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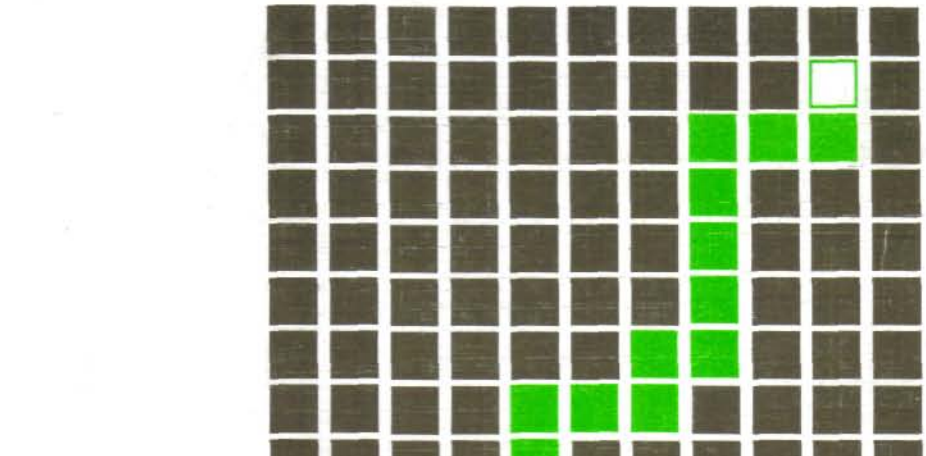

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Economic Reforms and Agricultural Supply Response in Jamaica

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Abstract

A number of economic reform programs have been undertaken in Jamaica over the past two decades. Designed largely by the International Monetary Fund (IMF) and the World Bank, these reforms focused on correcting internal policy weaknesses and creating an environment conductive to sustained growth. The reforms emphasized liberal trade and exchange rate regimes, a less intrusive and smaller public sector, and reliance on market forces to determine agricultural prices and qualities.

Against this background, this study investigates the impact of these recent economic reforms on agricultural crop supply responses in Jamaica. The estimation technique used an error correction modeling framework based on co-integration theory, within an estimation framework developed by Johansen. The results of the crop supply response estimation confirm that there is a long-run relationship between agricultural crop output and price incentives. Most of the estimated crop price elasticities are low, statistically significant, and fall within the range estimated by other studies on Jamaica. The adjustment process of the short-run was found to be slow for some crops and higher for others.

Using a counterfactual, which assumed no change in policy regime, fitted series of supply response functions from the pre-reform period were forecasted within a univariate (ARMA (p,q) framework and compared to fitted series of supply responses from the reform period. The results are mixed. It is found that the impacts of the economic reforms in Jamaica are crop and time specific. Mean output was higher in the reform period for four of the eight crops analyzed. Higher real price shifts were observed in the reform period for some crops but these price shifts were also accompanied by higher price-variability. This suggests that the pro-competitive effects that were expected to accompany the reforms may have outweighed the stability impulses of administered prices in the pre-reform era.

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INTRODUCTION

This paper investigates the impact of economic reforms on crop supply responses in Jamaica. Generally, supply response models in agriculture postulate a long-run relationship between output and agricultural incentives (Askari and Cummings, 1976). Deviations from this long-run equilibrium occur in the short-run and may involve considerable adjustment costs. This is especially the case when significant policy changes are implemented. Jamaica provides a good case for evaluating the connections between economic reforms and supply responses. The country has traditionally been heavily dependent upon agriculture for food, employment and export earnings. A combination of excesses in state intervention and adverse world economic conditions prompted major economic reforms since the late 1970s. These reforms took expression in progressive devaluation of the Jamaican dollar, elimination of state marketing boards, liberalization of agricultural input and output prices, privatization of state held monopolies and public enterprise, and generally, in policies aimed at re-orienting the economy towards a more liberal economic system.

Analysis of the Jamaican crop output and price data series over the 1962-1999 period reveals non-stationarity of the time series, a statistical problem that has not been addressed in applied research on Jamaican crop supply responses. The analytical approach used in this paper to deal with this problem differs from those previously used to model Jamaican crop supply responses in two very important ways. First, the multivariate co-integration modeling which is used in this study, is designed for this type of empirical work by explicitly classifying the non-stationary and stationary components and facilitating analyses in terms of the dynamics of short-run and long-run effects. Second, the data are analyzed as a full system of simultaneous equations thereby facilitating analyses of inter-actions among the variables.

Following this Introduction, Section 2 develops the modeling framework for the paper. Section 3 presents the empirical results on the long run relationships and adjustment processes in crop supply responses in Jamaica. The counterfactual analysis is presented in Section 4, and finally, the concluding remarks are made in Section 5.

Modelling Framework

Cointegration and Error Correction Modeling

One approach to capturing the long-run and short-run changes in agriculture supply response is to use the Nerlovian-type partial adjustment models (Askari and Cummings, 1976). Both quantity and prices can be modeled to adjust to their long-run or equilibrium path, and the model is capable of estimating both long-run and short-run parameters as well as the speed of adjustment towards the long run equilibrium. A potential complication in such an analysis is that if the time series data are non-stationary then the limiting distribution of the asymptotic variance of the parameter estimates is not finitely defined, hence the conventional t and F tests are inappropriate (Fuller, 1976). Further, non-stationarity gives rise to spurious correlation among variables (Greene, 1993).

Co-integration approaches the stationarity issue as linear combinations of economic series, rather than by differencing the series. The implication of this is that if a set of variables is co-integrated then, following the Granger Representation Theorem (Fuller, 1985) a valid error correction representation of the data exists. In effect co-integration is a test of the existence of a long-run relationship of variables that are integrated of the same order (Greene, 1993; Gujarati, 1995). However, an important feature of error correction models based on co-integration is that the data in both levels and differences are included, thereby facilitating investigation of both short-run and long run effects in the data.

Following the derivations by Nickell (1985) and Alogoskoufis and Smith (1991) the dynamically unrestricted version of the ECM for the c^{th} crop is:

(1)

$$\Delta Q_{c,t} = \alpha_{0c} + \alpha_{1c,t}\Delta Q_{c,t-1} + \sum_{j=1}^{2}\alpha_{2j}\Delta P_{c,t-j} + \sum_{k=1}^{2}\alpha_{3i,k}\Delta P_{si,t-k} + \sum_{l=1}^{2}\alpha_{4l}\Delta W_{t-1} + \sum_{m=1}^{2}\alpha_{5m}\Delta F_{t-m} + \alpha_6(Q_c - \delta_1 P_c - \delta_{2i} P_{si} - \delta_3 W_t - \delta_4 F_t)_{t-1};$$

where, Q=output, P_c=crop price, P_{si}=price of substitute crops, i=1,2..., W=wage rate, F=fertilizer price, and the random error term is suppressed. All variables are measured in logarithms.

The last term in (1) is the error correction term. In the empirical estimation of (1), the error correction term is usually specified as the residual from the co-integrating relationship. To test for, and estimate possible multiple co-integrating vectors, Johansen (1988) and Johansen and Juselius (1990) have devised an appropriate method within the following framework. Define a standard vector autoregressive (VAR) model with lag length k as:

(2)

$$X_t = \Pi_1 X_{t-1} + \Pi_2 X_{t-2} + \ldots + \Pi_k X_{t-k} + \varepsilon_t$$

t=1...,T

where X is an Nx1 vector of N endogenous variables, ε_t~iid (0, Λ) with dimension NxN. The long run, or co-integrating matrix is:

(3) $I - \Pi_1 - \Pi_2 - \ldots - \Pi_k = \Pi,$

which can be then decomposed as:

(4) $\Pi = \alpha\beta'$

where β represents the matrix containing the r co-integrating vector, and α is the matrix of weights with which each co-integrating vector enters each of the differenced X equations. A large α value implies that the system will respond to any deviation from the long-run equilibrium path with a rapid adjustment. If α's are zero in some equations, this is a sign of a weak exogeneity, implying that the variable does not respond to the disequilibrium in the system. The parameters α and β form an over-parameterization of the model. However, the space spanned by β, sp(β), can be estimated, and shown to be the empirical canonical variates of X_{t-k} with respect to ΔX_t (Johansen, 1988).

Re-parameterizing (1), (detailed derivations are in Johansen, (1988) and Enders, (1995)), results in the following error correction model:

$$(5)\quad \Delta X_t = \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{k-1}\Delta X_{t-k+1} + \Gamma_k X_{t-k} + \varepsilon_t$$

where $\Gamma_i = -I + \Pi_1 + \Pi_2 + \ldots + \Pi_i$, i=1 ...k

Without any loss of information, the ECM in (5) is therefore a transformation of the VAR(k) model in equation (2), and is expressed in first differences and augmented by the error correction term, $\Gamma_k X_{t-k}$. The long-run equilibrium or impact matrix is the matrix Γ_k and is equivalent to $\Pi = \alpha\beta'$ in (4). The rank of Π is the basis of determining the number of co-integrating relationship between the variables in the ECM (5).

The log likelihood representation of

(5) is: $L(\alpha, \beta, \Omega) = |\Omega|^{-T/2}$

$$(6)\quad \exp\left[-\frac{1}{2}\sum_{t=1}^{T}(R_{0t}+\alpha\beta' R_{kt})'\,\Omega^{-1}(R_{0t}+\alpha\beta' R_{kt})\right]$$

Johansen's procedure begins by regressing ΔX_t on the lagged differences of ΔX_t and generating fitted residuals R_{0t}, then regressing X_{t-k} on the lagged differences and generating fitted residuals, R_{kt}. These fitted residuals are then used to construct the following product moment matrices:

$$(7)\quad S_{ij} = \frac{1}{T\sum_{i=1}^{T} R_{it}} R_{jt},\ i,j = 0,k$$

The product moment matrices (7) are then used to find the co-integrating vectors by solving the determinant:

$$(8)\qquad \left|\lambda S_{kk} - S_{k0}S_{00}^{-1}S_{0k}\right| = 0$$

This will yield the estimated eigenvalues ($\lambda_1, \ldots, \lambda_n$) and eigenvectors ($v_1,\ldots,v_n$), which are normalized such that:

$$(9)\qquad V' S_{kk} V = I$$

where V is the matrix of eigenvectors. The most significant eigenvectors then constitute the r co-integrating vectors, i.e.,

$$(10)\qquad \beta = (v_1, \ldots v_r)$$

Using (10), α is then estimated from (4).

The critical issue in all of this is to determine which, and how many, of the eigenvectors in (9) represent significant co-integrating relationships. First, the β vectors that have the largest partial correlation with ΔX_t, conditional on the lags of ΔX_t, are identified. Second, the eigenvectors that correspond to the r largest eigenvalues are chosen. Finally, to determine the value of r the following test statistics suggested by Johansen (1988) are employed:

$$(11)\ \Omega_1(q, n) = -T \sum_{i=q+1}^{n} \ln(1 - \lambda_i)$$

(12)

$$\Omega_2(q, q + 1) = -T\ln(1 - \lambda_{q+1})$$

The null hypothesis H0: r≤q is tested with (11), while H0: r = q is tested against H1: r = q + 1 with (12). The critical values for these tests are taken from Osterwald-Lenum (1992).

Data Sources and Estimation Procedure

The principal sources of annual time series data, which are used in this study, are the Food and Agriculture Organization (FAO) agricultural database (FAOSTAT), available on the Internet, and annual publications of various government agencies in Jamaica. The estimation procedure is based on the work of Johansen (1988) and Johansen and Juselius (1990). There are basically three steps in this estimation procedure: (i) test the order of integration of the variables and specify the lag length of the variables using a standard vector auto-regressive (VAR) specification; (ii) estimate the ECM and the number of co-integrating relationship(s) among the variables included in the ECM; and (iii) perform short-run analysis by conducting innovation accounting on the ECM. Estimation is done using the Regression Analysis for Time Series (RATS), version 4.3 (Doan, 1996), and Co-integration Analysis for Time Series (CATS) in RATS, (Hansen and Juselius, 1995), computer programs. The variables in each ECM include the output (quantity) of the crop of interest, the price of the crop, the price of a substitute (or alternative) crop, and two input prices, average agricultural wage rate and average fertilizer price.

The choice of a crop price variable is critical for the estimation of crop supply responses. In this regard, Askari and Cummings (1976) suggest using any one of the following prices: (ii) nominal farm gate price; (ii) Farm gate price deflated by any one of the following: (a) a price index of farmer's inputs; (b) a consumer price index; and (c) some index of the prices of competitive crops (or the price of the most competitive crop). An additional issue that is related to the choice of an appropriate price variable for the crop supply functions especially within the context of the IMF/World Bank programs in Jamaica, is that agricultural price incentives are influenced by various macroeconomic policies. For this purpose, the real producer price (RPP) was used following the World Bank's approach (Tsakok, 1990; Krueger 1992; and Schiff and Valdez, 1992a, 1992b), and is given as:

$$RPP = P_F/CPI = P_F/P_Be = e(WPI/CPI) = NPC*RER*p_B$$

where RPP is real producer price, P_F is the farm gate producer price, P_B is the border price, NPC is the nominal protection coefficient, and p_B is the real border price of the country's exports (World Bank, 1994).

Several substitute crops were initially included in each ECM but in all cases it was found that the inclusion of only one substitute crop price improved the statistical properties of the model. The alternative crops in each crop's ECM are reported in Table 1.

Table 1: Alternative (Substitute) Crops in Each ECM

Crop	Alternative Crops Considered
Banana	Sugar*, coffee, papaya
Sugar	Banana*, papaya
Coffee	Banana*, pimento, sugar, orange
Pimento	Banana*, coffee, cocoa bean
Yam	Cassava*, potato, sweet potato
Orange	Grapefruit*, tangerine, coffee
Cocoa Bean	Banana*, pimento, coffee
Potato	Cassava*, yam, sweet potato

* *Crop chosen as substitute crop.*

Results

Testing for Stationarity

A preliminary step in the estimation of the ECM models is to test the data for stationarity. Three tests are used in this study, viz., the Dickey-Fuller (D-F) and Augmented-Dickey-Fuller (ADF), the Weighted Symmetric (W-S), and the Phillips-Perron (P-P) tests. First, tests were conducted on the variables in levels, then on their first difference. For the Dickey-Fuller test, the following models were used:

(13) $$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \mu_t$$

(14) $$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \alpha_2 T + \mu_t$$

where T is time, X_t is a time series, $\forall_i$ are coefficients to be estimated, $:_t$ is white noise, and ΔX_t the first difference. The ADF tests were conducted on the following equations:

(15) $$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \beta_i \sum_{i=1}^{m} X_{t-i} + \mu_t$$

(16) $$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \alpha_2 T + \beta_i \sum_{i=1}^{m} \Delta X_{t-i} + \mu_t$$

The unit root tests indicate that for each variable tested, at least one test showed that the variable is non-stationary in levels, but stationary in first differences (Ballayram, 2001). Consequently, the estimation of crop supply response which follows is based on the conclusion that the variables included in the models are all integrated of order one, i.e., $Y_i \sim I(1)$, which implies that, $\Delta Y_i \sim I(0)$.

Long-run Elasticities

First, the vector of stochastic variables for each crop's ECM was specified as follows:

- Banana X_t = (lbanq, lbanpr, lsugpr, lwage, lferp);
- Sugar ECM: X_t = (lsugq, lsugpr, lbanpr, lwage, lferp)';
- Coffee ECM: X_t = (lcofq, lcofpr, lbanpr, lwage, lferp)';
- Pimento ECM: X_t = (lpimq, lpimpr, lbanpr, lwage, lferp)';
- Yam ECM: X_t = (lyamq, lyampr, lcaspr, lwage, lferp)';
- Orange ECM: X_t = (lorq, lorgpr, lbanpr, lwage, lferp)';
- Cocoa-bean ECM: X_t = (lcobq, lcobpr, lbanpr, lwage, lferp)';
- Potato ECM: X_t = (lpotq, lpotpr, lcaspr, lwage, lferp)';

where: lbanq = quantity of banana;

lbanpr = price of banana;
sugpr = sugar price (the alternative crop to banana);
lwage = average wage in the agricultural sector;
lferp = average price of fertilizer;
lsugq = sugar quantity;
lsugpr = price of sugar;
lcofq = coffee quantity;
lcofpr = price of coffee;
lpimq = pimento quantity;
lpimpr = price of pimento;
lyamq = yam quantity;
lyampr = price of yam;
lorq = orange quantity;
lorpr = price of orange;
lcobq = cocoa-bean quantity;
lcobpr = price of cocoa bean;
lpotq = potato quantity;
lpotpr = price of potato.

The 'l' that begins each variable name indicates logarithms.

Second, residual analysis was conducted to ensure that the models were appropriate for the data. Finally, the hypothesis of reduced rank was then tested on the matrix $\Pi = \alpha\beta'$, which defines the co-integrating vectors β and adjustment coefficients α. A normalization on the crop output variable is taken, and the normalized β and α vectors are reported in Table 4. The normalized coefficients are estimates of the long-run elasticities of crop output with respect to own price (P_o), price of the alternative crop (P_a), wage rate (W), and fertilizer price (F).

A number of inferences can be drawn from the information presented in Table 2. First, the estimates indicate a positive long-run relationship between supply and own-price. However, the relation-ship is inelastic for five of the eight crops. Crops that are price elastic are yam, orange and potato, with own-price elasticities of 1.7, 2.3, and 2.0, respectively. The own-price elasticity coefficients reported in Table 2 are generally within the range estimated by other studies for Jamaica.

A second point to note with respect to the information in Table 2 is the relatively low elasticities with respect to the substitute crop price. For the banana ECM it is -0.16, for the coffee ECM, 0.01, and for sugar and cocoa-bean ECMs, -0.64 and -0.08 respectively. Relatively higher elasticities are recorded for the pimento -0.85, yam –3.0, orange -1.62 and potato -1.03.

Third, the relationship between quantity and input-prices is generally inelastic for four of the crops studied. The exceptions are for wages in the yam orange and potato and cocoa bean ECMs, and for fertilizer price in the coffee, pimento, orange, and yam ECMs.

Adjustment Coefficients

The adjustment coefficients are reported in Table 3. Generally, the adjustment coefficients are significant. The exceptions include fertilizer price in the banana ECM, own-price, and wages in the coffee ECM, price of the alternative crop in the pimento ECM, and a few others. An insignificant adjustment coefficient, is a sign of weak exogeneity of the variable X_i in the vector of stochastic variables, X_t, in the ECM. Weak

Table 2: Cointegrated Vectors Normalized on Output for all Crops

Crops	P_o	P_a	W	F	C
Banana	0.640	-0.156	-0.567	-0.106	-3.795
Sugar	0.155	-0.640	-0.106	-0.563	-3.290
Coffee	0.474	-0.005	-0.448	-2.938	6.503
Pimento	0.576	-0.849	-0.534	-1.526	1.683
Yam	1.706	-2.958	-5.880	-1.700	23.210
Orange	2.347	-1.620	-1.979	-1.492	11.270
Potato	1.952	-1.030	-5.197	0.704	-38.815
Cocoa Bean	0.359	-0.081	-1.405	-0.983	-12.350

P_o = own-price; P_a = price of the alternative crop; W = average wage rate in agriculture sector; F = average price of fertilizer; C = constant (intercept).

Table 3: Estimated Adjustment Coefficients, α's for all Crops

Crops	Q	P_o	P_a	W	F
Banana	-0.141	-0.352	0.511	0.169	0.097
	(-1.909)[b]	(-1.949)[b]	(2.452)[a]	(3.469)[a]	(0.641)
Sugar	-0.141	0.511	0.352	0.169	0.097
	(-2.899)[a]	(2.452)[a]	(1.949)[b]	(3.329)[a]	(2.641)[a]
Coffee	0.049	-0.091	-0.100	-0.002	-0.193
	(2.717)[b]	(-1.911)[c]	(-1.930)[c]	(-2.091)[b]	(-5.697)[a]
Pimento	-0.047	-0.318	0.031	0.004	0.070
	(-2.763)[a]	(-6.173)[a]	(0.400)	(2.156)[b]	(2.455)[a]
Yam	-0.033	-0.062	0.026	0.021	-0.042
	(-2.851)[a]	(-3.240)[a]	(2.184)[b]	(2.257)[b]	(-2.189)[b]
Orange	-0.139	-0.366	0.021	0.062	0.174
	(-1.472)	(-1.858)	(0.094)	(2.134)	(3.047)
Potato	-0.053	-0.043	0.077	0.031	-0.068
	(-1.108)	(-1.273)	(4.035)[a]	(3.052)[a]	(-2.793)[a]
Cocoa Bean	-0.797	0.676	-0.841	-0.284	-0.062
	(-3.971)	(2.103)	(-3.449)	(-1.621)	(-0.694)

Note: Figures in parentheses are t-values.
[a], [b], [c], indicate statistical significance at one, five and ten percent levels, respectively.
Q = quantity; P_o = own-price; P_a = price of the alternative crop; W = average wage rate in agriculture sector; F = average price of fertilizer; C = constant (intercept).

exogeneity means that although a long-run relationship exists between X_i and the other variables in X_t, X_i does not adjust to deviations from the long-run equilibrium. As such, any deviation from the long-run equilibrium in the system after a shock, is restored by adjustments made by variables other than X_i in the system (Johansen and Juselius, 1990, 1992). According to Johansen (1995), this does not preclude X_i from the co-integrating relationship in X_t.

Analysis of Short-run Dynamics

Innovation accounting (analysis of impulse response functions and variance decompositions) has become a useful tool in the analysis of co-integrated systems (Enders, 1995, 1996; Lutkepohl and Reimers, 1992). The impulse response functions, specified as VARs, generate impact or dynamic multipliers. These coefficients capture the effects of exogenous shocks of each variable on its own time path, and on those of the other variables in the system.

Identification of the parameters in the VAR necessitates imposing some structure (via parameters restrictions) on the system. Sims (1980) and Bernanke (1986) have proposed a method of imposing restrictions for the identification of the VAR. In this scheme, exact identification of the structural model for an n-variable VAR necessitates $\left(n^2 - n\right)/2$ restrictions but additional (over identifying) restrictions can be imposed and tested statistically. The restrictions are based on economic theory.

The VAR in standard form (Enders, 1996), which is used for the impulse response analysis is specified as:

(17) $X_t = A_0 + A_1X_{t-1} + A_2X_{t-2} + \ldots + AX_{t-p} + e_t$

where:

$X_t = (\Delta Q, \Delta P_o, \Delta P_a, \Delta F, \Delta W)'$;

$X_{t-i} = (\Delta Q_{t-i}, \Delta P_{o,t-i}, \Delta P_{a,t-i}, \Delta F_{,t-i}, \Delta W_{,t-i})'$, I = 1,2...

A_i = parameters to be estimated;

e_t = vector of error terms.

All other variables as previously defined.

Restrictions on (17) are based on the relationships that are specified in Table 4. In effect, the specification suggests that P_o, P_a, F and W are exogenous variables, and further, that innovations in any one of these variables will induce contemporaneous changes in itself and on Q, but on no other variable in the system. However, this specification, when combined with the Sims-Bernanke error variance decomposition, does not rule out induced changes in the other variables in future periods. This is to be expected, given that the variables are co-integrated.

Related to impulse response functions are forecast error variance decompositions, which provide information about the proportion of the movements in a variable due to its own shocks and to those from other variables in the system (Enders, 1996). A twelve-period forecasting horizon is specified, and the Sims-Bernanke forecast error variance decompositions are used based on the restrictions implied in Table 4.

Table 4: Endogenous and Exogenous Variables in Crops' Impulse Response Functions

The Contemporaneous value of:	Is Affected by the Contemporaneous value of:
Q	All variables in the system
P_o	No other variable
P_a	No other variable
F	No other variable
W	No other variable

Notes: Q = crop output;
P_O = (own-price), i.e., price of output;
P_a = price of substitute crop;
F = fertilizer price;
W = average agriculture wage rate.

Table 5: Responses of Banana Quantity to Shocks in the Banana VAR

Responses to Shock in Sugar Price					
Period	*Dlsugpr*	*dlferp*	*Dlwage*	*Dlbanpr*	*Dlbanq*
1	0.210	0	0	0	-0.162
2	0.071	0.020	-0.051	0.171	0.092
Responses to Shock in Fertilizer Price					
Period	*Dlsugpr*	*dlferp*	*Dlwage*	*Dlbanpr*	*Dlbanq*
1	0	0.150	0	0	-0.039
2	-0.007	0.023	-0.047	0.014	0.018
Responses to Shock in Wage Rate					
Period	*Dlsugpr*	*dlferp*	*Dlwage*	*Dlbanpr*	*Dlbanq*
1	0	0	0.055	0	0.002
2	-0.014	0.020	0.031	-0.018	0
Responses to Shock in Banana Price					
Period	*Dlsugpr*	*dlferp*	*Dlwage*	*Dlbanpr*	*Dlbanq*
1	0	0	0	0.220	-0.165
2	0.081	-0.007	0.041	0.112	0.076

Notes: The prefix 'd' to the variable names

Impulses for 12 periods were examined for each crop's VAR and the first and second period results are reported in table format, while the plots for the entire forecast period are reported graphically (Ballayram, 2001). For all variables, the effects of the shocks after the fourth and fifth periods converge to zero or the equilibrium path, which is to be expected from a co-integrated system.

The results for the banana VAR are reported in Table 5. Thus, a one-standard-deviation shock in banana price (equal to 0.220 units) induces contemporaneous decrease of 0.165 units in banana quantity. By model specification, there is no contemporaneous change in the other variables. After one period, banana price is still 0.112 units above its mean, while banana quantity has increased by 0.076 units. In the second period, the shock in banana price has induced an increase in sugar price of 0.081 units, a decrease in fertilizer price of 0.007 units, and an increase in wage of 0.041 units.

To complement the results from the impulse response functions, the forecast error decompositions of the banana VAR are reported in Table 6. In applied research, it is typical for a variable to explain almost all of its forecast error variance at short horizons and smaller proportions at longer horizons (Enders, 1996). The Sims-Bernanke forecast error variance decompositions show that each variable explains 100% of its forecast error variance in the first period. However, after the first period, the forecast error variance of a variable, which is explained by its own shock, falls. In the case of the banana VAR, in the third period, sugar price explains 75.7% of its own forecast error variance, fertilizer price 71.2%, wage 33.0%, banana price 42.9%, and banana quantity 57.3%. These percentage distribution of the

Table 6: Variance Decomposition Percentage of One-period and Three-period Forecast Error Variance–Banana Var.

Forecast Error Variance in:	Percentage Forecast Error Explained by Shocks in:				
Sugar price	*Dlsugpr*	*Dlferpr*	*Dlwage*	*dlbanpr*	*Dlbanq*
1 Yr	100	0	0	0	0
3 yrs	75.712	0.105	0.613	10.395	13.176
Fertilizer price					
1 Yr	0	100	0	0	0
3 yrs	11.999	71.220	1.999	1.119	13.663
Wage					
1 Yr	0	0	100	0	0
3 yrs	24.430	24.341	32.961	18.196	0.072
Banana price					
1 Yr	0	0	0	100	0
3 yrs	21.262	0.149	0.340	42.880	35.368
Banana quantity					
1 Yr	19.407	1.105	0.004	19.940	59.543
3 yrs	21.416	1.147	0.006	20.094	57.337

Table 7: Responses of Quantity to Shocks in Exogenous Variables

Variable	Period	Responses of Quantity to Shocks in:			
		P_o	P_a	W	F
Banana	1	-0.165	-0.162	0.002	-0.039
Quantity	2	0.076	0.092	0	0.018
Sugar	1	-0.162	-0.165	0.002	-0.039
Quantity	2	0.092	0.076	0	0.018
Coffee	1	0.021	-0.006	-0.016	0.004
Quantity	2	-0.005	0.021	0.009	0.004
Pimento	1	0.022	-0.006	-0.023	-0.021
Quantity	2	0.033	0.078	0.019	-0.090
Yam	1	-0.087	-0.008	-0.046	-0.019
Quantity	2	0.100	0.018	0.014	0.026
Orange	1	-0.038	0.061	0.097	0.025
Quantity	2	0.210	-0.148	-0.026	0.023
Cocoa Bean	1	0.007	0.028	0.031	0
Quantity	2	-0.062	-0.005	-0.046	0.006
Potato	1	-0.194	-0.026	-0.050	0.049
Quantity	2	0.177	-0.028	0.021	-0.012

forecast error variance among the variables remain constant after the second and third forecast periods.

The cross-variable effects are zero in the first period (by model specification), but change with the time horizon. In Table 6, the cross-variable effects in the third period show that the shock in banana price can explain 43% of its own forecast error variance, shocks in banana quantity and sugar price account for 35% and 21%, respectively. Shocks in fertilizer price and the wage rate account for only 0.149% and 0.340%, respectively, of the forecast error variance in banana price. Similarly, in period three, the cross-price effect of a shock in fertilizer price can explain 71% of its own forecast error variance, while 14% and 12% are accounted for by shocks in banana quantity and sugar price, respectively. Finally, a shock in wage rate explains 33% of its own forecast error variance, while shocks in banana, fertilizer and sugar prices account for 18.2%, 24.3% and 24.4%, respectively.

The last two rows in Table 6 show the forecast error variance decompositions when the exogenous variables (P_o, P_a, W, F) are modeled to impact banana quantity in all time periods. Thus, the banana quantity variable explains 60% of its own 1-step ahead forecast error variance, and 57% in the 3-step ahead forecast error variance.

Similarly, in the first period, sugar and banana prices account for 19% and 20% of the forecast error variance in banana quantity, respectively. These percentages increase slightly in the 3-year-ahead forecast. Fertilizer price and wages account for negligible percentage variations in banana forecast error variance in both of the periods, suggesting thereby, the relative importance of own-price and price of the substitute crop on the short-run variations of banana quantity.

In order to present the information in a manner that is succinct and easy to read, a major portion of the estimates are summarized in Tables 7 and 8. Table 7 shows the responses of quantity to shocks in the exogenous variables in the system in periods one and two. Table 8 reproduces the last two rows of the tables that record the forecast error variance decompositions for the crops' ECM. That table shows the percentage forecast error variance in quantity, which is explained by the variables in the system.

The response of quantity to positive shocks in own-price (P_o) is expected to be positive. However, Table 7 shows that in period one, five of the eight crops (banana, sugar, yam, orange, and potato) show a decrease in output, which is induced by an own-price shock. Thus, in period one a one-standard-deviation-shock in banana price (equal to 0.220 units), induces a decrease in banana supply of 0.165 units. Other crops whose supply decrease in period one consequent upon a one-standard-deviation-shock in own-price are sugar (-0.162 units) and potato (-0.194 units). However, with the exception of coffee and cocoa bean, all crops increase supply in the second endogenous. Neither of these two extreme cases are observed in Table 8.

With respect to the issues of endogeniety/exogeniety and the results reported in Table 8, one point must be noted. With only a few exceptions, shocks in fertilizer price and wages appear to explain relatively small proportions of the forecast error variance in quantity. The exceptions are pimento, orange and to some extent cocoa-bean. This is also true for the coffee quantity shock reduces to 88%, while the proportion explained by the substitute crop price shock increases to five percent. Enders (1995, 1996) argues that if X_1 shocks do not explain any of the forecast error variance in X_2 in a VAR at all time horizons, then the X_2 sequence is exogenous. This means that the X_2 sequence evolves independently of shocks in X_1. On the other hand, if X_1 shocks explain all the forecast error variance in X_2 sequence at all forecast horizons, then X_2 is said to be period following a shock in own-price.

The response of quantity to positive shocks in the substitute crop price, P_a, wage, W, and fertilizer price, F, is expected to be negative. In period one this expectation is confirmed for shocks in P_a on all crop supply except orange and cocoa-bean. Thus, in the case of coffee supply response, a one-standard-deviation-shock in banana price (equal to 0.223 units), induces a contemporaneous decrease in coffee supply of 0.006 units. Interestingly, in the second period, with the exception of orange, cocoa-bean and potato supply, shocks in the substitute crops' price induce positive response in crop supply response for the other crops.

Wage rate shocks appear to have negligible contemporaneous effect and no effect in period two on banana and sugar responses. Wage shocks do have negative contemporaneous effect on coffee, pimento, yam, and potato supply responses. However, in period two, it appears that wage shocks generally have a positive impact on short-run supply response. The exceptions are orange and cocoa-bean.

Finally, shocks in fertilizer price have negative contemporaneous effect on banana, sugar, pimento and yam supply response. However, with the exception of potato, and pimento, supply response of crops to a shock in fertilizer price are positive in period two.

Table 8 shows the proportion of forecast error variances in quantity, which are attributable to the variables than one indicate that a model performs better (i.e., has a lower RMSE) than the naïve model. Doan (1996) claims that a Theil U of 0.8 or less is reasonable for a univariate forecast model.

The values of (p, q) were determined by the ACF and PACF. For an ARMA(p, q) process, the ACF begins to decay at lag q, and the PACF begins to decay at lag p. In addition to the ACF and PACF, the Ljung-Box Q-statistic was used in model selection. The Q-statistic is a chi-square (χ^2) test used to test the null hypothesis of no significant autocorrelations.

The two sets of fitted values, the (forecasted) `counterfactual' and `actual', for each crop, were then plotted on the same graph. These graphs are shown in Figures 1-8. From a visual inspection of those graphs the following observations are noted. First, banana is the only crop in the sample for which the fitted values from the reform period are clearly above the fitted values for the counterfactual over the entire 1980-1999 period. Excluding the years 1987-1988, this observation is also applicable for pimento. The interpretation of this observation, based

Table 8: Summary of Forecast Error Variance in Crop Quantities Explained by Variables in the VAR (Percentage)

Forecast Error Variance in:	Period	Percentage of Forecast Error Variance in Quantity Explained by Shocks in:				
		P_a	F	W	P_o	Q
Banana	1	19.407	1.105	0.004	19.940	59.543
	3	21.416	1.147	0.006	20.094	57.337
Sugar	1	19.940	1.105	0.004	19.407	59.543
	3	20.094	1.147	0.006	21.416	57.337
Coffee	1	0.394	0.150	2.727	4.564	92.165
	3	4.732	0.805	2.857	3.950	87.655
Pimento	1	0.070	0.839	0.948	0.917	97.226
	3	7.285	10.403	2.914	1.959	77.439
Yam	1	0.127	0.653	3.691	13.330	82.199
	3	1.869	2.100	3.244	25.605	67.183
Orange	1	6.461	1.110	16.195	2.465	73.769
	3	21.606	1.548	5.842	43.470	27.534
Cocoa Bean	1	2.026	0	2.451	0.141	95.383
	3	1.588	0.133	6.502	11.047	80.730
Potato	1	0.714	2.626	2.711	40.583	53.367
	3	1.485	2.440	2.459	54.282	39.334

upon the assumptions that have been used to generate the fitted and forecasted series, is that if there were no change in the policy regime in Jamaican over the 1980-1999 period, then the output of banana and pimento, with given price incentives, would have been lower than that which were actually observed under the reform policy regime. In other words, it appears that the reforms impacted positively on these two crops over the 1980-1999 period that are specified as exogenous in the VARs for each crop. As previously mentioned, it is common for a variable to explain a larger proportion of its contemporaneous forecast error variance and smaller proportions at later periods. This is generally the case for the crops shown in Table 8. Thus, 92% of coffee's contemporaneous forecast error variance is explained by its own shock, 5% by own-price (P_o), 3% by wage shocks and by negligible percentages in fertilizer and the substitute crop prices. However, in the third period, the percentage forecast error variance explained by price of the substitute crop in the cases of coffee, cocoa-bean and potato.

Counterfactual Analysis

In this paper, a counterfactual was constructed by dividing the actual observations into two separate sub-samples, 1962-1979 and 1980-1999, corresponding to the pre-reform and reform periods, respectively. Supply functions for each crop were estimated for each of the two sub-samples. The estimation procedure followed the Johansen method, which was outlined in chapter 4. Fitted values from the 1962-1979 period were then forecasted over the 1980-1999 period and these forecasts were used as the counterfactuals against which the fitted values from the 1980-1999 supply functions were compared graphically.

With respect to the forecasting exercise, the BOXJENK, COR-RELATE, and FORECAST instructions in the RATS computer software were used to identify, estimate and forecast the fitted series which were used as the counterfactual series. After some experimentation, the forecasts were modeled as mixed autoregressive-moving average processes, denoted as ARMA(p, q), where p and q are the autoregressive and moving average orders, respectively (Pindyck and Rubinfeld, 1991).

Following the Box-Jenkins methodology (Enders, 1995; Doan, 1996), the orders of p and q were determined by examining the sample autocorrelation functions (ACF), partial auto-correlations functions (PACF), and graphs of the fitted series. For each series, several models were fitted to the data and the final choice was determined on the basis of parsimony, and various diagnostic statistics. The test criteria used are the root-mean-square error (RMSE), Theil's Inequality Coefficient (Theil U), and the Ljung-Box Q-statistics. Low RMSE is a desirable quality from a forecasting model. The Theil U statistic is independent of the units of measurement. It is the ratio of the RMSE for the forecast model to the RMSE for a "naïve" forecast of no change in the dependent variable from the previous value (Doan, 1996). Values of Theil U that are less

Second, for some crops there are two distinct periods over 1980-1999 in which the fitted values from the reform period are either above or below the counterfactual. For example, over the 1980-1992 period the fitted values for sugar for the reform period were below those for the counterfactual. The reverse is observed for the series since 1992. Similarly, fitted values for coffee for the reform period have been above the counterfactual over the 1980-1995 period but the situation reversed after 1995. Similar observations can be made for orange and cocoa-bean.

Finally, the cases of yam and potato are different from the two patterns observed for the other crops. Yam shows an oscillating pattern. Fitted values for the counterfactual were below fitted values for the reform period over 1980-1985. Potato showed similar oscillations but with relatively wider gaps within each oscillation.

In effect, therefore, based on the counterfactual analysis, the data seem to suggest that the impact of the reforms is crop and time specific. For some crops it would appear that the reforms impacted negatively on output trends in the 1990s. This is the case of coffee, orange, cocoa-bean and potato. For banana and pimento the reforms appear to impact positively on output responses. For yam and potato, similar straightforward conclusions cannot be made since the reforms appear to impact positively on output response in some periods and negatively in others.

Conclusions

The reforms in Jamaica that began in the late 1970s engendered an entirely new economic environment for agriculture, constituting a fundamental departure from the basic policy directives that had been adopted in Jamaica from the 1960s through to the late 1970s. These policies encouraged inward looking industrialization; state-sponsored import substitution and nationalization of foreign enterprises; extensive use of price controls and subsidies; and, generally, a relatively strong populist approach to the solution of poverty, low income, unemployment, and other socio-economic problems.

The estimates on crop supply responses presented in this study suggest that long-run equilibrating relationships exist which link crop output and price incentives for the eight crops studied. This result has important policy implications insofar as it indicates a significant relationship between agricultural supply and price incentives. In particular the link between output and price incentives means that these variables move together over time and more importantly, respond to the same shocks in the system, albeit with varying degrees. Further, as markets become more competitive, this link becomes stronger since market signals are transmitted more effectively and efficiently.

Although economic theory is generally silent as to what constitutes a stimulative price shift for agricultural producers, the econometric evidence presented in this study indicates a positive relationship between output supply and own-price. Crops such as banana and sugar, whose prices are still determined by preferential agreements, enjoyed increased real prices over the reform period. With respect to bananas, EU's arrangements with the ACP countries are constantly being challenged by Central and Latin American (Dollar) banana countries. Proposals are for the individual ACP quotas to be replaced by a single global ACP group quota. While the tariff preference is expected to continue in the future, it is under constant review. The main implication is that Jamaican farmers must reduce cost of production in order to compete in the EU market.

There is strong evidence to suggest that there are considerable constraints in the economic system, which slow down the adjustment process for economic variables. This is evidenced by the prevalence of low adjustment co-efficients, which were estimated along with the long-run relationships. Own-price and quantity adjustments appear to exercise the major weight in the adjustment of the short-run to the long-run equilibrium process. While significant elasticities were observed for the input prices, generally these were low, but fall within the range of estimates reported in other studies on supply response in Jamaica. The low input price elasticities are not surprising since inputs such as wages and fertilizer constitute important components in the production process. However, if these inputs are not to appear as constraints to production, policy initiatives have to be undertaken to make them appealing to producers.

Given the biological lag between planting and harvesting seasons in agriculture, adjustments in the sector are necessarily slow processes. Additional factors that contribute to slow adjustments are the institutional and structural framework within which agricultural producers must operate. Slow adjustments in the short-run are signs of constraining government regulations, inadequate supportive infrastructure, and lack of credit to farmers.

The empirical evidence provides only partial support for the hypothesis that the reforms impacted significantly on agricultural supply responses. In particular, even when controlling for policy regime changes by constructing counterfactuals against which the reforms could be compared, it was found that for the eight crops included in this study, the effects are crop and time dependent. Although nominal crop prices have increased dramatically during the reform period, real crop prices have remained stable or have declined generally. Movements in the exchange rate and the general price level seem to be the immediate causes for these phenomena. It appears also that price variability increased significantly during the reform period. Given that farmers in Jamaica, as in most developing countries, can rarely mitigate against temporal price risk, the evidence seems to suggest that the pro-competitive effects of the reforms may have acted more as a depressive factor on supply response, compared to the stability of the pre-reform period characterized by stable and guaranteed markets and prices by government commodity boards.

Further insights into the impact of the reforms on crop supply responses in Jamaica would be obtained by more intensive study of single crops. This will allow more in-depth study, and guard against using the same modeling framework to accommodate crops whose supply dynamics may be different.

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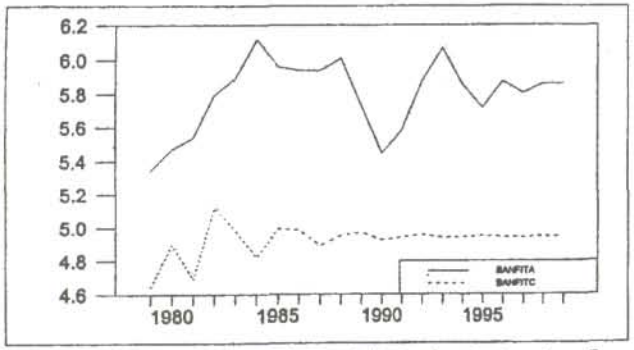

Figure 1: Banana--Fitted Output for Reform Period (BANFITA) and Counterfactual (BANFITC).

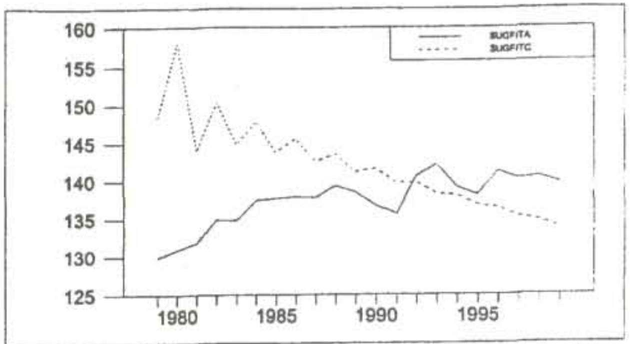

Figure 2: Sugar--Fitted Output for Reform Period (SUGFITA) and Counterfactual (SUGFITC).

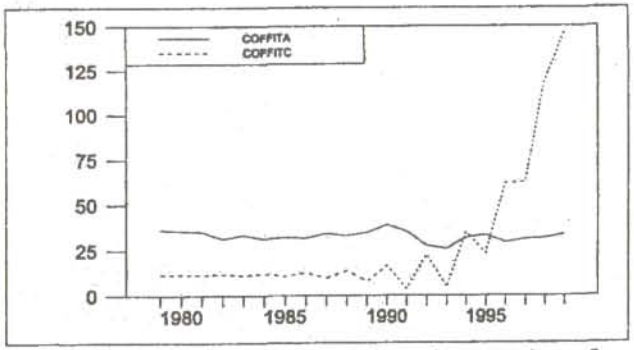

Figure 3: Coffee--Fitted Output for Reform Period (COFFITA) and Counterfactual (COFFITC).

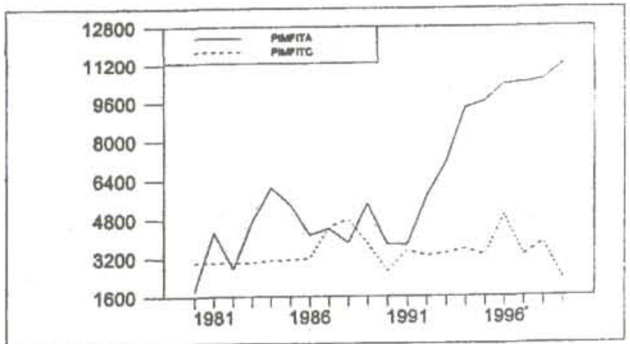

Figure 4: Pimento--Fitted Output for Reform Period (PIMFITA) and Counterfactual (PIMFITC).

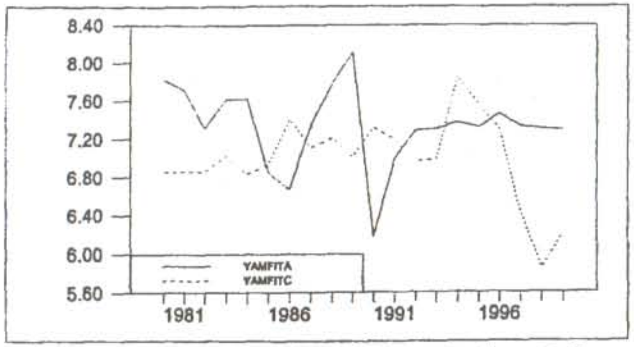

Figure 5: Yam--Fitted Output for Reform Period (YAMFITA) and Counterfactual (YAMFITC).

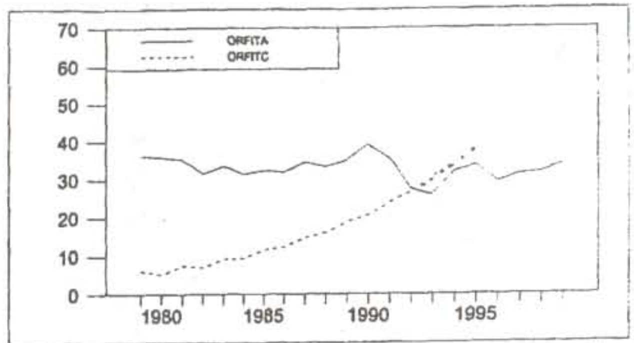

Figure 6: Orange--Fitted Output for Reform Period (ORFITA) and Counterfactual (ORFITC).

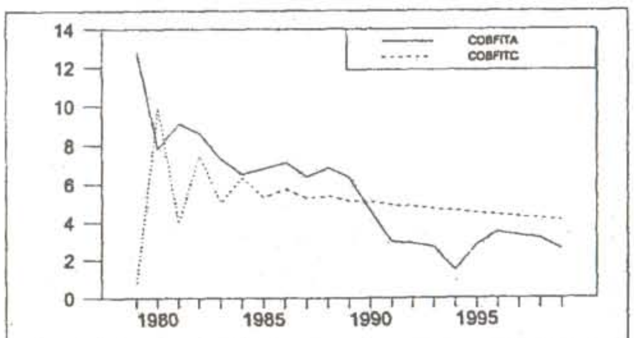

Figure 7: Cocoa-bean--Fitted Output for Reform Period (COBFITA) and Counterfactual (COBFITC).

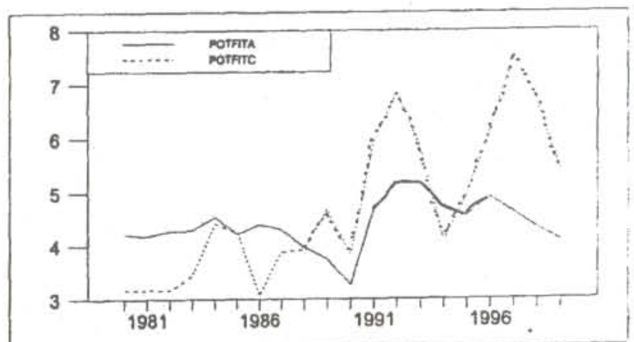

Figure 8: Potato--Fitted Output for Reform Period (POTFITA) and Counterfactual (POTFITC).