/P_A	-6.917659	-3.519050	-2.900137	-2.587409	0.209339	0.739000	0.463000	0.347000
Log of ratio of M price: L price P_M/P_L	-1.896252	-3.519050	-2.900137	-2.587409	0.949273	0.739000	0.463000	0.347000
Δ log of P_M/P_L	-3.216904	-3.519050	-2.900137	-2.587409	0.075447	0.739000	0.463000	0.347000
Log of WheatR&D	-2.579653	-3.552666	-2.914517	-2.595033	0.287417	0.739000	0.463000	0.347000
Δ log of WheatR&D	-13.026400	-3.552666	-2.914517	-2.595033	0.502321	0.739000	0.463000	0.347000
Log of CanolaR&D	-2.152296	-3.592462	-2.931404	-2.603944	0.820047	0.739000	0.463000	0.347000
Δ log of CanolaR&D	-5.654887	-3.596616	-2.933158	-2.604867	0.245974	0.739000	0.463000	0.347000

Table 3 Estimated Coefficients from Error Correction Model

Dependent variable	Exogenous variable	Coefficient	Std. Error	t-Statistic
Wheat: (F_w/A_w)	Intercept	16.10455	2.457301	6.553755
Fertilizer: Land ratio	$\Delta(F_w/A_w)_{t-1}$	-0.275099	0.141435	-1.945061
	$\Delta(P_F/P_A)_t$	-0.979659	0.322877	-3.034159
	$\Delta(P_F/P_A)_{t-1}$	-0.419824	0.381049	-1.101759
	$\Delta WheatR\&D_{-10}$	0.105563	0.258373	0.408569
	$(F_w/A_w)_{t-1}$	-0.407826	0.108812	-3.747967
	$(P_F/P_A)_{t-1}$	-0.849776	0.225547	-3.767621
	$WheatR\&D_{-10}$	0.143697	0.150694	0.953567
	$\Delta(P_A/P_L)_{t-1}$	-0.217833	0.404471	-0.538562
	$(P_A/P_L)_{t-1}$	0.161733	0.171471	0.943207
	Adj. R^2	0.415784		
	D.W.	1.423659		
Canola: (F_C/A_C)	Intercept	23.1031	1.709439	13.51502
Fertilizer: Land ratio	$\Delta(F_C/A_C)_{t-1}$	-0.493576	0.120426	-4.0986
	$\Delta(P_F/P_A)_t$	-0.867994	0.318064	-2.728989
	$\Delta(P_F/P_A)_{t-1}$	-0.568085	0.344233	-1.650295
	$\Delta CanolaR\&D_{-10}$	0.085711	0.083523	1.0262
	$(F_C/A_C)_{t-1}$	-0.758038	0.150026	-5.052698
	$(P_F/P_A)_{t-1}$	-0.804799	0.382979	-2.101416
	$CanolaR\&D_{-10}$	0.2316	0.086161	2.68798
	$\Delta(P_A/P_L)_{t-1}$	-0.376278	0.400714	-0.939019
	$(P_A/P_L)_{t-1}$	0.163383	0.230435	0.709018
	Adj. R^2	0.466132		
	D.W.	1.738947		
Wheat: (M_W/L_W)	Intercept	17.55871	1.242776	14.12862
Machinery: Labour ratio	$\Delta(M_W/L_W)_{t-1}$	0.229506	0.135381	1.695255
	$\Delta(P_M/P_L)_t$	-0.36656	0.345973	-1.059505
	$\Delta(P_M/P_L)_{t-1}$	-0.740248	0.374811	-1.974988
	$\Delta WheatR\&D_{-10}$	0.014094	0.105915	0.13307
	$(M_W/L_W)_{t-1}$	-0.040884	0.04661	-0.877142
	$(P_M/P_L)_{t-1}$	-0.141275	0.074446	-1.897688
	$WheatR\&D_{-10}$	0.037426	0.076445	0.489579
	Adj. R^2	0.513632		
	D.W.	2.097636		
Canola: (M_C/L_C)	Intercept	15.03413	1.002183	15.00138
Machinery: Labour ratio	$\Delta(M_C/L_C)_{t-1}$	0.105447	0.17515	0.602037
	$\Delta(P_M/P_L)_t$	-0.827957	0.3250501	-2.547121
	$\Delta(P_M/P_L)_{t-1}$	-0.511053	0.417786	-1.223243
	$\Delta CanolaR\&D_{-10}$	0.018092	0.042047	0.430288
	$(M_C/L_C)_t$	-0.174117	0.095324	-1.826575
	$(P_M/P_L)_{t-1}$	-0.266229	0.215503	-1.235383
	$CanolaR\&D_{-10}$	0.099206	0.050855	1.95077
	Adj. R2	0.429129		
	D.W.	1.785409		

Table 4. Long-Run Elasticities

	$(P_F/P_A)_{t-1}$	$P_M/P_L)_{t-1}$	WheatR&D	CanolaR&D
Wheat fertilizer: land ratio: (F_w/A_w)	-2.083672939	-	*Insignificant*	
Canola fertilizer: land ratio: (F_C/A_C)	-1.061686881	-	*Insignificant*	0.305525581
Wheat machinery: labour: (M_W/L_W)	-	-3.455508267		
Canola machinery: land ratio: (M_C/L_C)	-	-1.529023588		0.569766307

Figure 1 Wheat and Canola R&D in Canada