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**THE EFFECTS OF PERMANENT AND
TRANSITORY OUTPUT SHOCKS ON POVERTY**

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Abstract

Between the early 1960s and the mid-1980s, fluctuations in the U.S. poverty rate closely tracked changes in the economy's overall performance. Since the mid-1980s, however, the link appears to have weakened. This article reexamines the link between the poverty rate and economic activity. Using a structural VAR, we find that aggregate demand shocks have led to a decline in the poverty rate of roughly two percentage points since the mid-1980s. These declines were offset by a combination of aggregate supply shocks adverse to the poverty rate and by idiosyncratic shocks to the poverty rate itself.

I. Introduction

Between the early 1960s and mid-1980s, fluctuations in the U.S. poverty rate closely tracked changes in the economy's overall performance. In particular, cyclical upswings in output (declines in unemployment) tended to reduce poverty significantly while recessions tended to increase poverty [Blank and Blinder (1986) and Ellwood (1988)]. Since the mid-1980s, however, the link appears to have weakened. For example, annual output growth during the 1983 to 1993 period averaged about 2.8%, including one relatively short recession. The unemployment rate for males 20 years and older fell from 8.9% to 6.4% during the same interval, yet the poverty rate remained stubbornly high, falling slightly from 15.2% to 15.1%. Econometrically, this "breakdown" has been identified as a growing prediction error in estimated equations aimed at explaining the poverty rate [Cutler and Katz (1991), Blank (1991) and Tobin (1995)].

The apparent decreased response of poverty to macro fluctuations has highlighted a distinction between output growth unaccompanied by significant shifts in the income distribution and growth that is accompanied by such shifts. It is the latter experience that several researchers claim describes the past fifteen years and explains the apparent breakdown in the output/poverty nexus. That is, output growth during the past fifteen years has not been shared equally, with real incomes of individuals in the lower end of the income distribution falling while those of individuals in the upper end rising [see, e.g., Cutler and Katz (1991) and Blank (1991)]. Exactly why inequality has grown is unsettled, although structural explanations such as skilled-biased technological change, shifting industrial and trade patterns, and deregulation of business are frequently mentioned [Bailey, Burtless and Litan (1993)].

This article reexamines the link between the poverty rate and output growth and suggests that at least part of the recently documented breakdown reflects a failure in previous studies to distinguish between different sources of output shocks. It is commonly known that output shocks arise from various sources and may affect output at different frequencies. It is, moreover, reasonable to expect that these different shocks might uniquely affect the poverty rate. Demand-driven increments to output occurring at business cycle frequencies could, for instance, reduce poverty as laid-off, lower-skilled workers are called back. Alternatively, supply-driven increments at lower frequencies, perhaps reflecting technological changes, could cause higher poverty if the skills of lower-income individuals become superfluous.¹

Many existing empirical studies employ only one aggregate output shock, usually represented by the movements in the unemployment rate or by output growth. By contrast, the present study uses the methodology of Blanchard and Quah (1989) to identify two types of output shocks -- permanent and transitory -- and to explore their dynamic interaction with the poverty rate. The study finds that each output shock affects poverty in different ways and suggests a reinterpretation of the past decade's experience. While the results confirm earlier findings that relatively large idiosyncratic shocks to the poverty rate occurred in the period, the extent of the breakdown in the poverty/output growth link has been overstated because of restrictive modelling strategies.

II. Empirical Methodology

Incorporating Multiple Output Shocks. As a first step toward establishing the importance of distinguishing between different sources of output movements, static forecasts are generated

based on a regression of the official poverty rate on the civilian male unemployment rate and output growth. Both variables are included as a simple way of capturing different types of output shocks, say, aggregate demand and supply. (The identification of different output shocks is developed more precisely below.) Existing studies that document the breakdown, such as Blank (1991), follow the same strategy, except that they explain the poverty rate using equations with only one measure of macro activity, either the unemployment rate or output growth, and fairly restrictive dynamics.² These studies also employ other explanatory variables, including trend adjustments in the poverty rate. However, the simplicity of our specification serves to make the study's point more forcefully.

For consistency with earlier studies, the equation was estimated over the period 1959 to 1983. Two annual lags each of the unemployment rate, output growth (first difference of log GDP), and the poverty rate were used to capture dynamics. The poverty and unemployment rates are expressed in basis points. The estimated equation is:

Variable	const.	ΔY_{t-1}	ΔY_{t-2}	U_{t-1}	U_{t-2}	POV_{t-1}	POV_{t-2}
Coefficient	211.39	-41.697	1.730	-0.611	0.728	1.007	-0.118
t-statistic	1.983	-2.098	0.165	-1.570	1.969	2.865	-0.351

$$R^2 = 0.9536 \quad F(6,16) = 76.361 \quad Q(5-0) = 9.334$$

Static forecasts were produced by applying actual values of the explanatory variables to the estimated coefficients for the years 1984 to 1993. Figure 1 displays the results. As can be seen, the forecasts are quite accurate. The forecast slightly overpredicts poverty in the latter half of the 1980s, but comes very close to the actual rates in the 1990s. In contrast, Blank (1991) and

Cutler and Katz (1991) find that static predictions from their equations underestimate the poverty rate in the latter half of the 1980s, with the prediction error growing ever larger. Blank's (1991) equation underpredicts the 1989 poverty rate by 3.5 percentage points (9.3% compared to the actual rate of 12.8%). The largest static prediction error from our equation was 95 basis points in 1988. Thus, even accounting for different types of output shocks in a very naive way appears to eliminate much of the observed breakdown.

Given a conceptual basis for identifying possibly unique effects of different output shocks, and preliminary evidence that such a distinction has practical importance, the study now turns to a more detailed empirical analysis of the interaction between poverty and output. The analysis uses a three-variable structural vector autoregression (VAR) that includes the poverty rate, output growth, and the unemployment rate. The approach of Blanchard and Quah (1989) is employed to identify aggregate demand and aggregate supply shocks to output, as well as idiosyncratic poverty rate shocks. The resulting estimates are then used to interpret the link between the poverty rate and output during the past ten years, the period of most interest to researchers.

The Empirical Model. The empirical analysis begins with a description of the dynamic interrelationships among log real GDP (Y), the unemployment rate for males 20 years and older (U), and the official total poverty rate (POV). Such a description is given by:

$$A_0 X_t = \sum A_i X_{t-i} + e_t \quad (1)$$

or

$$A(L)X_t = e_t$$

where X is a 3×1 vector containing stationary transformations of output, the unemployment rate, and the poverty rate, e is a 3×1 vector of structural shocks, A_0 and A_i are structural parameters to be estimated, and $A(L)$ is a matrix of polynomials in the lag operator, L , given by $A(L) = A_0 - \sum A_i L^i$. The first element of e_t , denoted e_{st} , is interpreted as an economywide supply shock, the second element, e_{dt} , as an economywide demand shock, and the third element, e_{pt} , as an idiosyncratic poverty shock. Equation (1) is a dynamic representation of the three-variable system, with A_0 describing the structural contemporaneous relationships among the variables and the A_i , for $i \geq 1$, describing the dynamic effects. Essentially, equation (1) constitutes a structural vector autoregressive representation of the economy's dynamics. It is assumed that the matrix of polynomials, $A(L)$, is invertible, that A_0 is nonsingular, and that $e_t \sim \text{iid}(0, \Sigma)$.

Time-series properties of the data. A variety of unit-root tests were performed to investigate the stochastic properties of log output.³ The null hypothesis of a unit root was tested using both the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) t-tests. A strategy suggested by Kwiatkowski, Phillips, Schmidt and Shin (KPSS, 1992), which tests a null hypothesis of stationarity (or trend stationarity) against a unit-root alternative, was also conducted, given the acknowledged low power of the ADF and PP tests against near-unit-root alternatives. The results are presented in Table 1. The estimates suggest that log output is nonstationary, with both the ADF and PP tests failing to reject the null of nonstationarity. In addition, the KPSS test rejects the null of stationarity at the 1% level. In sum, the results indicate that the first-difference of log output is an appropriate stationary transformation for use in the empirical analysis.

Finding a proper empirical treatment of the unemployment and poverty rates presents a special problem. Visual inspection of both the unemployment and poverty rate series reveals what appear to be persistent movements within the sample. For example, the poverty rate fell dramatically through the 1960s and never again achieved its initial value. The unemployment rate experienced a protracted rise through the 1970s and a protracted decline through the 1980s. Despite the persistent movements, modelling either series as a random walk or even testing for the presence of a unit root is problematic. Because the series are bounded between zero and unity, their variances cannot approach infinity as the time horizon lengthens and, thus, neither can follow a random walk.⁴ Such reasoning implies that application of standard unit root tests, such as the ADF and PP tests, are meaningless since neither time series can arise from the data generating process assumed under the null hypothesis. In a similar vein, the KPSS test cannot be applied since it employs a unit-root alternative.⁵

Although the possibility of random walk behavior can be dismissed, the issue remains of how to account for apparent low frequency variation within the sample period. Existing studies have taken different approaches. For example, Blanchard and Quah (1989) linearly detrended the unemployment rate, while various authors have detrended the poverty rate series with variables such as the ratio of transfer payments to GDP [Blank and Blinder (1986)] and the ratio of the poverty line to mean income [Blank and Blinder (1986) and Tobin (1995)]. Some studies, such as Tobin (1995), use specifications based on the first differences of the poverty and unemployment rates.

The baseline estimations in the present study use the actual unemployment and poverty rates with no trend adjustment. As was noted, employing first differences of the unemployment

rate and poverty rate (i.e., modelling them as random walks) or treating each series as stationary around a deterministic trend is conceptually problematic in that both variables are bounded between zero and unity. These strategies thus must be appealed to as useful local approximations, although each necessarily imparts spurious dynamics to the system that could be significant. The alternative method of filtering the data using exogenous variables is both ad hoc and contrary to the VAR methodology in which all variables are endogenous. The study thus assumes as a baseline that the unadjusted unemployment and poverty rates are stationary, implying that X_t in equation (1) is $(\Delta Y_t, U_t, POV_t)$. However, the implications of detrending the unemployment and poverty rates are also examined.

Alternative model representations. Different aspects of the empirical analysis make use of alternative representations of (1). Estimation relies on the reduced-form vector autoregressive representation (VAR) of (1), which is derived by premultiplying both sides by $(A_0)^{-1}$:

$$X_t = \Sigma B_i X_{t-i} + v_t \quad (2)$$

or

$$B(L)X_t = v_t$$

where $B_i = (A_0)^{-1}A_i$, $B(L) = I - \Sigma B_i L^i$, and the v_t are reduced-form disturbances given by

$v_t = (A_0)^{-1}e_t$ with $v_t \sim \text{iid}(0, \Omega)$, $\Omega = (A_0)^{-1}\Sigma(A_0)^{-1'}$. Structural analysis of the model's

interrelationships requires a structural moving average representation, which is obtained by premultiplying both sides of (1) by $A^{-1}(L)$:

$$X_t = C(L)e_t \quad (3)$$

where $C(L) = A^{-1}(L)$. Parameterization of needed identifying restrictions is aided by the reduced-form moving average representation associated with (2), which is computed by premultiplying both sides of (2) by $B^{-1}(L)$ to yield

$$X_t = E(L)v_t \quad (4)$$

where $E(L) = B^{-1}(L)$.

Together, equations (1) - (4) provide four ways of representing the dynamic relationships among the variables in our empirical model. As noted above, the relationship between the reduced-form disturbances (v) and the structural disturbances (e) is given by $v_t = (A_0)^{-1}e_t$, which for notational convenience we now write as

$$v_t = Se_t \quad (5)$$

where $S \equiv (A_0)^{-1}$.

Model identification. To study the system's dynamics and to proceed with a structural analysis, some restrictions must be imposed to identify equation (1). These restrictions often have taken the form of zero restrictions on right-hand-side distributed lags. Such zero restrictions have been included in many empirical models of the poverty rate. But because distributed lags can reflect structural phenomena such as expectational effects and technological and institutional inertia, zero restrictions are generally inappropriate [Watson (1994)]. Structural VAR models of the present type instead employ restrictions on the structural cross-equation variances (Σ), on the matrix of contemporaneous interactions (A_0), and on the matrix of long-run multipliers ($C(1)$).

The well-known rank condition requires N^2 restrictions to just-identify an N -equation system. After imposing N ($=3$) normalizations (which are implemented by restricting the own

structural variances--the diagonal elements of Σ --to unity), additional $N(N-1)$ restrictions are imposed to just-identify the model. Following usual structural VAR practice, $N(N-1)/2$ additional restrictions are imposed by requiring zero covariance across the structural shocks (e). The remaining $N(N-1)/2$ just-identifying restrictions are partly comprised of an aggregate supply relation that requires that structural poverty and unemployment rate shocks have no long-run effects on the level of output. That is, $C_{12}(1)$ and $C_{13}(1) = 0$. A condition analogous to $C_{12}(1) = 0$ is imposed by Blanchard and Quah (1989), who assume that demand disturbances at most have a transitory effect on output. Gali (1992) also imposes such a condition. For present purposes, the same reasoning is extended to structural poverty shocks through the condition that $C_{13}(1) = 0$.

Economic theory offers little guidance in distinguishing between the structural poverty and unemployment equations. In the baseline identification, the unemployment and poverty equations are distinguished from one another by assuming that a structural poverty shock (e_p) does not affect output contemporaneously. Using equation (5) to substitute for v_t in (4) and equating the result with (3) yields $C(L)e_t = E(L)Se_t$. Since $C_{13}(0)$ measures the contemporaneous impact on output of a unit poverty shock and $E(0) = I$, the last just-identifying restriction is $S_{13} = 0$. Such a restriction is employed in the single-equation approach of Blank and Blinder (1986), who require such a condition to avoid simultaneous-equation bias. The implications of alternative identification schemes are examined below.

Model Estimation. Estimation proceeds as follows. First, the reduced-form VAR, equation (2), is estimated by OLS, and the OLS residuals are used to compute the maximum likelihood estimate of Ω . Second, the relation $\Omega = SS'$, along with our just-identifying restrictions [$C_{12}(1)=0$, $C_{13}(1)=0$, and $S_{13}=0$] are used to solve for the elements of S , using the

estimate of Ω . Finally, the A_i [$A_i = A_0 B_i \equiv S^{-1}B_i$] are computed given point estimates of the B_i and S . A simplex search procedure is used to solve $\Omega = SS'$ for the elements of S . Since the model is just-identified, a unique solution is guaranteed [Watson (1994)].

Analysis of the empirical model concentrates on estimated impulse response functions, variance decompositions, and historical decompositions. The impulse responses are given by $\{C_{ij,k}\}_{k=0,\infty}$, and are computed from equation (3), where $C_{ij,k}$, the ij th element of C_k , is the response of the i th variable (X_{it}) to a unit impulse in the j th structural shock k periods ago (e_{jt-k}). The variance decompositions, transformations of the impulse responses, compute the percent of a variable's forecast-error variance at a specified horizon attributable to each element of X . The historical decompositions, which also use representation (3), isolate the accumulated effects of the entire path of the estimated structural shocks on each element of X over time.

III. Empirical Results

System Estimates. Estimated reduced-form coefficients are presented in Table 2, and the estimated S matrix is shown in Table 3. Three sets of diagnostic tests were performed. The first investigated the possible presence of serial correlation using the Breusch-Godfrey LM test. The calculated χ^2 statistics failed to reject the null hypothesis of no serial correlation (5% level) for any equation. The relevant p-values [$\chi^2(1)$] for the output growth, unemployment rate, and poverty rate equations are 0.231, 0.683, and 0.057, respectively. The second set comprised block-exclusion tests that examined whether either output growth or the unemployment rate can be eliminated from the poverty equation. The associated likelihood ratio statistics imply that each variable contributes significant explanatory power to the poverty rate.

Finally, stability tests were run in which the stability of each equation in the system and the stability of the system as a whole were explored. For the single-equation stability tests, each equation was augmented with dummy variables interacted with each equation parameter. The dummy equals 1 for $t \geq 1983$ and the test statistic is $F(7,19)$. The null of parameter stability (all dummies=0) cannot be rejected in any equation. The p-values for the output growth, unemployment rate, and poverty rate equations are 0.95, 0.53, and 0.70, respectively. The systemwide stability test was conducted using a likelihood ratio statistic based on the log of the determinant of the estimated variance-covariance matrix for the unrestricted (dummies included) and restricted model. The test statistic is a $\chi^2(21)$ and, once again, the null of stability cannot be rejected (p-value=0.09).

Overall, the estimated system has desirable properties. The dynamic interactions between output growth, the unemployment rate, and the poverty rate implied by the system are now discussed.

Baseline Impulse Responses. Figures 2 through 4 display the poverty rate impulse responses for the fifteen years following an initial shock.⁶ As can be seen, the particular response of poverty to an output shock depends critically on the source of the output change. Figure 2 indicates that a positive aggregate supply shock that raises output by 40 basis points on impact leads to an initial increase in the poverty rate. The increase is approximately 15 basis points. Conceptually, such a positive reaction might arise from skilled-biased technological change, among other possible developments. The initial rise in poverty dissipates within two years, eventually pushing poverty below its starting level. The negative effects are small and, given the stationarity of poverty, eventually become zero. Figure 3 displays the response of the poverty

rate to an aggregate demand shock that raises output by 140 basis points. The response is broadly consistent with results typically found in existing studies. That is, a rise in aggregate demand drives the poverty rate down temporarily. The impact begins to reverse after two years and ultimately vanishes after about fifteen years. Figure 4 shows the dynamic response of poverty to an idiosyncratic shock. The poverty rate peaks after three years and then gradually returns to the baseline level within fifteen years.

Variance decompositions. Table 4 contains the variance decompositions for the poverty rate at horizons of one year, five years, ten years and fifteen years. In general, aggregate supply shocks appear to explain little of the variance in the poverty rate, accounting for less than 1.5% at most horizons. Aggregate demand shocks, by contrast, appear to drive most of the variation in the poverty rate, consistently accounting for between 70% and 75% of the variance at all horizons. Finally, idiosyncratic shocks to poverty account for about one-quarter of the variance in poverty, a substantial fraction. Overall, the variance decompositions present a view of poverty consistent with received wisdom: cyclical variations in aggregate demand are the major influence on poverty rate changes, while aggregate supply shocks produce little variation in poverty. These results do not imply, however, that differentiating between aggregate demand and supply shocks is unimportant in explaining movements in the *level* of the poverty rate. As indicated by the impulse responses, each shock has a noticeably different effect on the poverty rate. The importance of differentiating between different output shocks is more clearly understood by examining the historical decompositions of the poverty rate.

Historical decompositions. Recall that historical decompositions calculate movements in the poverty rate over the sample period arising from the entire sequence of estimated shocks to

specified variables and reflect the full system's dynamics. Panel A of Figure 5 presents the historical changes in the poverty rate due to estimated aggregate supply shocks for the period 1961 to 1993. Between 1961 and 1968, for example, aggregate supply shocks on average led to a lower poverty rate (a drop of about 40 basis points). In contrast, supply shocks tended to boost the poverty rate starting in the mid-1980s and continuing into the 1990s (a rise of about 45 basis points).

Panel B of Figure 5 contains the estimated historical variation in the poverty rate due to aggregate demand shocks. The estimates indicate that aggregate demand pushed the poverty rate down by about 150 basis points between 1961 and 1969. Demand shocks then contributed to a growing poverty rate from the mid-1970s into the mid-1980s (a rise of about 450 basis points). On average, demand shocks reduced the poverty rate from the mid-1980s to 1993 by about 200 basis points. These results appear consistent with conventional wisdom that poverty generally falls during demand-induced cyclical expansions and rises during recessions. Panel C indicates that idiosyncratic poverty shocks on average led to falling poverty from 1961 to the mid-1970s. This pattern was reversed in the subsequent fifteen years.

Both the magnitudes and the direction of the historical decompositions help to interpret the recently observed "breakdown" in the relationship between poverty and the level of economic activity. Aggregate demand shocks historically have had the largest impact on poverty. Reference to the scales of each panel in Figure 5 reveals that the range of movement in the poverty rate due to aggregate demand shocks is at times about eight to ten times that due to aggregate supply shocks and one-and-a-half times that due to idiosyncratic shocks. Thus, to the extent that the impacts of demand and supply shocks on poverty were of the same direction or

that the movements in poverty due to supply shocks were small relative to demand-driven changes, making a distinction between the sources of output change for the purpose of explaining changes in the level of the poverty rate is not very important.

These conditions have existed in broad terms throughout much of the historical period prior to the mid-1980s. The subsequent period, when the estimated link between poverty and output growth weakened, was different. Specifically, aggregate supply shocks caused a relatively sizeable increase in the poverty rate, about 45 basis points between 1984 and 1993. Aggregate demand shocks meanwhile, contributed a reduction of 200 basis points in poverty. Unlike previous periods, the direction of aggregate supply's contribution to poverty differed from aggregate demand's and the magnitude of aggregate supply's contribution was relatively large and prolonged, offsetting about one-quarter of aggregate demand's effects. During this period, the distinction between the sources of output change becomes important for understanding the change in the poverty rate. Thus, one reason for the apparent breakdown in the relationship between poverty and output during the past ten years is a neglect of the distinction in existing empirical studies. The present results also indicate that the positive contribution of idiosyncratic poverty shocks during the period was relatively large by historical comparison, and further offset the effects of aggregate demand shocks. The latter finding is broadly consistent with the estimates produced by simpler empirical specifications [e.g., Cutler and Katz (1991), Blank (1991), and Tobin (1995)].

Dynamic Forecasts. The significance of distinguishing between the sources of output change is also indicated by the estimated system's forecast performance. Forecast evaluation was accomplished by first reestimating the model using data for the period 1959 to 1983. A full

dynamic simulation was then produced for the period 1984 to 1993. The results of the exercise show that the model generally overpredicts poverty for the past decade, in contrast to the static underpredictions generated by existing studies using alternative specifications. It is interesting to note that where other studies have found a growing underprediction, the present model's prediction of the 1993 poverty rate is quite accurate -- 14.9% compared to the 15.1% actual rate.

IV. Robustness Checks

The sensitivity of the basic results was examined with respect to three aspects of model estimation -- identifying restrictions, trend adjustment procedures for the unemployment and poverty rates, and variable definitions.

Identifying Restrictions. The baseline specification identifies aggregate supply shocks using permanent output changes as in Blanchard and Quah (1989) and identifies poverty shocks by assuming that poverty changes have no permanent or contemporaneous effect on output [$C_{13}(1)=0$ and $S_{13} = 0$]. The latter restriction was chosen as a baseline because it is consistent with existing single-equation specifications in which poverty is regressed on contemporaneous output growth. And given these two restrictions, aggregate demand shocks are identified by default as shocks to the unemployment rate. To gauge the importance of the baseline restrictions, impulse responses and historical decompositions were recalculated by identifying aggregate demand shocks with the assumption that the poverty rate has no contemporaneous affect on the unemployment rate ($S_{23} = 0$). Aggregate supply shocks were identified as before, with poverty shocks identified by default.

The new identifying restrictions produce impulse responses virtually identical to the baseline responses.⁷ The responses are shown in Figures 6 through 8. The time profile of each

response is essentially unchanged with each response disappearing by the fifteenth year. The historical decompositions are also quite similar, as are the variance decompositions, although in both, poverty shocks are revealed to play a larger role than in the baseline. As in the baseline historical decompositions, demand shocks contributed to a large decline in the poverty rate during the past ten years, which was offset by the effects of supply and idiosyncratic shocks.

Methods for Detrending the Unemployment and Poverty Rates. While the use of actual non-detrended data is considered most appropriate in the present study, the implications of detrending are examined. Following Blanchard and Quah (1989), the unemployment rate is linearly detrended. Visual inspection of the data suggested that a continuous piecewise linear trend, with a trend change in 1974, was suitable for the poverty rate.

The resulting impulse responses are broadly consistent with the baseline findings, but some differences may be noted. The initial impact of a supply shock on the poverty rate is smaller than before (about $1/6$ as large), with the impact vanishing more quickly than before (about seven years compared to about fifteen years in the baseline). The response of the poverty rate to a demand shock appears quite similar in magnitude; however, the impact vanishes after about seven years as opposed to fifteen in the baseline. Likewise, the response of the poverty rate to an idiosyncratic shock is of the same magnitude as that in the baseline, with the impact disappearing more quickly (in about seven years). Not surprisingly, then, linearly detrending the poverty and unemployment rates produces less persistence in the empirical model. The variance decompositions again show that most variation in the poverty rate arises from variation in aggregate demand, although the fraction accounted for by idiosyncratic shocks is higher than in the baseline.

The historical decompositions based on the detrended data are noticeably different than the baseline results. As before, demand shocks contributed to a lower poverty rate during the 1984 to 1993 period. However, the magnitude of the decline is smaller (about 110 basis points compared to about 200 in the baseline). Aggregate supply shocks contribute to a higher poverty rate, as in the baseline, but, as with demand shocks, the magnitude is smaller than before (about 20 basis points instead of 45). The contribution of idiosyncratic poverty shocks is most different, leading to a decrease in the poverty rate of close to 53 basis points. Thus, the decision about whether to detrend the data matters. Nonetheless, not detrending is the preferred choice in the present instance, and so the baseline results are considered most informative.

Variable definitions. As a final robustness check, the white poverty rate and the unemployment rate for white males 20 years and older were substituted for the total poverty rate and the unemployment rate for males 20 years and older used in the baseline. The baseline identifying restrictions were employed. This variant was examined because some studies [e.g., Blank and Blinder (1986)] present evidence that the sensitivity of poverty rates to output differs by racial category. The impulse responses and historical decompositions based on the new variables were very close to the baseline findings, and there are no significant discrepancies to report. The variance decompositions reveal that a somewhat larger fraction of the poverty rate's forecast-error variance is explained by idiosyncratic shocks.

V. Conclusions

This article reexamined the empirical link between the poverty rate and output. Existing studies have identified a breakdown in estimated relationships, with models generally underpredicting the poverty rate during the past ten years. The present paper argued that part of the apparent breakdown resulted from a failure in previous studies to differentiate between sources of output change, especially during the last ten years. The analysis relied on a structural VAR that separately identified aggregate demand, aggregate supply, and poverty rate shocks. Historical decompositions and forecasts from the estimated model indicated that aggregate supply shocks led to a higher poverty rate during the last ten years, partly offsetting the favorable contributions of aggregate demand shocks and helping to explain the breakdown in simpler poverty/output relationships. Similar to results of existing studies, however, the present results also revealed that idiosyncratic shocks during the last ten years impacted the poverty rate with a magnitude large by historical comparison. Identifying the particular natures of both the aggregate supply and idiosyncratic poverty rate shocks warrants further attention.

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Table 1
Test Statistics for Unit Root and Stationarity Tests, 1959-1993^a

	ADF (H ₀ : unit root)	PP	KPSS (H ₀ : stationarity)
Log real GDP	-2.63	-1.95	0.22*

^a * indicates significance at 1%. Augmented Dickey-Fuller (ADF) tests employ two annual lags. Phillips-Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests set the lag truncation parameter to two. Test equations include a constant and trend. The sample period is 1959 to 1993, the period over which observations on the official poverty rate are available.

Table 2
Estimated Reduced Form Coefficients, 1959-1993*

	Explanatory Variables						
Equation	Const.	ΔY_{t-1}	ΔY_{t-2}	U_{t-1}	U_{t-2}	POV_{t-1}	POV_{t-2}
ΔY_t	-5.104 ^b	1.068 ^b	0.077	0.026 ^c	-0.020 ^c	-0.007	0.008
U_t	409.563 ^c	-70.626 ^c	-3.900	-0.478	1.074 ^c	0.331	-0.314
POV_t	230.214 ^c	-35.067 ^b	-0.467	-0.544 ^a	0.536 ^b	1.163 ^c	-0.257

*a, b, and c indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Unemployment and poverty rates are expressed in basis points.

Table 3
Estimated S Matrix^a

Element	Estimated Value
S11	0.4442
S12	-1.413
S21	5.638
S22	55.837
S23	-25.375
S31	14.800
S32	45.520
S33	23.809

a. Element S13 is constrained to equal 0. See the text for discussion.
Unemployment and poverty rates are expressed in basis points.

Table 4
Poverty Rate Variance Decompositions

	Percent of Variance in Poverty Rate Due to Variance in:		
Horizon	Supply Shocks	Demand Shocks	Idiosyncratic Shocks
1 year	7.7	72.5	19.8
5 years	1.1	72.0	26.9
10 years	1.2	73.0	25.8
15 years	1.3	73.2	25.5

Endnotes

1. Technological change need not always increase poverty. For example, the introduction of cash registers at fast-food establishments that use pictures of menu items instead of numbers presumably makes jobs available to lower skilled individuals. In this case, poverty could fall as a result of the new technology.
2. Several studies also include inflation, although the estimated coefficient generally is small in magnitude and/or statistically insignificant. These studies also employ specifications that constrain the dynamic response of the poverty rate. Thus, the present study omits inflation and employs more flexible dynamics.
3. Data for the study were obtained from standard government sources.
4. Phelps (1970) presents a review of theoretical models consistent with a stationary unemployment rate. A model in which the unemployment rate is allowed to follow a random walk is found in Summers and Blanchard (1986).
5. Theoretical problems notwithstanding, some studies have tested for unit roots in the unemployment rate, with nonstationarity generally rejected in longer samples. See, for example, Nelson and Plosser (1982) and KPSS (1992). Others that analyze unemployment rate movements over shorter horizons [e.g., Judd and Trehan (1989)] provide evidence consistent with nonstationarity.
6. Since the focus of the study is on the explanation of the poverty rate, only the responses of poverty to the model's three shocks are presented in the interest of space. A full set of responses is available on request.
7. Responses to aggregate supply shocks necessarily will equal those in the $S_{13}=0$ case.

Figure 1
Predicted vs. Actual Poverty Rates
(Basis Points)

Figure 2
Baseline Poverty Response to a Supply Shock*
(Basis Points)

* This figure shows the response of the poverty rate, measured in basis points, to an aggregate supply shock that raises output by 0.4 percentage points on impact.

Figure 3
Baseline Poverty Response to a Demand Shock*
(Basis Points)

* This figure shows the response of the poverty rate, measured in basis points, to an aggregate demand shock that raises output by 1.4 percentage points on impact.

Figure 4
Baseline Poverty Response to a Poverty Shock
(Basis Points)

Figure 5
Historical Decomposition of the Poverty Rate

Figure 6
Poverty Response to a Supply Shock*
(Alternative Identification, Basis Points)

* This figure shows the response of the poverty rate, measured in basis points, to an aggregate supply shock that raises output by 0.4 percentage points on impact.

Figure 7
Poverty Response to a Demand Shock*
(Alternative Identification, Basis Points)

* This figure shows the response of the poverty rate, measured in basis points, to an aggregate demand shock that raises output by 1.3 percentage points on impact.

Figure 8
Poverty Response to a Poverty Shock
(Alternative Identification, Basis Points)