Barter and Business Cycles: A Comment and Further Empirical Evidence

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Abstract

The purpose of this comment is a critical evaluation of the empirical analysis made by Cresti (2005) and her finding that commercial barter behaves differently than corporate barter during the course of business cycles. Here, we correct the arbitrary replacement of the missing observations by filling them with forecasts using the Box-Jenkins ARMA and Kalman filter methods before performing the unit root and cointegration tests. Although the ECM estimates for various measures of business cycle are occasionally inconsistent, overall the inventory measures and capacity utilization results suggest that barter transactions are counter-cyclical regardless of the size of the business. Additionally, we find that barter rises with inflationary trend, dissemination of access to computer technology, tax rates and tax laws requiring disclosure of barter transactions.

I. Introduction

In a recent article in this journal, Professor Cresti investigates barter in the U.S. economy (Cresti, 2007). The central theme of her paper is that two components of barter by barter exchanges in the U.S. behave differently in the course of the business cycle. She argues that while the volume of trade by commercial (small) barter is pro-cyclical, corporate (large) barter trade volume is counter cyclical. However, flaws in her argument, such as her failure to recognize the relevance of a large number of factors determining the level of barter, bring the validity of her claims into question. Because Cresti's article contains startling similarities to a paper which Marvasti and Smyth (authors of the present paper) published concerning empirical studies of barter in the U.S., it appears that Cresti either discounted or failed to compare her findings with the existing literature. In a series of papers, Marvasti and Smyth have analyzed various aspects of barter in the U.S. using the International Reciprocal Trade Association (IRTA) data. In a similar, yet more elaborate, analysis, Marvasti and Smyth in this journal examine various measures of the level of organized barter activities in the U.S. (Marvasti and Smyth, 1998). Our percentage change regression models find business inventory and large barter positively correlated, but the coefficient of business inventories is statistically insignificant in the small barter exchanges trade volume model. In the cointegration and Error Correction Model (ECM), other measures of business cycles such as unemployment are correlated with trade volume among large barter exchanges. Evidence of countercyclical behavior in barter is also found in the broadcasting industry, which engages in a significant amount of barter transactions. In a recent paper, analysis of panel data from television stations by Marvasti shows the relevance of a group of firm-specific as well as market-specific factors.

Specifically, Marvasti shows that barter transactions are positively correlated with measures of business cycles and inflation such as the unemployment rate and consumer prices (Marvasti, 2006).

Cresti's paper attempts to shed more light on the correlation between business cycles, including various breakdowns of inventories, and barter. However, in addition to replicating an existing work, her paper has raised the following concerns regarding the execution of her empirical analysis. First, extrapolation of the barter data for the period of 1996-1999 extends the trend in the data, raising questions about the validity of the stationarity and cointegration tests. On the other hand, the 1974 missing observation is replaced with the proceeding year's observation. Second, cointegration results are not presented and there is little discussion of the presence of cointegrating vectors. Third, the paper claims that the 1982 change in tax law and the tax rates are insignificant without having tested them. Similar unfounded claims are made regarding the relevance of inflation.

In this comment, we first deal with the data and the issue of the method used to fill the missing observation and present two alternative methods. Then, after the unit root tests, new cointegration and ECM estimates are presented. Conclusions regarding the correlation between the business cycles and barter are drawn at the end.

II. Data, Forecasting Missing Observations Issues, and Unit Root Tests

There are various issues related to transformation, forecasting and presentation of data in Cresti's paper.[1] Before dealing with the missing observations issue, there are a few data-related concerns in Cresti's paper. First, there are errors in the presentation of data in her Table 1 where the 1997 total barter figure is wrong (should read 9,669) and the size of the

1998 and 1999 total barters is also wrong because of the decimals used. Second, it is not clear as to whether Cresti has used the same time period for analysis of commercial and corporate barter. Her comment "in the case of corporate barter, we found it appropriate to consider all the years for which data were available" (P. 1963, first paragraph) suggests that perhaps her analysis on commercial and corporate barter involved different time frames. No explanation or justification is provided for this decision. Also, in the first paragraph on page 1961, Cresti argues that membership fee deters hit and run behavior. Cresti does not provide any dollar amount for membership fee. A modest fee of $300, in force during most of the study period, does not necessarily prevent a hit and run behavior. The fee appears to be $1,000 at the present time.

The most significant data issue in Cresti's paper is related to her method of dealing with the missing observations. While the 1974 missing observation is filled with the observation from the subsequent year, an arbitrary growth rate of 5% is used to fill the missing observations for 1996-1999. Cresti does not provide any rationale for using a 5 percent growth rate to fill the missing observations. Yet this is a serious decision which can potentially affect the outcome of the analysis. There are potentially significant consequences of the decision regarding whether or not to replace missing observations and the method selected. The choice of the method to replace missing observations must consider the characteristics of the time series. There are statistical consequences in replacing missing observations, especially in performing unit root tests and the cointegration method. While there are potential efficiency gains in expanding the sample size, especially when the dependent variable has missing observations, harm can be done due to bias created (Greene, 2000, P. 260). It is important to first investigate the reason for the missing observations to rule out systemic problems such as the sample selection bias (Greene, 2000, P. 259, Griliches, and Intriligator, 1986, P. 1485). Sometimes it is better to do nothing. In situations such as the barter study, where the sample size is small, filling the missing observations could be beneficial. In the case of missing data from the IRTA, our information points to apparent personnel changes in the organization and increasing lack of transparency within the IRTA in terms of sharing data with the public as the root of the missing observations problem.

Ruling out a systematic bias as the cause of the missing observations, there are various methods of replacing the missing observations to consider, which essentially require some knowledge of the characteristics of the series, particularly whether the observations are random or a trend is present (Greene, 2000; and Little and Rubin, 2002). Several methods have been suggested for filling missing observations. For example, in a zero-order regression method or the modified zero-order regression method, missing observations are essentially filled by the mean of the completed observations. This method lowers the R^2 and leads to bias in least square estimator. The method of filling the missing observations with the predicted values is also biased and, as a result, has questionable benefits because of insufficient information on the sample properties (Greene, 2000, P. 262). Greene argues that the results of the Monte Carlo studies, though difficult to generalize, indicate that bias is likely in filling in missing values in a single-equation regression context (Greene, 2000, P. 60 and 262). Other approaches include finding an appropriate proxy for a missing value by forecasting it using a regression of it on all independent variables (Kennedy, 2003, P. 171).

Here, two popular and robust forecasting methods are used to fill the missing observations for the volume of commercial and corporate barter transactions. First, the Box-Jenkins autoregressive-moving average method (ARMA) is applied where in a standard ARMA(p,q), p signifies the order of autoregressive (AR) dimension of the model and q signifies the moving average (MA) dynamics of the model. The appropriate values of p and q properties of the series are determined by, for example, viewing the correlogram to examine its autocorrelation properties and by diagnostic tests on the residuals such as the normality test. The autocorrelation function shows that both series have a moving average component of the first order while the partial autocorrelation function shows an autoregressive component of the third order for both series. This conclusion is also supported by examination of the statistical significance of the coefficients of alternative specifications of the ARMA models and their DW values (Table1). Coefficients of the ARMA models are also checked for both stationarity and invertibility.[2] Furthermore, the residuals of the series are examined to make sure that they are white noise (Harvey, 1981, p. 161; Enders, p. 76; Greene, 2003, p. 611). The Jarque-Bera (JB) normality test is distributed as a chi-square with 2 degrees of freedom. If the JB statistic exceeds the critical value of 5.99, the null hypothesis of normality is rejected. The JB test statistic could not reject the null hypothesis of normality for the residuals of either commercial or corporate barter at the 5% level. Therefore, a fairly parsimonious ARMA(3,1) model for a series such as y_t is applied as follows.

$$y_t = \phi y_{t-1} + \phi y_{t-2} + \phi y_{t-3} + \varepsilon_t + \theta \varepsilon_{t-1} \quad (1)$$

The second method applied for replacing the missing values is the state space or Kalman Filter model, which was initially developed by Kalman (1960) for applications in engineering and later adapted by Harvey (1981) for applications in econometrics. In this method, a recursive algorithm sequentially updates the one-step ahead estimate of the state mean and variance with the new information. This recursive process generates an efficient smoothing algorithm for calculating the exact likelihood function for an ARMA model using the prediction error decomposition (Harvey, 1981, and Little and Rubin, 2002). Using the AIC, SIC and the HQC to select the best fit for the Kalman filter resulted in ARMA(1,1), where the coefficients of y_{t-2} and y_{t-3} in equation (1) would be zero for both the commercial barter and corporate barter (Table1). The initial conditions are set by the program default to current values in the corresponding vector.

Having properly filled the missing observations in Cresti's paper with two alternatives, the Box-Jenkins ARMA and the Kelman filter, we proceed with testing the log of the series for the unit root test and examine the presence of cointegrating vectors among the series. Monte Carlo simulation results of series with missing observations show that, when missing observations are filled, the Augmented Dickey-Fuller (ADF) test produces a more powerful unit root test result than ignoring the missing observations (Ryan and Giles, 1998). Also, unit root tests are sensitive to the presence of deterministic regressors such as an intercept or time trend as well as the number of lags. Cresti may have used inappropriate regressors, invalidating the unit root results. If the number of lags is too few, the regression residuals may not behave like white-noise processes. On the other hand, entering too many lags decreases the power of the test in rejecting the null of a unit root because, as the number of lags increases, additional parameters must be estimated which lower the degrees of freedom. Cresti uses the McKinnon test to establish stationarity of the series and appears to have started with four lags, but it is not clear how many lags were ultimately used. Therefore, the presence of unnecessary lags could reduce the power of the ADF test to detect a unit root (Enders, 2004, p.191). Marvasti and Smyth (1998) use one lag based on the annual nature of the data and the limited number of observations, but did not test for the appropriate number of lags, either. Here we begin with five lags and use the t value of the regressors and SIC to find the optimum lag and the existence and nature of trend in each series. After the optimum lag is determined, diagnostic checking is conducted on the residuals to assure that structural breaks and serial correlations are absent. Table 2 presents the unit root test results for the variables. The optimum lag appears to be mostly one, which is consistent with Marvasti and Smyth (1998).

III. New Cointegration and ECM Estimates

In the cointegration method, we seek a linear combination of integrated variables that is stationary, though not necessarily among variables that are integrated of the same order. We performed the Johansen cointegration test to verify the presence of at least one cointegrating vector for each group of variables. The number of cointegrating vectors, based on the Mackinnon-Hang-Michelis test at the 5% level, for each group is presented in Tables 3 and 4. However, detailed information such as the eigenvalues is withheld for brevity. A stochastic trend is found to be the best fit for the commercial barter models and a linear deterministic trend for the corporate barter models. To examine conclusions drawn by Cresti, we focus on the Error Correction Model (ECM) and the long-run equilibrium relationship among variables. Economic theory must play a role in developing a cointegration model by selecting relevant explanatory variables and by identifying the long-run equilibrium relationship among them. We posit that the level of barter is determined by a group of macroeconomic variables, access to communication technology, and legislative developments as follows.

$$B = \alpha_0 + \alpha_1 BC + \alpha_2 I + \alpha_3 TX + \alpha_4 T + \alpha_5 DUM + e, \qquad (2)$$

where BC is a vector of business cycle variables such as the level of GDP, inventories, and capacity utilization, I is inflation, TX is a vector of tax incentives such as the personal and corporate income tax rates, T is access to computer technology, DUM is a dummy for new barter tax law and *e* is the error term. It is very likely that measures of national output are highly correlated with various measures of inventory as they both reflect stages of business cycles. Thus, their placement in the same equation may be redundant. Cresti acknowledges the sensitivity of her results to the simultaneous presence of these two types of variables (P. 1959), yet her conclusions regarding the relationship between barter and business cycles are based on such models. Also, Cresti in some models seems to use the GNP rather than the GDP (P. 1964) in some of her analysis, though the relevance of the GNP to domestic barter is not clear.

We first address the issue of the effect of using series with properly filled missing observations on Cresti's long-run equilibrium relationship in Tables 3 and 4 where her estimates alongside our ARMA and Kalman estimates are presented for comparison. The normalized cointegrating equation estimates from the ECM Models examine the long-run relationship between barter and other macroeconomic variables. Cresti has argued that commercial barter is pro-cyclical -- in her words, "follows business cycles."[3] Comparisons of identical models in Table 3 show that GDP and commercial barter move together as Cresti has estimated, though the size of the coefficients is smaller than hers. The services component of the GDP moves in an opposite direction to commercial barter in two of the three models. The results for the wholesale inventories are mixed, while the retail inventory variable result is consistent with Cresti's finding. Coefficient estimates for capacity utilization in most cases indicates that falling capacity utilization moves with the rising level of commercial barter. The ARMA and Kalman filter estimates appear to have produced similar results in terms of the sign of the coefficients. However, standard t values are not relevant to the ECM unless the residuals from the ECM are checked to make sure that they are white noise. The LM test is used with the null hypothesis of no serial correlation up to order 4, at the 5% level. The results indicate that the residuals of the normalized equations are mainly white noise. Also, the JB residual test for normalized ECM could not reject the null hypothesis of normality, at the 5% level. Therefore, the standard errors are applied for inference on the significance of the coefficients. Turning to Table 4, although the Kalman filter models produced more favorable estimates, the results from most models are mixed such that no clear conclusion can be drawn from the estimates regarding the relationship between barter and the variables representing the business cycles.

The second problem with Cresti's analysis is the omission of several relevant variables. Theoretically, several other variables are likely to be correlated with barter transactions. While Cresti acknowledges potential relevance of taxes, no statistical analysis is offered to demonstrate the absence of co-movements between taxes and barter. A few other variables tested in Marvasti and Smyth (1998) are re-entered into the cointegration system with the new breakdown of barter into commercial and corporate. Inclusion of these variables explains their role in barter as well as corrects some of the erroneous conclusions drawn regarding the relationship between barter and business cycles.

Business inventory shows a positive and statistically significant effect on total volume of barter transactions in the regression analysis of the percentage changes models by Marvasti and Smyth (1998). However, in the ECM models, business inventories do not exhibit any co-movements with the total volume of barter. Instead, the positive correlation between the unemployment rate and barter transactions signified the counter-cyclical nature of barter. Here, we apply equation (2) to develop systems with additional relevant macroeconomic variables including M2 money supply, personal income tax, personal computers, and a dummy variable for the 1982 Tax Equity and Fiscal Responsibility Act which are first tested for the presence of cointegrating vectors. We expect the rising money supply, signaling an inflationary trend, to encourage barter transactions resulting in a positive sign for its coefficient. Since rising personal income tax is also likely to coincide with the increasing volume of commercial barter for tax avoidance reasons, a positive sign is also expected for the coefficients of household income tax rate and corporate income tax rate. Increases in the number of personal computers facilitate barter transactions; thus, it is expected to correlate with barter transactions. Finally, the 1982 Tax Equity and Fiscal Responsibility Act which requires reporting equivalent market value of barter transactions for tax purposes is expected to discourage barter transactions motivated by tax evasions. Having established the expected signs for the coefficients of new variables in the system, we proceed with examination of the ECM estimates reported in Tables 5 and 6, for commercial barter and corporate barter, respectively.

Again, to be able to make standard inference from the standard errors, the LM serial correlation tests up to lag 4 and the JB normality test is performed on the residual of each model. The LM test results suggest the presence of some serial correlation in the first two sets of models in Table 5. Since the number of explanatory variables and number of observations here limits lags in the ECM to one, the serial correlation problem in the residuals could not be resolved. Thus, the significance of the coefficients in these two models should be judged with some caution. While the sign of the GDP coefficient confirms Cresti's pro-cyclical finding, the coefficient of GDP services disputes that outcome. In subsequent models in Table 5, other measures of business cycle including wholesale and retail inventories indicate that commercial barter rises as inventories increase over time. Yet, the last model in Table 5, which includes capacity utilization, contradicts this finding. However, it must be noted that the JB test result shows that the residuals from the ARMA model is not normally distributed and the significance levels should be treated with caution. Interestingly, the coefficients of all new variables in the ECM are statistically highly significant in all models with the expected signs. In summary, although the inventory measures of business cycles suggest that commercial barter is countercyclical, the GDP measures and capacity utilization measures, though not as reliable, produce an opposite outcome.

In Table 6, the sign of the coefficient of GDP in the first group of ECM estimates confirms the countercyclical nature of corporate barter, which is consistent with Cresti's estimates. Noting that the residuals from the second group of estimates are not normally distributed according to the JB test results, the sign of the coefficient for GDP corporations supports the argument that corporate barter is countercyclical. In the third group, the ARMA model shows a negative and statistically significant sign for wholesale inventory, which is consistent with Cresti's results as well as the results from our simple models in Table 4. The next group of models, with capacity utilization, however, contradicts this finding as it demonstrates a negative correlation between capacity utilization and corporate barter. Diagnostic checking of the model with non-farm inventory revealed that this equation is inadequate. In summary, although the results regarding the relationship between corporate barter and business cycles appears to be mixed, in models with no serial correlation or normality problems, the coefficients of GDP and capacity utilization support the counter cyclical argument.

VI. Conclusions

This study shows that Cresti's conclusion regarding the pro-cyclical nature of the relationship between corporate barter transactions is tenuous, at best. Cresti's analyses are unconvincing because of the questionable method used for filling the missing observations and her ignoring of a group of variables in her cointegration system which theoretically belongs to it. After properly replacing the missing observations using the ARMA and Kalman filter methods, we first analyzed business cycle variables in the same cointegration system as Cresti. Then, we added other relevant variables to the system. While the ECM results are mixed with regards to the GDP and its variants, there is more convincing evidence from the inventory variables and capacity utilization to confirm the Marvasti and Smyth's (1998) findings that barter by either corporations or individuals is counter cyclical. Furthermore, economic theory links barter to business inventories rather than to output. The ECM estimates also find that barter rises with inflationary trend, dissemination of access to the computer technology, and tax hikes. The tax evasion motive is consistent with the negative effect of the 1982 law on the level of barter.

Footnotes:

1. Since Cresti has not responded to our data request to replicate her work, we have used the Bureau of Economic Analysis (BEA) as a source to reproduce the GDP, inventory, and capacity utilization series. Although the industry code for the non-farm business inventories series changes from SIC to NAICS in 1997, examination of the overlapping years shows that the data is consistent. Whenever the data is not in real terms, appropriate deflators are used for transformation. The source of data for the remainder of the series is the same as Marvasti and Smyth (1998).

2. Invertibility is a concern for the commercial barter component because of the value of θ. However, after considering other statistical results such as the t statistic, AIC, and SIC, it was determined that ARMA(3,1) is the best fit for forecasting commercial barter.

3. No information on the statistical significance of the ECM coefficients is presented in Cresti's Tables 5 and 9. Also, the term "follows" implies causality, which has not been established in Cresti's paper (P. 1964).

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Table 1. Estimates of Missing Observations (1996-1999)

Statistics	Estimation Methods											
	Box-Jenkins ARMA						Kalman Filter					
	Commercial Barter			Corporate Barter			Commercial Barter			Corporate Barter		
AR Order	1	2	3	1	2	3	1	2	3	1	2	3
MA Order	1	1	1	1	1	1	1	1	1	1	1	1
AIC	-2.84	-2.73	-3.25	-4.89	-5.43	-5.57	-1.42	-1.19	-0.60	-4.01	-2.00	-3.99
SIC	-2.70	-2.53	-3.00	-4.74	-5.23	-5.32	-1.22	-0.95	-0.35	-3.81	-1.75	-3.69
HQC	-2.82	-2.69	-3.21	-4.86	-5.40	-5.53	-1.37	-1.14	-0.54	-3.96	-1.94	-3.92
DW	1.83	1.94	2.46	1.94	2.31	1.95						
JB (DF=2)	4.55	1.60	1.18	4.08	1.18	0.90						
MSE	0.078	0.076	0.040	0.026	0.20	0.022						

Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan-Quinn Criterion (HQC), Durbin-Watson (DW), Jarque-Bera (JB), Mean Squared Error (MSE).

Table 2. Unit Root Tests

Variable	Specification	SIC	ADF Statistic (Number of Lags)
Commercial Barter- ARMA	Intercept and trend	2.90	-3.57 (1)
Corporate Barter- ARMA	Intercept and trend	-5.90	-7.52 (1)
Commercial Barter- Kalman (First Difference)	Intercept and trend	-2.78	3.70 (1)
Corporate Barter- Kalman (First Difference)	Intercept Only	-5.87	-4.33 (2)
GDPR (Second Difference)	Intercept Only	-4.03	-5.15 (1)
GDP- Corporations (First Difference)	Intercept Only	-4.15	-3.19 (1)
GDP- Services (Second Difference)	Intercept Only	-6.27	3.51 (1)
Retail Inventories	Intercept Only	-3.64	4.62 (1)
Wholesale Inventories	Intercept Only	-3.64	-4.64 (1)
Non-Farm Business Inventories (First Difference)	Intercept Only	-3.26	-3.58 (1)
M2 Money Supply (Second Difference)	Intercept Only	-4.89	-3.21 (1)
Capacity Utilization	Intercept Only	-3.76	-3.18 (1)
Personal Computers	No Intercept, No Trend	3.59	-3.84 (1)
Corporate Tax Rate (First Difference)	Intercept and Trend	4.67	-3.82 (1)
Household Tax Rate (First Difference)	Intercept Only	-2.96	-3.61 (1)
DUM (First Difference)	Intercept Only	0.06	-3.39 (1)

The critical value at the 5% level for the trend and constant is 3.60 and for constant only is 3.00.

Table 3. Normalized Cointegrating Equation Estimates from the ECM Models- Commercial Barter

Models	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman
No. of Cointegrating Eq. (No. of Lags)		3 (1)	3 (1)		1 (1)	1 (2)		2 (1)	2 (1)		3 (2)	3 (2)		3 (3)	3 (2)
GDP	2.95	1.319[a]	1.692[a]	-	-	-	-	-	-	2.12	1.213[a]	1.302[a]	-	-	-
		(0.314)	(0.476)								(0.047)	(0.070)			
GDP-Services	-	-	-	1.84	-0.303	-0.246	0.99	-0.305	-0.679[a]	-	-	-	1.67	3.130[a]	2.185[a]
					(0.597)	(0.239)		(0.596)	(0.225)					(0.121)	(0.210)
Wholesale Inventory	-0.85	-0.310	-0.752[b]	-0.21	1.087[a]	-0.935[b]	-	-	-	-	-	-	-	-	-
		(0.307)	(0.465)		(0.150)	(0.059)									
Retail Inventory	-	-	-	-	-	-	1.10	1.088[a]	1.063[a]	-	-	-	-	-	-
								(0.150)	(0.057)						
Capacity Utilization	-	-	-	-	-	-	-	-	-	1.87	1.934[a]	1.892[a]	1.33	-2.570[a]	-4.320[a]
											(0.398)	(0.529)		(0.442)	(0.943)
Constant	-19.00	-2.784	-3.657	-11.27	3.553	3.816	-12.06	3.571	6.755	-15.95	-11.933	-12.473	-10.13	-8.065	7.345
Log Likelihood		167.24	162.73		175.51	179.29		175.54	178.54		191.45	183.80		208.71	196.02
AIC		-12.44	-12.06		-13.13	-13.24		-13.13	-13.37		-14.30	-13.63		-15.70	-14.70
SIC		-11.55	-11.18		-12.24	-11.91		-12.25	-12.50		-12.97	-12.30		-13.92	-13.36
JB test		(0.77)	(0.75)		(0.54)	(0.09)		(0.54)	(0.54)		(0.11)	(10)		(0.28)	(0.21)
LM test:															
Lag 1		(0.97)	(0.82)		(0.40)	(0.69)		(0.40)	(0.43)		(0.29)	(0.38)		(0.34)	(0.09)
Lag 2		(0.72)	(0.22)		(0.32)	(0.08)		(0.32)	(0.13)		(0.61)	(0.43)		(0.93)	(0.06)
Lag 3		(0.02)	(0.11)		(0.09)	(0.05)		(0.09)	(0.20)		(0.47)	(0.63)		(0.28)	(0.22)
Lag 4		(0.76)	(0.42)		(0.22)	(0.74)		(0.22)	(0.10)		(0.08)	(0.45)		(0.72)	(0.27)

Standard errors are in parenthesis.
a (b) Significant at the 5 (10) percent level.

Table 4. Normalized Cointegrating Equation Estimates from the ECM Models- Corporate Barter

Models	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman	Cresti	ARMA	Kalman
No. of Cointegrating Eq. (No. of Lags)		2 (2)	2 (2)		3 (2)	3 (2)		2 (2)	2 (2)		3 (2)	2 (2)		2 (2)	2 (2)
GDP	-0.19	-0.143 [a]	-0.151 [a]	-0.48	2.316 [a]	-29.990[a]	-	-	-	-0.78	1.573 [a]	-2.475[a]	-	-	-
		(0.016)	(0.017)		(0.475)	(6.922)					(0.229)	(0.368)			
GDP- Corporations	-	-	-	-	-	-	-0.28	0.832 [a]	1.036 [a]	-	-	-	-0.42	-0.263 [a]	0.003 [a]
								(0.205)	(0.277)					(0.041)	(0.092)
Non-Farm Inventory	-0.09	-0.081	0.281 [b]	-	-	-	-	-	-	-	-	-	-	-	-
		(0.123)	(0.126)												
Wholesale Inventory	-	-	-	-0.37	-2.558 [a]	31.865 [a]	1.10	-0.067 [a]	-0.023	-	-	-	-	-	-
					(0.486)	(6.774)		(0.041)	(0.056)						
Capacity Utilization	-	-	-	-	-	-	-	-	-	0.36	7.293 [a]	-11.02 [a]	0.22	0.204 [a]	0.161 [a]
											(0.933)	(1.464)		(0.029)	(0.066)
Time Trend	0.06	0.076 [a]	0.069 [a]	0.08	0.078 [a]	-	0.06	0.047 [a]	0.038 [a]	0.08	-0.017 [a]	0.185 [a]	0.07	0.066 [a]	0.059 [a]
		(0.004)	(0.004)		(0.006)			(0.007)	(0.009)		(0.023)	(0.037)		(0.001)	(0.003)
Constant	- 10.76	9.061	6.771	15.88	7.208	95.499	9.78	1.370	0.366	16.18	36.087	74.198	12.12	8.72	6.868
Log Likelihood		211.66	212.34		199.85	198.47		194.96	194.42		218.61	215.66		213.90	204.32
AIC		-15.97	-16.03		-14.94	-14.91		-14.52	-14.47		-16.57	-16.32		-16.17	-15.33
SIC		-14.59	-14.65		-13.56	-13.58		-13.14	-13.09		-15.19	-14.94		-14.78	-13.95
JB test		(0.35)	(0.36)		(0.16)	(0.15)		(0.17)	(0.14)		(0.18)	(0.20)		(0.15)	(0.07)
LM test:															
Lag 1		(0.85)	(0.81)		(0.77)	(0.59)		(0.30)	(0.26)		(0.39)	(0.48)		(0.68)	(0.47)
Lag 2		(0.19)	(0.06)		(0.73)	(0.38)		(0.31)	(0.46)		(0.36)	(0.20)		(0.71)	(0.56)
Lag 3		(0.36)	(0.78)		(0.54)	(0.49)		(0.05)	(0.07)		(0.19)	(0.18)		(0.09)	(0.79)
Lag 4		(0.36)	(0.15)		(0.86)	(0.50)		(0.79)	(0.39)		(0.56)	(0.60)		(0.65)	(0.92)

Standard errors are in parenthesis.
a (b) Significant at the 5 (10) percent level.

Table 5. Normalized Cointegrating Equation Estimates from the ECM Models- Commercial Barter New Models

Models	ARMA	Kalman	ARMA	Kalman	ARMA	Kalman	ARMA	Kalman	ARMA	Kalman
No. of Cointegrating Eq. (No. of Lags)	5 (1)	5 (1)	5 (1)	5 (1)	4 (1)	3 (1)	5 (1)	6 (1)	4 (1)	5 (1)
GDP	0.269[a]	0.102[c]		-	-	-	-	-	-	-
	(0.058)	(0.063)								
GDP- Services	-	-	-8.679[a]	-18.123[a]	-	-	-	-	-	-
			(0.412)	(0.839)						
Wholesale Inventory	-	-	-	-	0.313[a]	0.482[a]	-	-	-	-
					(0.13)	(0.105)				
Retail Inventory	-	-	-	-			0.481[a]	0.713[a]	-	-
							(0.105)	(0.115)		
Capacity Utilization	-	-	-	-	-	-	-	-	1.489[a]	3.259[a]
									(0.628)	(0.286)
Money Supply	0.202[b]	0.541[a]	4.238[a]	6.709[a]	0.580[a]	0.501[a]	0.502[a]	0.011[a]	0.266[a]	1.696[a]
	(0.107)	(4.607)	(0.155)	(21.495)	(0.227)	(2.730)	(0.183)	(0.200)	(0.116)	(0.053)
Income Tax	0.005[b]	0.011[a]	0.056[a]	0.090[a]	0.001	0.001	0.001	0.001	0.019[a]	0.072[a]
	(0.003)	(0.003)	(0.006)	(0.011)	(0.006)	(0.005)	(0.005)	(0.006)	(0.011)	(0.005)
Personal Computers	0.173[a]	0.197[a]	1.104[a]	2.152[a]	0.180[a]	0.130[a]	0.131[a]	0.075[a]	0.428[a]	0.107[a]
	(0.012)	(0.014)	(25.851)	(0.087)	(0.030)	(0.024)	(0.024)	(0.026)	(0.037)	(0.016)
DUM	-1.597[a]	-1.779[a]	-8.886[a]	-17.155[a]	-1.400[a]	-1.056[a]	-1.059[a]	-0.610[a]	-2.769[a]	0.399[a]
	(0.082)	(0.091)	(0.350)	(0.712)	(0.209)	(0.163)	(0.164)	(0.181)	(0.291)	(0.121)
Constant	4.424	2.906	41.464	97.270	0.038	-0.076	0.083	2.738	3.901	23.984
Log Likelihood	255.24	254.50	241.54	240.64	196.48	193.50	193.54	194.65	199.87	202.12
AIC	-16.77	-16.71	-15.63	-15.55	-11.87	-11.63	-11.63	-11.72	-12.16	-12.34
SIC	-14.12	-14.06	-12.98	-12.90	-9.22	-8.98	-8.98	-9.07	-9.51	-9.69
JB Test Statistic (Prob.)	(0.21)	(0.14)	(0.32)	(0.17)	(0.24)	(0.11)	(0.24)	(0.09)	(0.00)	(0.22)
LM Test (Prob.):										
Lag 1	(0.05)	(0.01)	(0.01)	(0.01)	(0.23)	(0.44)	(0.23)	(0.37)	(0.20)	(0.60)
Lag 2	(0.42)	().50)	(0.08)	(0.71)	(0.90)	(0.49)	(0.90)	(0.11)	(0.69)	(0.29)
Lag 3	(0.74)	(0.43)	(0.10)	(0.03)	(0.28)	(0.44)	(0.28)	(0.32)	(0.05)	(0.24)
Lag 4	(0.54)	(0.44)	(0.99)	(0.93)	(0.76)	(0.75)	(0.75)	(0.80)	(0.40)	(0.87)

Standard errors are in parenthesis.
a (b) Significant at the 5 (10) percent level.

Table 6. Normalized Cointegrating Equation Estimates from the ECM Models- Corporate Barter New Models

Models	ARMA	Kalman	ARMA	Kalman	ARMA	Kalman	ARMA	Kalman
No. of Cointegrating Eq. (No. of Lags)	6 (1)	6 (1)	4 (1)	5 (1)	6 (1)	6 (1)	4 (1)	4 (1)
GDP	-0.030 [a]	-0.206 [a]	-	-	-	-	-	-
	(0.011)	(0.015)						
GDP- Corporations	-	-	-0.369 [a]	-0.059 [a]	-	-	-	-
			(0.080)	(0.028)				
Non-Farm Inventory	-	-	-	-	-	-	-	-
Wholesale Inventory	-	-	-	-	-0.276 [a]	0.005	-	-
					(0.072)	(0.034)		
Capacity Utilization	-	-	-	-	-	-	-0.016	-0.203 [a]
							(0.019)	(0.033)
Money Supply	-0.128 [a]	0.075 [a]	0.439 [a]	0.058 [a]	0.749 [a]	-0.478 [a]	-0.125 [a]	0.111 [a]
	(0.012)	(0.016)	(0.046)	(0.016)	(0.098)	(0.047)	(0.009)	(0.015)
Corporate Tax	0.011 [a]	0.018 [a]	0.022 [a]	0.011 [a]	0.031 [a]	-0.001 [a]	0.009 [a]	0.012 [a]
	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.000)	(0.001)
Personal Comp.	-0.022 [a]	-0.048 [a]	0.134 [a]	0.018 [a]	0.268 [a]	-0.178	-0.015 [a]	0.025 [a]
	(0.003)	(0.004)	(0.013)	(0.000)	(0.022)	(0.010)	(0.003)	(0.001)
DUM	0.140 [a]	0.312 [a]	-1.345 [a]	-0.205 [a]	-2.432 [a]	1.517 [a]	0.078 [a]	-0.354 [a]
	(0.025)	(0.032)	(0.105)	(0.036)	(0.170)	(0.079)	(0.028)	(0.048)
Time Trend	0.080 [a]	0.100 [a]	0.056 [a]	0.071 [a]	0.034 [a]	0.113 [a]	0.076 [a]	0.067 [a]
	(0.001)	(0.002)	(0.003)	(0.001)	(0.007)	(0.004)	(0.001)	(0.001)
Constant	8.156	7.471	6.290	7.919	2.043	10.789	8.082	7.079
Log Likelihood	253.71	253.37	242.87	246.50	231.09	229.95	245.53	244.75
AIC	-16.56	-16.53	-15.66	-15.96	-14.67	-14.58	-15.88	-15.81
SIC	-13.86	-13.83	-12.96	-13.26	-11.97	-11.88	-13.18	-13.11
JB Test Statistic (Prob.)	(0.36)	(0.17)	(0.01)	(0.10)	(0.29)	(0.15)	(0.40)	0.16)
LM Test (Prob.):								
Lag 1	(0.57)	(0.27)	(0.54)	(0.20)	(0.09)	(0.33)	(0.73)	(0.72)
Lag 2	(0.17)	((0.11)	(0.47)	(0.51)	(0.73)	(0.85)	(0.16)	(0.57)
Lag 3	(0.29)	(0.27)	(0.59)	(0.11)	(0.42)	(0.08)	(0.07)	(0.09)
Lag 4	(0.66)	(0.02)	(0.15)	(0.16)	(0.29)	(0.42)	(0.07)	(0.29)

Standard errors are in parenthesis.
a (b) Significant at the 5 (10) percent level.