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Appendices for
"Commodity Price Volatility Across Exchange Rate Regimes"

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Appendix I:
<u>Measuring Volatility in Real Commodity Prices: Some Time Series Issues</u>

Any attempt to examine the variability in an economic time series needs an appropriate measure of variability. The most widely used measure in the macroeconomics literature is the variance of period-to-period percentage changes in the time series under consideration. This measure is obviously appropriate when the underlying data generating process is a random walk (with or without drift), which is usually a too strong assumption. If the time series is a more general unit root process where the first difference exhibits serial correlation, one might want to consider the variance of the innovations in the data generating process rather than the variance in the percentage changes of the series itself.

Because most of the relative and nominal time series examined in this project are arguably nonstationary, the series must be appropriately detrended or differenced to achieve stationarity before meaningful comparison of their variability over time can be made. Different detrending methods differ markedly in the degree to which they filter out particular frequencies.[1]

Besides the existence of significant serial correlation, the underlying data might be mean stationary or trend stationary. First differencing in these cases will generate a

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[1] See Baxter, M. (1988). Business cycles, stylized facts, and the exchange rate regime: Evidence from the United States. Rochester Center for Economic Research Working Paper, No. 169.

unit root in the moving average (MA) part of the error process. Depending on the specific econometric techniques used in examining the variability behavior over time, the test results may be seriously biased in either direction.

In light of these complications, the empirical investigations of this paper will begin with the unit root tests and considerations of alternative trend specifications. The variability in real macroeconomic variables is measured as the temporal variation of a time series around its mean (or trend), after taking an ARMA error process or GARCH effects into account.

Stationarity and Unit Root Tests

It is well known that for many economic time series, unit root tests fail to reject the null hypothesis of a unit root in the underlying data generating process. In an influential study, Nelson and Plosser (1982) showed that the unit root test failed to reject the null hypothesis for all but one of the 14 annual U.S. time series they considered. These results are basically not changed by subsequent research using more elaborate econometric techniques[2]. The presence of unit roots is important because stationarity of regressors is assumed in the derivation of standard inference procedures for regression models. Many standard results are invalidated if regressors are, in fact, nonstationary.

If there is a unit root in a time series, the correct procedure is to first difference the series before undertaking further empirical tests. However, if there is no unit root, first difference will introduce a unit root into the MA part of the error process. The

[2] See, however, Kwiatkowski et, al. (1992). They propose a test that sets the null hypothesis as trend stationary, instead of a unit root in the underlying data generating process. Applying the test to the Nelson-Plosser data, they can not reject the null of trend stationary for many of the series.

Augmented Dickey Fuller (ADF) and Phillips Perron (PP) tests are two commonly used formal tests to check the presence of unit roots. Phillips-Perron unit root test is used in this study because the variables are potentially heteroskedastic, due (for example) to variances being exchange rate regime dependent.

It is now well-known that unit root tests have low power, and that whether an intercept and time trend are included in the regression used to obtain the PP statistics is critical in interpreting the results. We follow the general-to-specific methodology by first including both a constant and a time trend in the estimation. (See Enders, 1995). If the null is not rejected in the most general version of the specification, the significance of the trend and intercept can then be tested in turn to see if they can be omitted, thereby increasing the power of the unit root test.

Table I-1 reports the results of the Phillips-Perron tests on the GY, the Boughton and the IFS data sets. For the real price series, the null of $\phi = 0$ is rejected at the 5% significance level for the monthly series of agricultural raw materials, metals and sugar. The third column indicates whether a time trend (T), or a constant (C), or neither term (N) is included in the Phillips-Perron test, using the method described in the previous paragraph.

Table I-1 Estimated t-statistics for the unit root hypothesis

	τ	*Specification in the Phillips-Perron test*
GY data set	-3.40	T & C
Boughton data set	-2.27	N
Agricultural Raw Materials	-4.30*	T & C
Beverages	-1.42	N
Fertilizer	-1.93	N
Food	-1.20	N
Metals	-3.48*	T & C
Sugar	-12.51*	T & C

* indicates rejection of the unit root hypothesis at the 5% significance level.

For the long-run time series used in this study, there had been mixed results in the literature on whether the difference stationary or the trend stationary model should be employed to describe the underlying data generating process. Therefore, both detrending methods, as well as the Hodrick-Precott filter, are considered in this case to see whether any test results are sensitive to the detrending method employed.

GARCH Models

It has long been observed that asset returns tend to be leptokurtic (i.e. they exhibit "fat tails"). Volatility clustering is also common, that is, large changes tend to be followed by large changes, and small changes tend to be followed by small changes. A univariate generalized autoregressive conditional heteroskedastic model (GARCH) is used in this study to account for time varying variance and covariance.

Engle's (1982) autoregressive conditional heteroskedastic (ARCH) model allows for persistence in conditional variance by specifying an autoregressive structure on the squared residuals. Specifically, the residual ε_t is modeled as an ARCH(m) process.

$$\varepsilon_t | I_{t-1} \sim N(0, h_t) \quad \text{(I-1)}$$

$$h_t = \delta + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 \quad \text{(I-2)}$$

where I_{t-1} is the information set through time t-1. ε_t is serially uncorrelated but not stochastically independent because they are related through their second moments. In order for ε_t^2 to be positive and covariance stationary, the following restrictions are required on the coefficients in equation (I-1): $\alpha_1>0$, $\alpha_i \geq 0$ for i=1,2,...,m, and $\alpha_1+\alpha_2+...+\alpha_m<1$. In practice, arbitrary declining weight structures are usually imposed to meet these coefficient restrictions.

Bollerslev (1986) develops the GARCH model which extends the ARCH(m) model to allow the conditional variance to be an ARMA process. Hence, instead of equation (I-2), the conditional variance is specified as:

$$h_t = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad \text{(I-2')}$$

The variance today depends on past news about volatility (the ε_t^2 terms) and past forecast variance (the h_t terms). The inclusion of lagged conditional variances might capture some sort of adaptive learning mechanism. The benefit of the GARCH specification (I-2') is that it is more parsimonious and entails fewer coefficient restrictions than equation (I-2). Sufficient conditions for well-defined variance and covariance only require all coefficients in equation (I-2') to lie inside the unit circle. For example, in a GARCH(1,1) process, it requires $\alpha>0$, $\beta>0$, and $\alpha+\beta<1$.

For asset prices, it is often observed that downward price changes are followed by higher volatilities than upward movements of the same magnitude. Glosten, Jagnanathan, and Runkle (1989) proposed the Threshold ARCH (TARCH) specification to model the conditional variance as:

$$h_t = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{r} \gamma_i \ \varepsilon_{t-i}^2 d_{t-i} + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad \text{(I-2")}$$

where d_t =1 if ε_t<0, and 0 otherwise. Hence, a positive ε_t has an impact of $\alpha(L)$ on the conditional variance while a negative ε_t has an impact of $\alpha(L)+\gamma(L)$.

For most financial time series, GARCH(1,1) provides a sufficiently good fit. This is also true for the real price variables studied in this paper. The squared residuals of GARCH(1,1) can be written as an ARMA(1,1) process. Specifically, ε_t can be decomposed into its conditional expectation (h_t) plus an innovation (v_t) term. The latter by definition is unpredictable based on the past:

$$\varepsilon_t^{\,2} = h_t + v_t \tag{I-3}$$

Substituting equation (I-3) into (I-2'), an alternative expression for the squared residuals is as follows:

$$\varepsilon_t^2 = \delta + (\alpha + \beta + \gamma)\varepsilon_{t-1}^2 + v_t - \beta v_{t-1} \qquad \text{(I-4)}^{3}$$

The conditional variance of ε_t is $E_{t-1}\varepsilon_t^2 = h_t$. The unconditional variance exists when $\alpha+\beta+\gamma<1$, and is defined as:

$$\sigma^2 = \tfrac{\delta}{1-\alpha-\beta-\gamma} \tag{I-5}$$

When σ^2 exists and is independent of time, the GARCH process is stationary. The sum $\alpha+\gamma+\beta$ measures the persistence of volatility shocks. When $\alpha+\beta+\gamma=1$, the ARMA process for ε_t^2 would have a unit root and the GARCH process is said to be integrated in variance (IGARCH) (Engle and Bollerslev, 1986). In this case the unconditional variance of ε_t is infinite, even though it is still possible for ε_t itself to be a strictly stationary process (Nelson, 1990). For IGARCH process, "current information remains important for the forecasts of the conditional variances for all horizons" (Engle and Bollerslev, 1986, p27).

[3] Note that v_t is not a white noise innovation.

Appendix II:
<u>Allowing for a Structural Break in 1920 for the Long-Run Data</u>

Previous commodity price studies have often argued that there was a structural break in the underlying data generating process for these prices around 1920. This appendix summarizes our analysis of the volatility in long-run *real* price series when structural break in 1920 is allowed. The TS specification in the text is generalized as follows:

$$log\ y_t = \omega + \theta * time + \varphi * Dum1920 + e_t \quad \text{(II-1)}$$

where *Dum1920* is the dummy variable that takes the value zero through the year 1919, and unity thereafter. Analogously, the DS specification becomes:

$$d\ log\ y_t = \varpi + \phi * D(Dum1920) + e_t \qquad \text{(II-2)}$$

where D(Dum1920) is a "spike" dummy that takes the value 1 in 1920 and 0 otherwise. The test results based on the detrending specifications (II-1) and (II-2) are presented in Table II-1 below. It can be seen that, even allowing for a shift in the mean of the series in 1920, μ_2 in the resulting variance equation (2) is significantly different from zero at the 5% level. Hence, our conjecture that volatility of real commodity price is higher under flexible exchange regimes is robust to the inclusion or omission of a structural break in 1920.

Table II-1.

Estimated Values of μ_2 and associated t-statistics when structural break in 1920 is allowed in the trend specification

	$\mu_1 \times 10^2$	$\mu_2 \times 10^2$	constant	time$\times 10^2$	Dum1920	Q(12)	Error Process
TS Models							
The GY Index	0.50	0.83	0.46	-0.80	-0.31	8.43	$(1-0.84L)e_t=(1-0.22L^2)\varepsilon_t$
	(2.62)	*(2.88*)*	*(3.61)*	*(-3.73)*	*(-3.92)*		*(11.17)* *(-1.67)*
The Boughton Index	0.30	0.75	0.23	-0.32	-0.07	6.70	$(1-0.72L)e_t=(1+0.48L)\varepsilon_t$
	(1.77)	*(2.63*)*	*(4.27)*	*(-2.84)*	*(-3.23)*		*(7.86)* *(5.02)*
DS Models							
The GY Index	0.52	0.84	-0.28		-0.47	9.87	$e_t=(1-0.30L^2)\varepsilon_t$
	(2.81)	*(3.06*)*	*(-0.40)*		*(-7.56)*		*(-2.78)*
The Boughton Index	0.31	0.75	0.54		-0.10	5.76	$(1+0.33L^2)e_t=(1+0.19L)\varepsilon_t$
	(1.99)	*(2.82*)*	*(-0.82)*		*(-3.03)*		*(-2.24)* *(1.82)*

The first two columns show the estimated parameters in the variance equation. The remaining columns show the parameters of the trend specification, TS in the top panel, and DS in the lower half of the Table.

Asterisks (*) indicate that the null hypothesis can be rejected at the 5% significance level.

Appendix III:
Estimated GARCH Models for the Monthly Relative Price Series When Exchange Rate Regime Shifts are Ignored

Here we examine whether GARCH models provide good descriptions of the behavior of the six monthly commodity price series if the effects of exchange rate regime shifts, which are accounted when modeling conditional variances of the monthly series in the text of the paper, are ignored.

The conditional variance is specified as GARCH or TARCH respectively:

$$h_t = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad \text{(III-1)}$$

$$h_t = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{r} \gamma_i \, \varepsilon_{t-i}^2 d_{t-i} + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad \text{(III-1')}$$

For most financial time series, GARCH(1,1) provides a sufficiently good fit. This is also true for the monthly commodity price series, except in the case of fertilizer.[4] For real metal price series, TARCH(1,1) provides a better fit. Table III-1 presents test statistics for both the mean and variance estimation, using the detrending method suggested by the unit root test results.

[4] For real fertilizer price index, although the negative ARCH term is not significant, the GARCH term is greater than one. A negative ARCH term can not ensure that the conditional and unconditional variances are positive for all realizations of ε_t.

Table III-1. Estimation of the GARCH(1,1) model (1951 January—1996 May)

	$\delta \times 10^3$	α	γ	β	**Log likelihood**
Agricultural Raw Material	0.03 *(1.97)*	0.23 *(4.37)*		0.75 *(13.50)*	1081.75
	$\log y_t = 0.0498 - 5.16E\text{-}05 * time + e_t$; $(1 - 0.98L + 0.07L^{13})\, e_t = (1 + 0.23L)\varepsilon_t$ *(2.66) (-0.57) (67.33) (-5.30) (4.29)*				
Beverages	0.03 *(1.16)*	0.11 *(3.12)*		0.89 *(4.63)*	817.82
	$d\log y_t = -0.0015 + e_t$; $(1 - 0.31L)\, e_t = (1 - 0.002L^2)\varepsilon_t$ *(-0.62) (5.84) (-0.04)*				
Fertilizer	0.01 *(3.45)*	-0.003 *(-0.34)*		1.01 *(46.49)*	743.28
	$d\log y_t = -0.002 + e_t$; $(1 - 0.30L^6)\, e_t = (1 - 0.44L^{24})\varepsilon_t$ *(-1.42) (7.27) (-11.20)*				
Food	0.10 *(1.50)*	0.15 *(2.65)*		0.86 *(18.81)*	1073.72
	$d\log y_t = 4.00 * 10^{-5} + e_t$ *(0.03)* $(1 - 0.26L)\, e_t = \varepsilon_t$ *(5.23)*				
Metals	0.02 *(2.43)*	0.34 *(5.40)*	-0.30 *(-4.65)*	0.80 *(26.51)*	980.65
	$\log y_t = 0.40 - 0.0013 * time + e_t$ *(3.62) (-3.89)* $(1 - 0.99L + 0.02L^{12}) e_t = (1 + 0.30L - 0.03L^4 - 0.07L^9 + 0.14L^{24})\varepsilon_t$ *(63.26) (-1.33) (6.70) (-0.70) (-1.87) (3.66)*				
Sugar	0.79 *(1.98)*	0.23 *(3.60)*		0.72 *(9.83)*	426.02
	$\log y_t = 0.0009 - 0.0007 * time + e_t$; $(1 - 0.95L)\, e_t = (1 + 0.30L + 0.06L^{10})\varepsilon_t$ *(1.13) (-1.18) (67.27) (6.12) (1.40)*				

The sum of $\alpha+\gamma+\beta$ measures the persistence of volatility shocks. For many commodity series, this sum is very close to unity. This implies that volatility shocks die out very slowly. For real food prices, the sum is greater than one. When $\alpha+\beta+\gamma>=1$, the ARMA process for ε_t^2 has a unit root and the GARCH process is said to be integrated in variance (IGARCH) (Engle and Bollerslev, 1986). Thus this specification is less satisfactory than the ones in the text which allow for exchange rate regime shifts. With this generalization of the variance process, the sum of $\alpha+\gamma+\beta$ is well below one.

Appendix IV:
<u>The Impact of Wars of Real Commodity Price Volatility</u>

A referee of an earlier version of this paper hypothesized that increases in commodity price volatility during various subperiods may be the result of wars, rather than the particular exchange rate regime in effect at the time. We agree that wars might shift the supply and/or the demand for particular commodities (some more than others; oil vs. cotton). But the supplies and demands for various *manufactured* goods may also be impacted. To the extent that there is a differential impact on primary commodities and manufactures, this would affect the *mean* of the stochastic process describing relative commodity prices. A subtler issue is whether wars would have a significant effect on relative price *volatility*. One might conjecture that there is greater year-to-year volatility in the supplies and/or demands for primary commodities and/or manufactured goods during war periods. These effects might, in turn, impact relative price volatility. But the direction of such impact (i.e., to increase or to decrease relative commodity price volatility) is unclear *a priori*.

To determine the possible influence of wars on the volatility of real commodity prices, we created a war dummy (DUMWAR) that takes the value "1" during any year in the sample (1880-1996) when a conflict was occurring, and zero otherwise. War years are shown in Table IV-1. A second dummy (BIGWAR) indicates major conflicts from the U.S. point of view. BIGWAR equals "1" during the years of WWI, WWII, the Korean War, and the years of the Vietnam War when the U.S. was intensively involved. (Note, however, that the period of the second world war is not included in analysis in the paper, as the commodity prices were unavailable and hence had been interpolated by earlier authors over this period.

Table IV-1

War	Dates
Chinese-Japanese War	1894-95
Spanish American War	1898
Boer War	1899-1902
Russia-Japanese War	1904-05
Balkan Wars	1912-13
World War I	**1914-18**
Russian Revolution	1917-18
Spanish Civil War	1936-39
World War II	**1939-45**
First Arab-Israeli War	1948-49
Korean War	**1950-53**
Vietnam War	1955-75(1965-1975)
Second Arab-Israeli War	1956
Six-Day War	1967
Yom Kippur War	1973
Afghan Civil War	1979-89
Iran-Iraq War	1980-88
Persian Gulf War	1991

Tables IV-2 presents cross tabulations involving the dummies, DUMFLEX and DUMWAR. Table IV-3 shows the analogous cross-tab for DUMFLEX and BIGWAR. The null hypothesis that the occurrence of flexible exchange regimes and wars are independent can not be rejected at conventional significance levels.

Table IV - 2:
Tabulation of DUMFLEX (down) versus DUMWAR (across), 1880-1992

	0.00000	**1.00000**	**Row Total**
0.00000	31	41	72
% table	27.43	36.28	63.72
%row	43.06	56.94	
%col	64.58	63.08	
1.00000	17	24	41
%table	15.04	21.24	36.28
%row	41.46	58.54	
%col	35.42	36.92	
Col Total	48	65	113
%table	42.48	57.52	100.00

Test of row-column independence for this table:
Chi-square(1) = 0.027102, Probability = 0.8692

Table IV-3:
Tabulation of DUMFLEX (down) versus BIGWAR (across), 1880-1992

	0.00000	**1.00000**	**Row Total**
0.00000	54	18	72
% table	47.79	15.93	63.72
%row	75.00	25.00	
%col	62.79	66.67	
1.00000	32	9	41
%table	28.38	7.96	36.28
%row	78.05	21.95	
%col	37.21	33.33	
Col Total	86	27	113
%table	76.11	23.89	100.00

Test of row-column independence for this table:
Chi-square(1) = 0.133532, Probability = 0.7148

The referee speculates that wars may, in fact, cause changes in exchange rate regime. This hypothesis can be examined by considering the cross correlation functions between (DumFlex and DUMWAR) and (DumFlex and BIGWAR), respectively. There were no significant lead-lag relationships running from either of the war dummies to the choice of exchange regime dummy, regardless of whether the dummies or the first-difference of the dummies are used.

Granger causality tests were also examined. As Table IV-4 shows, there were no statistically significant effects running from either of the war dummies to exchange rate regime. The only significant "G-causal" relationships at the 5% significance level were from DUMFLEX to BIGWAR and from D(DUMFLEX) to D(BIGWAR), suggesting rather implausibly that the switches to flexible exchange rate regimes ‘caused’ the big wars in the 20th century!

Table IV-4:
Granger Causality Tests,
1880-1992 (n=103; lags=10)

Null Hypothesis:	Obs.	F-Statistic	Probability
BIGWAR does not Granger Cause DUMFLEX	103	0.47359	0.90255
DUMFLEX does not Granger Cause BIGWAR		2.05691*	0.03754
DUMWAR does not Granger Cause DUMFLEX	103	0.21955	0.99381
DUMFLEX does not Granger Cause DUMWAR		1.11141	0.36379
D(BIGWAR) does not Granger Cause D(DUMFLEX)	102	0.53226	0.86252
D(DUMFLEX) does not Granger Cause D(BIGWAR)		1.97999*	0.04619
D(DUMWAR) does not Granger Cause D(DUMFLEX)	102	0.29440	0.98065
D(DUMFLEX) does not Granger Cause D(DUMWAR)		1.04750	0.41231

* indicates significance at the 5% level.

One further test on the war effect is done by checking the significance of the war dummies in the variance equation. Regardless of which detrending assumption is used, when both the war dummy and the exchange regime dummy are put in Equation (2), the dummy for exchange rate regime remains to be strongly significant, while the war dummies (both DUMWAR and BIGWAR) are not significant at all. This evidence provides further support for our main conjecture that the shift of relative commodity price volatility seems to be systematically linked to the nominal exchange rate arrangements, rather than another exogenous factors.

Table IV-4: **Estimated Values of Dummies (*10^2) in extended Equation (2)**
(*t-statistics in parenthesis* **)**

	$Var(\varepsilon_t)=\mu_1+\mu_2*DUMFLEX+\mu_3DUMWAR$		$Var(\varepsilon_t)=\mu_1+\mu_2*DUMFLEX+\mu_3BIGWAR$	
	DUMFLEX	DUMWAR	DUMFLEX	BIGWAR
The TS Model				
The GY Index	1.26 (2.13*)	-0.23 (-0.31)	1.28 (2.08*)	0.14 (0.24)
The Boughton Index	0.69 (2.30*)	0.19 (0.81)	0.65 (2.31*)	0.76 (1.35)
The DS Model				
The GY Index	1.46 (2.24*)	-0.36 (-0.44)	1.48 (2.15*)	-0.01(-0.12)
The Boughton Index	0.77 (2.64*)	0.20 (0.86)	0.73 (2.66*)	0.75 (1.33)
The HP Filter				
The GY Index	1.06 (2.40*)	-0.26 (-0.47)	1.13 (2.48*)	0.33 (0.91)
The Boughton Index	0.90 (3.23*)	-0.16 (-0.58)	0.90 (3.25*)	0.20 (0.59)

* indicates significance at the 5% level.

Appendix V:
Analysis of *Nominal* Commodity Price Volatility

This appendix summarizes our analyses of nominal commodity price volatility. The results are qualitatively similar to those using real price indices, reported in the paper.

Visual examination of Fig. V-1 (in log-levels) and Fig. V-2 (in percentage changes) points to striking differences in the nominal commodity price behaviors across exchange rate regimes.

Fig. V-1. Nominal Commodity Price Indices and Exchange Rate Regime

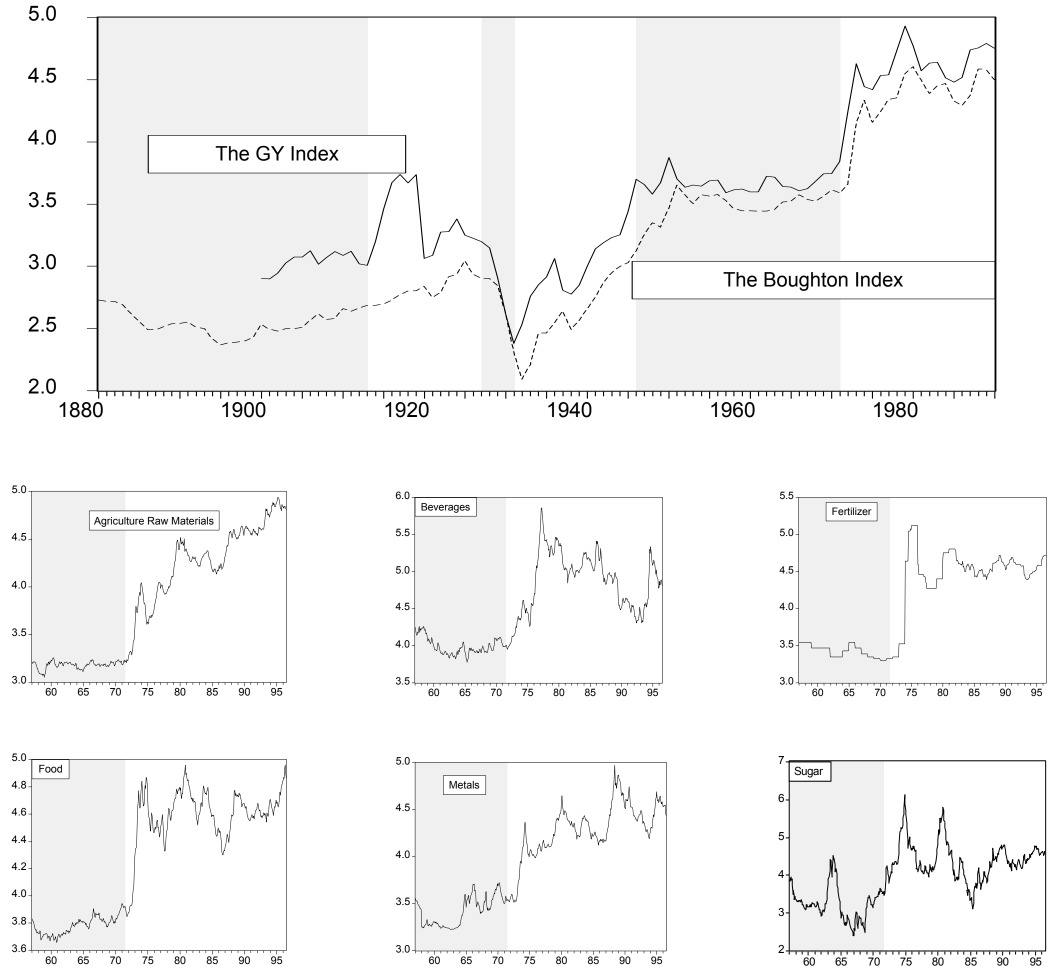
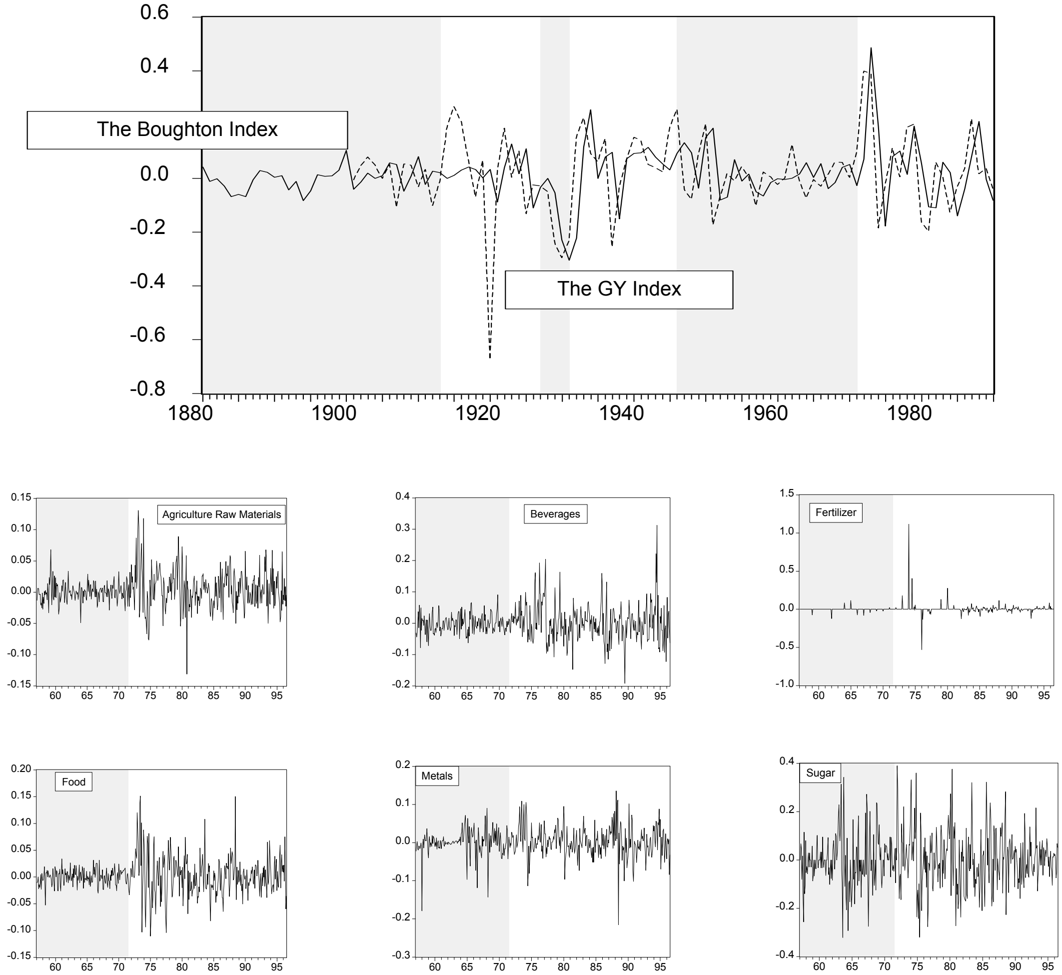


Figure V-2. Period-to-period Percentage Change of Nominal Commodity Prices



Testing for Unit Roots in the Nominal Price Indices

Most nominal price indices in our study are found to have a stochastic trend. The Phillips-Perron unit root tests in Table V-1 show that the null hypothesis of $\rho=1$ can not be rejected at the 5% significance level, except for sugar price series.

Table V-1. Estimated t-statistics for the unit root hypothesis

	Nominal Commodity Price Index
GY data set	1.18
Boughton data set	1.49
Agricultural Raw Materials	1.69
Beverages	0.20
Fertilizer	0.59
Food	1.05

Metals	0.63
Sugar	-2.96*

* Asterisk indicates rejection of the unit root hypothesis at the 5% significance level.

Nominal Commodity Price Volatility Shifts across Exchange Rate Regimes

(a) The Long Run Data

For the two long-run nominal commodity price series, the null hypothesis that volatility does not change significantly across exchange regimes can be rejected at the 5% level, regardless of whether the TS or DS trend specification is used. The test results are summarized in Table V-2.

$$Var\ (\varepsilon_t)=\mu_1+\mu_2 * DUMFLEXIBLE \qquad \text{(V-1)}$$

Table V-2. Estimated Values of μ_2 and Associated t-Statistics

The TS Model						
	$\mu_1\times10^2$	$\mu_2\times10^2$	**constant**	time$\times10^2$	**Q(12)**	**Error Process**
The GY Index	0.96	1.36	2.59	2.17	6.16	$(1-0.86L)e_t=(1+0.36L)\varepsilon_t$
	(2.59)	*(2.53*)*	*(8.26)*	*(4.40)*		*(12.79) (2.81)*
The Boughton Index	0.44	0.75	1.29	2.59	3.33	$(1-0.95L)e_t=(1+0.49L-0.23L^2)\varepsilon_t$
	(1.98)	*(2.08*)*	*(1.50)*	*(2.95)*		*(34.90) (5.05) (-2.34)*
The DS Model						
The GY Index	0.92	2.50	0.02		8.56	$e_t=(1+0.3L)\varepsilon_t$
	(1.04)	*(1.97*)*	*(1.01)*			*(2.41)*
The Boughton Index	0.43	0.82	0.01		2.71	$e_t=(1+0.5L-0.22L^2)\varepsilon_t$
	(1.91)	*(2.22*)*	*(1.39)*			*(5.54) (-2.41)*

(b) The Monthly Data

For all monthly price series, except fertilizer, the GARCH (1,1) model provides a sufficiently good fit.[5] For the price series of agricultural raw materials, TARCH(1,1) provides a better fit. The test statistics for both the mean and variance estimation are presented in Table V-3. The sum $\alpha+\gamma+\beta$ measures the persistence of volatility shocks.

[5] For nominal fertilizer price series has a significant *negative* ARCH term, which has the undesirable implication that the variance may be negative.

For the series of food and metals, the sum exceeds unity, implying an integrated ARCH error process.

Table V-3. Estimated GARCH(1,1) Models

	$\delta\times10^3$	α	γ	β	Log likelihood
Nominal Price Index					
Agricultural Raw Material	0.02 *(2.71)*	0.19 *(3.58)*	-0.13 *(-2.21)*	0.84 *(22.67)*	1127.86
	$dlogy_t$=0.0018+e_t ; (1-0.24L) e_t=ε_t *(1.55) (4.42)*				
Beverages	0.04 *(1.55)*	0.15 *(3.56)*		0.84 *(20.63)*	830.64
	$dlogy_t$= -0.0003+e_t; (1-0.34L) e_t=(1+0.02L^2)ε_t *(-0.11) (6.85) (0.49)*				
Fertilizer	2.55 *(1.07)*	-0.01 *(-2.24)*		0.59 *(1.24)*	612.39
	$dlogy_t$=0.003+e_t; (1-0.12L^6) e_t=(1-0.08L^{24})ε_t *(1.19) (0.75) (-0.30)*				
Food	0.01 *(1.5)*	0.15 *(2.65)*		0.86 *(18.81)*	1073.71
	$dlogy_t$=0.04+e_t; (1-0.26L) e_t=ε_t *(0.03) (5.23)*				
Metals	1.06×10^{-3} *(0.75)*	0.31 *(4.43)*		0.77 *(17.42)*	953.4
	$dlogy_t$=0.0006+e_t; (1-0.099L^5-0.078L^{24}) e_t=(1+0.32L)ε_t *(0.70) (1.87) (2.48) (6.81)*				
Sugar	0.75 *(2.10)*	0.24 *(3.66)*		0.71 *(10.11)*	429.16
	$logy_t$= 3.02 + 0.004*time+e_t; (1-0.95L) e_t=(1+0.31L+0.07L^{10})ε_t *(15.07) (5.33) (75.73) (6.51) (1.61)*				

Accounting for the exchange rate regime shift in the GARCH process significantly improves the fit of the model. In addition, the persistence of volatility shocks clearly declines. Recall that Diebold (1986, p.55) suggests that regime shifts may cause the appearance of integrated ARCH. The evidence reported here supports his conjecture: The sum $\alpha+\gamma+\beta$ no longer greater than one except for the nominal price of metals once regime shifts are allowed.

Table V-4. Accounting for the Exchange Regime Shift in the GARCH(1,1) Model

	$\delta_1\times10^3$	$\delta_2\times10^3$	α	γ	β	*log likelihood*	*likelihood ratio*
Nominal Price Index							
Agricultural Raw Material	0.03 *(1.90)*	0.06 *(1.71*)*	0.20 *(2.56)*	-0.13 *(-1.87)*	0.76 *(8.04)*	1133.50	11.28**
Beverages	0.07	0.25	0.14		0.76	839.96	18.64**

	(1.92)	*(2.38**)*	*(2.84)*		*(9.74)*		
Fertilizer	0.36 *(1.02)*	2.82 *(1.63*)*	-0.01 *(1.59)*		0.55 *(1.21)*	751.61	278.44**
Food	0.02 *(1.73)*	0.10 *(1.77*)*	0.09 *(2.04)*		0.80 *(9.45)*	1086.89	26.36**
Metals	1.49×10^{-3} *(0.98)*	0.07 *(1.72*)*	0.31 *(3.83)*		0.72 *(11.44)*	959.44	12.08**
Sugar	0.56 *(2.20)*	0.90 *(1.72*)*	0.29 *(4.10)*		0.64 *(7.87)*	432.27	6.22**

*Rejecting the null at the 10% significance level.

** Rejecting the null at the 5% significance level.

Appendix VI:
Using dollar/SDR rate as a proxy for international monetary system

Since during the period of 1957-1998 the US dollar was the dominant currency in the international monetary system, the volatility of the US dollar/SDR rate, denoted as *var_u*s, is chosen as the quantitative proxy for the exchange rate uncertainty in the global market as a whole. Volatility is defined here as the square of the period-to-period change in the logarithm of the US dollar/SDR exchange rate, and is plotted in Figure 1. The value of the SDR is determined by the IMF on the basis of a basket of currencies with each currency assigned a weight in the determination of that value. It currently contains 0.582 U.S. dollars, 0.446 Deutsche marks, 27.2 Japanese yen, 0.813 French francs, and 0.105 pound sterling.

Given this definition of the USD/SDR exchange rate, it is clear that var_us, which is the square of its period-to-period percentage, will be affected not only by the squares of the percentage changes in the five component currencies, but also their pairwise correlations. As Fig. 1 shows, the values of var_us were very small during the Bretton-Woods period (through 1973), but increased considerably thereafter.[6] Not surprisingly, employing var_us in place of the exchange regime dummy, DUMFLEX, in our earlier work produces very similar results. Specifically, the conditional variance is specified as:

$$h_t = \delta_1 + \delta_2 * \mathrm{var}\_us + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{\mathrm{i}=1}^{\mathrm{r}} \gamma_i \ \varepsilon_{t-i}^2 d_{t-i} + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad \text{(VI-1)}$$

[6] Examining Fig.?, we noted that the sterling crisis in the late 1960s does not show up. This is because dollar/SDR rate was fixed during this period. The redefinition of the SDR in terms of a basket of currencies was introduced only after the Bretton Woods fixed exchange rate commitment collapsed.

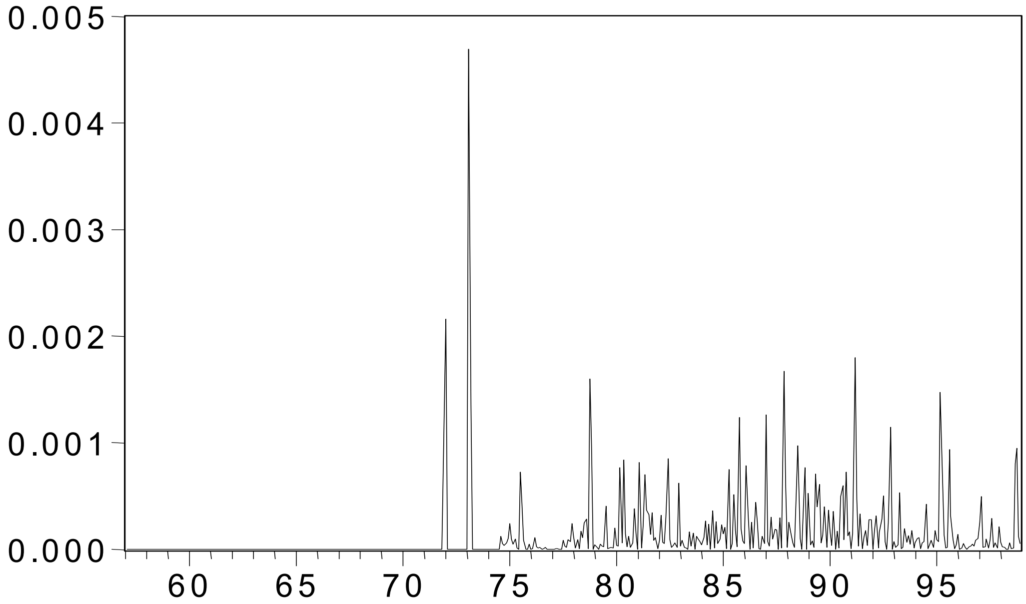
The estimation results are shown in Table 1. Except for fertilizer, the qualitative results are similar to those using the dummy variable as the proxy for the international monetary system.

Table VI-1. Accounting for Exchange Rate Fluctuations in the GARCH(1,1) Model

	$\delta_1 \times 10^3$	δ_2	α	γ	β	***likelihood ratio test comparing models w/out var_US***
Agricultural Raw Material	0.02 *(1.53)*	0.14 *(1.75*)*	0.19 *(4.12)*		0.76 *(17.65)*	5.39**
Beverages	0.04 *(2.23)*	0.52 *(3.24**)*	0.12 *(4.18)*		0.84 *(29.60)*	13.47**
Fertilizer	1.33 *(1.59)*	-0.78 *(-8.07**)*	-1.78×10^3 *(-0.28)*		0.68 *(3.09)*	NA
Food	0.01 *(3.66)*	0.24 *(1.73*)*	0.04 *(2.67)*		0.92 *(46.04)*	27.77**
Metals	1.22×10^{-3} *(1.66)*	0.31 *(2.95**)*	0.37 *(6.79)*	-0.28 *(-4.43)*	0.78 *(32.83)*	18.66**
Sugar	0.65 *(2.01)*	2.74 *(3.02**)*	0.26 *(4.70)*		0.70 *(12.18)*	5.15**

*Rejecting the null at the 10% significance level.

Figure VI-1: Volatility of the US Dollar/SDR Exchange Rate


0.005
0.004
0.003
0.002
0.001
0.000
60
65
70
75
80
85
90
95