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ABSTRACT

The relationship between unemployment and health continues to absorb social scientists. The primary reason is the potential significance of an association. If a substantial deterioration in aggregate health is related to economic downturns, then the cost of a recession may be much greater than the foregone output.

This paper investigates the aggregate time-series relationship between unemployment and low birthweight with monthly data from the state of Tennessee from 1970 through 1989. The study differs from previous work in that we decompose the unemployment rate into its structural and cyclical components. Moreover, we use vector autoregressions to test the reduced form relationship between unemployment and low birthweight. The well-defined exogeneity of unemployment and the lag length restriction imposed by the duration of a pregnancy strengthens the specification considerably. We fail to find a relationship between unemployment and low birthweight. This basic finding remains unchanged irrespective of whether we test structural or cyclical unemployment, or whether we use total or race-specific rates of low birthweight.

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Unemployment and Infant Health:
Time-Series Evidence from the State of Tennessee

Introduction

The relationship between unemployment and health continues to absorb social scientists. The primary reason is the potential significance of an association. If a substantial deterioration in aggregate health is related to economic downturns, then the cost of a recession may be much greater than the foregone output. Another reason is that the evidence of a causal relationship between unemployment and health has been strongly contested, which has stimulated the search for better data and more rigorous tests.

Much of the earlier research on unemployment and health was based on aggregate time-series analysis. Brenner (1973, 1979, 1987), for example, consistently reported a direct relationship between annual rates of unemployment and mortality. Yet, except for McAvinchey (1984), subsequent work with similar data failed to replicate Brenner's findings, were critical of his methods, and recommended that future studies rely on panel data whenever possible (Gravelle et al. 1981; Forbes and McGregor 1984; Gravelle 1984).

Longitudinal data, however, are expensive to collect, take a long time to amass, and unless designed specifically to address the question of unemployment and health, may lack sufficient power. Björklund (1985), for instance, used panel data from the Swedish Level of Living Survey to test whether unemployment worsened mental health. The results from the fixed effects model did not support the findings from the cross-section analyses that the unemployed have worse mental health. Björklund concluded that imprecise estimates obviated any strong conclusions, and his final remarks focused on the need for better data.

A well-designed time-series study is an inexpensive means of suggesting a relationship over a large, diverse population in less than real time, and thus, can serve as an important complement to more controlled studies. In a recent example, Joyce (1990) used aggregate time-series data on birth outcomes to examine the relationship between unemployment and infant health in New York City. The study represented an improvement over previous time-series analyses in several ways. First, data were monthly as opposed to annual which greatly increased the degrees of freedom. Second, the ten month span from pregnancy to birth provided a natural restriction on the lag length of unemployment. Previous time-series work, with its emphasis on total mortality, had lagged unemployment in an ad hoc manner. Third, Joyce distinguished between trend stationary and difference stationary time series to lessen the possibility of spurious associations. Joyce found no relationship between unemployment and infant health.

The present study is an aggregate time-series analysis of unemployment and infant health which builds on the work of Joyce in a number of ways. First, the data pertain to the State of Tennessee and thus, provide another test from a different region of the country. Second, the Tennessee unemployment rate varies over a greater range but displays lower frequency variation than the unemployment rate from New York City. Joyce cautioned that the preponderance of high frequency variation in the unemployment rate may have reduced the power of the test. Third, following Beveridge and Nelson (1981), we decompose the unemployment series into its cyclical and trend components. Most time-series studies of unemployment and health have suggested that the cyclical and structural effects of unemployment are different (Brenner 1979; Forbes and McGregor 1984), but none have explicitly attempted to model the two. Fourth, we use vector autoregressions (VARs) to test the bivariate relationship between between unemployment and infant health. Given the exogeneity of unemployment and the well-founded restriction on lag length, a VAR represents a straight forward means of testing the dynamic relationship between unemployment and infant health.

Analytical Framework

Economic models of infant health emphasize the distinction between the health production function and the input demand functions (Rosenzweig and Schultz 1983; 1988; Corman, Joyce, and Grossman 1987). The former represents the technical relationship between the birth outcome and the health inputs, whereas the latter focuses on the factors which determine the use of the health inputs. To illustrate, let B represent infant health and let M be a health input such as prenatal care.

(1) $B = f_1(M,S)$

(2) $M = f_2(P,Y)$

(3) $S = f_3(P,Y,U)$

To complete the model, let S represent other inputs such as maternal age, parity, as well deleterious substances such as cigarettes, alcohol and drugs; let P stand for price and availability measures, Y for income or command over resources, and U for unemployment. In Brenner (1973) and Joyce (1990) unemployment enters the structural production function as a proxy for maternal stress. In our specification unemployment is a determinant of stress, and thus is restricted to the input demand function. Moreover, business cycle downturns may have indirect effects that operate through M and S. A rise in unemployment decreases income and increases the proportion of uninsured pregnant women; as a result the demand for prenatal care falls and the incidence of adverse birth outcomes rises.

The estimation of a structural production function, such as equation (1), with aggregate time-series is problematic for two reasons. First, there is a lack of data on the relevant health inputs especially medical care. In the mortality studies, national health or welfare expenditures have served as proxies for medical care whereas medical technology has been controlled with trend terms (Gravelle et al. 1981; Forbes and McGregor 1984; Brenner 1987). Even when a proximate control for medical care is employed, other important inputs are missing. Joyce (1990), for example, used a standard measure of prenatal care, but he lacked information on other inputs such as cigarettes, illicit drugs, and weight gain during pregnancy. The second problem is that input use is endogenous (Rosenzweig and Schultz 1983; Grossman and Joyce 1990). This may be less relevant with aggregate data, but the test for endogenous regressors makes greater demands on the data. The present study will focus on the reduced form production function. In particular, the substitution of equations (2) and (3) into (1) yields the following:

$$(4) \qquad B = f_4(P,Y,U)$$

The reduced form production function obviates the need for data on the health inputs; there is also no problem with endogeneity. What is sacrificed is the ability to distinguish the potential direct effects from the indirect effects of economic downturns on birth outcomes. However, given the weak and conflicting time-series evidence associating unemployment and health, it would seem prudent to establish a relationship before testing for relevant pathways.

Empirical Implementation

Data

Data on infant health are from vital statistics from the State of Tennessee which have been aggregated from individual records, by month and race from January, 1970 through December, 1988. We use the total percentage as well as the race-specific percentage of low birthweight (LBW) births as our measures of infant health. In a time-series test of unemployment and health, low birthweight is superior to infant mortality as a measure of newborn health because there is less potential confounding due to technological change. The rapid decline in infant mortality in the United States over the past 20 years has been attributed to advances in management of newborn care. By contrast, the rate of low birthweight has shown no improvement. In Tennessee, for instance the total infant mortality rate fell 43 percent between 1970 and 1987 -- from 21.5 deaths per 1000 live births in 1970 to 12.3 deaths per 1000 live births in 1987. Over the same time period the rate of low birthweight actually rose 5.2 percent -- from 7.7 low birthweight births per 100 live births in 1970 to 8.1 per 100 live births in 1987 (Tennessee Department of Health and Environment 1987).

The unemployment rate has been maintained since January, 1970 by the State of Tennessee Department of Employment Security under a Federal-State cooperative program. Estimates of employed and unemployed workers are from a number of sources which include surveys of establishment payrolls and claims for unemployment insurance. The methodology follows standard procedures developed by the U.S. Bureau of Labor Statistics.

Cyclical versus structural employment

Many researchers have speculated that the short-term and long-term effects of unemployment on health are likely to differ (Brenner 1979; Forbes and

Mcgregor 1984; Gravelle 1984). Prolonged or structural unemployment is associated with permanent layoffs caused by, among other things, the migration or decline in industries due to foreign competition or technological change. By comparison, cyclical unemployment is associated with business cycles and is viewed as temporary. It is hypothesized that both types of unemployment worsen health by inducing stress; moreover, economic downturns not only increase cyclical unemployment, but they can exacerbate structural unemployment as well. What distinguishes the two is that structural unemployment is more likely to result in a substantial loss of income, and thus, diminished investments in health. Because cyclical unemployment results in smaller loss of income, and possibly no loss of health insurance, the income effect on health may be minimal. Despite the anticipated difference in the health effects of cyclical and structural unemployment, there have been no explicit attempts to test the proposition with aggregate time-series data. In this paper, we decomposed the Tennessee unemployment rate into its permanent and transitory components and used them as proxies for structural and cyclical unemployment, respectively. The decomposition is based on a seminal paper by Beveridge and Nelson (1981, BN). Specifically, let x_t, the unemployment rate in the state of Tennessee, be the sum of a trend (s_t) and cyclical (c_t) component such that

$$(5) \quad x_t = s_t + c_t,$$

$$(6) \quad s_t = \mu + s_{t-1} + e_t, \qquad \text{and} \qquad c_t = \theta(B)e_t,$$

where $\theta(B)$ is a polynomial in the backshift operator B, and e_t is white noise with the variance σ_e^2. Equation (6) characterizes the trend component as a random walk with drift whereas the cyclical component is specified as a stationary process. Note that if $\sigma_e^2=0$, the trend becomes linear and non-stochastic.

BN prove that any variable that has an autoregressive integrated moving average (ARIMA) representation of *(p,1,q)* contains a random walk stochastic trend. They further illustrate how the trend and stationary components can be estimated by an ARIMA model. In particular, denote $\omega_t = \Delta x_t$, where x_t is non-stationary, but ω_t is a covariance-stationary series. According to the Wold decomposition theorem, ω_t can be written as

$$(7) \qquad \omega_t = \mu + \epsilon_t + \lambda_1\epsilon_{t-1} + \lambda_2\epsilon_{t-2} \ldots,$$

where μ is the long-run mean of the series, and ϵ's are serially uncorrelated random disturbances with zero mean and constant variance. As defined by BN, the trend component is the current observed value of x plus all forecastable future changes in the series beyond the mean rate of drift (μ). In other words,

$$(8) \qquad s_t = x_t + \lim_{k\to\infty} \{[\hat{\omega}_t(1)+\hat{\omega}_t(2)+\hat{\omega}_t(3)+\ldots+\hat{\omega}_t(k)]-k\mu\},$$

where s_t is the permanent component, x_t is the observed value of the series at time *t*, and $\hat{\omega}_t(j)$ is the j-step ahead conditional forecast for ω created at time j. The second term on the right-hand side of equation (8) is the difference between x's permanent component and its current value which BN interpret as the transitory or cyclical component.

$$(9) \qquad c_t = \lim_{k\to\infty} \{[\hat{\omega}_t(1) + \hat{\omega}_t(2) + \hat{\omega}_t(3) + \ldots + \hat{\omega}_t(k)] - k\mu\}$$

$$= (\sum_{1}^{\infty} \lambda_i) e_t + (\sum_{2}^{\infty} \lambda_i) e_{t-i} + \ldots$$

Equation (9) indicates that the cyclical component, c_t, is a stationary finite order moving average process.

Vector autoregressions

We use vector autoregressions (VARs) to test whether unemployment explains low birthweight holding constant lagged values of low birthweight (Sims 1980). VARs represent a relatively unrestrictive means of highlighting important correlations in the data so as to empirically confirm or questions various hypothesized relationships. The model we estimate can be specified as follows:

$$(10) \qquad U_t = C^1 + \sum_{i=1}^{10} \alpha_i LBW_{t-i} + \sum_{i=1}^{10} \beta_i U_{t-i} + \xi_t$$

$$(11) \qquad LBW_t = C^2 + \sum_{i=1}^{10} \alpha_i' LBW_{t-i} + \sum_{i=1}^{10} \beta_i' U_{t-i} + v_t$$

where C^j is a vector containing the constant, the seasonal dummies, and where appropriate a linear trend term and the percentage of black births. LBW_t is the total or race-specific rate of low birthweight at time *t*, and U_t is either the structural or cyclical unemployment rate at time *t*.

Vector autoregressions have come under criticism in the macro-econometric literature because they impose restrictions on causal orderings and lag length that lack a theoretical rationale (Cooley and LeRoy 1985). However, in a test of unemployment and infant health, these criticisms are less applicable. First, we estimate a reduced form model in which the unemployment rate is clearly exogenous to low birthweight. There is little theoretical justification for why low birthweight might cause unemployment. In the unlikely event that low birthweight explains unemployment, then misspecification, and not reverse causality, would be the appropriate interpretation. Second, since pregnancies last at most 10 months, we have a meaningful restriction on the lag length of unemployment in the low birthweight equation. Such well-founded restrictions are clearly lacking in the macroeconomic applications of VARs. The appropriate lag length for unemployment in the unemployment equation is less certain. Therefore, we will lag each variable 10 months in the birthweight equation. In the unemployment equation we will use the Akaike criteria to determine an optimal lag length. If the number of lags used in equations (10) and (11) differs, then the system will be estimated by seemingly unrelated regression methods. If the number of lags in each equation is identical, then each may be estimated consistently by single-equation least squares.

A number of tests and diagnostics will be used to check the adequacy of the specification and to determine whether the residuals are white noise. The specification tests are important because we have no data on the price of the health inputs, and no direct measure of income [equation (4)]. If the price of prenatal care, for instance, leads changes in unemployment, and if the price of prenatal care is an important determinant of low birthweight, then as mentioned above, rejection of the null hypothesis that $\alpha_i = 0$ in equation (10) would signal the presence of an omitted variable. Similarly, if variations in unemployment are unrelated to changes in income, then the omitted variable bias would reveal itself as information contained in the errors. As an additional check for misspecification, we will test whether future lags in the unemployment rate explain low birthweight (Eckstein, Wolpin, and Schultz 1985). Given that unemployment is exogenous to low birthweight, future lags in unemployment could only explain low birthweight through an omitted third variable. One part of the residual diagnostics will be based on an examination of the residual correlogram in order to determine whether the errors are white noise. We will also apply a Lagrange multiplier test which is a general test for higher autocorrelation and is valid when the set of regressors includes lagged dependent variables (Godfrey 1978).

Results

We could not reject the null hypothesis that the unemployment rate is governed by a stochastic trend based on the Dickey-Fuller and Pierre Perron tests for units roots; however we easily rejected the null that the rates of low birthweight (black, white and total) were integrated processes. The unemployment rate could be characterized as a third order autoregressive process integrated to order one [ARIMA(3,1,0)]. With this univariate representation we decomposed the unemployment rate into its structural and cyclical components as described above. The resultant series are displayed in Figure 1. As can be seen, the structural unemployment rate accounts for the greatest portion of the variation in total unemployment. The structural unemployment rate rises from 4 percent in 1971 to roughly 12 percent in 1983 before falling to approximately 5 percent in 1988. By construction, the cyclical unemployment rate is stationary around zero.

As noted above, the rate of low birthweight is available on a race-specific basis, whereas the unemployment rate for the State of Tennessee is not. Moreover, the structural and cyclical unemployment rates are tested separately. Thus, we fit three versions of the model specified by equations (10) and (11) based on the three the rates of low birthweight, and each model is estimated twice: first with the cyclical unemployment rate and then with the structural unemployment rate. Table 1 presents the bivariate tests of cyclical unemployment and the three rates of low birthweight. Table 2 displays the analogous results with structural unemployment. The results are based on a specification that included 10 lags of unemployment and birthweight in the birthweight equation, but 10 lags of birthweight and 14 lags of unemployment in the unemployment equation. Each column in the tables shows the χ^2 statistics on the set of lags of each variable in each equation, the adjusted R-squared, and the residual diagnostics. The specification test based on the future lags of the unemployment rate in the low birthweight equation is also included.

There is no evidence that lags in the cyclical unemployment rates explain either the total, or race-specific rates of low birthweight. The same is true for structural unemployment in Table 2. There is also no indication of feedback from low birthweight to unemployment in any of the six specifications in Tables 1 and 2. Low birthweight has no explanatory power in the unemployment equations, and we could not reject the null that the coefficients on the leads of the unemployment rate do not explain low birthweight at conventional levels. Although we did not expect low birthweight to explain unemployment, or leads in unemployment to explain low birthweight, rejection of the null in either case would have challenged the specification.

As is seen in the bottom halves of Tables 1 and 2, the Durbin-Watson and Ljung-Box Q statistics indicate that the errors are not different from white noise. We also report the first 12 autocorrelations of the residual series from each equation. At all lags, the autocorrelations are statistically insignificant. The Lagrange multiplier tests yield similar conclusions in the birthweight equations: the null hypothesis that the residuals are white noise cannot be rejected. In two of the cyclical unemployment equations (Table 1), however, we found evidence of twelfth-order autocorrelation ($p < .05$). Since there was no evidence of first- or sixth order autocorrelation, the most likely explanation is that the seasonal dummies may be inadequate controls for seasonal variation in the cyclical unemployment specifications. We do not believe the type and degree autocorrelation threatens, in any substantive way, the basic conclusion that unemployment has no impact on infant health.

As an additional characterization of the system's dynamics, we applied a shock in the unemployment rate of one standard deviation to the moving average representation of the system. Sims (1980) refers to these as impulse response functions. The impulse response functions allow for interactions across equations; in addition, the effect of each variable is not limited by the number of lags in the autoregressive specification (see Eckstein, Wolpin, and Schultz 1984). If the system is stable, the impulses will diminish to zero and the cumulative effect of the shock is the sum of the impulse responses. Figures 2A, 2B, and 2C show the effect of a one standard deviation increase in the innovations in the cyclical unemployment rate on the total, the white and the black rates of low birthweight respectively. In each figure, the response is the same: the rate of low birthweight fluctuates around zero as successive impulses become weaker before dampening to zero at approximately 20 months. The effect of a shock in the innovations in the structural unemployment is similar (Figures 3A, 3B, and 3C). Moreover, as can be seen from the two sets of figures, the cumulative change in the total, black and white rates of low birthweight to a shock in either cyclical or structural unemployment is essentially zero. In addition, the results are insensitive to whether a causal ordering is imposed on the contemporaneous innovations across equations, or whether the shock are left unordered. In short, the impulse response functions reinforce the findings from the autoregressive specification: changes in the unemployment rate have no impact on aggregate infant health.

To determine whether the results were sensitive to the decomposition, we estimated equations (10) and (11) with the total unemployment rate in place of the structural and cyclical unemployment rates. Since the we could not reject the null hypothesis that the unemployment rate is a difference stationary process, we estimated the model with the first difference of the unemployment rate. We also estimated the model without differencing the unemployment rate. Neither the autoregressive nor the impulse response functions changed in any meaningful manner.

Conclusion

We investigated the aggregate time-series relationship between unemployment and low birthweight with monthly data from the state of Tennessee from 1970 through 1988. The study differed from previous work in that we decomposed the unemployment rate into its trend and stationary components and used these as measures of structural and cyclical unemployment. Moreover, we used vector autoregressions to test the reduced form relationship between unemployment and low birthweight. The well-defined exogeneity of unemployment and the lag length restriction imposed by the duration of a pregnancy strengthened the specification considerably. We found no relationship between unemployment and low birthweight. This basic finding remained unchanged irrespective of whether we tested structural or cyclical unemployment, or whether we used total or race-specific rates of low birthweight. The results are consistent with the findings of Joyce (1990) and they contradict the work of Brenner (1973, 1979, 1987) who has repeatedly reported a direct association between unemployment and infant mortality.

One drawback to the present study is the lack of a race-specific measure of unemployment since blacks have consistently experienced higher rates of unemployment than whites. Based on national data, however, the zero order correlation between the total unemployment rate with the black unemployment rate is extremely high ($r=.95$), as is the correlation between the total unemployment rate and the unemployment rate among blacks 20 to 34 years of age ($r=.94$). If the analogous unemployment rates in Tennessee are as highly correlated, then only the magnitude of the effect, and not the statistical significance of the association would have been affected.

Another explanation for the lack of an association between unemployment and low birthweight in light of previous work linking unemployment and infant mortality is the different measures of infant health. As noted above, the infant mortality rate has fallen substantially within Tennessee as well as across the United States, whereas the rate of low birthweight has shown modest improvement nationwide and no improvement within Tennessee. The widely accepted explanation for the decrease in infant mortality is the advances in management of newborn care (McCormick 1985). The difficulty of controlling for technological change in aggregate time-series analysis combined with the lack of a relationship between unemployment and low birthweight seriously challenge Brenner's findings that unemployment and infant mortality are related.

A similar point can be generalized to aggregate time-series studies of unemployment and health. In the time-series analyses of unemployment and age- or cause-specific mortality, not only is there little justification for a specific lag length, but time spans between the onset of a recession and subsequent increases in mortality have been estimated at between 1 to 10 years (Brenner 1979; MacAvinchey 1984). The possible confounding from non-economic factors would appear to be great. The major advantage of birth outcomes as a measure of health is that the relatively short duration of a pregnancy should lessen the potential confounding due to coincident trends and technological change. We suggest that future time-series analyses of unemployment and health focus on outcomes which have the potential to respond shortly after downturns in employment.

Table 1
Estimation Results and Specification Tests
of the Vector-Autoregressive Models with
the Cyclical Unemployment Rate

	Total LBW		White LBW		Black LBW	
	Equation[a]		Equation		Equation	
	CYL	LBW	CYL	LBW	CYL	LBW
χ^2-statistic of CYL[b]	708.16	12.26	705.12	16.49	679.09	8.72
	(0.00)	(0.27)	(0.00)	(0.09)	(0.00)	(0.56)
χ^2-statistic of LBW	8.08	19.10	7.21	21.48	6.25	8.63
	(0.62)	(0.04)	(0.71)	(0.02)	(0.79)	(0.57)
Adjusted R^2	0.74	0.32	0.74	0.25	0.73	0.22
Degrees of freedom	161	164	162	165	162	165

Residual Diagnostics

	Total LBW		White LBW		Black LBW	
	Equation		Equation		Equation	
	CYL	LBW	CYL	LBW	CYL	LBW
Durbin-Watson	1.96	2.02	1.96	2.03	1.97	1.97
Q(42)	35.66	41.73	35.19	30.46	38.60	33.40
	(0.74)	(0.48)	(0.76)	(0.91)	(0.62)	(0.82)
χ^2-statistic of 10 leads of CYL		12.48		8.99		8.37
		(0.25)		(0.53)		(0.59)

The first twelve autocorrelations of the residuals of the Rate of Low Birthweight Equations[c]

r_1	0.014	-0.027	0.012	-0.035	0.010	0.010
r_2	0.017	-0.032	0.013	-0.029	0.015	-0.001
r_3	-0.032	-0.006	-0.043	-0.025	-0.030	0.002
r_4	0.017	0.017	0.027	0.016	0.035	0.034
r_5	0.047	0.007	0.035	0.017	0.058	0.000
r_6	0.043	0.004	0.055	0.021	0.037	-0.004
r_7	-0.013	-0.060	-0.023	-0.074	-0.015	0.014
r_8	-0.041	-0.016	-0.036	-0.047	-0.020	-0.008
r_9	0.058	-0.013	0.051	0.007	0.047	-0.033
r_{10}	-0.021	-0.023	-0.009	-0.050	0.009	0.003
r_{11}	-0.049	0.126	-0.052	0.113	-0.045	0.081
r_{12}	-0.091	0.029	-0.092	-0.006	-0.091	0.035

Table 1 (continued)

Lagrange-Multiplier Tests[d]

	Total LBW		White LBW		Black LBW	
	Equation		Equation		Equation	
	CYL	LBW	CYL	LBW	CYL	LBW
χ^2 for						
$H_0:\rho_1=0$	1.44	0.09	0.96	0.23	1.30	1.10
$H_0:\rho_1=\ldots=\rho_6=0$	9.88	7.26	11.35	9.29	7.90	7.73
$H_0:\rho_1=\ldots=\rho_{12}=0$	24.39	14.88	16.22	13.39	22.77	20.08

[a] CYL is the cyclical unemployment. LBW is the rate of low birthweight.
[b] χ^2 statistic of a variable is the joint significance of the lags of the variable in the corresponding equation. The values in paretheses are the marginal significance levels.
[c] r_i is the *i*th order autocorrelation coefficient. The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{n}$, where n is the sample size. For our sample sizes of 198, the 0.05 confidence interval is approximately $\pm$ 0.14.
[d] ρ_i is the *i*th order serial correlation coefficient. In the LM test for serial correlation, the residuals from the low birthweight equations are regressed on the same right-hand side variables and a set of lagged residuals. χ^2 statistic is the significange for the coefficients of the lagged residuals, where the number of autocorrelations in the null hypothesis is the degrees of freedom. The critical values for χ^2 at the 5% level for 1, 6 and 12 degrees of freedom are 3.84, 12.59 and 21.03, respectively.

Table 2
Estimation Results and Specification Tests
of the Vector-Autoregressive Models with
the Structural Unemployment Rate

	Total LBW		White LBW		Black LBW	
	Equation[a]		Equation		Equation	
	ΔSTR	LBW	ΔSTR	LBW	ΔSTR	LBW
χ^2-statistic of STR[*]	103.89	10.40	99.47	17.01	103.27	6.38
	(0.00)	(0.41)	(0.00)	(0.07)	(0.00)	(0.78)
χ^2-statistic of LBW	9.74	15.75	9.47	20.93	10.76	7.73
	(0.46)	(0.11)	(0.49)	(0.02)	(0.38)	(0.65)
Adjusted R^2	0.56	0.31	0.56	0.26	0.56	0.21
Degrees of freedom	160	163	161	164	161	164

Residual Diagnostics

	Total LBW		White LBW		Black LBW	
	Equation		Equation		Equation	
	ΔSTR	LBW	ΔSTR	LBW	ΔSTR	LBW
Durbin-Watson	1.97	2.01	1.94	2.02	1.94	1.96
Q(42)	34.75	35.96	30.37	28.42	34.95	31.42
	(0.78)	(0.73)	(0.91)	(0.95)	(0.77)	(0.88)
χ^2-statistic of 10 leads of STR		18.34		13.97		10.91
		(0.05)		(0.17)		(0.36)

The first twelve autocorrelations of the residuals of the Rate of Low Birthweight Equations[c]

r_1	0.005	-0.014	0.018	-0.013	0.025	0.008
r_2	-0.018	-0.024	-0.021	-0.029	-0.032	-0.004
r_3	-0.019	-0.015	-0.012	-0.039	0.011	0.003
r_4	-0.044	-0.003	-0.039	-0.009	-0.052	0.026
r_5	0.049	0.013	0.042	0.019	0.064	-0.003
r_6	0.048	-0.018	0.025	0.006	0.010	-0.013
r_7	-0.036	-0.041	-0.038	-0.034	-0.027	0.003
r_8	0.012	-0.016	-0.001	-0.043	0.023	-0.021
r_9	-0.018	-0.016	0.033	-0.021	-0.022	-0.018
r_{10}	0.047	-0.021	-0.003	-0.037	0.008	0.004
r_{11}	0.043	0.098	0.019	0.094	0.033	0.080
r_{12}	-0.001	-0.015	-0.000	-0.051	-0.006	0.011

Table 2 (continued)

Lagrange-Multiplier Tests[d]

	Total LBW		White LBW		Black LBW	
	Equation		Equation		Equation	
	ΔSTR	LBW	ΔSTR	LBW	ΔSTR	LBW
χ^2 for						
$H_0:\rho_1=0$	0.07	0.49	0.99	0.35	1.95	0.92
$H_0:\rho_1=\ldots=\rho_6=0$	10.96	4.13	6.24	4.12	11.81	8.18
$H_0:\rho_1=\ldots=\rho_{12}=0$	18.31	6.32	12.72	13.73	17.67	15.10

[a] STR is the structural unemployment. LBW is the rate of low birthweight. Δ stands for the first difference.

[b] χ^2 statistic of a variable is the joint significance of the lags of the variable in the corresponding equation. The values in paretheses are the marginal significance levels.

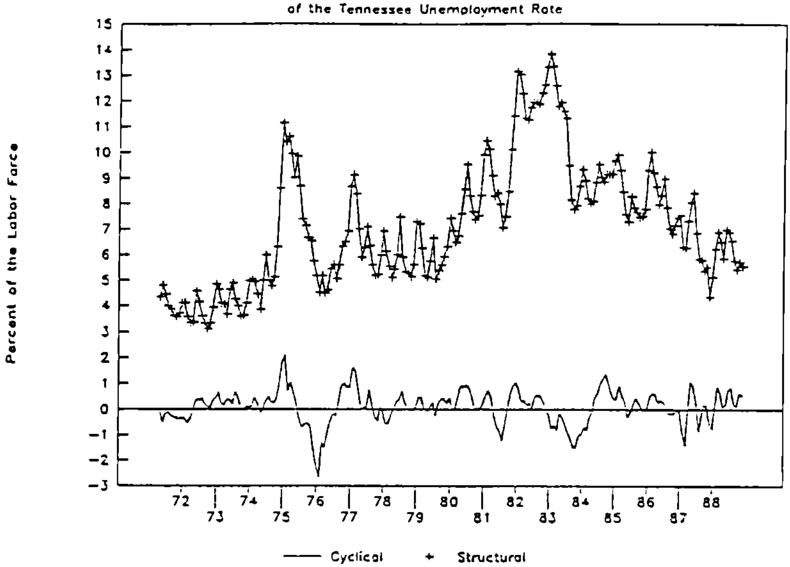
[c] r_i is the *i*th order autocorrelation coefficient. The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{n}$, where n is the sample size. For our sample sizes of 198, the 0.05 confidence interval is approximately $\pm$ 0.14.

[d] ρ_i is the *i*th order serial correlation coefficient. In the LM test for serial correlation, the residuals from the low birthweight equations are regressed on the same right-hand side variables and a set of lagged residuals. χ^2 statistic is the significange for the coefficients of the lagged residuals, where the number of autocorrelations in the null hypothesis is the degrees of freedom. The critical values for χ^2 at the 5% level for 1, 6 and 12 degrees of freedom are 3.84, 12.59 and 21.03, respectively.

Decomposition

of the Tennessee Unemployment Rate

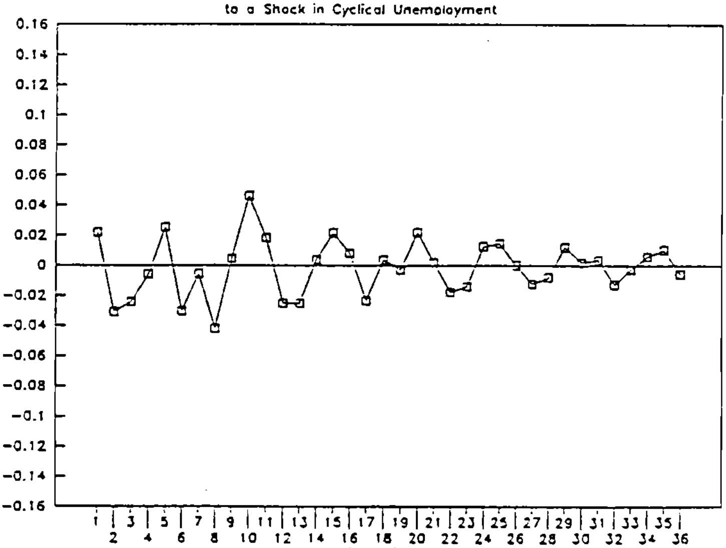
Figure 1



Reaction of the Rate of Total LBW

to a Shock in Cyclical Unemployment

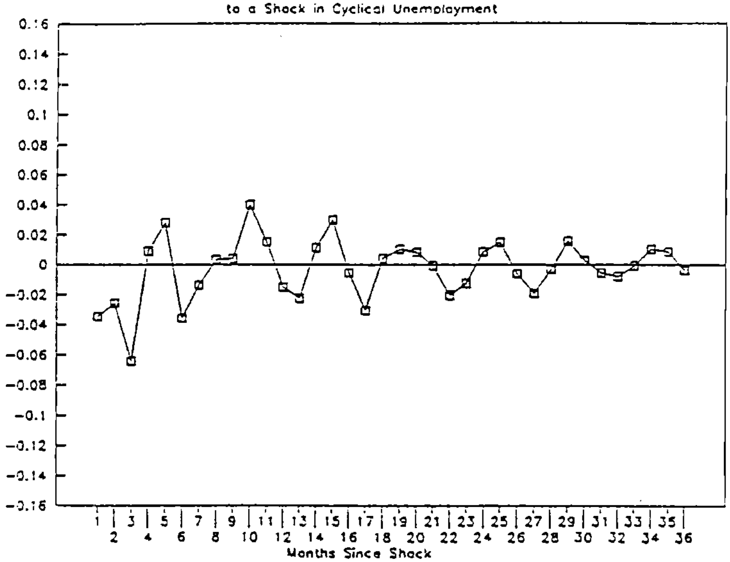
Figure 2A



Reaction of the Rate of White LBW

to a Shock in Cyclical Unemployment

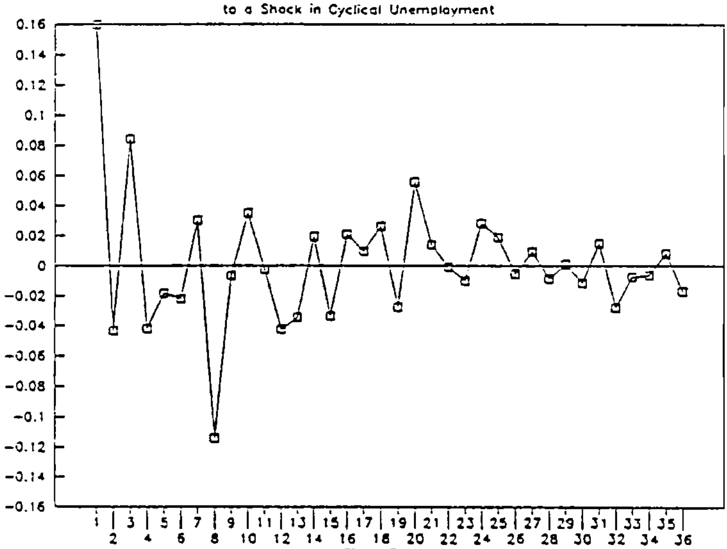
Figure 2B



Reaction of the Rate of Black LBW

to a Shock in Cyclical Unemployment

Figure 2C



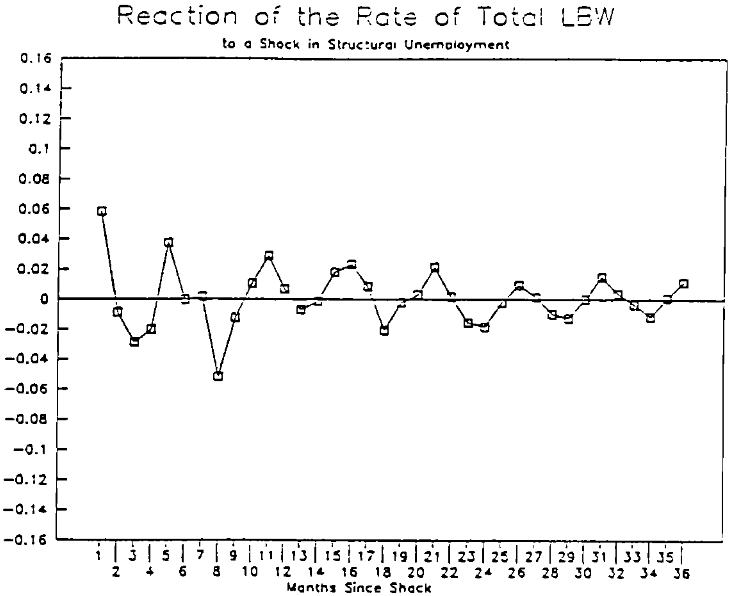


Figure 3A

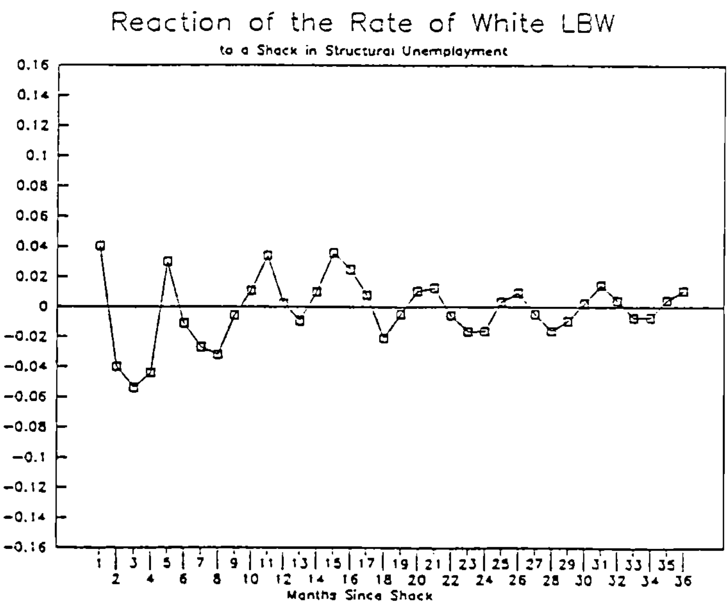
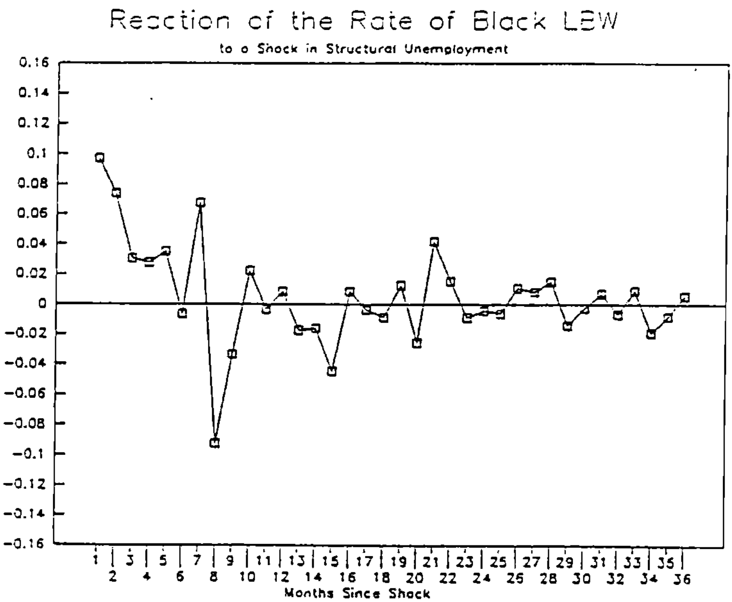


Figure 3B

Figure 3C



Reaction of the Rate of Black LBW
to a Shock in Structural Unemployment
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35
2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36
Months Since Shock

Endnotes

1. There is epidemiological evidence that pregnant women who work in physically demanding jobs may be at a greater risk of preterm delivery (Naeye and Peters 1982; Mamelle, Lauman and Lazar 1984). This would imply that adverse birth outcomes vary procyclically. However, a recent study of female physicians during residency found no such links to prematurity which strongly suggested that the results from previous studies had been confounded by socioeconomic factors (Klebanoff, Shiono and Rhoads 1990).

2. One will recognize Friedman's permanent income hypothesis in this formulation (Friedman 1957).

3. Prior to Beveridge and Nelson (1981), it was common in the macroeconomic literature to assume that cyclical movements in economic time series fluctuated around a deterministic trend. For a lucid description of stochastic trends and their evolution, see Stock and Watson (1988).

4. Traditional methods of decomposition have assumed a linear deterministic trend. However, failure to distinguish between trend stationary processes and difference stationary processes can yield seriously misleading results (Nelson and Kang 1984; Stock and Watson 1988).

5. The assumption that the unemployment rate is integrated to order one does not appear to be an overly restrictive assumption. Nelson and Plosser (1982) show that most economic time series appear to contain a stochastic trend. In fact, only with the United States unemployment rate were the authors able to reject the null hypothesis of a stochastic trend. We used the Dickey Fuller test and the Phillips Perron tests for unit roots to determine whether the Tennessee unemployment rate and rate of low birthweight contained a stochastic trend. Only with the unemployment rate we were unable to reject the null hypothesis of a stochastic trend. A description of the tests and the results is presented in the Appendix.

6. Such tests of temporal orderings are referred to as tests "Granger causality" (Granger 1969). Following Leamer (1985) we avoid the use to the term, "Granger causality," in order to minimize the confusion between Granger's definition of causality, and causality as defined by philosophers of science.

7. The stylized facts indicate that since 1970, both the relative price of medical care and utilization of early prenatal care have trended sharply upwards across

the United States. This suggests that at the aggregate level, the relative price of medical care is not an important determinant of its utilization. The upward trend in prenatal care is probably best explained by the increase number of women covered by health insurance, the anti-poverty programs most notably Medicaid, and higher levels of education among women (Corman and Grossman 1985).

8. A more detailed description of the tests and the results are in the Appendix.

9. The structural unemployment rate was a random walk with drift, where the drift term was 0.35, and the first-order autoregressive coefficient was 0.95. Because the structural unemployment rate is non-stationary, we use its first difference in regressions.

10. Akaike criterion was minimum when the lag length of structural unemployment was 14. In the models with cyclical unemployment, it yielded an optimum lag length of 16, which was very close to the one obtained with 14 lags. For consistency, we included 14 lags of unemployment into unemployment equations in all models.

11. Sims (1980) recommends that the variance-covariance matrix of the contemporaneous errors be transformed in such a manner so as to impose a specific causal ordering to the shocks. If the contemporaneous correlations among the residuals are substantial, then the impulse response functions can be sensitive to the causal ordering imposed.

APPENDIX

Trend Properties of the Variables

Recent developments in time-series econometrics have underscored the importance of differentiating between difference-stationary processes (DSP) and trend-stationary processes (TSP) (Nelson and Plosser 1982). Failure to distinguish between the two can generate misleading results (Nelson and Kang 1984, Stock and Watson 1988). Series belonging to DSP type should be detrended by differencing, whereas inclusion of time variables is most appropriate for TSP type series. We employ unit root tests developed by Dickey and Fuller (1981), and Phillips and Perron (1986) to test the hypothesis that a particular series belongs to DSP type against the alternative that it belongs to TSP type.
To implement the Dickey-Fuller test we estimate

$$\text{(A1)} \quad \Delta z_t = \alpha_0+\beta_0 t+\beta_1 z_{t-1}+ \sum_{i=1}^{k}\delta_i \Delta z_{t-i}+\epsilon_t,$$

where z_t is the variable of interest, ϵ_t is the white noise error term at time t, and Δ is the difference operator. The variable z belongs to DSP type if $\beta_0=\beta_1=0$. The results of Dickey-Fuller tests are displayed in the first column of Table A1. The Phillips-Perron tests account for possible correlation in the first differences of time series using a nonparametric correction, and allow for the presence of a non-zero mean and a deterministic linear time trend (Ambler 1989). Following Perron(1988), two test statistics are calculated which are based on the equation

$$\text{(2)} \quad z_t = \mu+\beta(t-T/2)+\alpha z_{t-1}+\epsilon_t.$$

The second and third columns of Table A1 depict the statistics $Z(\alpha)$ and $Z(t_\alpha)$ as defined in Perron (1988) that test the hypothesis $\alpha=1$ for the level of z_t. We report the results of Dickey-Fuller statistic for $k=6$ in equation (A1). The Phillips-Perron statistics depend on a truncation parameter, ℓ. The results in Table A1 are for $\ell=6$. Increasing ℓ and k to 12 in Phillips-Perron and in Dickey-Fuller tests, respectively, did not alter the conclusions.

Table A1

Tests for Unit Roots

Variables	DF	$Z(\alpha)$	$Z(t_\alpha)$
Unemployment rate	2.02	-3.39	-0.12
Rate of low birthweight (Total)	8.33*	-169.61*	-11.26*
Rate of low birthweight (Whites)	10.24*	-175.13*	-11.48*
Rate of low birthweight (Blacks)	10.26*	-294.49*	-14.57*

The critical value for the DF statistic can be found in Dickey and Fuller(1981,p.1063).

The critical values for $Z(\alpha)$ and $Z(t_\alpha)$ can be found in Fuller(1976, p.371) and Fuller(1976, p.373), respectively

* Significant at 1%

Sims Exogeneity Test

For illustrative purposes suppose the following VAR model is the correct specification:

$$LBW_t = \alpha_1 LBW_{t-1} + \alpha_2 LBW_{t-2} + \alpha_3 Y_{t-1} + \alpha_4 Y_{t-2} + \alpha_5 U_{t-1} + \alpha_6 U_{t-2} + e_t,$$

$$Y_t = \beta_1 LBW_{t-1} + \beta_2 LBW_{t-2} + \beta_3 Y_{t-1} + \beta_4 Y_{t-2} + \beta_5 U_{t-1} + \beta_6 U_{t-2} + u_t,$$

$$U_t = \phi U_{t-1} + v_t,$$

where LBW is the rate of low birth weight, and Y is the other endogenous variable; U is the rate of unemployment, which is exogenous, hence explained by its own dynamics. If one estimates the equation

$$LBW_t = \gamma_1 LBW_{t-1} + \gamma_2 LBW_{t-2} + \gamma_3 U_{t-1} + \gamma_4 U_{t-2} + \gamma_5 U_{t+1} + \tau_t,$$

omitting the lagged values of Y, but including the future value of the exogenous variable, the chain of correlation between U_{t+1} and Y_t may give rise to a significant estimate of $\gamma_5 \neq 0$, which represents the specification error of the model, since the future value of the exogenous variable is not expected to influence the current value of the endogenous variable.

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