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Macroeconomic Fluctuations and Poverty

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Abstract and Keywords

This article examines the dynamic relationship between macroeconomic performance and measures of poverty in the United States. The article is organized as follows. Section 2 presents insights on the relationship between poverty and macroeconomic performance that emerge from the literature. The emphasis is on empirical studies from 1986 to 2011. Section 3 provides a snapshot of the change in poverty over National Bureau of Economic Research-dated recessions for a variety of poverty measures. Section 4 uses vector autoregressions (VARs) to characterize the response of poverty to innovations in various social indicators and measures of macroeconomic performance. Section 5 expands the empirical analysis to include alternative measures of poverty—a consumption-based poverty rate constructed by Meyer and Sullivan (2010) and an income-based poverty rate constructed by Broda and colleagues (2009) by using a consumer price index that has been adjusted for substitution and quality bias. Section 6 conducts a forecasting exercise for income poverty and consumption poverty. Section 7 concludes and offers suggestions for future research.

Keywords: macroeconomic performance, poverty measures, recessions, consumption, poverty rates, income poverty

1. Introduction

Once a society commits to measuring regularly the fraction of its population that lives in poverty, it invites study of how and why that fraction changes over time. This chapter presents a review of the scholastic effort to answer, from a macroeconomic perspective, the how and why questions for poverty in the United States over the past three decades. Additionally, it provides an updated quantitative summary of aggregate poverty facts using elementary statistical methods that are commonly used in modern business cycle analysis. A motivation for understanding what has been done before and what we know today is that lessons learned might improve the design and implementation of future antipoverty policy.

This chapter is structured as follows. In Section 2, we convey insights on the relationship between poverty and macroeconomic performance that emerge from the literature. Our emphasis is on empirical studies from 1986 to 2011. In Section 3, we provide a snapshot of the change in poverty over NBER-dated recessions for a variety of poverty measures. In the remainder of the chapter, we go behind the scenes of this snapshot. In Section 4, we use vector autoregressions (VARs) to characterize the response of poverty to innovations in various social indicators and measures of macroeconomic performance. There we emphasize the distinction (p. 520) between the ability of unemployment to forecast poverty and the dynamic response of poverty to unemployment innovations. Further, we provide evidence that inflation innovations may be a more important source of fluctuations in income poverty rates than previously acknowledged. In Section 5, we expand our empirical analysis to include alternative measures of poverty—a consumption-based poverty rate constructed by Meyer and Sullivan (2010) and an income-based poverty rate constructed by Broda and colleagues (2009) by using a consumer price index (CPI) that has been adjusted for substitution and quality bias. In Section 6, we conduct a forecasting exercise for income poverty and consumption poverty. We predict poverty rates for 2008 and 2009 with a VAR that is estimated by using data from 1984 to 2007. When using the official income poverty rate, we make poor forecasts of the 2008 and 2009 rates. This suggests the presence of structural changes between 2007 and when the financial crisis of 2008–9 took hold. In contrast, we make relatively successful forecasts of consumption poverty in 2008 and 2009. This suggests that the smoothness of consumption poverty was relatively robust to the financial and economic shocks experienced in the 2007–9 period. Section 7 concludes and offers suggestions for future research.

2. Poverty and Macroeconomic Activity: An Overview of Previous Research

Since Blank and Blinder (1986), studies on the relationship between poverty and the macroeconomy have aimed largely for three goals: (1) an explanation of how macroeconomic conditions affect the well-being of the poor and quantification of the relationship using various econometric methodologies; (2) a consideration of how the poverty-macroeconomy nexus has changed over time and the reasons behind the changing relationship; and (3) documentation of how the poverty-macroeconomy relationship varies across demographic groups, regions, states, and countries.

A strong economy is likely to lift people out of poverty. During business-cycle upswings, average income increases and the percentage of people below an absolute poverty line decreases if the shape of income distribution does not change (Blank and Blinder 1986; Romer and Romer 1998). Economic growth, however, is not the only channel through which the macroeconomy affects the well-being of the poor in a country. Previous studies consistently find that several macroeconomic factors may influence poverty: unemployment, inflation, government transfers, income inequality, and median earnings of workers (Blank 2000; Blank and Blinder 1986; Cutler and Katz 1991; Freeman 2003; Gundersen and Ziliak 2004; Haveman and Schwabish 2000; Hoover et al. 2008; Hoynes et al. 2006; Iceland et al. 2005; Lang 2007; Meyer and Sullivan 2011; Murthy 2002; Romer and Romer 1998). Among these factors, unemployment and inflation have received the most attention.

(p. 521) The literature has generally emphasized the role of unemployment over that of inflation in influencing the well-being of the poor (Blank 2000; Blank and Blinder 1986; Freeman 2003; Haveman and Schwabish 2000; Hoover et al. 2008; Hoynes et al. 2006; Iceland et al. 2005; Meyer and Sullivan 2011; Murthy 2002; Romer and Romer 1998). Unemployment may lead to a high poverty rate by reducing job opportunities. The harmful effect of unemployment may be greater for the poor because they tend to have fewer skills and less investment in human capital. Therefore, they tend to be the last hired and the first fired over the course of the business cycle (Blank and Blinder 1986; Murthy 2002). Thus, when unemployment rises, the average income of the poor may decline and the income distribution may also widen.

The empirical evidence suggests that the effect of unemployment on poverty rates is generally strong, positive, and statistically significant (Blank 2009; Blank and Blinder 1986; Haveman and Schwabish 2000; Meyer and Sullivan 2011; Romer and Romer 1998). Murthy (2002), who focuses on African American families, confirms a positive relationship between the unemployment and poverty rates. Some researchers, however, have found that the link between poverty and unemployment weakened during the 1980s. Hoynes and colleagues (2006) examine the effects of unemployment on poverty for all persons, controlling for median wages, wage inequality, the fraction of female workers, and year and Census division fixed effects. The authors find that during 1980–2003 compared to 1967–79, the effect of unemployment on poverty is weaker but still significantly positive at the 1 percent level. Freeman (2003) finds that the effect of unemployment on poverty for all persons is insignificantly negative for 1982–92 but significantly positive for 1993–2001. More recently, Bitler and Hoynes (2010) examine whether poverty and participation in social safety-net programs have become more cyclically sensitive in the post-welfare reform (post-1996) period. They focus on the nonelderly, families with children, and reforms to the cash assistance system. The unemployment rate is their measure of economic activity. They find that food-stamp participation and a measure of participation in noncash safety-net programs broadly defined increase more in response to an increase in unemployment in the postwelfare reform period.

The effect of inflation on poverty, however, is modest, positive, and often statistically insignificant (Balke and Slottje 1993; Blank and Blinder 1986; Meyer and Sullivan 2011; Romer and Romer 1998). Theoretically, the impact of inflation on the poor can work in multiple directions. Inflation can worsen poverty rates by increasing the price level of necessities and decreasing the real value of nominal wages and transfers unless the latter two are indexed with inflation (Romer and Romer 1998). Romer and Romer (1998) note that real welfare benefits fell in the 1970s potentially due to inflation. On the other hand, a rise in inflation might not be as harmful as expected. Unanticipated inflation can reduce the real value of nominal liabilities and help the poor if they are net nominal debtors (Romer and Romer 1998). Additionally, over 90 percent of the pension income of the elderly poor lies in Social Security, which is indexed.

(p. 522) Using data from 1959 to 1983, Blank and Blinder (1986) report that inflation increases the poverty rate modestly. Using data from 1969 to 1994, Romer and Romer (1998) find that with only anticipated inflation as a regressor, a rise in inflation is associated with lower poverty. They find, however, that neither anticipated nor unanticipated inflation have significant effects on poverty when controlling for changes in unemployment rate and a trend. They suggest that the negative effect of anticipated inflation is absorbed by unemployment. Moreover, the potential redistributive effects of unanticipated inflation on the poor through capital gains and losses are modest because the mean levels of financial assets and liabilities among the poor are too small to be affected by inflation, and the large majority of the poor do not have many financial assets or liabilities in the first place (Romer and Romer 1998).

Balke and Slottje (1993), however, have put together one of the few studies that finds a potentially strong impact of inflation on poverty. They examine the impact of inflation on the growth of poverty using a structural VAR. They use data from 1959 to 1989 on federal expenditures, transfers, the money supply, the GNP deflator, and the unemployment rate. They report that inflation shocks account for a greater portion of poverty's forecast error variance in the long run than in the short run whereas the opposite is true for unemployment shocks. The impulse response functions they calculate indicate that inflation has a positive impact on poverty growth at the 10 percent level. They argue that if the incomes of the poor tend to grow at a slower rate than inflation, while the poverty threshold is indexed with inflation, poverty will rise when inflation increases.

Other macroeconomic variables such as transfer payments, median earnings, and income inequality can also have significant impacts on the well-being of the poor (Balke and Slottje 1993; Blank 2009; Blank and Blinder 1986; Hoynes et al. 2006). Transfer payments have the potential to greatly enhance the well-being of the poor because the major sources of cash welfare benefits for the nonelderly poor (Temporary Assistance to Needy Families [TANF], General Assistance, and the earned income-tax credit [EITC]) and the major sources of in-kind benefits (food stamps, Medicaid, and housing assistance) can make a substantial contribution to helping families make ends meet (Hoynes et al. 2006). TANF benefits are distributed to low-income families with children, and most of the recipient families are female-headed. The EITC is a federal tax credit targeted at low-income working families with children. Transfer programs like these that focus on reducing welfare dependence can directly help raise the income of the poor and indirectly induce more labor force participation from the poor (Hoynes et al. 2006).

The poverty-reducing effect of the EITC and in-kind transfers, however, will be lost on the official poverty rate because the official definition of income counted for poverty measurement is money-income before taxes, excluding in-kind benefits. Hoynes and colleagues (2006) also argue that TANF will have little effect on the poverty rate because TANF benefits are phased out at income levels much below the poverty threshold while holding constant any behavioral changes. They examine the changes in poverty rates across various measures of poverty, including (p. 523) or excluding transfer benefits. In 2003, the poverty rate based on money income minus all taxes plus the EITC lowered nonelderly poverty by 0.5 percentage points while the poverty rate with full income less taxes with means-tested cash transfers decreased poverty by 1.3 percentage points. In a regression of the poverty rate on the different government transfer programs with state and year fixed effects, Hoynes and colleagues (2006) confirm that changes in government spending over time explain little of the variation in poverty rates. Freeman (2003) also supports this result: transfers as a share of income are negatively associated with poverty but have no significant effect.

Balke and Slottje (1993) show that the growth rate of federal transfers has a significantly negative impact on the growth rate of overall poverty at the 10 percent level using a structural VAR.[1] Their forecast error variance decomposition results indicate that only from 5.2 to 10.3 percent of the error made in forecasting the growth of poverty is attributed to the growth of transfers, the second lowest after the growth of federal expenditures. Overall, government transfers seem to have a modest effect on poverty rates although they have a considerable effect on the poverty gap, which is the difference between family income and the poverty threshold (Hoynes et al. 2006).

Income inequality is another macroeconomic factor that potentially influences poverty. Researchers often suspect that rising income inequality in the economy will worsen poverty, and they report that inequality mitigated the favorable effects of good macroeconomic performance on poverty especially in the 1980s (Blank 2000, 2009; Freeman 2003; Iceland et al. 2005). Ferreira (in this volume) shows, however, that poverty, growth, and inequality share a “triangular relationship” in which, other things being equal, the impact of an increase in inequality on poverty is theoretically ambiguous. Empirical researchers control for income inequality by including the ratio of the 50th or 90th percentile to the 10th percentile of income, or the ratio of the median weekly wage to the 20th percentile of the weekly wage in their poverty regressions (Freeman 2003; Hoynes et al. 2006; Lang 2007, this volume).

Income inequality is not consistently found to have a significant effect on the poverty rate (Freeman 2003; Haveman and Schwabish 2000; Hoover et al. 2008; Hoynes et al. 2006). Hoynes and colleagues (2006) find a significantly positive association between log of the ratio of median to the 20th percentile weekly wages and the poverty rate for their full sample period, 1967–2003, and the subsample periods, 1967–79 and 1980–2003. On the other hand, Haveman and Schwabish (2000) use the variance of log earnings of all workers as the indicator of labor market inequality. They find a positive association between the variance of earnings and poverty but it is not statistically significant. Similarly, Freeman (2003) fails to find a statistically significant effect of income inequality on national poverty but shows a significant effect on the regional poverty rate, using the Gini coefficient in his estimation. Hoover and colleagues (2008) use the ratio of third-to-first quartile wage income and find that wage inequality only affects black poverty. Freeman (2003) suggests that including both transfers and an inequality measure in a model (p. 524) will make coefficients on both variables insignificant and smaller as inequality is factored into the decision to make transfers.

Previous research also notes that it is important to control for the real median (weekly) wage, earnings, or income, or the ratio of poverty line to mean or median income not only because labor market conditions have a potentially large impact on the well-being of the poor but also because the overall trend of rising income or economic growth can decrease the poverty rate (Blank and Blinder 1986; Freeman 2003; Hoynes et al. 2006; Lang 2007, this volume). The official poverty rate is an absolute poverty measure, which counts the number of persons or families earning incomes below a certain poverty threshold (i.e., the poverty line). An increase in the overall income level in the economy will reduce the number of people that fall below the poverty line and will decrease the absolute poverty rate.

There are, however, several issues that researchers need to consider when using median wages in the specification. First, Hoynes and colleagues (2006) have found that it is debatable whether median wages or median income is a better indicator of general growth in personal income. The former is an hourly price of labor but might not capture effectively a rise in per capita GDP whereas the latter mixes pure labor market opportunities with individual choices of hours of labor supply. However, they also conclude that using either median wages or median income does not change the results. They find that an increase in median wages has a negative and statistically significant effect on poverty. Second, it must be decided whether to use income data for all workers or for only male workers. Lang (2007) argues that median earnings for male workers are preferred because they better indicate the state of the labor market. Females' earnings have fluctuated due to rapid changes in the rate of female labor force participation and changes in the composition of the female labor force (Hoynes et al. 2006; Lang 2007). Male earnings are more insulated from these changes (Lang 2007). Lang finds a negative relationship between poverty and median male earnings.

We have reviewed how macroeconomic conditions can affect poverty by looking at specific macroeconomic indicators. These variables, however, may have a different impact on poverty depending on the measure of poverty. To represent the welfare of the poor, researchers use not only the official poverty rates calculated by the US Census Bureau but also alternative measures of poverty. The official poverty rate measures the fraction of people earning an amount of pretax money income that excludes in-kind transfers below a certain fixed-income threshold indexed with annual inflation (Dalaker 2005). The official poverty rate, however, has been criticized for several reasons. First, before-tax income excludes noncash benefits and omits important sources of income for the poor, such as in-kind transfers and tax credits, that have been key antipoverty programs since the 1990s (Meyer and Sullivan 2010). Second, there are flaws with adjustment for family size and lack of reliability of the real value of the poverty thresholds over time due to biases in the CPI for all urban consumers (CPI-U) (Broda et al. 2009).

Cutler and Katz (1991), Slesnick (1993), and Meyer and Sullivan (2010) argue that changes in consumption provide a better indicator of the effect of the (p. 525) macroeconomy on living standards of the poor than changes in income. When measured income fluctuates, consumption may vary little throughout the business cycle if additional credit channels like transfers from extended family members or in-kind social benefits are available to protect families from experiencing transitory changes in income (Meyer and Sullivan 2010). Moreover, while both consumption and income data are subject to measurement errors, consumption is reported more accurately than income especially for low-income people (Meyer and Sullivan 2010). In recessions, off-the-books income, interfamily transfers, and government transfers tend to be more prevalent and underreported in household surveys (Meyer and Sullivan 2010).

Two examples of alternative measures of poverty are consumption poverty and income poverty with a corrected CPI. First, Meyer and Sullivan (2010, this volume) construct a consumption poverty rate by calculating the percentage of individuals who live in families with resources that are below some poverty threshold. The poverty threshold varies by family size and composition, and the threshold in 1980 was adjusted so that consumption poverty equaled the official income poverty in that year to facilitate comparisons across measures (Meyer and Sullivan 2010). The Meyer-Sullivan poverty thresholds are also adjusted for inflation by using the CPI-U-RS to resolve a part of the biases in the standard CPI-U for the official poverty thresholds. Meyer and Sullivan (2010) find that the consumption poverty rate is typically lower than the official poverty rate.

Second, Broda and colleagues (2009) calculate an adjusted CPI, called C-CPI-U-BW, which adjusts for substitution bias and quality/new goods bias. C-CPI-U-BW tends to report lower inflation than the CPI-U: this makes the poverty thresholds adjusted with the C-CPI-U-BW lower than those updated with the CPI-U, and consequently Broda-Leitag-Weinstein's income poverty rate is lower than the official income poverty rate. For example, the poverty rate in 2005 with a corrected CPI would be half what the official poverty rate suggests (Broda et al. 2009).

Thus far, we have given an overview of the effects on poverty of macroeconomic performance in terms of unemployment, inflation, transfers, income inequality, and median earnings. We have also commented on alternative measures of poverty that can be used in poverty-macroeconomy research. Over the last three decades, researchers working in this area have also paid attention to three additional issues. First, researchers investigate why the relationship between poverty and macroeconomic activity has changed over the course of the business cycle (Blank 2009; Cutler and Katz 1991; Freeman 2003; Haveman and Schwabish 2000; Herbst 2008; Hoynes et al. 2006; Jefferson 2008). Second, researchers also examine how the effects of macroeconomic activity on poverty differ across race or ethnicity, gender, age, immigration status, education level, family structure, and welfare policy (Balke and Slottje 1993; Blank 2000; Blank and Blinder 1986;

Gundersen and Ziliak, 2004; Herbst 2008; Hoynes et al. 2006; Jefferson 2006; Murthy 2002). Third, the sample data have also diversified from national to regional-level or state-level or cross-national data (Burkhauser et al. 2008; Freeman 2003; Gundersen and Ziliak 2004; Hoover et al. 2008; Iceland et al. 2005; Romer and Romer 1998). Of course, (p. 526) our list of references here is far from exhaustive. It is meant to provide the reader with entry points to a large and vibrant literature.

3. Poverty and NBER-Dated Recessions

Table 16.1 offers an overview of poverty-rate changes during NBER-dated recessions from the 1960s through 2009. The table covers not only the official poverty rate but also alternative poverty measures that have been adjusted for taxes, biases in the CPI, and one based on consumption data. The different measures of poverty show different extents and direction of fluctuation in poverty rates. For example, during the recession of 1980 (the first recession with data on all of the different poverty measures), poverty rates for all people, after taxes, and with the corrected CPI, increased by 0.8 to 1.2 percentage points. On the other hand, for the same period, the consumption-based poverty rate declined by 0.2 percentage points, which is the opposite direction and also smaller in absolute value. Other notable features of Table 16.1 include the reduction in the magnitude of changes in income-based poverty rates in the three recessions before the recession of 2007–9; the decline in consumption poverty for two of the four recessions for which we have consumption poverty data; and the large impact that recessions have on female-headed households and black families.

Table 16.1 provides only a snapshot of the relationship between poverty and the macroeconomy and as such it has limitations. First, the table fails to capture the poverty-macroeconomy link during economic expansions. That relationship may be different from what it is during a recession. Second, the table is silent on any potential lagged response of poverty rates after the recession. The impact of a recession is not just contemporaneous. It lasts over time through such channels as high unemployment, which does not always decrease instantly as the economy recovers. Finally, it tells us nothing about possible reasons for the relationships we observe.

4. Poverty Dynamics: A Quantitative Summary

Many of the insights and issues that are related to poverty dynamics and macroeconomic performance we discussed in the previous research cited in Section 2 can be summarized empirically by using VARs. To examine the predictive power of several variables for future poverty, we use reduced-form VARs of the form:

$$y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \varepsilon_t$$

(p. 527) (p. 528) where Y_t is a $n \times 1$ vector of variables at date t, $\boldsymbol{\alpha}$ is a $n \times 1$ vector of constants, ϕ_j is a $n \times n$ matrix of coefficients (j = 1, 2), and ε_t is an $n \times 1$ vector of error terms with a zero mean vector and $n \times n$ covariance matrix Σ. We use recursive VARs implied by the Cholesky factorization of Σ to calculate the dynamic effect on poverty of innovations in several macroeconomic variables. As opposed to single-equation regressions that include lagged values of one or two macroeconomic variables and the poverty rate, VAR analysis allows us to better capture the multiplicity of interactions and feedback that is likely to characterize the actual economy. Table 16.2 provides descriptive statistics on the data that are used in the VAR analysis. The sources are reported in the data appendix.

Table 16.1 NBER Recessions and Changes in Alternative Poverty Rates

Peak	Trough	AllPeople[1]	Aftertax[2]	Corrected-CPI[3]	Consumption[4]	Female-Head[1]	Black[1]
April 1960 (II)	February 1961 (I)	–0.3				–0.3	
December 1969 (IV)	November 1970 (IV)	0.5				–0.2	1.6
November 1973 (IV)	March 1975 (I)	1.2		0.8		0.3	–1.0
January 1980 (I)	July 1980 (III)	1.0	1.2	0.8	–0.2	1.9	1.9
July 1981 (III)	November 1982 (IV)	1.0	0.9	0.9	NA	1.7	2.2
July 1990 (III)	March 1991(I)	0.7	0.5	0.6	0.3	2.2	1.1
March 2001 (I)	November 2001 (IV)	0.4	0.4	0.3	–0.3	0.1	0.8

December 2007 (IV)	June 2009 (II)	1.8	0.9	NA	0.6	1.6	0.6

Notes: Quarter of the year in parentheses. When trough occurs in the same year as the peak, the poverty rate for the next year is used to compute difference. NA = not available. Changes are in percentage points.

(1.) Based on the Census Bureau's measure of money income and official threshold.

(2.) Based on after-tax income = money income + capital gains (losses) – federal and state income taxes – payroll taxes. This measure includes the value of tax credits such as the EITC and uses the official threshold, corrected for inflation using CPI-U-RS. This poverty measure was created by Meyer and Sullivan (2010).

(3.) Based on the official threshold that has been corrected for inflation using Broda and colleagues' (2009) adjusted CPI that corrects for substitution and quality bias in the standard CPI. This series ends in 2006.

(4.) Based on consumer expenditure survey data and thresholds corrected for inflation by using CPI-U-RS. This consumption-based poverty measure was created by Meyer and Sullivan (2010).

Sources: See the data appendix.

Table 16.2 Data Summary Statistics

Variable	Coverage	Mean	Std. Dev.
pchgdp	1967–2009	2.81	2.08
pov_allppl	1967–2009	12.98	1.14
pov_femhh	1967–2009	31.87	2.81
pov_black	1967–2009	26.93	3.70
unemp	1984–2009	5.83	1.22
infl	1984–2009	2.95	1.14
transfers	1984–2009	6.41	3.00
med_earnings	1984–2009	45,796.28	1097.68
50/10 ratio	1984–2009	2.42	0.07
pov_allppl	1984–2009	13.22	0.99
pov_consump	1984–2009	11.37	1.99
bwpov	1984–2006	7.34	2.11

Notes: Annual data. pchgdp = Real GDP growth (%); pov_allppl = Poverty for all persons (%); pov_femhh = Poverty for female-headed families (%); pov_black = Poverty for black families (%); unemp = Unemployment rate (%); infl = Inflation rate (%); transfers = Growth rate of government social benefits to persons (%); med_earnings = Real median earnings for full-time, year-round male workers ($); 50/10 ratio = Ratio of the median to the 10th percentile real income; pov_consump = Meyer-Sullivan (2010) consumption poverty rate (%); bwpov = Broda-Leitag-Weinstein (2009) poverty rate (%).

Sources: See the data appendix.

Our analysis has three objectives: (1) to represent poverty dynamics in the presence of multiple indicators of macroeconomic conditions over a multiyear horizon; (2) to consider how alternative poverty measures, including a consumption-based measure, alter our understanding of poverty dynamics; and (3) to forecast future poverty rates, paying particular attention to whether a VAR for poverty could have accurately forecasted poverty rates for 2008 and 2009 by using data through 2007.

4.1. The Canonical Dynamic Pattern

To provide a backdrop for the analysis to follow, we first characterize the canonical response of income poverty to growth innovations. We do this by relating real GDP (p. 529) growth to official poverty rates for all people, female-headed families, and black families in a VAR estimated by using data from 1967 to 2009. Real GDP growth is a representative indicator of the business cycle. The ordering in the VAR is real GDP growth, official poverty rates for all people, female-headed households, and black families. The lag length is one.

The Granger predictive causality tests in Table 16.3, Panel A, show that real GDP growth helps predict each poverty rate at the 5 percent level. Table 16.3, Panel A, also indicates additional marginal predictive relationships among income poverty measures. Poverty for black families helps predict the poverty rate for female-headed families, but poverty for all people do not. Poverty for all people and poverty for female-headed families also help predict poverty rate of black families. The results for poverty of female-headed families and black families show that the poverty rates for one of these population subgroups is an indicator for future hardship for the other and vice versa.

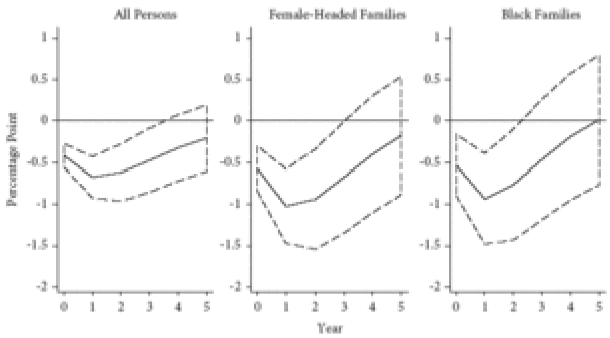

Figure 16.1 Responses of the poverty rate to one standard deviation shock in real GDP growth

Figure 16.1 shows the impulse responses of poverty rates to a one standard deviation innovation in GDP growth and the associated 95 percent confidence intervals. [2] A one standard deviation innovation in GDP growth is associated with (p. 530) a greater decrease in the female-headed and black family poverty rates than in the all-persons poverty rate. The contemporaneous reduction in the poverty rates for all persons, female-headed families, and black families is -0.42, -0.58, and -0.53 percentage points, respectively. The peak effect for all-persons poverty is -0.68 percentage points one year after the shock. The peak effect for poverty for female-headed families is -1.02 percentage points one year after the shock. The peak effect for black-family poverty is -0.94 percentage points one year after the shock. This evidence suggests that, in the short run, poverty rates for female-headed and black families are more responsive to economic expansion. A positive GDP growth innovation helps these groups more.

Table 16.3 Descriptive Statistics for the Poverty VAR

A. Granger-Causality Tests				
	Dependent Variable in Regression			
Regressor	**pchgdp**	**pov_allppl**	**pov_femhh**	**pov_black**
pchgdp		0.00*	0.00*	0.01*
pov_allppl	0.40		0.65	0.01*
pov_femhh	0.80	0.91		0.04*
pov_black	0.84	0.84	0.01*	

Notes: p-values from the F-tests that evaluate the null hypothesis that the lagged values of each regressor variable in column 1 do not help predict the current value of the dependent variable when the three other controls are held constant; the lag length is one.

(*) = significant at the 5% level

B. Variance Decompositions from the Recursive VAR Ordered as pchgdp, pov_allppl, pov_femhh, pov_black; Impulse = pchgdp			
	Response Variables		
ForecastHorizon (year)	**pov_allppl**	**pov_femhh**	**pov_black**
1	0.58*	0.34*	0.17
	(0.10)	(0.12)	(0.11)
3	0.80*	0.60*	0.38*
	(0.08)	(0.13)	(0.16)
5	0.83*	0.58*	0.33
	(0.08)	(0.16)	(0.18)

Notes: Standard errors in parentheses. Each coefficient is the fraction of the forecast error variance of each variable due to the real GDP growth (impulse variable); the lag length is one.

(*) = significant at the 5% level.

Table 16.3, Panel B, reports the forecast error variance decompositions for this VAR. For all-persons poverty, the fraction of the forecast error variance due to GDP growth innovations grows throughout the forecast horizon. This suggests that overall economic performance becomes more important for this poverty rate over time and rises to over 80 percent in the fifth year. The fraction of the forecast error variance for the female-headed family poverty rate due to growth innovations rises to 60 percent over the first three years of the forecast horizon and then declines. For the black-family poverty forecast error variance, the importance of growth innovations is never greater than 40 percent throughout the five-year horizon and it becomes insignificant after the third year.

4.2. Unemployment, Inflation, and Income Poverty

Having described the canonical dynamic pattern for poverty, we begin our more detailed examination of the dynamics of poverty over the business cycle by estimating a baseline VAR using unemployment, inflation, and the official (all-persons) **(p. 531)** income poverty rate. Inflation and unemployment are central variables in many macroeconomic models and they are important gauges of macroeconomic performance. As noted above, these two variables have played a key role in the development of the empirical macroeconomics poverty literature. We restrict the sample period to 1984–2009. Our reasons for the sample restriction are two-fold. First, Meyer and Sullivan's (2010) consumption-based poverty rate data exist continuously over this period only and we want to compare results by using consumption poverty with those using income poverty. Second, we want to conduct a forecasting exercise that uses the period 1984–2007 as a base for forecasting. Consistent with the smaller sample size, we emphasize the 10 percent significance level when reporting the VAR results below.

In this three-variable VAR, the Granger causality tests in Table 16.4, Panel A, indicate that inflation and unemployment predict the all-persons poverty rate. Inflation predicts unemployment, and unemployment predicts inflation. All-persons poverty does not predict inflation or unemployment.

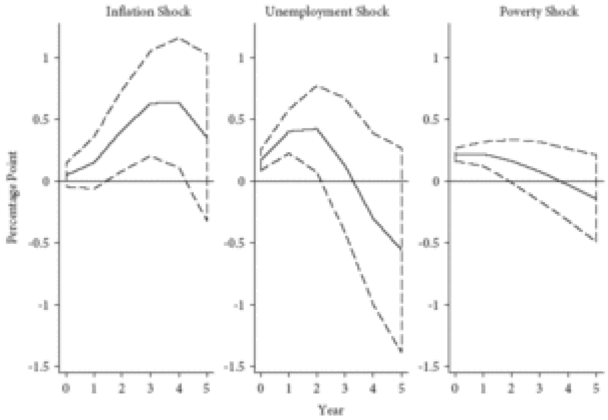

Figure 16.2 Responses of the official poverty rate to one standard deviation shock (three-variable VAR)

Figure 16.2 shows the impulse response of the official poverty rate to a one standard deviation innovation in inflation, unemployment, and to official poverty (p. 532) itself and the associated 90 percent confidence intervals.[3] The contemporaneous effect of a one standard deviation innovation in unemployment on poverty is 0.17 percentage points, which is larger than the corresponding effect of an inflation innovation of less than 0.06 percentage points. The impact of the unemployment innovation peaks at 0.47 percentage points two years later and then becomes statistically insignificant afterward. On the other hand, the impact of the inflation innovation continues to build, reaching its statistically significant peak of 0.64 percentage points four years after the shock.

Table 16.4 Descriptive Statistics for the Three-Variable VAR

A. Granger-Causality Tests

	Dependent Variable in Regressionn		
Regressor	**infl**	**unemp**	**pov_allppl**
infl		0.02*	0.00*
unemp	0.04*		0.05*
pov_allppl	0.18	0.57	

Notes: p-values from the F-tests that evaluate the null hypothesis that the lagged values of each regressor variable in column 1 do not help predict the current value of the dependent variable when the two other controls are held constant; the lag length is two.

(*) = significant at the 10% level.

B. Variance Decompositions from the Recursive VAR Ordered as infl, unemp, pov_allppl Response = pov_allppl			
	Impulse Variables		
ForecastHorizon (year)	**Infl**	**unemp**	**pov_allppl**
1	0.03	0.37*	0.59*
	(0.07)	(0.15)	(0.15)
3	0.28	0.54	0.18
	(0.26)	(0.29)	(0.11)
5	0.62*	0.30*	0.08
	(0.18)	(0.17)	(0.06)

Notes: Standard errors in parentheses. Each coefficient is the fraction of the forecast error variance of the official income poverty rate due to the impulse variable in each column; the lag length is two.

(*) = significant at the 10% level.

The forecast error variance decompositions shown in Table 16.4, Part B, provide a useful perspective on the roles of unemployment and inflation innovations in poverty dynamics. Over a short forecast horizon (the first year), unemployment and own-poverty innovations dominate the forecast error variance for poverty. In the first year, unemployment innovations explain 37 percent of the forecast error variance for poverty whereas inflation shocks explain 3 percent. Unemployment's share of the forecast error variance for poverty is even larger in the third year, although it is not statistically significant. Eventually, inflation innovations take over. Inflation innovations account for a large fraction of the forecast error variance for poverty, including a substantial 62 percent in the fifth year. This share is more than double the unemployment innovation share.

Our results on inflation are most closely aligned with those of Balke and Slottje (1993). Using a structural VAR with data from 1959–89, they find a significantly positive impact of inflation on the growth rate of poverty at the 10 percent (p. 533) level. Moreover, similar to our forecast error variance decomposition result, their analysis shows that inflation shocks explain a greater proportion of the forecast error variance of poverty in the long run than in the short run, and unemployment shocks follow the opposite pattern.

The finding of a significantly positive association between inflation and poverty that is stronger than the relationship between unemployment and poverty in the long run may appear to be counterintuitive. Therefore, we consider possible explanations for this "price puzzle" in the relationship between poverty and the macroeconomy (Balke and Emery 1994). Our explanations are analogous to those given by Sims (1992) for the conventional "price puzzle" in the relationship between the federal funds rate and inflation.

First, when inflation rises or is expected to rise, the Federal Reserve systematically raises the federal funds rate, which may end up decreasing output and raising the poverty rate. If we believe that the conventional "price puzzle," in which an increase in the federal funds rate is associated with rising inflation, is present in our estimation period of 1984–2009, then it may be the case that the Federal Reserve raises the federal funds rate to cool down the economy but not by enough to prevent inflation from actually rising (Balke and Emery 1994). Then, such a monetary contraction leads to a higher poverty rate, which explains the strong and long-lasting impact of inflation on the poverty rate. Second, if inflation tends to rise faster than the growth of the incomes of the poor while the poverty line is indexed with inflation, then the poverty rate will increase (Balke and Slottje 1993).

4.3. Incorporating Broad Social and Economic Indicators

A shortcoming of the three-variable VAR is that it excludes several variables that poverty scholars believe are important for understanding the evolution of poverty. We now proceed to a richer VAR analysis that includes social indicators and measures of macroeconomic performance. We augment the previous three-variable VAR by adding the growth rate of transfers, the ratio of the 50th to the 10th percentile income for male workers, and real median earnings for full-time, year-round male workers. These variables play an important role in many of the studies reviewed above. They are proxies for the social safety net, income inequality, and the trend in the overall income level in the economy, respectively. Again, our sample period is 1984–2009, and the VAR contains two lags of each variable. The ordering is median earnings for males, inflation, unemployment, 50/10 ratio, growth rate of transfers, and the official poverty rate for all people.

The Granger causality tests in Table 16.5, Panel A, show that inflation and growth of transfers help to predict the poverty rate while median earnings, unemployment, and the 50/10 ratio do not. In general, the VAR suggests considerable interaction between the variables with respect to marginal predictive power. Every variable, except unemployment, is predicted by at least one other variable. Every variable, except median earnings, predicts at least one other variable. These findings support insights from the literature that suggest that the connections between (p. 534) these variables should be strong. The inability of past unemployment to forecast future poverty once other factors are controlled for does not mean that unemployment does not matter for poverty. There is a distinction to be made between marginal predictive power and exogeneity.

Table 16.5 Descriptive Statistics for the Six-Variable VAR with Official Income Poverty

A. Granger-Causality Tests

	Dependent Variable in Regression					
Regressor	**median earnings**	**infl**	**unemp**	**50/10 ratio**	**transfers**	**pov_allppl**
median earnings		0.33	0.61	0.60	0.27	0.57
infl	0.16		0.97	0.61	0.07*	0.04*
unemp	0.33	0.71		0.05*	0.27	0.73
50/10 ratio	0.07*	0.32	0.32		0.75	0.33
transfers	0.04*	0.03*	0.58	0.52		0.03*
pov_allppl	0.10*	0.19	0.26	0.13	0.39	

Notes: p-values from the F-tests that evaluate the null hypothesis that the lagged values of each regressor variable in column 1 do not help predict the current value of the dependent variable when the five other controls are held constant; the lag length is two.

(*) = significant at the 10% level.

B. Variance Decompositions from the Recursive VAR Ordered as median earnings, infl, unemp, 50/10 ratio, transfers, pov_allppl; Response = pov_allppl						
	Impulse Variables					
ForecastHorizon (year)	**median earnings**	**infl**	**unemp**	**50/10 ratio**	**transfers**	**pov_allppl**
1	0.04	0.10	0.73*	0.02	0.03	0.08*
	(0.07)	(0.11)	(0.13)	(0.02)	(0.02)	(0.03)
3	0.05	0.10	0.73*	0.05	0.05	0.02
	(0.11)	(0.21)	(0.29)	(0.08)	(0.08)	(0.02)
5	0.03	0.50*	0.39*	0.02	0.04	0.01
	(0.07)	(0.16)	(0.16)	(0.08)	(0.05)	(0.01)

Notes: Standard errors in parentheses. Each coefficient is the fraction of the forecast error variance of the official income poverty rate due to the impulse variable in each column; the lag length is two.

(*) = significant at the 10% level.

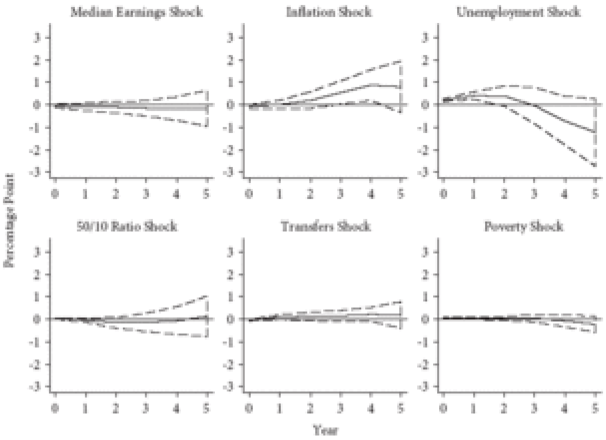

Figure 16.3 Responses of the official poverty rate to one standard deviation shock (six-variable VAR)

Figure 16.3 shows the responses of the poverty rate to a one standard deviation innovation in each of the variables in the six-variable VAR and the associated 90 percent confidence intervals.[4] The responses to inflation and unemployment innovations are slightly different than in the three-variable VAR. The effect of a one standard deviation innovation in unemployment on poverty is 0.21 percentage points contemporaneously and peaks at 0.41 percentage points one year later. The sign of the effect also changes to negative after two years although the effect (p. 535) becomes insignificant after one year. On the other hand, the effect of a one standard deviation innovation in inflation on poverty starts at -0.08 percentage points contemporaneously, but rises to 0.88 percentage points four years later. The effect of inflation innovations on poverty, however, is significant three and four years after the innovation. Comparing the result for unemployment innovations to that for inflation innovations in this six-variable model shows that the latter elicits a longer-lived rise in poverty that is also greater in magnitude than the former. Although we do not argue for a causal relationship among the variables with this VAR, the impulse responses indicate that inflation innovations are more strongly associated with poverty-rate responses when controlling for additional macroeconomic and social variables.

Poverty has a negative contemporaneous response to an innovation in transfers. The magnitude, -0.05 percentage points, is not large but is statistically significant at the 10 percent level. Transfer innovations are associated with higher poverty rates from one to five years after the innovation. The response of poverty to transfers is greatest, at 0.21 percentage points, four years after the innovation although none of the out-year responses are statistically significant. The positive relationship between transfers and poverty is counterintuitive because transfers are usually expected to lower the poverty rate. A possible explanation for this result is that the government, anticipating a higher poverty rate in the near future, raises transfer payments but not by enough to lower the poverty rate. Thus, a rise in the growth of transfers is followed by an increase in the poverty rate. This explanation (p. 536) is supported by Granger causality tests, which show that the growth rate of transfers helps predict the current poverty rate.

As mentioned earlier, median earnings control for the possibility that an upward trend in the overall income level in the economy decreases the poverty rate. Median earnings innovations are associated with a lower poverty rate. The effect of median earnings on poverty, however, is not statistically significant throughout the five-year horizon.

Rising income inequality has been identified as one of the major culprits that offset the favorable effects of a sound macroeconomy on the poverty rate from the mid-1980s through 2006 (Blank, 2000, 2009). In this six-variable VAR, the response of poverty to an innovation in the ratio of the 50th to the 10th percentile income for male workers is significant but modest at 0.04 percentage points contemporaneously. Over the remainder of the five-year horizon, the response is not statistically significant.

The forecast error variance decompositions for this VAR are shown in Table 16.5, Panel B. Over 70 percent of the forecast error variance for poverty is due to unemployment innovations in the short run whereas inflation innovations become more important in the long run. Innovations in median earnings, transfers, and the 50/10 ratio (income inequality) explain very little of the forecast error variance at the 10 percent level throughout the five-year horizon.

The impulse response functions and forecast error variance decompositions associated with this VAR exhibited a slight sensitivity to different orderings of the variables. If either transfers or unemployment were ordered first, some of the impulse response functions had wider confidence intervals, different point estimates in some of the out years, and a few changes in sign in the point estimates in some of the out years. By construction, these differences carried over to the forecast error variance decompositions. Placing transfers or unemployment first, however, suggests that they are in a sense causally prior to the other variables in the VAR.[5]

5. What Measure of Poverty?

In Section 2, we noted that it has been argued that the official poverty rate does not represent the true well-being of the poor because the definition of money income does not cover taxation and in-kind transfers. Furthermore, CPI-U, the index used to calculate the official poverty thresholds, is biased. In this section, we replicate the previous six-variable VAR but replace the official income poverty rate with alternative measures of poverty. The goal of this analysis is to examine whether the relationship between poverty and macroeconomic variables found earlier is robust to alternative definitions of poverty rate. For alternative poverty rates, we use Meyer and Sullivan's (2010) consumption-based poverty rate calculated using (p. 537) expenditures data and Broda and colleagues' (2009) poverty rate calculated using their own inflation index corrected for the substitution and quality biases in the CPI-U.[6]

Meyer and Sullivan (2011) study the behavior of income poverty and consumption poverty over the business cycle. Their results using national-level data from 1981 to 2008 are most comparable to what follows. They find that unemployment has a larger impact on after-tax income poverty than on consumption poverty. They study these effects jointly by specifying autoregressive distributed lag models estimated using seemingly unrelated regressions. In these models, they control for inflation and capture other macroeconomic factors with a time trend. Because they are interested in changes by decades, they also include decadal dummy variables in some of their specifications. An aspect of their findings that persists in the VAR framework below is the relative smoothness of consumption poverty at the national level.

We re-estimate the six-variable VAR by substituting Meyer and Sullivan's consumption poverty in the place of the official income poverty rate. The results are reported in Table 16.6. The Granger causality tests in Table 16.6, Panel A, show that only unemployment helps to predict consumption poverty. This finding does not necessarily imply that consumption poverty does not respond to innovations in other social and macroeconomic indicators.

Figure 16.4 shows the responses of consumption poverty to a one standard deviation innovation in each of the variables in the six-variable VAR and the associated 90 percent confidence intervals.[7] Innovations in unemployment and the 50/10 ratio are significantly associated with higher consumption poverty although these impacts are short-lived. In comparison to the income poverty VARs, both unemployment and inflation innovations have greater contemporaneous effects on consumption poverty although the relative importance of unemployment to inflation is greater with consumption poverty. In particular, an unemployment innovation yields a greater peak poverty response of 0.57 percentage points one year after the innovation, which is also statistically significant at the 10 percent level. The consumption poverty responses to an innovation in unemployment are positive throughout the five years of the forecast horizon while the income poverty responses become negative after two years. At the same time, the consumption poverty responses to inflation innovations peak at 0.36 percentage points five years later but these responses are not statistically significant in any year over the five-year horizon. Therefore, in contrast with the impulse responses using the official income poverty rate, the impulse responses using consumption poverty indicate that unemployment is a relatively more important source of short-run consumption poverty fluctuations than inflation, which is consistent with previous research findings.

A 50/10 ratio (income inequality) innovation is positively associated with consumption poverty in the first two years after the innovation. Contemporaneously, the poverty response is 0.33 percentage points and is statistically significant at the 10 percent level. Innovations in median earnings and the growth of transfers are (p. 538) negatively associated with consumption poverty in the short run but these associations are relatively modest and not statistically significant.

Table 16.6 Descriptive Statistics for the Six-Variable VAR with Consumption Poverty

A. Granger-Causality Tests

	Dependent Variable in Regressionn					
Regressor	**median earnings**	**infl**	**unemp**	**50/10 ratio**	**transfers**	**pov_consump**
median earnings		0.01*	0.72	0.91	0.29	0.77
infl	0.43		0.28	0.66	0.00*	0.89
unemp	0.39	0.00*		0.43	0.30	0.09*
50/10 ratio	0.46	0.86	0.51		0.35	0.71
transfers	0.27	0.02*	0.22	0.98		0.48
pov_consump	0.91	0.08*	0.15	0.10	0.01*	

Notes: p-values from the F-tests that evaluate the null hypothesis that the lagged values of each regressor variable in column 1 do not help predict the current value of the dependent variable when the five other controls are held constant; the lag length is two.

(*) = significant at the 10% level.

B. Variance Decompositions from the Recursive VAR Ordered as median earnings, infl, unemp, 50/10 ratio, transfers, pov_consump						
Response = pov_consump						
	Impulse Variables					
ForecastHorizon (year)	**median earnings**	**infl**	**unemp**	**50/10 ratio**	**transfers**	**pov_consump**
1	0.03	0.05	0.13	0.31*	0.00	0.47*
	(0.07)	(0.09)	(0.12)	(0.14)	(0.02)	(0.14)
3	0.06	0.02	0.64*	0.09	0.02	0.17
	(0.12)	(0.05)	(0.27)	(0.10)	(0.03)	(0.15)
5	0.05	0.06	0.63	0.14	0.02	0.11
	(0.12)	(0.26)	(0.40)	(0.07)	(0.04)	(0.21)

Notes: Standard errors in parentheses. Each coefficient is the fraction of the forecast error variance of the consumption poverty rate due to the impulse variable in each column; the lag length is two.

(*) = significant at the 10% level.

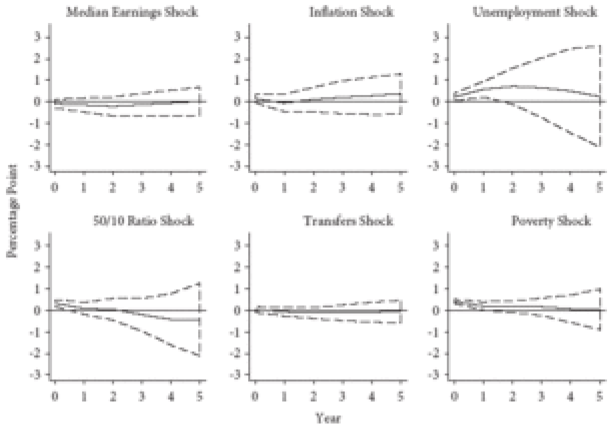

Figure 16.4 Responses of the consumption poverty rate to one standard deviation shock (six-variable VAR)

The differences from the income poverty VARs carry over to the forecast error variance decomposition results. Table 16.6, Panel B, indicates that, at short horizons, income inequality and consumption poverty itself account for a significant fraction of the forecast error variance in consumption poverty. Innovations in the 50/10 ratio account for a statistically significant 31 percent of the forecast error variance in the first year; thereafter, the fraction of the forecast error variance explained by these innovations decreases substantially. Unemployment innovations explain 64 percent of the forecast error variance for consumption poverty three years after the innovation. Inflation innovations, however, account for at most 6 percent of the (p. 539) forecast error variance of consumption poverty in the fifth year and account for a persistently smaller fraction of the variance than unemployment. Moreover, the fraction of the forecast error variance explained by inflation innovations is not statistically significant throughout the five-year horizon. This is consistent with the implication from our impulse response results that unemployment has a relatively stronger association with consumption poverty than inflation.

Innovations in median earnings and transfers explain modest fractions of the forecast error variance of consumption poverty and are not statistically significant throughout the five-year horizon. Median earnings and transfer shocks explain at most 6 and 2 percent of the forecast error variance, respectively.

In contrast to the findings for income poverty, none of the innovations in the social and macroeconomic variables account for a significant fraction of the forecast error variance in consumption poverty five years later. These forecast error variance decomposition findings suggest that the long-run relevance of social and macroeconomic indicators for consumption poverty is quite tentative.

The six-variable VAR using Broda and colleagues' (2009) income poverty rate with an adjusted CPI yields slightly different results.[8] The inflation rate is weaker but still a statistically significant predictor of poverty dynamics relative to the case where the official poverty rate is used. The impulse responses suggest that inflation innovations have a positive and statistically significant impact on poverty contemporaneously and over the first three years after the innovation; the magnitude of these responses range from 0.11 percentage points contemporaneously (p. 540) to 0.38 percentage points in the third year. The contemporaneous response of this measure of poverty to an innovation in unemployment is also positive (0.19 percentage points) and statistically significant. Thereafter, however, they are positive through the third year but are insignificant. The forecast error variance decomposition for poverty associated with this VAR indicates that in the very short run (the first two years), unemployment innovations account for statistically significant shares, 55 and 39 percent, respectively; inflation innovations then take over, rising from 38 percent in the second year to 72 percent in the fifth year. These inflation innovation shares are statistically significant. Overall, the finding that unemployment and inflation innovations are associated with higher poverty rates remains unchanged.

6. Poverty Forecasts

We forecast official and consumption poverty rates for 2008 and 2009 based on the estimation of the six-variable VARs for 1984–2007. The main purposes of forecasting these poverty rates are to examine whether the estimated models could have predicted actual poverty rates and to examine whether it would have been possible to detect evidence of structural change in the economy during the financial crisis and recession in 2008 and 2009.

We forecast by using three different methods: out-of-sample forecasts, one-step-ahead forecasts, and updated one-step-ahead forecasts. Each forecast method yields the same predicted poverty rates for out-year one: we estimate a VAR using the full sample period excluding the last two years and use the estimated coefficients to predict the poverty rate for out-year one using only data within the sample. The difference among the forecast methods lies in the prediction for out-year two.

First, for the out-of-sample forecast for out-year two, we use the same coefficients as for out-year one and the estimated data for all variables in out-year one. Second, for the one-step-ahead forecast, we use instead the actual values of all the variables for out-year one to predict out-year two, but we still use the same coefficients as for out-year one. By updating the input data with actual observations, the one-step-ahead forecast has the potential to improve forecast performance over the out-of-sample forecast. Third, for the updated one-step-ahead forecast, we not only feed the actual data for out-year one but we also reestimate the VAR after extending the sample period by one year to 2008. By reestimating the VAR, we update the coefficient on each variable.

The results for the six-variable VARs are shown in Table 16.7 and Figure 16.5.[9] Using the official income poverty rate and all five macroeconomic indicators—median earnings, inflation, unemployment, transfers, and the 50/10 income ratio—causes us to underpredict the 2008 income poverty rate by 0.61 percentage (p. 541) points. For 2009, all three forecasts diverge farther from the mark. The updated one-step-ahead forecast, which uses the most current data, predicts 12.98 percent in 2009, lower than the actual rate of 14.3 percent. The large forecast errors in 2008 and 2009 suggest that there may have been structural change starting after 2007 that raised the poverty rate but is not captured in this model. For example, perhaps surprisingly, the updated one-step-ahead forecast for 2009 is also lower than the one-step-ahead forecast for this year. This is a consequence of reestimating the VAR using the 2008 data, which induced a shift in key coefficients and thereby weakened the model's ability to predict the dramatic outcomes of 2009. The evidence for structural change is bolstered by the fact that the realized income poverty rates for 2008 and 2009 are well outside of the 95 percent confidence interval for the out-of-sample forecast. The Great Moderation of 1984–2006 featured an overall decline in macroeconomic volatility (Bernanke 2004). Our estimation, based on the period of the Great Moderation, suggests that the official poverty rate would have been lower in 2008 and 2009 if the relationship between poverty and the macroeconomy had held steady.

Table 16.7 Forecast Performance

	Income Poverty		
	2008	**2009**	**RMSE**
Actual	13.20	14.30	
Out of Sample	12.59	12.24	1.52
One-Step-Ahead	12.59	13.14	0.92
Updated One-Step-Ahead	12.59	12.98	1.03
	Consumption Poverty		
	2008	**2009**	**RMSE**
Actual	7.70	8.80	
Out of Sample	7.70	7.22	1.12
One-Step-Ahead	7.70	9.08	0.20
Updated One-Step-Ahead	7.70	9.08	0.20

Notes: Income poverty is the official rate for all persons (%); consumption poverty is the Meyer-Sullivan consumption (2010) poverty rate (%); RMSE is the root mean square error over the two-year forecast horizon.

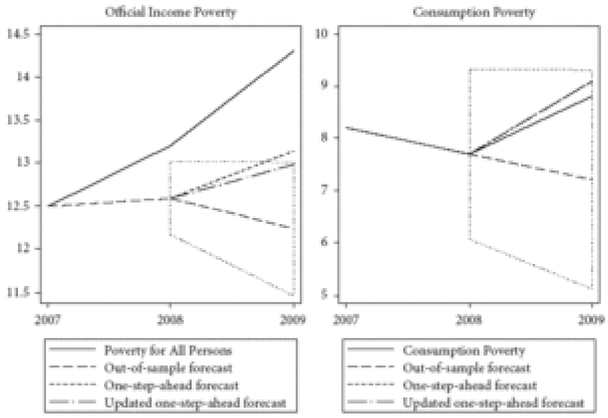

Figure 16.5 Poverty-rate forecasts

In contrast with the forecasts of the income poverty rate, the forecasts of consumption poverty in Table 16.7 and Figure 16.5 suggest that the relationship between poverty and macroeconomic performance has changed less dramatically after 2007. The forecasts predict the consumption poverty rate in 2008 almost perfectly. For 2009, the one-step-ahead forecast and the updated one-step-ahead forecast are not far from the mark. The root mean square error (RMSE) from the updated one-step-ahead forecast is 0.20 percentage points, which is much lower than the RMSE from the same method using income poverty. The evidence for (p. 542) structural change is not strong because the realized consumption poverty rates for 2008 and 2009 are within the 95 percent confidence interval for the out-of-sample forecast. Based on the Granger causality test results from the consumption poverty VAR, we know that these forecasting results are mainly due to the ability of past consumption poverty and unemployment to forecast future consumption poverty. The other variables in the VAR do not contain significant predictive information over and above that contained in past consumption poverty.

7. Conclusions and Suggestions for Future Research

This chapter has overviewed the literature that relates poverty to macroeconomic conditions and has provided an updated quantitative summary of the dynamics of poverty in the United States. Traditionally, the literature has focused on income-based measures of poverty. Many studies in this tradition emphasize the role of the labor market via unemployment or median earnings in determining the level of poverty we observe. For example, a common finding is that unemployment is positively related to poverty and median earnings are negatively related to poverty. In many studies, inflation is not an important determinant of poverty. Using more recent data and an empirical methodology that permits more interaction (p. 543) and dynamic feedback between macroeconomic indicators, we find that inflation innovations have had more of an impact on income poverty than traditionally thought.

Because of conceptual as well as practical shortcomings in how poverty is traditionally measured, researchers have begun to introduce alternative poverty measures. One example of these alternatives is a consumption-based poverty measure. We find that a consumption-based poverty rate has a weaker dynamic relationship with standard macroeconomic variables that are thought to influence poverty. Therefore, replacing an income-based poverty measure with a consumption-based poverty measure is likely to alter one's understanding of the relationship between poverty and the macroeconomy.

Our discussion of the dynamic relationship between poverty and the macroeconomy when using different measures of poverty suggests that further investigation will have to be made into how to measure poverty and how that choice influences what we know about the poverty-macroeconomy nexus. Among the many interesting questions that could be considered in future research are the following: What policies combat consumption poverty? How are we to assess the likely impact of these policies? Will the unemployment–income poverty nexus be enriched or diminished as a result of the recession of 2007–9? What is the dynamic response of poverty to macro-financial crises? Should measures of financial shocks be included directly within empirical poverty models? Answer to these questions will have to wait until more data are available. Nevertheless, their formulation suggests that research on the connection between macroeconomic fluctuations and poverty will bear fruit for the foreseeable future.

8. Data Appendix

8.1. Measures of Poverty as Dependent Variables

We use mainly three poverty rates as dependent variables: the official income poverty rate, the Meyer-Sullivan consumption poverty rate, and the Broda-Leitag-Weinstein income poverty rate with adjusted CPI. For the official income poverty rate, we use the poverty rate for all persons in all the models except for in our first VAR that examines the relationships among real GDP growth, poverty for all persons, poverty for female-headed families, and poverty for black families. The official poverty rate data come from the US Census Bureau; Meyer-Sullivan consumption poverty from Meyer and Sullivan (2010); and Broda-Leitag-Weinstein income poverty from Broda, Leitag, and Weinstein (2009).

The US Census Bureau publishes the poverty rates annually after surveying the incomes of all people through the Annual Social and Economic Supplement (ASEC) to the Current Population Survey (CPS). Those in the poverty universe (p. 544) contain all people except individuals under age 15 who are not part of a family by birth, marriage, or adoption. People are said to be poor if their incomes fall below a certain absolute threshold. There are 48 poverty thresholds of dollar amounts and those thresholds vary by size and composition of family and the ages of the members. See the US Census Bureau website for a detailed definition of the official poverty rate: http://www.census.gov/hhes/www/poverty/about/overview/measure.html.

Official poverty for all persons: These data covering all individuals in the poverty universe come from the US Census Bureau, Table 2, in Historical Poverty Tables—People, http://www.census.gov/hhes/www/poverty/data/historical/people.html.

Official poverty rate for female-headed families: The data contain the poverty rate for female-headed families without husbands for all races, both with and without children under 18 years, from 1959 to 2009. These data come from the US Census Bureau, Table 4, in Historical Poverty Tables—Families, http://www.census.gov/hhes/www/poverty/data/historical/families.html.

Official poverty rate for all black families: We use the poverty rate for all black families both with and without children under 18 years for years 1967 to 2001. We use the poverty rate for black alone families with and without children under 18 years from 2002 to 2009. Black alone refers to people who reported black and did not report any other race category. We use slightly different criteria for all black families for the two periods above because the data narrow the coverage of black families from 2002. These data come from the US Census Bureau, Table 4, in Historical Poverty Tables—Families, http://www.census.gov/hhes/www/poverty/data/historical/families.html.

Meyer-Sullivan consumption poverty rate: These data are provided by Bruce D. Meyer and James X. Sullivan (2010). The series in the original paper is published in Table 1, column 5, in the July 2010 version. This poverty rate is based on consumer expenditure survey data and the official thresholds are corrected for inflation using CPI-U-RS. Note the series covers 1980 to 2009 but is missing data for 1982 and 1983 because the survey on which the poverty rate is based was not conducted for those two years.

Broda-Weinstein income poverty rate: These data are provided by Christian Broda, Ephraim Leitag, and David E. Weinstein (2009). This poverty rate is based on income poverty thresholds adjusted with a CPI that corrects for substitution and quality biases in the standard CPI. This series is available from 1970 to 2006.

8.2. Independent Variables

Real GDP growth rate (annual percent): The data are the annual percentage change in GDP in chained 2005 dollars from the Bureau of Economic Analysis, http://www.bea.gov/national/#gdp.

(p. 545) **Unemployment rate** (percent): The data are from Labor Force Statistics from the CPS, Bureau of Labor Statistics. We use annual unemployment, seasonally adjusted, for citizens 16 years and older.

Inflation rate (percent): The original value of CPI-U with 1982–84 as a base period is obtained from Bureau of Labor Statistics, http://www.bls.gov/cpi/#tables. We first-difference the log of annual values to calculate the annual percentage change in CPI-U.

Real median earnings (dollars): The data are from Income, US Census Bureau, Table P-38, http://www.census.gov/hhes/www/income/data/historical/people/. We use the median earnings for full-time, year-round male workers in 2009 CPI-U-RS adjusted dollars. In the VARs, we divided these real median earnings by 1000.

50/10 ratio (income inequality): We use the ratio of median to the 10th percentile income in 2008 CPI-U-RS adjusted dollars for full-time, year-round male workers. The data come from Income, US Census Bureau, Table IE-2, http://www.census.gov/hhes/www/income/data/historical/inequality/index.html.

Transfer growth (annual percent): The original transfer data covering the federal, state, and local government social benefits to persons (billions of dollars) come from NIPA Table 3.12, Bureau of Economic Analysis, http://www.bea.gov/national/nipaweb/SelectTable.asp?Selected=N. We take a first difference of the log of transfers and multiply by 100 to calculate the annual percentage change in transfers.

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Notes:

(1.) Balke and Slottje (1993) additionally find that transfer shocks have a stronger impact on black poverty over time than on the overall or white poverty rate. Hoover and colleagues (2008), however, find that transfers, measured by a percentage of personal income, have a larger negative effect on white poverty although transfers still have a significantly negative effect on black poverty.

(2.) The size of a one standard deviation innovation in real GDP growth is 2.02 percent.

(3.) The sizes of the one standard deviation innovations in Figure 16.2 are 0.99 percentage points for inflation; 0.52 percentage points for unemployment; and 0.22 percentage points for poverty.

(4.) The sizes of the one standard deviation innovations in Figure 16.3 are 0.76 thousands of 2009 dollars for real median earnings; 0.66 percentage points for inflation; 0.50 percentage points for unemployment; 0.05 (a unitless number) for the 50/10 ratio; 0.95 percent for growth of transfers; and 0.07 percentage points for official income poverty.

(5.) Unemployment is traditionally categorized as a slow-moving and lagging economic indicator. Some components of transfers adjust slowly. Recall, for example, the multiple extensions of unemployment benefits as a result of the recession of 2007–9.

(6.) Note that a consumption-based poverty measure is income-based. The relevant notion of income for consumption-based poverty is permanent income.

(7.) The sizes of the one standard deviation innovations in Figure 16.4 are 0.90 thousands of 2009 dollars for real median earnings; 0.59 percentage points for inflation; 0.52 percentage points for unemployment; 0.05 (a unitless number) for the 50/10 ratio; 0.70 percent for growth of transfers; and 0.41 percentage points for consumption poverty.

(8.) Detailed results using Broda and colleagues' income poverty rate are not reported but are available upon request.

(9.) The 95 percent confidence intervals (the dotted trapezoids) in Figure 16.5 are those associated with the out-of-sample forecast. They provide a measure of the range of uncertainty surrounding the point forecast. Of the three types of forecasts, the out-of-sample forecast is based on the smallest information set.

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