A Time Series Analysis of the Relationship between the Capital Stock and Federal Debt

A Comment by James R. Barth, Frank S. Russek, and George H. K. Wang

In the current controversy over the economic effects of federal debt, a conventional and widely held view is that an increase in federal debt adversely affects the capital stock. The alternative and more recent view that is increasingly attracting attention is that increases in federal debt do not generate adverse capital stock effects.[1] The resolution of this important controversy depends heavily upon the empirical evidence pertaining to the realtionship between these two variables. Unfortunately, the evidence accumulated thus far is quite meager. The recent and important study of this relationship by de Leeuw and Holloway (1985) is therefore quite timely and merits careful consideration.

The "reduced-form" of de Leeuw and Holloway's model suggests "that the debt/income ratio has an unambiguous negative relationship to the capital/output ratio" (p. 337).[2] de Leeuw and Holloway's analysis employs annual observations of a new measure of the cyclically adjusted U.S. federal debt and presents "regression results (which) confirm a strong negative relationship" (p. 240) between this federal debt measure and the aggregate capital stock for the period 1955–1983.

Our analysis extends the work of de Leeuw and Holloway in two important dimensions. First, we attempt to replicate de Leeuw and Holloway's results both for the aggregate capital stock and for the major disaggregated capital stock components using their original statistical methodology. While our results generally reconfirm de

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[1]For a more thorough discussion of these competing views, see Barth, Iden and Russek (1984) and the references cited therein.

[2]de Leeuw and Holloway 1985, p. 337. Their theoretical model does not include the cyclically adjusted measure of the federal debt. Its use in their empirical work apparently is based on considerations of statistical bias resulting from the endogeneity of the unadjusted measure. For a discussion of why a cyclically adjusted measure is desirable, see de Leeuw and Holloway (1983, p. 27, fn. 6).

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Journal of Money, Credit, and Banking, Vol. 18, No. 4 (November 1986)
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Leeuw and Holloway's, we find mixed results of the disaggregated components series regressions. Second, we present evidence that an alternative time series technique may be more appropriate than the original estimation procedure adopted by de Leeuw and Holloway. Employing these alternative techniques, our results suggest that the "strong" relationship between the capital/output ratio and the federal debt/output ratio found by de Leeuw and Holloway may in fact be a spurious relationship.[3]

Statistical Issues and Empirical Results

The regression results reported by de Leeuw and Holloway have high $\bar{R}^2$s but very low Durbin-Watson statistics. As discussed by Granger and Newbold (1974), this phenomenon may be indicative of a spurious relationship between the levels of two independent random walk variables. To determine whether there is a true rather than a spurious relationship, Granger and Newbold suggest that the regressions should be run in first-difference form. These considerations motivated our research strategy.

To determine whether the regression equations specified by de Leeuw and Holloway should be estimated in first-difference form, two informal testing procedures were employed along with two formal tests of whether the variables are trend stationary (TS) or difference stationary (DS).[4] First differences are appropriate if the levels of the time series belong to the DS class. The data consist of annual time series from 1955 through 1983 and were obtained directly from de Leeuw and Holloway. Specifically: D^* = current dollar par value of cyclically adjusted federal government debt held by the public;[5] P = GNP price deflator, $Y\$^*$ = cyclically adjusted (trend) GNP in current dollars; $K(CD)$ = net stock of consumer durable goods in constant 1972 dollars; $K(PE)$ = private net stock of nonresidential fixed capital in 1972 dollars; $K(SL)$ = net stock of state and local government equipment and structures in 1972 dollars; $K(RES)$ = net stock of residential structures in constant 1972 dollars; and K = total nonfederal net capital stock in constant 1972 dollars $[= K(CD) + K(PE) + K(SL) + K(RES)]$.

The initial regression results with variables expressed in level form are presented in Table 1. The first two rows are our re-estimation of de Leeuw and Holloway's aggregate results, and they confirm the original finding of a significantly negative relationship between the cyclically adjusted federal debt and the aggregate capital stock, with both variables scaled by trend GNP.[6] The remaining rows in the table present results (not reported by de Leeuw and Holloway) for the relationship between the disaggregated components of the capital stock and the cyclically adjusted federal debt, again with the variables scaled by trend GNP. As with the aggregate capital stock series, all the regressions are estimated by both ordinary least squares (OLS) and generalized least squares (GLS).

[3]For a recent and interesting time series analysis of the effect of government debt on stock yields, see Auerbach (1985).

[4]For a discussion of these two types of stationarity, see Nelson and Plosser (1982).

[5]Based upon economic and statistical considerations, Auerbach (1985) among others has argued in favor of using a present value measure of government debt rather than the par value.

[6]de Leeuw and Holloway (1985, p. 240) use trend GNP rather than actual GNP as the denominators of these ratios "to focus on long-term trends and to avoid the statistical complications of correlated short-run disturbances in the two denominators."

TABLE 1

REGRESSION RESULTS FOR VARIABLES IN LEVEL FORM (TIME PERIOD: 1955–1983)

Dependent Variable	Method of Estimation	Intercept	$D^*/Y\$^*$	$\bar{R}^2$	SER	DW_{u_t}	$u_t = \frac{a_t}{(1-\rho_1 L)}$	DW_{a_t}[a]	$r_{a_t}(1)$[b]
1. $PK/Y\$^*$	OLS	2.571 (147.43)	−0.872 (−18.86)	0.93	0.022	0.56	—	—	—
	GLS[d]	2.529 (65.01)	−0.756 (−7.81)	0.96	0.015	—	0.77 (6.73)	1.26	0.36
2. $PK(CD)/Y\$^*$	OLS	0.513 (24.27)	−0.467 (−8.34)	0.71	0.027	0.13	—	—	—
	GLS	0.394 (6.58)	−0.103 (−1.27)	0.98	0.007	—	0.99 (31.79)	0.63	0.57
3. $PK(PE)/Y\$^*$	OLS	0.921 (56.76)	−0.411 (−10.07)	0.78	0.019	0.19	—	—	—
	GLS	0.864 (13.56)	−0.219 (−2.55)	0.96	0.008	—	0.99 (19.64)	0.91	0.50
4. $PK(SL)/Y\$^*$	OLS	0.462 (30.59)	−0.178 (−4.49)	0.41	0.019	0.01	—	—	—
	GLS	0.448 (11.36)	−0.203 (−3.81)	0.96	0.005	—	0.99 (33.53)	0.35	0.81
5. $PK(RES)/YS^*$	OLS	0.675 (48.59)	0.185 (5.03)	0.46	0.018	0.19	—	—	—
	GLS	−0.003 (−0.49)	0.010 (0.57)	0.13	0.005	—	0.41 (2.34)	1.64	0.11

NOTE: The numbers in parentheses under the estimated coefficients are t-statistics.

[a] These are the Durbin-Watson statistics for GLS residuals, a_t.

[b] These are the estimated first-order autocorrelation coefficients of the GLS residuals, a_t. The estimated standard error under the null hypothesis of zero first-order autocorrelation is approximately $1/\sqrt{n}$, where n is the number of observations.

In five of the eight regressions, the results for the disaggregated series generally resemble those for the aggregate capital stock. In the case of $PK(CD)/Y\$^*$, however, the GLS estimate suggests that the negative coefficient on the debt variable is insignificant. In the regressions for $PK(RES)/Y\$^*$, the debt variable has a positive coefficient which is significant under OLS and insignificant with GLS. Thus, the disaggreated results provide some instances that are not consistent with the view that federal debt adversely affects capital formation. Moreover, in the GLS regressions for $PK(CD)/Y\$^*$, $PK(PE)/Y\$^*$, and $PK(SL)/Y\$^*$, the estimated first-order autocorrelation coefficients, ρ_1, are all 0.99, while the Durbin-Watson statistics for the GLS residuals, DW_{a_t}, are all very low—ranging from 0.35 to 0.91. These results suggest that the finding of a significant (negative) coefficient on the debt variable in the $PK(PE)/YS^*$ and $PK(SL)/Y\$^*$ regressions may not be valid, because the residuals are still autocorrelated.[7]

As an informal first step in determining whether the individual time series belong to the TS or to the DS class of models, we calculated the autocorrelation functions for each of the time series in both level and first-difference form (Table 2). For the level form, all the autocorrelations start at about 0.9 and then decay slowly as the lags increase. For the first-difference form, the autocorrelation functions display significantly positive serial correlation at the first lag—which may very well be due to temporal aggregation of a shorter interval of observation as discussed by Tiao (1972) and Working (1960), while most of the remaining lags are not significant at the 5 percent level. These findings suggest that the variables belong to the DS class, and have time series properties consistent with the random walk hypothesis as noted by Wichern (1973).

As another informal but more discriminating procedure, we fitted a time series model for each of the variables. The results in Table 3 indicate that all of the variables are characterized as ARIMA (0, 1, 1) models, except for $PK(SL)/Y\$^*$ which is characterized as a (0, 2, 1) model. These findings together with our failure to reject the hypothesis that the residuals are white noise—see the $\hat{r}_{\hat{e}_t}(1)$ and $Q(12)$ statistics in Table 3—again are consistent with the variables being random walks.

Our first formal check on the type of nonstationarity involved unit root tests based on the equation[8]

$$y_t = \beta_0 + \beta_1 t + \delta_1 y_{t-1} + \sum_{j=1}^{p} \delta_{j+1}(1 - L)y_{t-j} + \varepsilon_t , \tag{1}$$

[7]It should also be noted that in small sample situations, say, $n = 30$, even the GLS standard errors may be misleading in regressions with nonstationary independent variables and first-order autocorrelated errors. In such cases, the hypothesis test results are biased toward rejecting the null hypothesis that the coefficient of the independent variable is zero. For a further discussion of this point, see Park and Mitchell (1980, p. 199).

[8]A referee suggested that the following explanation of tests for nonstationarity may be helpful to some readers. In his words, "The question [which these tests address] is whether or not the time series parametric estimates of the economic process show convergence. If they do not, there are no measures of central tendency that can be identified except in spurious testing procedures. The most troubling problem in estimates of coefficients from time series is separating out the underlying process from the effects of unknown variables that create periodicities and trends that show up as serial correlation." A more technical explanation of these tests appears in a longer version of this paper which is available from the authors upon request.

TABLE 2

AUTOCORRELATIONS OF FEDERAL DEBT AND CAPITAL STOCKS (TIME PERIOD: 1955–1983)

	Levels						First Differences					
	*D**	*PK*	*PK(CD)*	*PK(PE)*	*PK(SL)*	*PK(RES)*	*D**	*PK*	*PK(CD)*	*PK(PE)*	*PK(SL)*	*PK(RES)*
Simple												
1st	0.87	0.89	0.93	0.90	0.86	0.90	0.53	0.47	0.60	0.43	0.89	0.58
2nd	0.75	0.78	0.86	0.78	0.70	0.75	0.23	−0.09	0.19	0.22	0.75	0.12
3rd	0.65	0.69	0.77	0.68	0.54	0.63	0.17	−0.22	0.03	−0.28	0.60	−0.03
4th	0.55	0.59	0.67	0.58	0.40	0.53	0.21	−0.16	0.02	−0.20	0.50	−0.02
5th	0.45	0.52	0.55	0.49	0.24	0.24	0.23	0.07	0.06	−0.16	0.43	0.05
6th	0.35	0.43	0.44	0.40	0.14	0.33	0.05	0.15	−0.01	−0.17	0.36	0.01
Partial												
1st	0.87	0.89	0.93	0.90	0.86	0.90	0.53	0.47	0.60	0.43	0.89	0.58
2nd	−0.05	−0.08	−0.09	−0.13	−0.12	−0.25	−0.08	−0.41	−0.27	−0.49	−0.22	−0.32
3rd	−0.01	0.00	−0.13	−0.01	−0.09	0.06	0.12	0.05	0.08	0.11	−0.07	0.11
4th	−0.02	−0.09	−0.15	−0.04	−0.06	−0.02	0.11	−0.10	0.02	−0.29	0.13	−0.03
5th	−0.07	0.02	−0.14	−0.03	−0.06	−0.02	0.09	0.20	0.06	−0.05	0.05	0.10
6th	−0.03	−0.08	−0.08	−0.01	−0.10	−0.11	0.19	−0.09	−0.15	−0.29	−0.10	−0.13

NOTE: All level variables were scaled by trend GNP. The first differences are the changes in these ratios.

TABLE 3

FITTED TIME SERIES MODELS FOR THE VARIABLES (TIME PERIOD: 1955–1983)

Variable	ARIMA Model	$\hat{r}_{\hat{e}_t}(1)^a$	$Q(12)^b$
1. $PK/Y\$*$	$(1 - L)Z_{1t} = (1 + \underset{(0.109)}{0.786}L)e_{1t}$	−0.01	4.20
2. $D*/Y\$*$	$(1 - L)Z_{2t} = \underset{(0.003)}{0.009} + (1 + \underset{(0.028)}{0.923}L)e_{2t}$	0.09	4.64
3. $PK(CD)/Y\$*$	$(1 - L)Z_{3t} = \underset{(0.001)}{0.004} + (1 + \underset{(0.121)}{0.721}L)e_{3t}$	0.12	3.55
4. $PK(PE)/Y\$*$	$(1 - L)Z_{4t} = \underset{(0.002)}{0.004} + (1 + \underset{(0.028)}{0.932}L)e_{4t}$	0.04	5.94
5. $PK(SL)/Y\$*$	$(1 - L)^2Z_{5t} = (1 + \underset{(0.145)}{0.286}L)e_{5t}$	−0.06	10.09
6. $PK(RES)/Y\$*$	$(1 - L)Z_{6t} = (1 + \underset{(0.090)}{0.729}L)e_{6t}$	0.12	9.27

NOTE: The numbers in parentheses under the estimated parameters are the associated standard errors.
[a]This is the first-order autocorrelation coefficient of the residuals, $\hat{e}_t$. The estimated standard error under the null hypothesis of zero first-order autocorrelation is approximately $1/\sqrt{n}$, where n is the number of observations. With $n = 28$, the corresponding 95 percent confidence interval is ± 0.39. All the estimated first-order autocorrelations, $\hat{r}_{\hat{e}_t}(1)$, fall within this interval, indicating that the null hypothesis—white noise residuals—cannot be rejected.
[b]This joint test statistic is defined as

$$Q(12) = n(n + 2) \sum_{k=1}^{12} (n - k)^{-1} \hat{r}_{\hat{e}_t}(k),$$

where n is the number of data observations remaining after the application of the difference operator, and $\hat{r}_{\hat{e}_t}(k)$ is the k^{th}-order sample correlation of the residual, $\hat{e}_t$. $Q(12)$ has a χ^2 distribution in large samples, and is used to determine whether the residuals constitute a white noise process. The critical values for χ^2 with 10 (MA with intercept) and 11 (MA without intercept) degrees of freedom at the 5 percent level of significance are 18.31 and 19.68, respectively. Hence, we fail to reject the null hypothesis that the residuals are distributed approximately as white noise in these ARIMA models.

where L is the lag operator and the ε_t's are independently and identically distributed random variables with mean zero and variance σ^2_ε. Specifically, as suggested by Fuller (1976) and Dickey and Fuller (1979), we tested the joint null hypothesis that $\delta_1 = 1$ and $\beta_1 = 0$ with univariate autoregressive models for each data series in our sample. These results are reported in Table 4 for the case in which an autoregressive process of order 2 is assumed. Based upon critical values for the test statistic, $\hat{\tau}(\hat{\delta}_1)$, of −4.38 and −3.60, corresponding to 1 percent and 5 percent significance levels with a sample of 25 (Fuller 1976, p. 373), we fail to reject the null hypothesis that the data have unit roots (and thus belong to the DS class) for all the series at the 1 percent level and for all except $PK(PE)/Y\$*$ at the 5 percent level.[9]

The other formal check involved a test of the null hypothesis that the residuals, u_t, from the level form of the de Leeuw and Holloway least squares regression are generated by a Gaussian random walk process.[10] Such a finding would provide additional evidence that the first-difference form of the regression is appropriate. The specific test statistic developed by Sargan and Bhargava (1983) is the g-statistic,

$$g = \hat{e}'\hat{e}/\hat{u}'\hat{u}, \tag{2}$$

[9]With respect to the coefficient on the trend term, β_1, the t ratio for testing $H_0\colon \beta_1 = 0$ is biased toward indicating a trend. However, according to Nelson and Plosser (1982, p. 144, fn. 8), testing $\delta_1 = 1$ is sufficient for the model considered here.

[10]This additional check is appropriate because a limitation of the unit root test is that it has low power to discriminate between a first-order unit root and a first-order autocorrelation coefficient slightly below unity.

TABLE 4

TESTS FOR AUTOREGRESSIVE UNIT ROOTS (TIME PERIOD: 1955–1983)
$y_t = \beta_0 + \beta_1 t + \delta_1 y_{t-1} + \delta_2(y_{t-1} - y_{t-2}) + u_t$

Variable	n	$\hat{\beta}_0$	$t(\hat{\beta}_0)$	$\hat{\beta}_1$	$t(\hat{\beta}_1)$	$\hat{\delta}_1$	$\hat{\tau}(\delta)$[a]	SER	DW_{u_t}[b]
(1) $PK/Y\$*$	27	0.504	1.58	0.002	1.17	0.777	−1.59	0.013	1.61
(2) $D*/Y\$*$	27	−0.003	−0.12	0.001	0.86	0.996	−0.06	0.009	1.61
(3) $PK(CD)/Y\$*$	27	0.065	3.15	0.001	3.13	0.812	−3.08	0.004	1.87
(4) $PK(PE)/Y\$*$	27	0.323	3.83	0.002	3.71	0.581	−3.82	0.005	1.77
(5) $PK(SL)/Y\$*$	27	0.000	0.01	−0.0002	−2.12	0.999	−0.06	0.002	1.38
(6) $PK(RES)/Y\$*$	27	0.189	3.22	−0.001	−3.29	0.756	−3.21	0.004	1.72

[a]For $n = 25$, the cut-off points for $\hat{\tau}_T$ at $\alpha = 0.01$, 0.025, and 0.05 are −4.38, −3.95, and −3.60, respectively (Fuller 1976, Table 8.5.2, p. 373).
[b]These are the Durbin-Watson statistics for the residuals, u_t.

where $\hat{e}$ is the least squares residual vector from the first-difference form of the equation, and $\hat{u}$ is the least squares residual vector from the equation estimated in level form. This procedure is equivalent to testing the null hypothesis, H_0: $\phi_1 = 1$, against the alternative hypothesis H_a:$|\phi_1| < 1$, in the error equation, $u_t = \phi_1 u_{t-1} + e_t$. The relevant information is presented in Table 5. These results indicate that the residuals of the regression when the variables are expressed in level form are generally consistent with the random walk hypothesis. That is, we cannot reject $\phi_1 = 1$ at the 1 percent level, except in the case of $PK(RES)/Y\$*$ where the g-statistic falls in the inconclusive range.

On the basis of the preceding formal and informal statistical findings, the various regressions were reestimated in first-difference form with and without an intercept and with the error terms appropriately modeled if they displayed autocorrelation.[11] The empirical results for this exercise are presented in Table 6. As may be seen, the "strong" negative relationship between the aggregate capital stock, ($PK/Y\$*$), and the cyclically adjusted federal debt ($D*/Y\$*$), generally no longer exists. Moreover, row 2 and row 4 both indicate that (1) the coefficient of ($D*/Y\$*$) is very small and statistically insignificant, and (2) the coefficient of the moving average term in the residuals, $\theta_1 = 0.787$ (row 2) and $\theta_1 = 0.784$ (row 4), are virtually the same in magnitude as $\theta_1 = 0.786$ in the first row of Table 3. These findings indicate that the fitted time series model for the dependent variable, $PK/Y\$*$, is almost the same as the regression of $\Delta(PK/Y\$*)$ on $\Delta(D*/Y\$*)$ with a first-order MA term in the residuals. This situation is only likely to occur when one random walk variable is regressed on another independent random walk variable. Thus, as Granger and Newbold (1983, p. 10) warned, "if the two individual variables are random walks, or, more generally, are integrated or ARIMA processes, then spurious 'relationships' will often be 'found' by using classical estimation procedures."

In the case of the disaggregated capital stock variables, no negative and statistically significant relationships to the cyclically adjusted federal debt were found

TABLE 5

CALCULATED g-STATISTICS FOR TESTING H_0: $\phi_1 = 1$ AND H_a: $|\phi_1| < 1$ FOR LEAST SQUARES REGRESSION RESIDUALS, u_t AND e_t (TIME PERIOD: 1955–1983)

Regressions[a] (in levels and first differences)	Calculated g-Statistics[b]
1. $PK/Y\$*$ on $D*/Y\$*$	0.484
2. $PK(CD)/Y\$*$ on $D*/Y\$*$	0.053
3. $PK(PE)/Y\$*$ on $D*/Y\$*$	0.144
4. $PK(SL)/Y\$*$ on $D*/Y\$*$	0.100
5. $PK(RES)/Y\$*$ on $D*/Y\$*$	1.238

[a]The g-statistic is calculated as $\hat{e}'\hat{e}/\hat{u}'\hat{u}$, where $\hat{e}$ is the vector of residuals from the first-difference form of the regressions, and $\hat{u}$ is the vector of residuals from the level form of the regressions.
[b]Sargan and Bhargava (1983) do not provide critical lower and upper bound values of the g-statistic for the specific number of observations, 29, considered here. However, they do provide critical values for $n = 21$ and $n = 31$. At the 1 percent level of significance, the lower bounds are 1.409 for $n = 21$ and 1.050 for $n = 31$, while the corresponding upper bounds are 1.960 and 1.480. At the 5 percent level, the critical lower bound values are 1.022 for $n = 21$ and 0.747 for $n = 31$, while the corresponding upper bound values are 1.560 and 1.156.

[11]We used the transfer function approach to model the relationships. This approach is discussed in Box and Jenkins (1976, Chapters 10 and 11). One of the early macroeconomic applications of this approach appears in Barth, Phaup, and Pierce (1975).

TABLE 6

Regression Results for Variables in First Difference Form (Time Period: 1955–1983)

Variable	Intercept	$\Delta[D^*/Y\$^*]$	$\bar{R}^2$	SER	$e_t = \frac{(1-\theta_1 L)}{(1-\rho_1 L)} a_t$	DW	$r(1)$
(1) $\Delta[PK/Y\$^*]$		−0.522 (−2.99)	0.24	0.015	—	1.27	0.34
		0.018 (0.07)	0.47	0.012	$\theta_1 = 0.79$ (9.48)	1.85	−0.03
	0.004 (1.14)	−0.375 (−1.76)	0.07	0.015	—	1.23	0.37
	0.007 (1.43)	0.160 (0.63)	0.38	0.012	$\theta_1 = 0.78$ (9.22)	1.92	0.30
(2) $\Delta[PK(CD)/Y\$^*]$		−0.086 (−1.05)	0.04	0.007	—	0.59	0.59
		0.03 (0.10)	0.55	0.005	$\theta_1 = 0.79$ (9.08)	1.29	0.08
	0.005 (4.13)	0.105 (1.33)	0.03	0.006	—	0.75	0.61
	0.006 (3.52)	0.161 (1.82)	0.50	0.004	$\theta_1 = 0.70$ (7.66)	1.63	0.18
(3) $\Delta[PK(PE)/Y\$^*]$		−0.207 (−2.37)	0.17	0.008	—	0.90	0.50
		−0.15 (−1.19)	0.37	0.006	$\rho_1 = 0.54$ (3.34)	1.66	0.14
	0.004 (2.21)	−0.078 (−0.77)	−0.02	0.007	—	1.07	0.45
	0.003 (1.19)	−0.103 (−0.74)	0.19	0.006	$\rho_1 = 0.47$ (2.70)	1.61	0.19

(Continued)

TABLE 6 (Continued)

Variable	Intercept	$\Delta[D^*/Y\$^*]$	$\bar{R}^2$	SER	$e_t = \frac{(1-\theta_1 L)}{(1-\rho_1 L)} a_t$	DW	$r(1)$
(4) $\Delta[PK(SL)/Y\$^*]$		−0.208 (−3.84)	0.35	0.005	—	0.35	0.80
$\Delta^2[PK(SL)/Y\$^*]$ on $\Delta^2[D^*/Y\$^*]$		0.012 (0.37)	0.01	0.002	—	1.31	0.22
$\Delta[PK(SL)Y\$^*]$	−0.002 (1.82)	−0.276 (−4.31)	0.39	0.005	—	0.58	0.71
$\Delta^2[PK(SL)/Y\$^*]$ on $\Delta^2[D^*/Y\$^*]$	−0.001 (−1.93)	0.026 (0.08)	−0.01	0.002	—	1.47	0.23
(5) $\Delta[PK(RES)/Y\$^*]$		−0.026 (−0.36)	0.01	0.006	—	0.75	0.55
		0.108 (1.23)	0.52	0.004	$\theta_1 = 0.76$ (11.18)	1.51	0.22
	−0.003 (−2.13)	−0.133 (−1.55)	0.05	0.006	—	1.08	0.44
	−0.002 (−1.02)	0.066 (0.69)	0.45	0.005	$\theta_1 = 0.76$ (10.06)	1.61	0.18

NOTE: DW and $r(1)$, respectively, are the Durbin-Watson statistics and the estimated first-order autocorrelations for the residuals. In the equations where the residuals are not modeled, these statistics apply to e_t. In the equations where the residuals are modeled, these statistics apply to a_t.

when changes in the variables were used and the error terms were appropriately modeled. These findings are consistent with those reported above, and reinforce the view that de Leeuw and Holloway's regression results may be spurious. It is important to point out that using first differences — as we have done here — removes a deterministic but not a stochastic growth component from the time series (Nelson and Plosser 1982, p. 160). Thus, to the extent that de Leeuw and Holloway did successfully remove the cyclical component from their debt series, the first differences of this series are the first differences of the secular component. In this case, the coefficient on the independent variable would reflect its long-term rather than its cyclical relationship to the dependent variable.

Conclusions

This paper has taken a time series approach to analyzing the relationship between the capital stock and the cyclically adjusted federal debt. The reason for taking this particular approach is that, as Granger and Newbold (1974, p. 117) point out, "the econometrician can no longer ignore the time series properties of the variables with which he is concerned — except at his peril." Even de Leeuw and Holloway (1985, p. 241) conclude their paper "by encouraging tests of the impacts of fiscal policy employing the new measures and using a full range of theoretical frameworks and statistical techniques." In this case, however, our alternative statistical technique applied to their data does not confirm their original finding of a "strong" negative relationship between the capital stock/income ratio and the cyclically adjusted federal debt/income ratio. The motivation for the approach adopted here is Granger and Newbold's statement (1974, p. 119) that "if a 'good' theory holds for levels, but is unspecific about the time-series properties of the residuals, then an equivalent theory holds for changes so that nothing is lost by model building with both levels and changes." Given the importance of de Leeuw and Holloway's findings for understanding the economic effects of federal debt, our results suggest that still more work needs to be done to determine the nature of the relationship between the capital/output ratio and the cyclically adjusted federal debt/output ratio.

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AN ANALYSIS OF INFORMATIONAL RESTRICTIONS ON THE LENDING DECISIONS OF FINANCIAL INSTITUTIONS

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Lenders are assumed to use formal credit scoring schemes in order to evaluate borrower credit worthiness. Variables used in these schemes may be measured with error resulting in credit scores which include the effects of biased parameter estimates, and in lending decisions that appear to be discriminatory although lenders are not prejudiced. Regulations which restrict the information used in credit scoring schemes may produce undesirable credit supply results. Theoretical models are supplemented with illustrative empirical analysis of mortgage lending in which use of information on property location is prohibited. The empirical results indicate that the quantitative impact of such regulations is modest.

I. INTRODUCTION

In recent years federal and state legislatures increasingly have become interested in the criteria which lenders use to decide upon the amount of credit to extend to individual borrowers. In response to borrower allegations of arbitrary or discriminatory treatment when applying for loans, major regulations have recently been enacted to limit the type of information lenders may use to determine which borrowers are acceptable credit risks. The Equal Credit Opportunity Act of 1976 and the Community Reinvestment Act of 1977, for example, either expressly prohibit or specifically discourage the use of certain information to determine credit-worthiness. In principle, these laws are intended to remove non-economic barriers to credit for various groups which would otherwise qualify for credit. However, in some non-trivial cases such regulations may produce the opposite effect. Chandler and Ewert (1976) and Chandler and Coffman (1980), for instance, have argued that women on average actually are better credit risks than men. Forcing creditors to ignore sex in assessing credit-worthiness may, therefore, reduce credit supply to the very group that supposedly is being protected.

This paper examines analytically and empirically the potential effects of regulations that restrict the information set available to financial institutions when making lending decisions. The next section of the paper presents a simple model of the credit market which demonstrates the role of credit-scoring schemes and econometric default loss models in lender decisions. Section III examines explicitly the effects of limiting the use of certain types of information on a lender's determination of the credit-worthiness of a borrower, and hence, on the overall impact of such limitations on lender behavior. In section IV the potential effects of informational restrictions are quantified using unique estimates of a default loss equation for mortgage loans. The final section summarizes the principal conclusions and suggests some policy implications of our analysis.

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Economic Inquiry
Vol. XXI, July 1983