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Forecasting With Statistical Models and a Case Study of Retail Sales

By Dan M. Bechter and Jack L. Rutner

Methods of economic forecasting have become increasingly elaborate. Highly refined statistical techniques are now being used to extract information from historical data and to project future values of economic variables. To a large extent, these advances in the science of economic forecasting have been made possible by progress in computer technology. But high-speed computers and sophisticated statistical techniques do not provide perfect forward vision. There is a lot of truth to the observation that economic forecasting is more art than science. It remains to be seen just how much the forecasting of economic variables can be improved by strengthening only the more scientific aspects of this activity.

This article has two purposes. The first is to review various approaches to economic forecasting, including a relatively new technique as well as traditional methods. The second is to report on a case study in which the performances of alternative ways of forecasting retail sales are compared.

FORECASTING MODELS

Many forecasters depend heavily on models to help in forecasting. A model consists of mathematical expressions, or equations, which describe relationships among economic variables. A forecaster's choice of a forecasting model is of key importance. A model that contains the wrong variables, or that incorrectly specifies relationships among variables, will be of little use in forecasting.

Economic Models

Economic theory usually provides a good guide to the selection of variables and the relationships for a model's equations, and a model based on theory is sometimes called an "economic model." For example, suppose a forecaster wants to predict retail sales. Since retail sales are closely associated with consumer spending, economic theory suggests that the dollar volume of retail sales during any period may be largely explained by the levels of personal income and personal wealth in that period. It is not realistic, however, to believe that changes in retail sales will always behave strictly in accordance with changes in income and wealth. Deviations will result from factors such as omitted variables (for example, unseasonable weather) and other considerations that are essentially random in their effects upon retail sales. The reasons for these deviations are not explained in economic models, but allowance is made for them by adding a disturbance term, or error term, to the assumed relationship.

To illustrate, the relationship between retail sales and other variables could constitute an economic model that can be expressed mathematically as:[1]

$$(1) \qquad S_t = a + bI_t + cW_t + u_t$$

where
S_t = retail sales during period t
I_t = personal income during period t
W_t = personal wealth during period t
u_t = error term during period t
a, b, c = unknown constants.

The model in equation (1) states that the variable, retail sales, is determined by the variables, personal income and wealth; that the relationship is defined basically by the parameters a, b, and c; and that the relationship is inexact, requiring the inclusion of an error term. The variable, retail sales, is referred to as an endogenous variable because it is being explained and is to be forecast. Income and wealth are exogenous variables because they are being used to explain retail sales and are not to be forecast.

The unknown constants, or parameters, must be estimated by reference to data for some particular historical period. The estimation procedure usually used, linear regression, determines values for the parameters a, b, and c that give the best fit of retail sales to personal income and personal wealth over the estimation period selected. In its estimated form, the economic model can be expressed as:

$$(2) \qquad \hat{S}_t = \hat{a} + \hat{b}I_t + \hat{c}W_t$$

where the symbol $\wedge$ denotes estimated values of the variables or parameters. In equation (2), retail sales in any period is expressed in terms of the actual values of personal income and personal wealth in that period, and numerical estimates of the parameters. The actual value of retail sales in any month will usually differ somewhat from its estimated value, and this difference is the value of that period's error term.

After the model is estimated, it may be used for forecasting. Forecasting with the estimated model is accomplished by solving the equation for the variable to be forecast after plugging in the appropriate period's values for the exogenous variables.

An estimated economic model of the type shown in (2) may not be particularly well suited for forecasting. Its principal drawback is that the values of the explanatory variables, I and W, would themselves have to be forecast before S could be forecast. One way around this problem is to choose a model in which current values of the variable to be explained depend on past, or lagged, values of the explanatory variables. Fit in this fashion, the estimated model might be:

$$(3) \qquad \hat{S}_t = \hat{a} + \hat{b}I_{t-1} + \hat{c}W_{t-1}.$$

From relationship (3), it follows that next period's retail sales (S_{t+1}) can be forecast by

1 In the absence of any good reason to believe otherwise, it is usual to assume that changes in the variable to be explained (in this example, retail sales) are proportional to changes in the explanatory variables (personal income and personal wealth). This assumption implies a linear relationship in which retail sales in any month are equal to some constant, plus some constant proportion of personal income in that month, plus some constant proportion of personal wealth in that month. More complicated models could, however, suggest a nonlinear relationship such as retail sales being a function of the items in (1) plus a sine curve of time and a constant. This formulation of (1) would require nonlinear estimation procedures.

using this period's personal income and personal wealth.

The use of lagged explanatory variables, besides being helpful in forecasting, also has some justification in theory. For example, retail sales may not react quickly to changes in current income because individuals may be slow in changing their spending behavior. In recognition of how some economic behavior may be better described by a weighted average of past values of certain variables, it is common for an equation in an economic model to include lags of different lengths for the same variable.

Economic models often consist of more than one equation. Indeed, some large models contain hundreds of relationships among variables. As an illustration, the single-equation economic model given by equation (1) might be expanded to a two-equation model in which personal income, as well as retail sales, are endogenous variables:

$$\text{(4a)} \qquad S_t = a + bI_t + cW_t + u_{1t}$$

$$\text{(4b)} \qquad I_t = d + eN_t + u_{2t}$$

where N_t = labor input, an exogenous variable, as well as personal wealth.

A system of equations such as (4a, b) is generally referred to as "structural" in that these equations describe how a particular segment of the economy operates according to a structure consistent with economic theory. In the structural model (4a, b), retail sales depend ultimately on wealth and labor input, the exogenous variables. Moreover, in general, for any structural model, the endogenous variables depend ultimately on the exogenous variables. When endogenous variables are expressed as depending only on exogenous variables, the model is referred to as a reduced form model.[2]

Time Series Model

A second type of forecasting model is constructed solely from the past values of the variable to be forecast. This type of model may be termed a "single-variable time series" model. A very naive application of this type of model is to forecast the value of a variable in the next period to be the same as it is in the current period. If the variable to be forecast has some trends and cycles in it, a better naive forecast may be achieved by forecasting next period's change in the value of a variable to be equal to the most recent change in its value. A somewhat more sophisticated, but still naive, single-variable time series model is the commonly used time-trend forecasting model, in which next period's value of the variable of interest is forecast to lie along a trend line, fitted by eye or by regression techniques to past values of the variable.

In recent years, significant advances have been made in the development of certain types of single-equation time series models known collectively as "autoregressive" models. Such forecasting models are purely self-determining: the variable to be forecast is related only to its past values, plus an error term. In its simplest

2 Economic forecasting models need not be relationships justified by economic theory. Besides economic models, there are other types of models that may be used for forecasting purposes. One such type is the "expectations" model, in which the explanatory variables are indicative of the intentions or mood of the people whose actions determine the value of the variable to be forecast. For example, if the forecaster is interested in next month's retail sales, he may choose indexes of consumer confidence and consumer buying plans for explanatory variables in his expectations model. Although the expectations approach provides an interesting alternative to economic theory in model building, it is not considered further here.

unrefined form, an autoregressive model for forecasting retail sales would be expressed as

$$S_t = a + bS_{t-1} + u_t, \quad (5)$$

where, as before, S_t represents retail sales in month t, a and b are parameters, and u_t is the error term.[3]

One of the most sophisticated forms of autoregressive models is the ARIMA model. The acronym ARIMA stands for "autoregressive integrated moving average," which describes the model. The first term, autoregressive, has already been defined to mean a model in which a variable is a function of only its past values except for deviations introduced by an error term. "Integrated" indicates that period-to-period changes in the level of the original variable are employed in the estimation procedure, rather than the level of the variable itself. "Moving average" means that a moving average procedure has been used to eliminate any intercorrelations of the error term to its own past or future values.

The elimination of intercorrelations among error terms from different periods is a key feature of ARIMA and other sophisticated models. When this intercorrelation is not eliminated, the model violates a requirement for obtaining valid parameter estimates: the requirement that the error term is a random disturbance to the model in each time period, unrelated to the error terms of other time periods. Invalid estimation procedures are likely to lead to forecasts that are inferior to those obtained from models that satisfy basic requirements of no interdependence among error terms.

COMPARATIVE PERFORMANCES IN FORECASTING: ARIMA VS. ECONOMIC MODELS

Several studies have compared ARIMA's forecasting accuracy with the forecasting accuracy of economic models. In any such comparison, there are six steps involved. The first step is to select some variable or variables to forecast, such as gross national product (GNP), employment, or the variable to be examined in the second part of this article, retail sales. The second step is to select economic models to use in the comparison.

Selecting the economic model is by no means easy, since no very good economic model may exist, in which case it will have to be constructed and estimated. Or it may be that hundreds of economic models exist for forecasting the variable selected, in which case some choice will have to be made. No selection problem is presented in the case of the ARIMA model, of course, since it is defined solely with reference to past values of the variable to be forecast.

The third step is to choose estimation and forecast periods. Since forecasting accuracy cannot be determined without reference to actual values, the forecast period must be selected to be part of the past. To simulate actual forecasting, therefore, the estimation period used to arrive at parameter estimates of the forecasting models must end before the forecast period begins.

The fourth step is to statistically estimate the parameter values of the models, using the historical data selected. The forecasts themselves are the fifth step. As indicated earlier, forecasting with an estimated model involves using the parameter estimates and the values of the exogenous variables to solve for the variable being forecast. The sixth and final step requires choosing some measure of

[3] More complex autoregressive models would include the possibility that the current value of the variable is related to its value in many different preceding periods, not just to its value in the last period.

forecasting accuracy, and then determining how well the ARIMA and the economic models perform, based on these measures.

All measures of forecast accuracy compare the values forecast by the models with those that actually were observed. The difference between the actual and the forecast values is the forecast error. Forecast errors are usually calculated for values of the forecast variable outside (beyond the last date) of the estimation period but, conceptually, a forecast error is closely related to an estimated value of an error term within the estimation period. Usually forecasts for several periods are made, so some summary statistics are needed. Among those commonly used are mean algebraic error (MALE), mean absolute error **(MABE)**, and mean square error (MSQE). MALE is calculated by summing a model's forecast errors (differences between actual and forecast values) and taking the average. **MABE** is computed by summing the forecast errors without regard to sign (that is, summing the absolute values of these errors), then taking the average. MSQE is the average of the sum of the squared forecast errors.

Several researchers have compared the forecasting accuracy of ARIMA with that of economic models of the aggregate economy. Examples of macroeconomic models of the U.S. economy include those developed by the Bureau of Economic Analysis of the U.S. Department of Commerce, and by the Wharton School of Business of the University of Pennsylvania. Because of the macroeconomic nature of these models, the comparisons of their forecasting accuracy with that of ARIMA have involved forecasts of variables such as GNP, the GNP price deflator, and the national unemployment rate.

Ronald Cooper compared the forecasts of **33** endogenous variables from seven macroeconomic models with ARIMA forecasts of those same variables. The ARIMA model forecast 18 of **33** variables better than any of the economic models, although it should be noted one of the variables ARIMA did not forecast well was inflation. Charles Nelson compared the forecasts of **14** endogenous variables from the Federal Reserve-MIT-Pennsylvania **(FMP)** model with ARIMA forecasts, and found ARIMA forecast 9 of the **13** variables better than FMP, but again ARIMA did not forecast the rate of inflation well. In another study, J. Phillip Cooper and Charles Nelson obtained mixed results when they compared ARIMA forecasts of six variables to those generated by the St. Louis model (a model developed by the Federal Reserve Bank of St. Louis) and the FMP model. Nariman Behravesh found **ARIMA's** forecasts of inflation, not unexpectedly, to be decidedly inferior to forecasts of inflation generated by a lineal descendant of the FMP model.'

The principal conclusion that can be drawn from these model comparisons is that for some variables, single-equation ARIMA **models** forecast better than do macroeconomic models. But that is not necessarily surprising. Macroeconomic models are constructed with several objectives in mind, among which are forecasts

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[4] The articles cited here are the following: Ronald L. Cooper, "The Predictive Performance of Quarterly Econometric Models of the United States," in *Econometric Modeb* of *Cyclical Behavior*, Vol. 2, Bert G. Hickman, ed., National Bureau of Economic Research *Studies in Income and Wealth*, No. 36, Columbia University Press, New York and London, 1972. Charles R. Nelson, "The Prediction Performance of the FRB-MIT Model of the U.S. Economy," *American Economic Review*, pp. 902-17, Vol. 72, No. 5, December 1972. J. Phillip Cooper and Charles R. Nelson, "The ExAnte Prediction Performance of the St. Louis and FRB-MIT-PENN Econometric Models and Some Results on Composite Predictions," *Journal of Money, Credit and Banking*, pp. 2-32, Vol. 7, No. 1, February 1975. Nariman Behravesh, "Forecasting Inflation: Does the Method Make a Difference?" Federal Reserve Bank of Philadelphia *Monthly Review*, September/October 1976.

of many, not just one variable, with special attention to forecasting turning points in the business cycle, as well as to showing the effects of fiscal and monetary policies on various sectors in the economy. To keep the size of a macroeconomic model within reasonable limits, the model builder may be forced to sacrifice the forecasting accuracy of individual variables for some broader goal. Then, too, not all equations from macroeconomic models are econometrically sound, especially with regard to the attention they give to intercorrelations among error terms through time.

An appropriate test of ARIMA's forecasting accuracy with that of an economic model would seem to call for the choice of a variable to be forecast, and then the construction of an economic model designed with forecasting that variable as its only purpose. It was with this objective that a case study, described in the next section, was undertaken.

ARIMA VS. ECONOMIC MODELS: FORECASTING RETAIL SALES

This section compares the forecasting accuracy of ARIMA with that of two economic models designed expressly for forecasting one variable: retail sales. The comparisons also include a mixed model, with both autoregressive and economic features. The forecasting abilities of all three of these sophisticated techniques—the ARIMA, the economic, and the mixed models—are also compared with the forecasting ability of a naive time trend model.

Retail sales is an appropriate variable to use in comparing the forecasting accuracies of various models. Data on retail sales are important economic indicators, watched closely by analysts of business conditions. This is especially true of the monthly reports, which are based on larger samples than those used in compiling the weekly figures. Because of the economic importance placed on month-to-month percentage changes in retail sales, and because monthly observations provide a long enough series to adequately estimate ARIMA and economic models and to compare their forecasts, monthly percentage changes in retail sales (hereafter abbreviated as $\dot{S}$)[5] was selected as the forecast variable.[6]

Having selected $\dot{S}$ as the variable to be forecast, the next step was to choose the models whose forecasts were to be compared. The ARIMA model presented no problem, since it is defined once the forecast variable is selected. In choosing from among various possibilities for alternative economic models, it was decided that only single-equation models containing no more than two explanatory variables would be considered. Since one of the appealing features of the ARIMA model is its single-equation simplicity, it seemed appropriate to use a simple single-equation economic model for comparison, unless the findings indicated that fairly complex economic models were required to improve upon the forecasts of ARIMA.[7]

5 A dot above a symbolic character will denote its rate of growth.

6 Another reason for choosing $\dot{S}$ is that it varies a great deal, even after seasonal adjustment. An easy-to-forecast variable, such as one that remains constant or grows at a constant rate, provides little chalienge to even the naive models. The real test of sophisticated models comes when the naive methods do not forecast very well.

After the analytic work on this article was completed, the Bureau of Census published the results of extensive changes in the monthly surveys of retail trade. The results reported here, therefore, are based on the "final" monthly retail sales data available before this latest revision.

7 The use of a single-equation model is analogous to estimating a reduced form in which all the explanatory variables in the model can be viewed as exogenous. A single-equation model rather than a multi-equation model was used to maintain control of the major source of problems with many models—the intercorrelations among error terms from one period to the next.

The two explanatory or exogenous variables chosen for inclusion in one set of economic models were personal income ($\dot{I}$); and nonfinancial personal wealth ($\dot{W}$), as measured by an index of the price of common stocks.' As indicated early in this article, economic theory argues for the use of both personal income and *personal wealth in a relationship explaining consumer spending, which is closely related to retail sales.[9] An alternative economic model employs the money supply (M) as the sole explanatory variable.[10] According to monetarist theory in economics, changes in the stock of money directly and indirectly result in an increase in the demand for commodities. Finally, past values of retail sales were included in alternative models that mixed autoregressive and economic components.

Before forecasts of S could be made, the various statistical models had to be estimated with historical data. The basic estimation period used for this purpose began in January 1947 and ended with December 1974, the month prior to the forecast period. The fitted models were then used to make forecasts for each of 30 consecutive months of retail sales, beginning in January 1975, and ending in June 1977. These forecasts were made in one-month-ahead fashion. That is, the forecast of each month's retail sales was made using the actual values of explanatory variables for preceding months.

With forecast values in hand, the forecast errors were easily obtained by subtracting the actual values of monthly retail sales from the forecast values. Table 1 summarizes the results for five models, using one measure of forecasting accuracy, the mean absolute error. The first column in Table 1 gives the 30-month mean absolute error—the average absolute value of the forecast error--over the entire 2%-year forecast period. The next five columns, which show the MABE for 6-month intervals, indicate if the forecasting accuracy of the models degenerated the further the forecast month was from the end of the estimation period.

The principal conclusion that one can draw from the empirical results summarized in Table 1 is that, based on the MABE's calculated for this experiment, ARIMA did not forecast retail sales any better than did the naive model, and not as well, on the average, as did the economic models. The mixed model had a better record over the entire 30-month forecast period than did any of the other three models.''

Another conclusion indicated by Table 1 is that none of the models forecast retail sales very well—a one percentage point absolute error in the forecast of the month-to-month percentage change in retail sales is very large,

8 There are more complete measures of personal wealth than wealth in common stocks, of course. But almost all of the variation in total personal wealth is due to fluctuations in the stock market; other components of personal wealth grow at fairly constant rates.

9 While not all retail sales are sales to consumers, and while much of consumer spending (mostly on services) is not included in retail sales, the correlation between consumer expenditures and retail sales is very high.

10 Two measures of the money supply were tried: the narrowly defined money supply (M1) consisting of currency plus demand deposits, and the more broadly defined money supply (M2) consisting of M1 plus time deposits at commercial banks (except large negotiable certificates of deposit). Since M2 performed better than M1, references in the text to the money supply are to M2.

11 Only the results for the best naive, the best two economic, and the best mixed models are shown. It should be noted, however, that the difference-in results in the economic and mixed models that used M instead of $\dot{I}$ (or vice versa) was small. It should also be noted that the residuals (estimated error terms) of each estimated economic model and mixed model were examined for serial correlation (evidence of correlation of error terms between time periods). If serial correlation was found to be present, it was eliminated by an appropriate filter.

Table 1
THE FORECAST ACCURACY OF FIVE MODELS OF RETAIL SALES
(Mean Absolute Error in Per Cent Per Month)

Type of Model	Functional Form: Variables Whose Past Values Explain Retail Sales ($\dot{S}$)	Forecast Period					
			Six Months Ending				
		30 Months January 1975 Through June 1977	June 1975	Dec. 1975	June 1976	Dec. 1976	June 1977
Naive	Time	1.35	1.64	.80	1.16	1.48	1.67
ARIMA	$\dot{S}$	1.35	1.46	.76	1.35	1.53	1.63
Economic	I	1.34	1.56	.96	1.05	1.63	1.50
Economic	*M*	1.24	1.41	.69	1.17	1.17	1.76
Mixed	$\dot{S}$, $\dot{I}$, W	1.12	1.62	.91	.81	1.69	1.24

considering the fact that the average monthly rate of growth of retail sales over the forecast period was itself about 1 per cent. The breakdown into 6-month periods also suggests that when one model forecasts poorly relative to its average, the other models are likely to be forecasting relatively poorly also. This is probably due to some omitted variable or variables in all the models.

The 6-month breakdowns do not indicate a degeneration of forecasts by the models, for all the models forecast the **final** 6 months about as poorly as the first 6 months, after showing some improvement in between. It was felt, however, that most forecasters probably would reestimate their models periodically, so an experiment to simulate such reestimation was carried out. Each of the models was refit four times by successive additions of 6 months of data to the original estimation period. After each of the four reestimations of the models, monthly forecasts were computed for the remainder of the forecast period, which was reduced in length as the estimation period was extended. As before, forecast errors were calculated. With a few scattered exceptions, there was no indication that **refitting** the model by updating the estimation period improved the forecasting accuracy of any model.[12]

The additional reestimations and forecasts did serve to provide more comparisons of the forecasting abilities of the various models. One such comparison is summarized in Table 2. In the simulated forecasting experiment reported on in this table, the forecaster is assumed to refit his forecasting model every 6 months, from December 1974 through December 1976, then make one-month-ahead forecasts for the 6 months immediately after the end of the estimation period. The entries in Table 2 thus represent the forecasts for the 6-month period immediately following the reestimation of the model.

12 It must be admitted, however, that if shorter estimation periods had been used and if the oldest data were dropped when the newest data were added, the results may have been improved.

Table 2
THE FORECASTING ACCURACY OF MODELS OF RETAIL SALES, ESTIMATED WITH DATA UP TO THE BEGINNING OF 6-MONTH FORECAST PERIODS

Type of Model	Functional Form: Variables Whose Past Values Explain Retail Sales ($\dot{S}$)	Forecast Period: Average Of 6-Month Period Forecasts	Six Months Ending: June 1975	Dec. 1975	June 1976	Dec. 1976	June 1977
Naive	Time	1.30	1.64	.78	.85	1.59	1.65
ARIMA	$\dot{S}$	1.45	1.46	.93	1.72	1.52	1.64
Economic	I	1.34	1.56	.95	1.02	1.64	1.51
Economic	M	1.22	1.41	.68	1.14	1.31	1.75
Mixed	$\dot{S}$, i, W	1.25	1.62	.87	.85	1.68	1.26

The conclusions from Table 2 are much the same as those from Table 1. Although ARIMA does better than one or two of the alternative models some of the time, most of the time ARIMA does not forecast as 'accurately as a very simple economic model.[13]

SUMMARY AND'CONCLUSIONS

There are 'various kinds of models that can be used to forecast economic variables. Among those developed in recent years is the ARIMA model, which has the appealing characteristic of being based on the simple notion that a variable's future value can be forecast with reference only to its current and past values. Several studies have compared the forecasting accuracy of the ARIMA model to that of economic models of the U.S. economy. On balance, these studies seemed to indicate that ARIMA forecasts single variables better than such models. It is quite another thing, however, to conclude that ARIMA can forecast better than an economic model designed with the forecast of a single variable as its sole purpose. The experiment reported on in this article does, in fact, indicate quite the contrary. In comparative forecasts of monthly percentage changes in retail sales, ARIMA forecasts were usually no better and often worse than forecasts generated by a simple single-equation economic model.

13 Other measures of forecast accuracy (MALE and MSQE) were calculated, and they led to the same conclusions.

The Problem of Rising Teenage Unemployment: A Reappraisal

By Steven P. Zell

An anecdote is told about Thomas Alva Edison who had been attempting for some time to develop a practical light bulb. Asked whether he was making any progess, Edison replied, "Why certainly. I've learned a thousand ways in which you can't make a light bulb." Like Edison, economists and policymakers have gained much experience in the long and frustrating attempt to solve the problem of high youth unemployment. Yet, although numerous programs have been developed to deal with the problem, little observable progress has been made. Nor does it appear that a solution is imminent. If anything, the problem of high youth unemployment seems to be worsening. In 1975, for example, the average overall teenage unemployment rate reached a postwar high of nearly 20 per cent, a level almost twice the average rate for teenagers in the mid-1950's and late 1960's. Furthermore, in the third quarter of 1977, 10 quarters after the recent recession's trough, the overall rate of teenage unemployment still exceeded 17.6 per cent, a level greater than the highest average rate of any quarter in any prior postwar business cycle.[1]

Why has it been so difficult to deal with the problem of high youth unemployment? The principal reason is that the problem is far more complex than can be indicated by a single statistic like the teenage unemployment rate. Not only do the size and composition of youth unemployment fluctuate widely as the economy moves through the business cycle, but over time, the structure of the labor market and the causes of unemployment have been changing as well.[2] Furthermore, the problems of teenagers in the labor market extend well beyond unemployment into issues like the types of jobs and training they receive, the differences in the experience of blacks and whites and of males and females, and the relationship between schooling and the youth labor market experience.

This article examines the problems of teenagers in the labor market to put this complex situation in better perspective. Two approaches are used in the analysis. In the first part of the article, an overview of youth labor market characteristics and problems is presented. In the second part, the youth population is divided into eight groups by race,

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[1] For labor market purposes, teenagers are defined as those persons 16-19 years of age.

[2] See Steven P. Zell, "The Behavior of the Labor Market Over the Business Cycle," Monthly *Review*, Federal Reserve Bank of Kansas City, April 1977, pp. 3-16.

sex, and school status and, through the adaptation of a demographic technique known as direct standardization, these groups are examined to uncover the interrelationship between unemployment growth and changes in unemployment rates, labor force participation rates, and population growth over the 1967-76 period.[3]

YOUTH LABOR MARKET CHARACTERISTICS: AN OVERVIEW

Of the many problems experienced by teenagers in the labor market, certainly the most dramatic is their high rate of unemployment. This situation is illustrated in Chart 1, which compares the unemployment rate of teenagers, both sexes combined, with that for adult men and adult women. Over the period considered, the first quarter of 1%7 through the fourth quarter of 1977, the underlying pattern of the three series is similar: they tend to move up and down together over the business cycle. Nevertheless, the teenage unemployment rate is 'striking because of its significantly higher level and its wider and more frequent fluctuations than those of the two adult groups.

But this comparison hides almost as much as it reveals. Though extremely high compared with adult rates, the overall teenage unemployment rate conceals a difference between white and black teenagers that is almost as large in ratio terms, and is far greater in percentage point terms, than that between teenagers and adults.' For example, in the first quarter of 1967, a period of almost full employment, the overall teenage unemployment rate was 12.2 per cent, compared with an overall adult rate of only 3.0 per cent. Among teenagers, however, white teenagers had an unemployment rate of 10.5 per cent while 26.2 per cent of black teenagers in the labor force were unemployed. At their greatest recent difference, in the second quarter of 1976, the white teenage unemployment rate was 16.5 per cent, while that for black teenagers was 38.8 per cent.[5]

These large differences by population group can be observed in other labor market characteristics as well. As may be seen in Chart 2, within two pairs of major population subgroups (w tes and blacks, males and females), substantial differences also exist in the changes between 1967 'and 1976 of such characteristics* 'as population, employment, civilian labor force size, participation rate, and unemployment level. In some series, all groups show growth over this period, though at different rates. Panels 1 through 5 illustrate that, for both whites and blacks, and for males and females, the five characteristics of unemployment rate, population, unemployment, employment, and civilian labor force all grew between 1967 and 1976. On the other hand, in panel 6, some groups show an increase

[3] A group's participation rate is the percentage of that group's population that is in the civilian labor force. Persons in the civilian labor force are either employed, or unemployed and looking for work.

[4] As used in this article, the population group "black" refers to all persons not enumerated as "white" in the Labor Department's household survey. Currently referred to in Bureau of Labor Statistics publications as "black and other," approximately 89 per cent of this group were black in the 1970 census. The remainder were American Indians, Eskimos, Orientals, and all other nonwhite groups. Most persons of Spanish origin are enumerated as white.

[5] The unemployment rate difference between male and female teenagers or between male and female teenagers of the same race has, in general, been ,relatively small, with the female rate usually the larger of the two.

Chart 1
SELECTED UNEMPLOYMENT RATES
1967-77, QUARTERLY

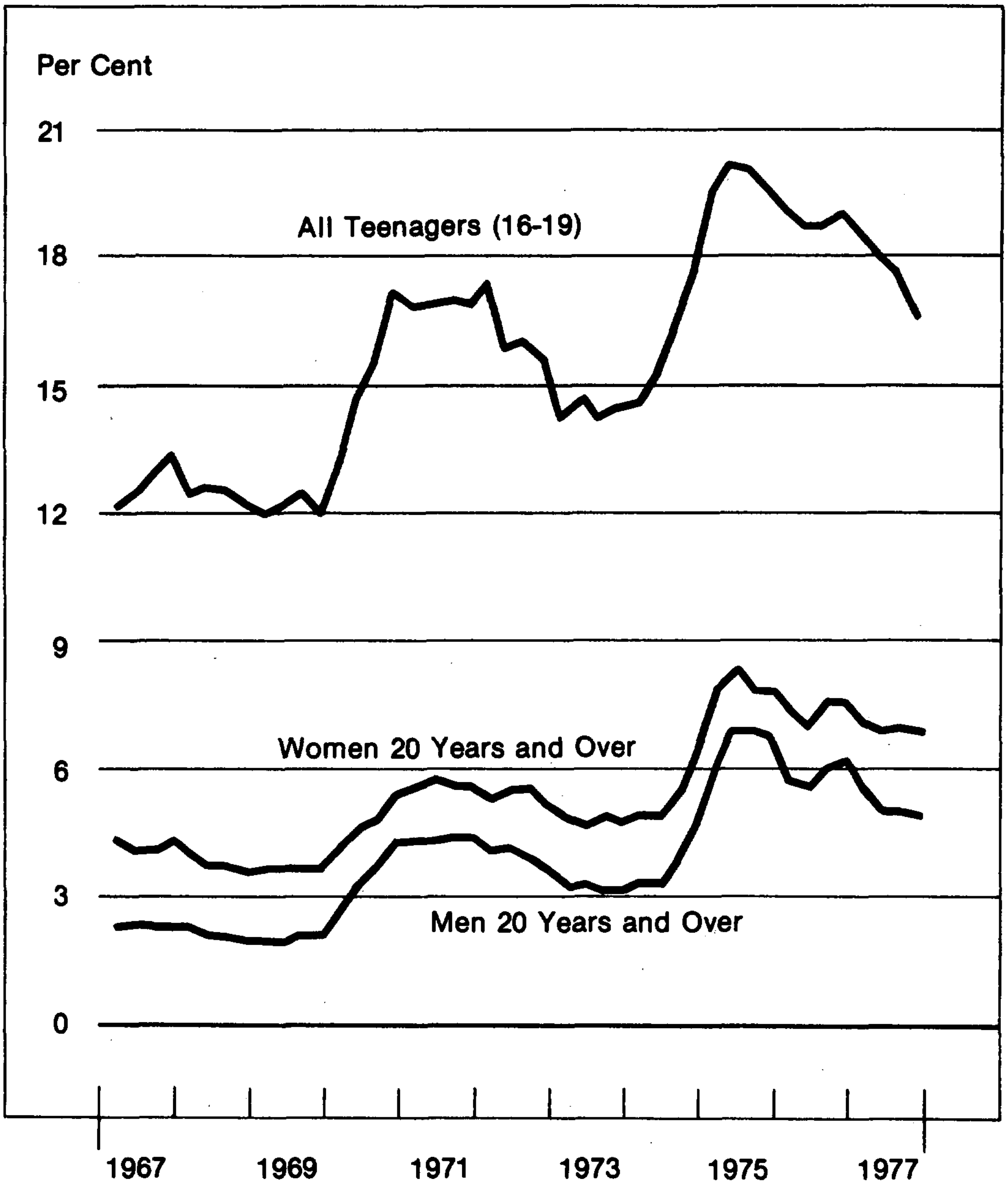
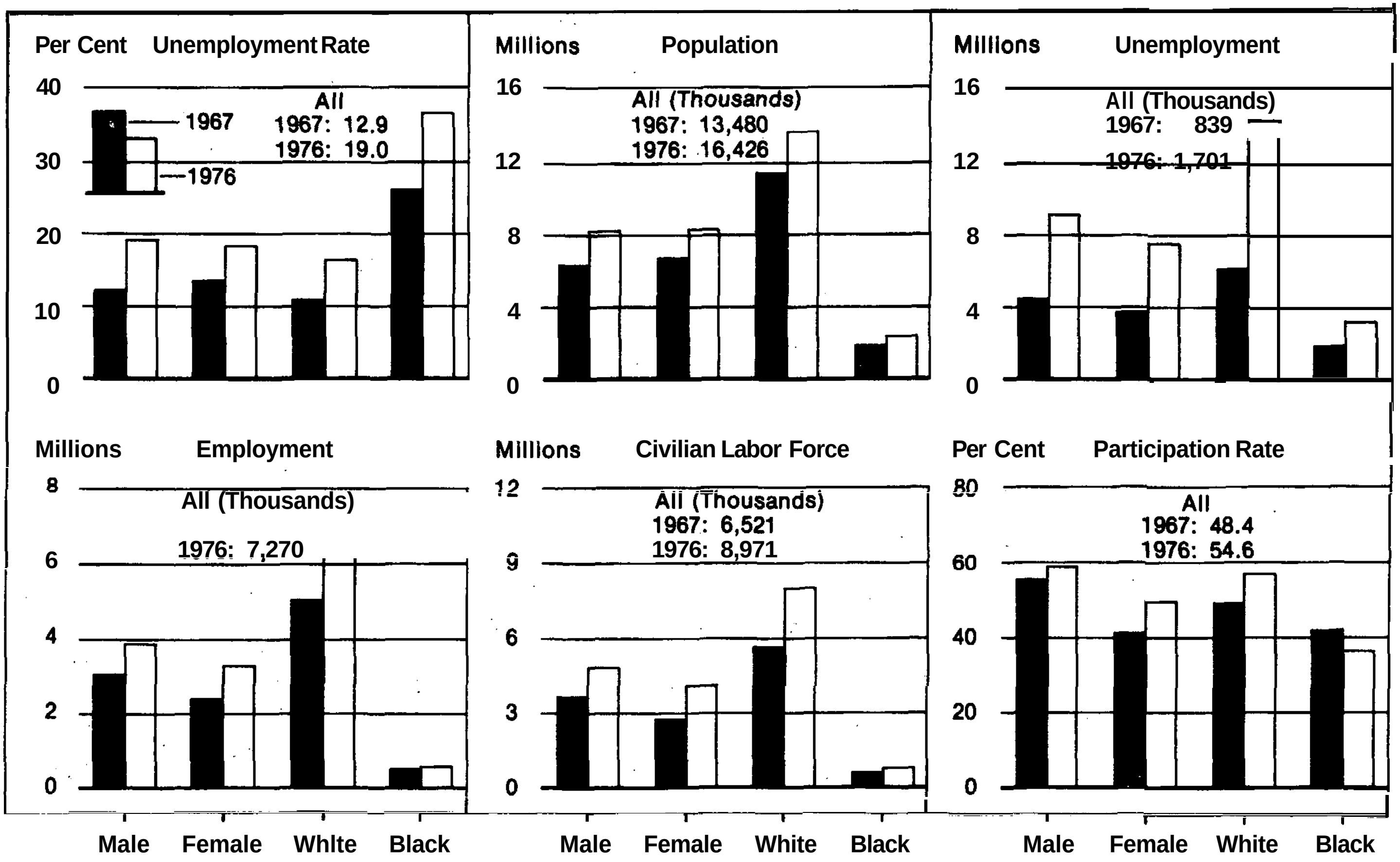


Chart 2
A COMPARISON OF THE LABOR MARKET CHARACTERISTICS OF TEENAGERS BY RACE AND BY SEX, 1967 AND 1976



in their participation rate while others experienced a decline.

The many changes shown in Chart 2 are, of course, not strictly independent. The 38 per cent growth in'the teenage civilian labor force over this period is due to several factors including changing group participation rates and differential group population growth rates. Similarly, the increase in teenage unemployment, from an annual average of 839,000 in 1%7 to 1,701,000 in 1976, is the result of the interaction of the factors that increased the civilian labor force as well as changes in group specific unemployment rates.

The second section of this article uses the interrelationships among these various labor market characteristics to explain the increase in teenage unemployment. For this purpose, the teenage population is divided into eight subgroups by sex, race, and school status.[6] For each subgroup, the increase in unemployment is attributed to specific changes in that group's labor market characteristics, and then related to the total change in teenage unemployment.

YOUTH, SCHOOLING, AND THE LABOR MARKET EXPERIENCE

From October 1967 to October 1976, the number. of unemployed teenagers in the U.S. labor force nearly doubled. Rising from a relatively low 828,000 in October 1967, teenage unemployment climbed by 739,000 in these 9 years to reach a level of 1,567,000 in October 1976. This tremendous increase in youth unemployment was, of course, the result of many factors. Of central interest to this article is the identification of those factors—those sources of growth of teenage unemployment—that can be attributed to changes in the behavior of specific subgroups of the teenage population.[7]

For this analysis, the teenage population was fust divided into four groups by race and sex (black and white males, and black and white females), and then further divided into those members of each group who, at the time of the survey, were either still enrolled in the regular school system, or had either graduated or dropped out of school (not in school).[8] The reason for this further distinction is important. Students who seek jobs during the school year tend to seek part-time jobs. In addition, students tend to live with their families and the income they earn in part-time employment is generally supplemental. Yet, the broad statistics of the U.S. Bureau of Labor Statistics make no distinction between the employment of full- or part-time workers nor, more

6 The school status delineation turns out to be particularly important and is permitted by the availability of data from two special labor force, studies on the employment of school-age youth in October 1967 and October 1976. See Ann McDougall Young, Students, Graduates, and Dropouts in the *Labor* Market, October *1976*, Special Labor Force Report 200, Bureau of Labor Statistics, and Forrest A. Bogan, Employment of School Age Youth, Special Labor Force Report 98, Bureau of Labor Statistics. The author thanks Mrs. Young for providing copies of these reports as well as some unpublished tables.

7 The methodology used in this analysis is an adaptation of that used by Ralph E. Smith in "Sources of Growth of the Female Labor Force, 1971-75," Monthly *Labor* Review, August 1977. Thanks are due Dan M. Bechter, Federal Reserve Bank of Kansas City, for his helpful suggestions toward the development of this approach. Note that the data used in the remainder of this article all refer to the specific months of October 1967 and October 1976.

8 Enumerators for the special surveys were instructed to count as enrolled anyone who had been enrolled at any time during the current term or school year in day or night school in any type of public, private, or parochial school in the regular school systems. Such schools included elementary, junior and senior high schools, and colleges and universities. Those enrolled only in trade, business. or correspondence courses outside the school system were counted as "not in school."

importantly for this analysis, in their unemployment. Certainly it is true that some in-school teenagers and their families badly need the supplemental income. Similarly, the inability to find employment is potentially damaging to the work experience of in-school **teenagers.**[9] Nevertheless, there is a fundamental difference between the unemployment of students and that of teenagers who have entered the full-time labor force to earn their living. Partly for this reason, most foreign countries do not count as unemployed those teenagers in full-time education who are seeking jobs during the school year. In this context, some American economists have suggested that the needs of many of the unemployed in-school youth could be met through education and income maintenance policies rather than through job policies. Another suggestion is that "paid services within the schools or community [might] also be used for this purpose [as well as] to reduce the competition for jobs between in- and out-of-school youth."[10]

Methodology

How may the increase in teenage unemployment be explained? This article explains the increase in total teenage unemployment by first examining the sources of unemployment growth for each of the eight population subgroups. For each group, the increase in unemployment is attributed to changes over the period in question in several other labor market characteristics. The influence of each of these factors on the total level of teenage unemployment is then taken as the sum of each effect over the eight groups."[11]

The sources of unemployment growth for each of the teenage subgroups fall into three major categories. First, even if its unemployment rate had remained constant, each group's unemployment would have increased solely because the **size of** its **labor force grew** over the period in question. Between October 1%7 and October 1976, these labor force increases totaled 2.5 million. The overall level of teenage unemployment increased by **286,000** from this source because, for each group, some percentage of these new, labor force participants became unemployed. Labor force growth thus accounted for 39 per cent of the total unemployment **increase.**[12]

The level of unemployment of each population group also changed as a result of the second major source of growth, **changing group unemployment rates.** Even if no group had experienced an increase in the size of its

9 For a development of this argument, see ***Manpower Report of the President,*** March **1972,** p. **81.**

10 Beatrice **G.** Reubens, "Foreign Experience," ***The Teenage Unemployment Problem: What are the Options?,*** Congressional Budget **Office,** October **14, 1976,** pp. **53-61.**

11 An alternative approach is to look first at the total increase in teenage unemployment and explain this increase by changes in several of the labor market characteristics of the ***overall*** teenage population. Changes in each of these overall characteristics may then be attributed to changes in the same characteristics for the population groups of interest. The two approaches yield similar, but not identical, results. While the latter method is that used by Smith, the first method was chosen for this article because it is both simpler mathematically and its results are much easier to interpret.

12 For each population group, the increase in unemployment due to labor force growth is calculated by holding the group's unemployment rate at its October **1967** level and multiplying the labor force growth by the fixed unemployment rate. A similar method is used throughout this **article** in calculating the contribution of the various sources to unemployment. The source of unemployment **(e.g.,** changing labor force **size)** is allowed to vary while the other relevant factors are held constant at their **1967** levels. Using **1967** "weights" in all the calculations yields an unambiguous meaning to the statement "holding' other things constant" that is not provided by other possible weighting procedures.

Table 1
TEENAGE CIVILIAN LABOR FORCE COMPOSITION AND UNEMPLOYMENT RATES
October 1967 and October 1976

Group	Labor Force Share (Per Cent of Teenage Labor Force)		Unemployment Rate (Per Cent)	
	1967	1976	1967	1976
Total	100.0	100.0	13.5	18.2
White	87.5	90.2	11.5	16.0
Male	47.6	47.9	10.7	16.2
In School	28.9	26.0	10.5	16.1
Out of School	18.7	21.9	11.0	16.3
Female	39.9	42.3	12.3	15.9
In School	18.4	23.1	9.5	13.9
Out of School	21.5	19.2	14.8	18.3
Black	12.5	9.8	28.0	38.0
Male	6.9	5.4	28.2	37.4
In School	3.4	2.8	36 4	34.7
Out of School	3.5	2.6	20.4	40.3
Female	5.5	4.3	27.6	38.5
In School	2.4	1.9	23.1	36.4
Out of School	3.2	2.5	31.1	40.1
Male	54.5	53.3	12.9	18.3
Female	45.5	46.7	19.2	18.0

SOURCE: Ann McDougall Young, **Students, Graduates, and Dropouts in the Labor Market, October 1976,** Special Labor Force Report 200, Bureau of Labor Statistics; and Forrest A. Bogan, Employment of School Age Youth, Special Labor Force Report 98, Bureau of Labor Statistics.

labor force, all but one—black male students—would have increased their number of unemployed solely because their unemployment rates increased (Table 1). Between October 1%7 and October 1976, the overall rate of teenage unemployment rose from 13.5 per cent to 18.2 per cent. This large increase reflects similarly sharp unemployment rate increases for most of the teenage groups. As a result of these unemployment rate changes, the eight teenage groups experienced a total rise in unemployment of **332,000,** or 45 per cent of the total increase.

The third major contribution to the growth in teenage unemployment is related to the first two. The unemployment effect of the first two sources of growth, labor force size and unemployment rates, were each calculated by assuming the other factor was held constant at its 1967 level. A third. major source of unemployment growth, which may be thought of as a residual term, arises because both the labor force size and unemployment rate of each group changed simultaneously. This interaction **effect** is thus calculated as the product of both changes, and is usually substantially smaller than the other two sources of growth. Summed over all eight groups, this interaction effect explains the remaining **121,000** increase in teenage unemployment.

Sources of Labor Force Growth: Participation Rate and Population Changes

Greater insight into the sources of unemployment growth may be gained by a closer examination of the factors responsible for the changing size of the labor force.

The change in the size of the labor force of any population group arises from two sources and their interaction. First, the **participation rate** of each group—the percentage of each group's population in the labor **force—tends** to change over time. For any given population size, a change in a group's participation rate, either up or down, will change the size of its labor force in the same direction. As a group's labor force sue changes from this source, some percentage of the new participants—given by the group's unemployment rate—become unemployed, and the number of unemployed teenagers changes.[13] Table 2 shows the participation rate of each group of teenagers in October **1967** and October 1976. Over this period, all four groups of white teenagers experienced an increase in participation rates, thereby increasing the **size** of their respective labor forces and their number of unemployed. On the other hand, all four groups of black teenagers experienced a decline in their rates of participation, and thus, from this factor, actually reduced the size of their labor forces and their unemployment.

The second source of change in the size of a group's labor force is its population growth. Over time, all eight population groups grew, though at different rates and by different amounts. Given each group's participation rate, an increase in the size of its population was translated into a proportional increase in the size of its labor force. This, in turn, given group unemployment rates, resulted in an increase in each group's unemployment. What were the relative contributions to rising teenage unemployment of these two sources of growth in labor force size? As will be discussed later, the relative contributions of these two sources of unemployment varied widely over the eight groups. When summed over all groups, however, the total increase in unemployment due to group population growth equaled 74 per cent of the total unemployment increase due to changing labor force size. Changing group participation rates explained another 24 per cent of this total "changing labor force effect" while the interaction of these two sources explained the remaining 2 per cent.

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13 Of course, if a group's participation rate declines, its labor force shrinks, and a percentage of this reduction, again given by the unemployment rate, leaves unemployment.

Table 2
TEENAGE POPULATION COMPOSITION AND PARTICIPATION RATES
October 1967 and October 1976

Group	Population Share (Per Cent of Teenage Population) 1967	1976	Participation Rate (Per Cent) 1967	1976
Total	100.0	100.0	45.7	52.4
White	86.5	84.9	46.2	55.7
Male	41.7	42.3	52.1	59.4
In School	31.7	29.3	41.6	46.5
Out of School	10.0	13.0	85.4	88.5
Female	44.7	42.7	40.7	52.0
In School	28.7	28.0	29.3	43.4
Out of School	16.0	14.7	61.3	68.3
Black	13.5	15.1	42.2	33.9
Male	6.5	7.3	48.8	38.8
In School	4.6	5.4	33.8	27.1
Out of School	1.9	1.9	85.4	72.2
Female	7.0	7.8	36.1	29.3
In School	4.2	5.3	26.1	18.8
Out of School	2.8	2.5	51.2	51.1
Male	48.2	49.6	51.7	56.4
Female	51.7	50.5	40.1	48.5

SOURCE: See Table 1.

AN OVERVIEW OF TOTAL UNEMPLOYMENT CHANGES

From October 1%7 to October 1976, the number of unemployed teenagers increased by 739,000. Part of this increase was the result of a substantial growth in the teenage population, with its consequent impact on the size of the teenage labor force. The remainder was due to changes in the labor market behavior of the several subgroups of the teenage population. For each teenage subgroup, Table 3 shows the influence on unemployment growth of both population growth and changes in group participation rates and unemployment rates. Most of the remaining discussion in this article is based upon data in Table 3.

Table 3
SOURCES OF GROWTH IN TEENAGE UNEMPLOYMENT
October 1967 to October 1976
(In Thousands)

Group	IMPACT ON UNEMPLOYMENT OF CHANGE IN:						
	Participation Rate (PR) (1)	Population (Pop) (2)	Interaction (ΔPR ΔPop) (3)	Labor Force Size (CLF)* (4)	Unemployment Rate (UR) (5)	Interaction (ΔUR ΔCLF) (6)	All Sources† (7)
Total	68.83	212.20	5.02	286.03	332.03	120.72	738.78
White	100.34	144.23	18.38	262.94	255.68	115.58	634.20
Male	26.46	99.01	5.59	131.06	159.92	65.70	356.68
In School	21.88	24.52	2.89	49.29	99.18	26.32	174.79
Out of School	4.58	74.49	2.70	81.77	60.74	39.38	181.89
Female	73.88	45.22	12.78	131.88	95.76	49.88	277.52
In School	51.62	20.71	9.97	82.30	49.63	38.15	170.08
Out of School	22.26	24.51	2.81	49.58	46.13	11.73	107.44
Black	–31.51	67.97	–13.35	23.09	76.35	5.14	104.59
Male	–21.88	43.92	– 8.30	13.73	39.43	1.43	54.60
In School	–15.07	33.64	– 6.68	11.88	– 3.55	– 0.56	7.77
Out of School	– 6.81	10.28	– 1.62	1.85	42.98	1.99	46.83
Female	– 9.63	24.05	– 5.05	9.36	36.92	3.71	49.99
In School	– 9.51	18.03	– 5.04	3.47	19.55	2.00	25.02
Out of School	– 0.12	6.02	– 0.01	5.89	17.37	1.71	24.97
Male	4.58	142.93	– 2.71	144.79	199.35	67.13	411.28
Female	64.25	69.27	7.73	141.24	132.68	53.59	327.51

NOTE:
'Column 4 = Columns 1 + 2 + 3.
†Column 7 = Columns 4 + 5 + 6.
SOURCE: See Table 1.

Unemployment Rate Changes

By far the largest part of the increase in total teenage unemployment was the result of changes in the unemployment rates of specific groups (Table 3, column 5). Almost 45 per cent of the overall unemployment increase was due to this source.[14] This increase may reflect more accurately the lingering impact of the recent recession than does the official unemployment **rate change.** It may be shown that the rise of 4.68 percentage points in the official teenage unemployment rate between October 1967 and October 1976 reflects not only group unemployment rate changes but changes in labor force shares as well.[15] Because the participation rates and population of the various teenage groups changed over this period, generally by different amounts, group labor force size varied as did the share of the labor force represented by each group (Table 1). If labor force shares had not changed, the total unemployment rate would have risen by 5.41 percentage points. The lower official unemployment rate rise is largely the result of groups with high unemployment rates reducing their shares of the labor force. In particular, all four black groups reduced their labor force shares, partly because of the increased difficulty of finding employment.[16]

Labor Force Growth

Population. The second largest impact on unemployment arose from the effect of the growth of the teenage population on the size of the teenage labor force (Table 3, column 2). Other things equal, if all population groups had grown at the same rate, the labor force and unemployment of all groups would also have risen at the same rate and their population shares at the end of the period would have been unchanged. But part of the total population growth reflects the fact that all groups grew at different rates. Because of the differential rates of growth, each group represented a different share of the population in 1%7 than in 1976. Groups that grew faster than average increased their share of the population and labor force and, thereby, contributed to rising unemployment. Groups that grew more slowly than average reduced their unemployment from this effect. As Table 2 shows, the major shifts in shares of the population took place from white females and white male students to black students and out-of-school white males. Overall population growth contributed 212,000 to unemployment growth, of which about 20,000 is attributable to share shifts between specific groups.[17]

Labor Force Participation. Finally, the remaining impact on unemployment growth

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14 Another 16 per cent of the unemployment rise is explained by the interaction of changing unemployment rates with growing labor force size.

15 Each group's ***labor force share,*** presented in Table 1, is that group's percentage of the total teenage labor force. The change in the total unemployment rate is the sum of the weighted average of group unemployment rate changes, holding labor force shares constant, plus the sum of group labor force share changes, holding unemployment rates constant.

16 The unemployment increase reported in Table 3 under "unemployment rate" effect, reflects for each group the increase in unemployment due solely to unemployment rate changes, holding constant the impact upon unemployment of other, possibly offsetting, changes in group labor market **characteristics.** In this sense, it provides a more accurate picture of the continuing impact of the recession on unemployment and unemployment rates than the **official** measure.

17 The net impact of population share **shifts** on the total level of unemployment depends on the unemployment rate and participation rate characteristics of the various groups. If groups with low participation and unemployment rates become a smaller share of the population while groups with high rates increase their population shares, a net increase in unemployment will result.

arose from the changing labor force participation of the various teenage groups (Table 3, column 1). Because certain groups of the population chose to substantially increase their participation in the labor market between 1967 and 1976, the overall level of teenage unemployment rose by 69,000, despite the fact that all black groups reduced their participation. The sum of the unemployment increases resulting from the population growth changes and the participation rate changes constitutes the total effect of changing labor force size on teenage unemployment.

SPECIFIC GROUP EFFECTS

Whites

How have changes in the characteristics of different population groups affected total unemployment? Of the eight teenage population groups, white out-of-school males had the largest net impact on unemployment (Table 3). Although they represented only 10 per cent of the teenage population in 1967, and 13 per cent in 1976, the changing labor market characteristics and growing population of this group explain almost 25 per cent of the total teenage unemployment increase. Not only were out-of-school white males the one group of white teenagers to increase their share of the population, but their 3 percentage point increase in population share was the largest of any of the eight groups.[18] Population growth, especially that part due to rising population share, contributed most strongly to the large unemployment gain of this group. The 74,000 unemployment contribution from this total source was augmented by a 61,000 increase due to their rising unemployment rate. Interaction effects made up most of the remaining increase in unemployment, as the small participation rate increase of these teenagers contributed only slightly to their total unemployment gain of 182,000.

White female students and white male students had the next two largest impacts on the total increase in teenage unemployment. Together they contributed 47 per cent of the total unemployment increase. The unemployment gains of these two groups were approximately equal, and each group's gain was just slightly smaller than the contribution of out-of-school white males.

White female students alone experienced an unemployment increase of 170,000, almost one-third of which can be explained by an exceptionally large increase of over 14 percentage points in their rate of labor force participation (Table 2). No other group had anything near this participation rate increase nor its impact on the level of teenage unemployment. Of the total white unemployment increase of 100,000 that was due to rising participation rates alone, white female students explain over one-half. Almost another third of their unemployment increase was the result of a climb in their unemployment rate from 9.5 per cent in 1967 to 13.9 per cent in 1976. In spite of this large increase, the unemployment rate of in-school white females remained below that of any other group and apparently had little discouraging impact on their labor market participation.

White in-school males also contributed strongly to the total growth in unemployment. The largest source of their unemployment

18 See Table 2. Part of the reason for the large increase among white males in the nonstudent share of the teenage population, and the declining population share of white male students, is found in the changing age distribution of white males. Between 1967 and 1976, the cohort of 18-19 year old white males grew almost twice as fast as that of 16-17 year olds. Thus, the 1976 white male population should have included relatively more persons no longer in school.

growth of 175,000 was an increase in their rate of unemployment, followed by much smaller contributions of participation rate change, population growth, and their interactions with rising unemployment rates. Their declining population share, discussed earlier, lowered the net impact on unemployment of the change in this group's population.

Blacks

An interesting result of the analysis is that, despite their extremely large unemployment rate increases and their increasing population, black teenagers contributed only 14.2 per cent of the total teenage unemployment rise, approximately equal to their share of the population (13.5 per cent in 1967). However, if their population and participation rates had not changed, blacks would have accounted for 23 per cent of the unemployment increase due to rising unemployment rates alone (Table 3, column 5). The reason for this surprising result is that the higher unemployment that would have resulted from their rising unemployment rates alone was sharply reduced because blacks also experienced declining participation rates over the 9-year period. This result is an illustration of the discouraged worker phenomenon. The worsening economic opportunities for black workers, indicated in part by their rising unemployment rates, significantly reduced the degree to which they participated in the labor force. This reduced participation, in turn, reduced the apparent impact of labor market conditions on black workers by lowering their measured unemployment.[19]

Of the four black groups, out-of-school males had by far the largest impact on the total unemployment gain. It is noteworthy that this relatively small group (1.9 per cent of the population) explained 13 per cent of the total teenage unemployment increase due to higher unemployment rates alone (Table 3, column 5), but only 6 per cent of the total unemployment increase (Table 3, column 7). This discrepancy between the 13 per cent and 6 per cent of the unemployment increase explained is the principal example of the discouraged worker phenomenon.

Unlike out-of-school black males, black male students actually decreased their level of unemployment due to unemployment rates alone. Like all other black groups, however, these students lowered their rate of participation. Thus, their small total unemployment increase was solely the result of rising population and a rising population share.

Like their male counterparts, black female students also increased their share of the population. But black females not in school reduced their population share, and the share of black males out of school remained constant (Table 2). An interesting hypothesis for this apparent shifting of black population shares from nonstudents to students is that, as with reduced participation rates, the population share shifts are another response to the perceived worsening of labor market conditions. One partial test of this hypothesis may be made by examining the population growth of the black groups, divided into 16-17 and 18-19 year old cohorts. If the younger age

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19 If no other changes had taken place in the labor market characteristics of blacks, their rising unemployment rates alone would have raised their unemployment by over 76,000. However, their reduced participation rates, holding population constant, lowered the size of the black labor force by 116,000 and, through this, lowered their unemployment by 31,500. The interaction of falling participation with rising population lowered unemployment by another 13,000. Rising population and population shares raised black unemployment by 68,000, for a net increase of 105,000.

group had been growing more rapidly, this might explain the share shifts toward more students without any reference to labor market conditions. In fact, however, the opposite is true. For both black male and black female teenagers, the **18-19** year old cohort has grown about **7** percentage points faster than the younger group. This would tend to favor nonstudents becoming a larger share of the population instead of the actual student growth that took place.

SUMMARY AND CONCLUSION

By most measures, teenagers have had a difficult time in the labor market over the past decade. The most dramatic illustrations, of course, have been the near doubling of their unemployment and the 50 per cent increase in their unemployment rate. The interpretation of these broad statistics, however, is not completely clear. Like all averages, they hide almost as much as they reveal. Which groups of teenagers have contributed most to this unemployment gain? What were the proximate causes of these increases? That is, how much of the unemployment gain was due to population growth and how much to factors like increased labor force participation?

This article has attempted to answer these and similar questions by dividing the teenage unemployment increase for each of eight groups into that part caused by population growth and that which resulted from changes in labor market behavior.

By this approach, it was shown that several complex changes have contributed to the teenage unemployment increase. Among blacks, the discouraged worker phenomenon is apparent. Had worker discouragement not significantly reduced labor force participation, rising unemployment rates alone would have resulted in much greater unemployment of black teenagers than that conventionally measured. Black teenagers out-of-school actually reduced their share of the teenage population. The increase in the total black share of the population was entirely due to the rising number of black students. This increase may, in turn, have been partly due to a perceived worsening of conditions in the labor market.

Among all teenagers, white female students had one of the largest total impacts on unemployment, primarily as the result of their increasing labor force participation, but also due to higher unemployment rates. White male students also had a major unemployment impact due to these two factors. Together, these two groups account for almost **47** per cent of the total increase in teenage unemployment. This result is an important finding. As discussed earlier, the appropriate economic policy to combat youth unemployment is probably quite different for student (especially white student) unemployment than for that of out-of-school teenagers. The large proportion of the total unemployment increase explained by students should certainly be taken into consideration in assessing the appropriate scope and direction for such economic policies.

This conclusion, of course, does not imply the absence of a teenage unemployment problem. White males out-of-school have become an increasing share of the teenage population and their unemployment rates are quite high. Indeed, white out-of-school males had the largest net impact on unemployment growth from **1%7** to **1976** of all groups studied. Similarly, out-of-school white females have experienced fairly large increases in their unemployment rates. The unemployment rates of even these two groups, however, are small when compared with those of any of the four black groups. Furthermore, because of the discouragement effect, even these high rates understate the black unemployment problem, especially for out-of-school males. Rather than the absence of a problem, then, these findings appear to point to a need to view the high unemployment of teenagers as a situation arising from a variety of factors, some of which may call for no attention and others of which may require a similarly varied set of more clearly targeted policy procedures.