Communications

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

I. 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 McGreggor 1984), but none have explicitly attempted to model the two. Fourth, we use vector autoregressions (VARs) to test the bivariate relationship between unemployment and infant health. Given the exogeneity of unemployment and the well-founded restriction on lag length, a VAR represents a straightforward means of testing the dynamic relationship between unemployment and infant health.

II. 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 that 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 as 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 structrual 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.[1]

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 demand on the data. The present study will focus on the reduced form

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. A recent study of female physicians during residency, however, 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).

production function. In particular, the substitution of equations (2) and (3) into (1) yields the following:

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

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.

III. Empirical Implementation

A. 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. Figure 1 presents the White, Black, and total rate of low birthweight from 1970 through 1988. The data have been smoothed by a 2×12 moving average in order to highlight any cyclical variation. All three rates of low birthweight evidence little trend. There is cyclical variation, especially for Blacks. The rate of Black low birthweight demonstrates a 15 percent increase between 1970 and 1972; it then drifts back to the 1971 level by the mid 1970s. There are upswings between 1976 and 1978, 1980 and 1982, and 1986 and 1988 by 6 percent, 10 percent, and 5 percent, respectively. In the case of Whites, the increase between 1970 and 1972 is 11 percent. Two other notable upswings take place between 1976 and 1978, and 1986 and 1988, which are 6 percent and 5 percent, respectively. The 1980 upturn of the Black series is not visible for Whites. The behavior of the total rate of low birthweight is very similar to that of the Whites.

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 1,000 live births in 1970 to 12.3 deaths

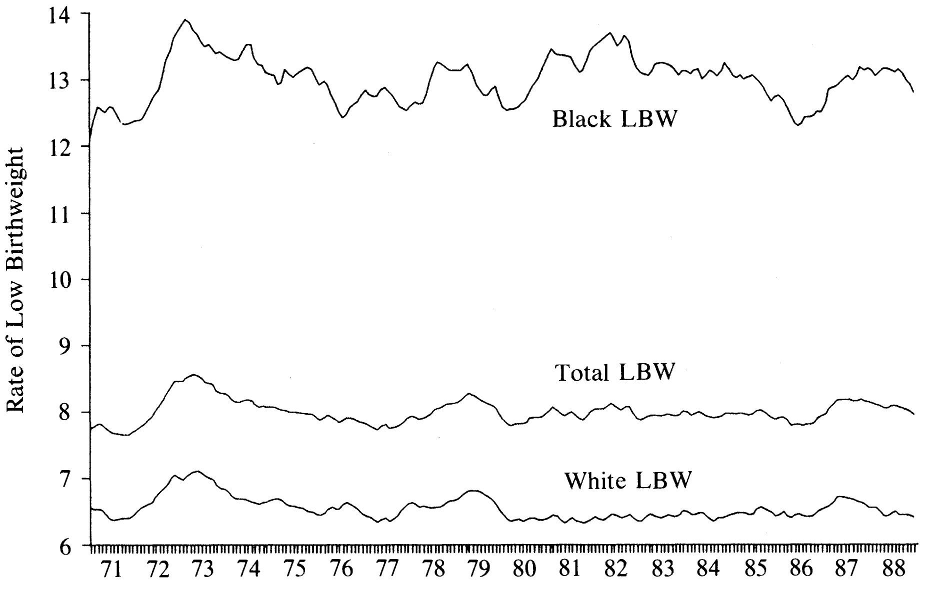

Figure 1
Black, White, and Total Low Birthweight (2 × 12 Moving Average)

per 1,000 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 1989).

We use the total unemployment rate for the State of Tennessee which has been maintained by the State of Tennessee Department of Employment Security. Breakdowns by race and sex are not available.[2] 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.

B. 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,

2. As a proxy for stress and family income, a sex specific unemployment rate, for example the female unemployment rate, is inferior to the total or race-specific unemployment rate since it might fail to capture the loss of work by a member of the other sex, in this case a male head of household.

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.[3]

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 decompose the Tennessee unemployment rate into its permanent and transitory components and use them as proxies for structural and cyclical unemployment, respectively. The decomposition is based on a seminal paper by Beveridge and Nelson (1981, BN).[4] Specifically, let x_t, the unemployment rate in the state of Tennessee, be the sum of trend (s_t) and cyclical (c_t) components such that

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

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

where $\theta(L)$ is a polynomial in the lag operator L, 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 nonstochastic.[5]

BN prove that any variable that has an autoregressive integrated moving average (ARIMA) representation of (p, l, q) contains a random walk

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

4. 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).

5. 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).

stochastic trend.[6] 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 nonstationary, but ω_t is a covariance-stationary series. According to the Wold decomposition theorem, ω_t can be written as

$$(7)\quad \omega_t = \mu + \varepsilon_t + \lambda_1 \varepsilon_{t-1} + \lambda_2 \varepsilon_{t-2} \ldots ,$$

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,

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

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 t. 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.

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

$$= \left(\sum_{1}^{\infty} \lambda_i\right) \varepsilon_t + \left(\sum_{2}^{\infty} \lambda_i\right) \varepsilon_{t-i} + \ldots$$

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

C. Vector Autoregressions

We use vector autoregressions (VARs) to test whether unemployment explains low birthweight holding constant lagged values of low birthweight (Sims 1980).[7] VARs represent a relatively unrestrictive means

6. 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.

7. Such tests of temporal orderings are referred to as tests "Granger causality" (Granger 1969). Following Leamer (1985) we avoid the use of the term, "Granger causality," in order

of highlighting important correlations in the data so as to empirically confirm or question various hypothesized relationships. The model we estimate can be specified as follows:

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

$$(11)\quad LBW_t = C^2 + \sum_{i=1}^{10} \alpha'_i LBW_{t-i} + \sum_{i=1}^{10} \beta'_i U_{t-i} + \nu_t$$

where C^j is a vector containing the constant, 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 macroeconometric 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 unemploy-

to minimize the confusion between Granger's definition of causality, and causality as defined by philosophers of science.

ment, 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.[8] 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, Schultz, and Wolpin, 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 then the set of regressors includes lagged dependent variables (Godfrey 1978).

IV. Results

We could not reject the null hypothesis that the unemployment rate is governed by a stochastic trend based on the Dickey-Fuller (1981) and Pierre Perron (1988) tests for units roots; however we easily rejected the null that the rates of low birthweight (Black, White and total) were integrated processes.[9] 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 2. 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

8. 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 increased number of women covered by health insurance, the antipoverty programs, most notably Medicaid, and higher levels of education among women (Corman and Grossman 1985).

9. A more detailed description of the tests and the results are available upon request.

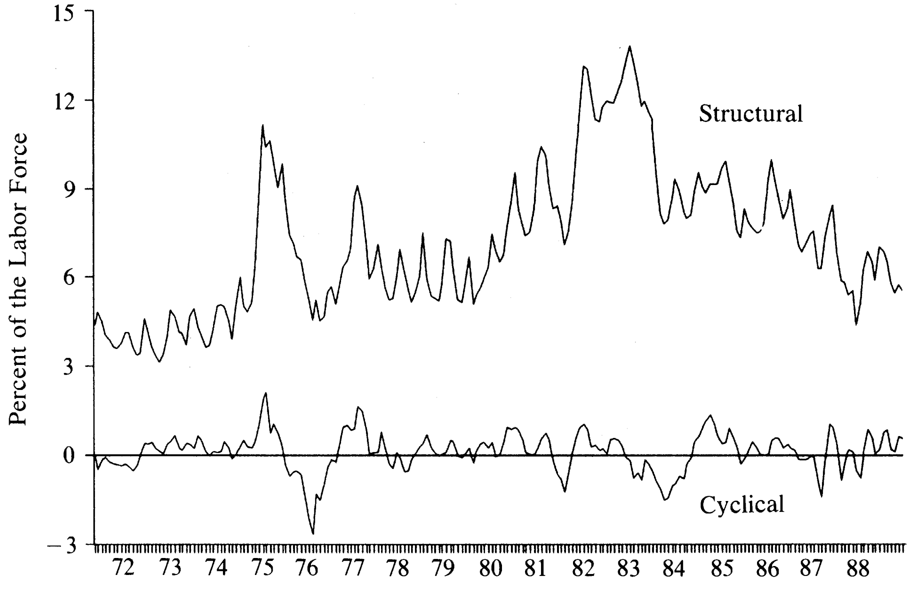

Figure 2
Decomposition of the Tennessee Unemployment Rate

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 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 includes 10 lags of unemployment and birthweight in the birthweight equation, but 10 lags of birthweight and 14 lags of unemployment in the unemployment equation.[10] 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 or structural unemploy-

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.

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

	Total LBW Equation[a]		White LBW Equation		Black LBW 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						
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
Lagrange-Multiplier Tests[d]						
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 parentheses are the marginal significance levels.
c. r_i is the ith 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 ith 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 significance 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 percent 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 Equation[a]		White LBW Equation		Black LBW Equation	
	ΔSTR	LBW	ΔSTR	LBW	ΔSTR	LBW
χ^2-statistic of STR[b]	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						
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, 10 leads, 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
Lagrange-Multiplier Tests[d]						
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 parentheses are the marginal significance levels.
c. r_i is the ith 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 ith 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 significance 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.

ment rate explain either the total or Black rate of low birthweight (Tables 1 and 2). There is weak evidence that the unemployment rate explains the White rate of low birthweight. There is 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 that the type and degree autocorrelation threatens, in any substantive way, the basic conclusion that unemployment has no impact on infant health.

Since the VAR specifications clearly confirmed the exogeneity of the unemployment rate, we estimated one-sided distributed lag models in which the measures of low birthweight were regressed on a constant, a trend term, monthly dummies, and ten lags of the unemployment rate (changes of structural, and levels of cyclical).[11] The results are reported in Table 3. The data strongly reject the hypothesis that unemployment worsens infant health. In none of the specifications is the sum of the estimated coefficents statistically different from zero, and in all but one instance, the sum of the coefficients is negative. Thus, the marginally significant relationship between unemployment and the White rate of low birthweight from the VAR estimates is not present in the more parsimonious distributed lag specification, nor is the direction of the effect as hypothesized.

11. The models with the total and White low birthweight rate are estimated with Hildreth and Lu's (1960) Grid-Search procedure to correct for the autocorrelation in the errors. No correction was necessary for the models with the Black rate of low birthweight.

Table 3
Estimation Results of Distributed Lag Models[a]

	Total LBW	White LBW	Black LBW
Models with Structural Unemployment			
$\Sigma\hat{\beta}_i$	−0.180	−0.286	0.282
t-statistic[b]	−1.052	−1.752	0.764
Adjusted-R^2	0.34	0.26	0.24
Durbin-Watson	2.01	2.00	1.93
$Q(42)$	32.25	34.59	38.60
Models with Cyclical Unemployment			
$\Sigma\hat{\beta}_i$	−0.087	−0.054	−0.162
t-statistic[b]	−0.982	−0.641	−0.853
Adjusted-R^2	0.33	0.25	0.24
Durbin-Watson	2.01	2.01	1.88
$Q(42)$	39.20	37.06	43.27

a. All models include a constant, a linear trend term, and eleven monthly dummies.
b. t-statistic pertains to the sum of the estimated unemployment rate coefficients.

To determine whether the results were sensitive to the decomposition, we estimated the VAR and distributed lag models with the total unemployment rate in place of the structural and cyclical unemployment rates. Since we could not reject the null hypothesis that the unemployment rate is a difference stationary process, we estimated the models using the first difference of the unemployment rate. We also estimated the models using the level and the trend deviations of the unemployment rate. The results did not change in any meaningful manner.

V. 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. In the VAR specifications we found no relationship between structural or cyclical unemployment, and total or Black rate of low birthweight. A weak relationship was indicated for Whites. Estimation of the VAR models confirmed the exogeneity of the unemployment measures. Thus, we estimated one-sided distributed lag models of low birthweight on unemployment. There was no relationship between unemployment and low birthweight 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.

Some cautionary remarks are in order. First, the possibility remains that at the individual level unemployment is a risk factor for low birthweight. What we have demonstrated is that the relationship is not sufficiently widespread, nor of sufficient magnitude, to register on aggregate indicators. We believe this to be a noteworthy finding because cyclical variation in output and employment have been linked, not only in the popular press but by academic economists as well, to aggregate increases in crime (Cook and Zarkin 1985), industrial accidents (Catalano and Serxner 1987), and adult mortality (McAvinchey 1984). In other words, the notion that economic downturns precipitate a range of adverse social consequences, we believe, is widely held.

Birth outcomes are especially good indicators with which to examine the aggregate consequences of unemployment. Unlike the crime and industrial accidents, the lag length is well-defined; and compared to adult mortality, the relatively short duration of pregnancy lessens the confounding due to coincident trends and technological change. Yet, even with birth outcomes, differences exist. As we have argued, the rate of low birthweight is superior to infant mortality because of the difficulty of controlling for technological change, the most plausible explanation of the rapid decline in newborn mortality over the past 25 years. The lack of agreement between Brenner's (1973, 1979) findings and our own may be attributable to his use of infant mortality.

An additional caveat is that in any bivariate analysis such as ours, omitted variables present a threat to the validity of the conclusions. We have focused our concern on omitted variables that might cause a spurious rejection of the null, but the possibility exists that an omitted variable might lead to a Type II error. For instance, an increase in unemployment among marginal workers uncovered by health insurance could increase the percentage of births to women financed by Medicaid as unemployed families become eligible for public assistance. If increases in Medicaid coverage lead to increases in prenatal care, then the impact of unemployment in a specification that controls for health insurance might be greater. As we have noted, however, any omitted variable that varies systematically with the included regressors should lead to a rejection of the null that the residuals are white noise. Thus, if the percentage of births to women covered by Medicaid were correlated with the unemployment rate, either coincidentally or through some lag structure, then we would expect some order of autocorrelation to emerge.[12]

A similar issue relates to the composition of the female birth cohort over the business cycle. If changes in unemployment cause changes in fertility patterns either procyclically or countercyclically,[13] which alter the distribution of births in various risk factors, either favorably or unfavorably, then the hypothesized nexus between unemployment and low birthweight caused by stress and loss of income may be obscured in a reduced form analysis.[14] Only a full structual model can adequately sort out the relationship between unemployment, fertility, and birth outcomes. Inclusion of lagged low birthweight in the VAR specification, however, is an effective means of controlling for possible shifts in the distribution of risk. Strong contemporaneous effects would not be captured, but lags would be undoubtedly important given the nine months of a pregnancy. Further, if results from the distributed lag specification conflicted with the results from the VAR, then the likelihood of such indirect effects would rise. Since we found no difference between the results from VAR and distributed lags specifications, this source of confounding is unlikely.

Another concern is the lack of a race-specific measure of unemployment since Blacks have consistently experienced higher rates of unemployment than Whites. Moreover, the rate of low birthweight among Blacks is not only higher than among Whites, but it also evidences greater variation over time. Based on national data, however, the zero order correlation between the total unemployment rate with the Black unem-

---

12. As a specific response to this particular example, Tennessee has one of the lowest income standards for public assistance, and until mandated by the U.S. Congress effective in October 1990, was one of only 16 states in 1989 not to offer public assistance to two-parent families that meet income standards when the principal earner is unemployed. Consequently, Tennessee would appear an unlikely state in which there would be an important countercyclical demand for prenatal care caused by increased Medicaid enrollees.

13. Time-series evidence remains equivocal theoretically and empirically as to whether fertility varies pro- or countercyclically (Butz and Ward 1979, Macunovich and Easterlin 1988, Mocan 1990).

14. We credit an anonymous referee with this insight as well as the previous comment regarding the possibility of Type II error.

ployment 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. In sum, the various caveats notwithstanding, we find no evidence to support the hypothesis that economic downturns have any appreciable impact on aggregate measures of infant health.

References

Beveridge, S., and C. Nelson. 1981. "A New Approach to Decomposition of Economic Time Series Into Permanent and Transitory Components With Particular Attention to Measurement of the Business Cycle." *Journal of Monetary Economics* 7(2):151–74.

Bjöklund, A. 1985. "Unemployment and Mental Health: Some Evidence from Panel Data." *Journal of Human Resources* 20(4):469–83.

Brenner, M. H. 1973. "Fetal, Infant and Maternal Mortality During Periods of Economic Instability." *International Journal of Health Services* 3(2):145–59.

———. 1979. "Mortality and the National Economy: A Review, and the Experience of England and Wales 1936–76." *The Lancet ii* 314(3143):568–73.

———. 1987. "Relation of Economic Change to Swedish Health and Social Well-Being." *Social Science and Medicine* 25(2):183–96.

Butz, W. B., and M. P. Ward. 1979. "The Emergence of Countercyclical U.S. Fertility." *American Economic Review* 69(3):318–28.

Catalano, R., and S. Serxner. 1987. "Time Series Designs of Potential Interest to Epidemiologists." *American Journal of Epidemiology* 126(4):724–31.

Cook, P., and G. Zarkin. 1985. "Crime and the Business Cycle." *Journal of Legal Studies* 14(1):115–28.

Cooley, T. F., and S. F. LeRoy. 1985. "Atheoretical Macroeconomics: A Critique." *Journal of Monetary Economics* 16(2):283–308.

Corman, H., and M. Grossman. 1985. "Determinants of Neonatal Mortality Rates in the U.S.: A Reduced Form Model." *Journal of Health Economics* 4(3):213–36.

Corman, H., Joyce, T., and M. Grossman. 1987. "Birth Outcome Production Functions in the United States." *Journal of Human Resources* 22(3):339–60.

Dickey, D., and W. Fuller. 1981. "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root." *Econometrica* 49(4):1057–72.

Eckstein, Z., Schultz, T., and K. Wolpin. 1985. "Short-run Fluctuations in Fertility and Mortality in Pre-Industrial Sweden." *European Economic Review* 26(3):296–317.

Forbes, J., and A. McGregor. 1984. "Unemployment and Mortality in Post-war Scotland." *Journal of Health Economics* 3(3):239–58.

Friedman, M. 1957. *A Theory of the Consumption Function*. Princeton: Princeton University Press.

Fuller, Wayne. 1976. *Introduction to Statistical Time Series*. New York: John Wiley.

Godfrey, L. G. 1978. "Testing for Higher Order Serial Correlation in Regression Equations When the Regressors Include Lagged Dependent Variables." *Econometrica* 46(6):1303–10.

Granger, C. W. J. 1969. "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods." *Econometrica* 37(3):424–38.

Gravelle, H. 1984. "Time Series Analysis of Mortality and Unemployment" *Journal of Health Economics* 3(3):297–305.

Gravelle, H., Hutchinson, G., and J. Stern. 1981. "Mortality and Unemployment: A Critique of Brenner's Time-series Analysis." *The Lancet ii* 318(8249):675–79.

Grossman, M., and T. Joyce. 1990. "Unobservables, Pregnancy Resolutions, and Birth Weight Production Functions in New York City." *Journal of Political Economy* 98(5):983–1007.

Hildreth, C., and J. Lu. 1960. "Demand Relations with Autocorrelated Disturbances." *AES Technical Bulletin 276*. East Lansing: Michigan State University.

Joyce, T. 1990. "A Time-Series Analysis of Unemployment and Health: The Case of Birth Outcome in New York City." *Journal of Health Economics* 8(4):419–36.

Klebanoff, M., Shiono, P., and G. Rhoads. 1990. "Outcomes of Pregnancy in a National Sample of Resident Physicians." *New England Journal of Medicine* 323(45):1040–45.

Leamer, E. 1985. "Vector Autoregressions for Causal Inference?" In *Understanding Monetary Regimes* (supplement to *Journal of Monetary Economics* 22), ed. K. Brunner and A. Meltzer, 367–78.

Macunovich, D. J., and R. A. Easterlin. 1988. "Application of Granger-Sims Causality Tests to Monthly Fertility Data, 1958–1984." *Journal of Population Economics* 1(1):71–88.

Mamelle, N., B. Lauman, and P. Lazar. 1984. "Prematurity and Occupational Activity During Pregnancy." *American Journal of Epidemiology* 119(3):309–22.

Mocan, H. N. 1990. "Business Cycles and Fertility Dynamics in the United States: A Vector Autoregressive Model." *Journal of Population Economics* 3:125–46.

McAvinchey, I. 1984. "Unemployment and Mortality: Some Aspects of the Scottish Case, 1950–1978." *Scottish Journal of Political Economy* 31(1):1–27.

Naeye, R., and E. Peters. 1982. "Working During Pregnancy: Effects on the Fetus." *Pediatrics* 69(6):724–27.

Nelson, C., and H. Kang. 1984. "Pitfalls in the Use of Time as an Explanatory Variable in Regression." *Journal of Business and Economic Statistics* 2(1):73–82.

Nelson, C., and C. Plosser. 1982. "Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications." *Journal of Monetary Economics* 10(2):139–62.

Perron, P. 1988. "Trends and Random Walks in Macroeconomic Time Series." *Journal of Economic Dynamics and Control* 12:297–332.

Phillips, B., and P. Perron. 1988. "Testing for a Unit Root in Time Series Regression." *Biometrica* 75(2):335–46.

Rosenzweig, M., and T. P. Schultz. 1988. "The Stability of Household Production Technology: A Replication." *Journal of Human Resources* 23(4):535–49.

———. 1983. "Estimating a Household Production Function: Heterogeneity, the Demand for Health Inputs and Their Effects on Birth Weight." *Journal of Political Economy* 91(5):723–46.

Sims, C. 1980. "Macroeconomics and Reality." *Econometrica* 48(1):1–48.

Stock, J. H., and M. W. Watson. 1988. "Variable Trends in Economic Time Series." *Economic Perspectives* 2(3):147–74.

Tennessee Department of Health and Environment. 1989. *Annual Bulletin of Vital Statistics for the Year 1987*. Nashville: State of Tennessee, Department of Health and Environment.

LINKED CITATIONS

You have printed the following article:

Unemployment and Infant Health: Time-Series Evidence from the State of Tennessee
Theodore Joyce; Naci Mocan
The Journal of Human Resources, Vol. 28, No. 1. (Winter, 1993), pp. 185-203.
Stable URL:
http://links.jstor.org/sici?sici=0022-166X%28199324%2928%3A1%3C185%3AUAIHTE%3E2.0.CO%3B2-Q

[Footnotes]

[5] **Pitfalls in the Use of Time as an Explanatory Variable in Regression**
Charles R. Nelson; Heejoon Kang
Journal of Business & Economic Statistics, Vol. 2, No. 1. (Jan., 1984), pp. 73-82.
Stable URL:
http://links.jstor.org/sici?sici=0735-0015%28198401%292%3A1%3C73%3APITUOT%3E2.0.CO%3B2-T

[7] **Investigating Causal Relations by Econometric Models and Cross-spectral Methods**
C. W. J. Granger
Econometrica, Vol. 37, No. 3. (Aug., 1969), pp. 424-438.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28196908%2937%3A3%3C424%3AICRBEM%3E2.0.CO%3B2-L

[12] **The Emergence of Countercyclical U.S. Fertility**
William P. Butz; Michael P. Ward
The American Economic Review, Vol. 69, No. 3. (Jun., 1979), pp. 318-328.
Stable URL:
http://links.jstor.org/sici?sici=0002-8282%28197906%2969%3A3%3C318%3ATEOCUF%3E2.0.CO%3B2-B

References

The Emergence of Countercyclical U.S. Fertility
William P. Butz; Michael P. Ward
The American Economic Review, Vol. 69, No. 3. (Jun., 1979), pp. 318-328.
Stable URL:
http://links.jstor.org/sici?sici=0002-8282%28197906%2969%3A3%3C318%3ATEOCUF%3E2.0.CO%3B2-B

Crime and the Business Cycle
Philip J. Cook; Gary A. Zarkin
The Journal of Legal Studies, Vol. 14, No. 1. (Jan., 1985), pp. 115-128.
Stable URL:
http://links.jstor.org/sici?sici=0047-2530%28198501%2914%3A1%3C115%3ACATBC%3E2.0.CO%3B2-P

Birth Outcome Production Function in the United States
Hope Corman; Theodore J. Joyce; Michael Grossman
The Journal of Human Resources, Vol. 22, No. 3. (Summer, 1987), pp. 339-360.
Stable URL:
http://links.jstor.org/sici?sici=0022-166X%28198722%2922%3A3%3C339%3ABOPFIT%3E2.0.CO%3B2-D

Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root
David A. Dickey; Wayne A. Fuller
Econometrica, Vol. 49, No. 4. (Jul., 1981), pp. 1057-1072.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198107%2949%3A4%3C1057%3ALRSFAT%3E2.0.CO%3B2-4

Testing for Higher Order Serial Correlation in Regression Equations when the Regressors Include Lagged Dependent Variables
L. G. Godfrey
Econometrica, Vol. 46, No. 6. (Nov., 1978), pp. 1303-1310.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28197811%2946%3A6%3C1303%3ATFHOSC%3E2.0.CO%3B2-U

Investigating Causal Relations by Econometric Models and Cross-spectral Methods
C. W. J. Granger
Econometrica, Vol. 37, No. 3. (Aug., 1969), pp. 424-438.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28196908%2937%3A3%3C424%3AICRBEM%3E2.0.CO%3B2-L

LINKED CITATIONS

Unobservables, Pregnancy Resolutions, and Birth Weight Production Functions in New York City
Michael Grossman; Theodore J. Joyce
The Journal of Political Economy, Vol. 98, No. 5, Part 1. (Oct., 1990), pp. 983-1007.
Stable URL:
http://links.jstor.org/sici?sici=0022-3808%28199010%2998%3A5%3C983%3AUPRABW%3E2.0.CO%3B2-K

Pitfalls in the Use of Time as an Explanatory Variable in Regression
Charles R. Nelson; Heejoon Kang
Journal of Business & Economic Statistics, Vol. 2, No. 1. (Jan., 1984), pp. 73-82.
Stable URL:
http://links.jstor.org/sici?sici=0735-0015%28198401%292%3A1%3C73%3APITUOT%3E2.0.CO%3B2-T

The Stability of Household Production Technology: A Replication
Mark R. Rosenzweig; T. Paul Schultz
The Journal of Human Resources, Vol. 23, No. 4. (Autumn, 1988), pp. 535-549.
Stable URL:
http://links.jstor.org/sici?sici=0022-166X%28198823%2923%3A4%3C535%3ATSOHPT%3E2.0.CO%3B2-2

Estimating a Household Production Function: Heterogeneity, the Demand for Health Inputs, and Their Effects on Birth Weight
Mark R. Rosenzweig; T. Paul Schultz
The Journal of Political Economy, Vol. 91, No. 5. (Oct., 1983), pp. 723-746.
Stable URL:
http://links.jstor.org/sici?sici=0022-3808%28198310%2991%3A5%3C723%3AEAHPFH%3E2.0.CO%3B2-W

Macroeconomics and Reality
Christopher A. Sims
Econometrica, Vol. 48, No. 1. (Jan., 1980), pp. 1-48.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198001%2948%3A1%3C1%3AMAR%3E2.0.CO%3B2-A