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Poverty, Government Transfers, and the Business Cycle: Evidence for the United States

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Poverty, Government Transfers, and the Business Cycle: Evidence for the United States

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We examine the impact of government transfers and the business cycle on poverty in the United States in the context of a poverty function that includes the official poverty rate, three types of government transfers, real wages, the number of female-headed families, and a business cycle variable. Using cointegration techniques, we find ─ contrary to most previous studies ─ that government transfer programs play an important poverty-reducing role. In addition, the findings suggest that the business cycle is one of the key variables in explaining poverty in the US. Furthermore, the empirical results show that the size and composition of public transfer payments change over the business cycle. We also find poverty to have a significant effect on government transfers, the business cycle, and the structure of households.

I. INTRODUCTION

The question of whether, how, and to what extent public transfer payments affect poverty in the United States has been debated over decades, with no consensus in sight (see, e.g. Hoynes et al., 2005). At the center of this debate are basically two arguments. The first, quite obvious argument, which is based on the generally poverty-reducing role of public transfers, is that transfers *decrease poverty* by raising the incomes of the poor. The second argument hypothesizes that antipoverty benefits *increase poverty* by decreasing the labor supply of current and all potential future transfer recipients. The logic behind this is that antipoverty benefits act as a substitute for income from

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[1] In one of four equations Gottschalk and Danziger (1984) find a statistically significant negative effect of transfers.

employment. Increases in benefit payments thus make dependency on the government more attractive than the alternative of self-support. Furthermore, as the marginal poor spend more time being dependent upon transfers and less time working, their skills depreciate, in turn reducing their chances of finding a job, earning money, and moving out of poverty. Hence, through the negative impact of higher transfer payments on work incentives, they can seriously raise the poverty rate ─ not only by increasing the number of transfer recipients but also by increasing the duration of poverty (see, e.g., Gwartney and McCaleb, 1985). As this "work disincentive effect" acts against the "income effect" of transfer payments, the net poverty effect of government transfers is theoretically indeterminate and thus becomes an empirical issue.

Unfortunately the empirical evidence is mixed as well. Peterson and Rom (1989), using US state panel data, find a statistically significant positive correlation between government transfers and changes in the poverty rate. Similarly, the aggregate time series regressions by Blank and Blinder (1986) suggest that after 1982, increases in welfare spending in relation to GNP were linked to increases in poverty. In contrast, the time series results by Gottschalk and Danziger (1984),[1] Balke and Slottje (1993), Formby et al. (2001), Vedder and Gallaway (2001), Enders and Hoover (2003), and Hoover et al. (2004) show no statistically significant relationship between government transfers and poverty. Osberg (2000) and Hoynes et al. (2005), also using US state panel data, find that increases in government transfers actually lead to statistically significant reductions in poverty rates. However, most of these studies suffer from serious econometric shortcomings.

A major limitation of the existing studies is that they fail to consider whether government transfers and poverty are cointegrated and thus whether there exists a long-run relationship between government transfers and poverty. The vast majority of these studies impose the restriction that the relationship between benefit payments and the poverty rate be in *growth rates* or *first differences* (see, e.g., Balke and Slottje, 1993); Vedder and Gallaway, 2001; Enders and Hoover, 2003; and Hoover et al., 2004). It is well known that the use of stationary *first differences* or *growth rates*

avoids spurious correlations, but this precludes the possibility of a long-run or cointegrating relationship between the *level* of government transfers and the *level* of poverty a priori. Moreover, if government transfers and poverty rates are cointegrated, the conclusion that there is no statistically significant relationship between *changes* or *first differences* in transfers and poverty does not necessarily hold in the context of cointegration modeling that allows for a relationship between transfer payments and poverty both in *levels* and in *first differences*. Hence, simply using *first differences* or *growth rates* can lead to serious misspecification problems (see, e.g., Hendry, 1995). Indeed, some studies estimate a static regression model of the relationship between the *level* of government transfers and the *level* of the poverty rate (see, e.g., Gottschalk and Danziger, 1984; Blank and Blinder, 1986; Hoynes et al., 2005). However, such regression models are subject to spurious correlation if government transfers and poverty rates are nonstationary and not cointegrated. But even in the case of cointegration, the distribution of the estimates from standard static models is non-normal. Therefore, no final judgment can be passed on the significance of the estimated coefficients.

Against this background, the objectives of this paper are threefold. Our first objective is to reexamine the impact of government transfers on poverty, applying cointegration techniques to aggregate time series data for the United States over the period 1964–2004. Our main finding using the single equation cointegration tests proposed by Engle and Granger (1987), Pesaran et al. (2001), and Ericsson and MacKinnon (2002) is that a long-run relationship exists in levels between the poverty rate, three types of government transfers (including cash transfers, medical care, as well as food and housing assistance), and other control variables such as real wages and the number of female-headed households. Furthermore, our estimates of the long-run parameters using the dynamic modeling methods of both Stock (1987) and Stock and Watson (1993) indicate that government transfers play a significant role in reducing poverty in the US. These results are in

sharp contrast to most of the previous studies and cast serious doubts on the appropriateness of the methods employed therein.

The second issue we want to address is the cyclicality of the US poverty rate, which is characterized by rising poverty during recessions and declining poverty during upswings (Freeman, 2001). Typically, the literature on the determinants of poverty in the US uses the (male) unemployment rate as a measure of the business cycle in regression models (see, e.g., Blank and Blinder, 1986; Freeman, 2001; Hoover et al., 2004; Hoynes et al., 2005; Hines et al., 2005). Given statistically significant unemployment rates, this literature generally concludes that the business cycle is an important determinant of poverty in the US. However, the unemployment rate certainly does not capture the full effects of the business cycle on poverty. Other channels through which the business cycle might affect poverty include wage fluctuations of low-wage workers and business-cycle-induced changes in labor hours that lead to volatility in incomes of the working poor. Also, the business cycle might affect the ability of families and communities to engage in income redistribution. Furthermore, the amount of government transfers may vary in response to the business cycle. Hence, the business cycle can have a major impact on poverty. For this reason, our poverty function includes not only government transfers and the control variables mentioned above, but also the business cycle, measured by detrended output. Using this variable to capture the overall cyclical effects, our estimation results suggest that the business cycle is one of the key determinants in explaining poverty in the US. We find that a one percent increase/decrease of output above/below its trend is related to a 2.9 percent decrease/increase in the poverty rate on average during the sample period. Accordingly, in the case of the US, the poverty impact of the business cycle appears to be larger in magnitude than the poverty impact of any other relevant variable.

Finally, we do not want to exclude a priori the possibility that business cycle as well as government transfers themselves are affected by poverty. Furthermore, as stressed by Hoynes et al. (2005), one can assume that poverty rate dynamics reflect a complicated set of interactions between

government policies and macroeconomic factors. Surprisingly, however, little research has been done to examine these issues. Thus, the third objective of this paper is to investigate the dynamic interactions between poverty, government transfers, and the business cycle. For this purpose, we construct a small dynamic model for the underlying variables using a vector error correction approach, similar to the one proposed by Lütkepohl and Wolters (2003). Our results suggest that the size and the composition of public transfer payments change significantly over the business cycle. Additionally, we find significant feedback effects of poverty on government transfers, the business cycle, and the structure of households.

The remainder of the paper proceeds as follows. In the next section we present the poverty function to be estimated and discuss the underlying data, including their basic properties. In Section III, we test for cointegration, estimate the long-run parameters of our poverty function, and discuss the individual equations of our structural vector error correction model. Concluding remarks are contained in Section IV.

II. VARIABLES, DATA, AND THEIR TIME SERIES PROPERTIES

A. *Data and Specification of the Poverty Function*

The objective of this study is to investigate if and how aggregate poverty in the US is affected by government transfers and the business cycle. To this end, we estimate an aggregate poverty function by means of cointegration techniques. As our measure of poverty, we use the official US Census Bureau poverty rate, defined as the number of people below the poverty line divided by the total population. The poverty line, which is based on the Department of Agriculture's 1961 Economy Food Plan, reflects the different consumption requirements of unrelated individuals as well as families and is updated every year in accordance with the Consumer Price Index. In 2004,

for example, the poverty threshold for a family of four was about $19,000, and for a single individual it was approximately $10,000 (Hoynes et al., 2005).[2]

The government transfer programs that we focus on are: (a) medical care, (b) food and housing assistance, and (c) public assistance. The first consists primarily of Medicare and Medicaid; and food and housing assistance programs include public housing, the food stamp program, child nutrition and special milk programs, supplemental food programs, and commodity donations. While both medical care and food and housing assistance are based on non-cash transfers, the public assistance program is purely cash-based. It is composed of supplemental social security income, family support payments, temporary assistance for needy families (TANF) / aid to families with dependent children (AFDC),[3] low-income home energy assistance, earned income tax credit, and veterans' non-service connected pensions.[4] All data stem from the Historical Tables of the Budget of the United States Government, Fiscal Year 2006, and have been converted into real 2000 dollars using the implicit GDP deflator from the National Income Accounts.

However, as pointed out by Freeman (2001), many poor families, for whom government transfers are important, rely more on labor income than on any other resources. Consequently, as real wages rise, more workers might be able to earn sufficient income to escape poverty. To account for this, we utilize the average real hourly earnings from the US Bureau of Labor Statistics expressed in constant 2000 dollars.[5] Given that these data are available from 1964 onwards, the period under investigation covers the years 1964-2004.

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[2] Income used to compute official poverty status does not include non-cash government transfers. Alternative poverty measures that include non-cash transfers thus show lower poverty rates compared to official statistics. However, as noted by Hoynes et al. (2005), the trend in poverty rates is quite similar across the official and alternative poverty measures.

[3] ADF was reformed in 1996 and replaced by TANF.

[4] Foster care, adoption assistance, legal services, and day care assistance also comprise a small part of the public assistance programs.

[5] Since the level of real wages is, of course, related to the level of unemployment, we have decided not to consider unemployment explicitly. In doing so, we minimize the possibility of multiple cointegrating vectors and thus reduce the complexity of the empirical analysis. Moreover, a large body of evidence supports that unemployment is related to poverty in the US (see, e.g., Gottschalk and Danziger, 1984; Osberg, 2000; Blank, 2000; Formby et al., 2001; Enders and Hoover, 2003; Hoover et al., 2004). In contrast, there is little evidence on the poverty impact of real wages.

Moreover, as several authors have suggested, there should be a variable that controls for the structure of American families (see, e.g., Formby et al., 2001; Enders and Hoover, 2003; Hoover et al., 2004) given the much higher poverty rate among female-headed families than among the total population below the poverty line (see, e.g., Blank, 2000; Freeman, 2001). We therefore include the number of female-headed families from the March Current Population Surveys of the US Census Bureau in our poverty function.

In order to investigate the impact of the business cycle on aggregate poverty, we need an operational definition of the cyclical component of economic activity. Given that the business cycle is typically characterized by recurring periods of economic expansion followed by periods of economic contraction, we measure it in terms of fluctuations of real GDP around a trend:

$$LGDP_t = CY_t + \mu_t,\ t = 1, ..., T,\quad T = 41\ [1964\text{-}2004], \tag{1}$$

where $LGDP_t$ is the natural logarithm of the Department of Commerce's real GDP, which is evaluated at constant 2000 prices, CY_t is the business cycle, and μ_t is the trend. Here, we impose a linear trend, since the augmented Dickey-Fuller (ADF) test for $LGDP_t$ clearly rejects the unit root hypothesis in favor of trend-stationarity (see Table I). Note that the trend-stationary model of US GDP, in which the business cycles are modeled as stationary fluctuations around a linear trend, is supported by several studies. Ben-David and Papell (1995), Ben-David, Lumsdaine, and Papell (2003), Papell and Prodan (2004), for example, reject the unit root null for long-term US real GDP in favor of a deterministic trend with structural breaks in 1929 (the Great Depression) and/or 1940 (World War II). Hence, assuming that $LGDP_t$ is trend-stationary and that there has been no permanent shock to output during the 1964–2004 period, we measure the business cycle as a linear detrended log of real GDP ─ that is, we use the residuals from a regression of $LGDP_t$ on a constant and a time trend.

Hence, the long-run poverty function we have in mind is of the following form:

$$LPOV_t = \alpha_1 LM_t + \alpha_2 LHF_t + \alpha_3 LPA_t + \alpha_4 LW_t + \alpha_5 LF_t + \alpha_6 CY_t + error_t, \tag{2}$$

where $LPOV_t$ is the logarithm of the poverty rate, LM_t is the logarithm of real medical care expenditures, LHF_t is the logarithm of real housing and food expenditures, LPA_t is the logarithm of real public assistance, LW_t is the logarithm of the real wage, LF_t is the logarithm of the number of female family heads, CY_t is the business cycle, $error_t$ is a stationary error term, and a_1, a_2, a_3, a_4, a_5, a_6 are constant elasticities.

It is important to note that there should be two cointegrating relations in equation (2). We expect $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t to be integrated and possibly cointegrated. The other is presumably given by CY_t, because the business cycle is expected to be stationary and thus to be cointegrated with itself.

B. *Time Series Properties*

In Figure I $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, LF_t and CY_t are plotted for the period 1964–2004. In order to determine the time series properties of these variables, we have carried out ADF tests. Because LM_t, LHF_t, LPA_t, LW_t, and LF_t are trending, a linear time trend was included in the test regressions. To test whether a linear trend is necessary in the testing equation for $LPOV_t$, we estimated the ADF regression initially with a linear time trend. Since the trend, however, turned out to be insignificant, it was excluded from the regression. The ADF test for the residuals, i.e., the business cycle (CY_t), was conducted without a constant and trend.

[**Figure 1 around here**]

Given the considerable evidence that data-dependent methods of selecting the lag length k are superior to the a priori choice of a fixed k (Perron, 1997), we used the t-sig method to choose the

number of lags in the ADF regressions. Here k max was specified to be six. If the last included lag was insignificant, the number of lags was reduced by one and the test regressions were reestimated until a significant lagged variable was found. If none of the coefficients on the lagged variables were found to be significant, no lags were utilized in the tests. Table I reports the results.

[Table 1 around here]

As can be seen, for $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t and LF_t, we cannot reject the unit root null at the 5% level of significance. Since the unit root hypothesis can be rejected for the first differences, we conclude that $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t and LF_t are integrated of order one, $I(1)$. According to the results in Table I, CY_t, in contrast, can clearly be treated as stationary.

III. Modeling Poverty

A. *Testing for Cointegration*

Because $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t are $I(1)$, the next step in our analysis is an investigation of the cointegration properties of these time series. The business cycle is stationary and can thus already be regarded as a cointegration relationship. Therefore CY_t is excluded from the cointegration analysis of $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t. Note that such an analysis should generally be conducted using system techniques, but we have a relatively large number of variables and few observations. Hence, we use single-equation models.

First we use the Engle-Granger (1987) approach to test the null of no cointegration. The null of no cointegration implies that the estimated residuals, $\hat{e}_t$, from the equation

$$LPOV_t = c + \alpha_1 LM_t + \alpha_2 LHF_t + \alpha_3 LPA_t + \alpha_4 LW_t + \alpha_5 LF_t + e_t \tag{3}$$

are $I(1)$, whereas the alternative hypothesis implies that the estimated residuals are $I(0)$. We estimate the augmented Dickey-Fuller (ADF) regression

$$\Delta\hat{e}_t = \rho\hat{e}_{t-1} + \sum_{j=1}^{k}\beta_j\Delta\hat{e}_{t-j} + v_t, \tag{4}$$

where the null of no cointegration is rejected if $\left|t_{\hat{\rho}}\right|$ is greater than the critical values reported by MacKinnon (1991).[6]

To determine the lag length k, we again use the t-sig method. Starting with six lags, this procedure selects five lags for our regression. Using $k = 5$, the estimated ADF t-statistic amounts to $\left|5.25\right|$. Comparing this value with the corresponding 5% critical value, $\left|5.13\right|$, we can reject the null of no cointegration at the 5% level.

However, the Engle-Granger approach has been criticized among other things for imposing a common factor restriction on the dynamics of the relationship between the variables, which is only appropriate when the short-run elasticities equal the long-run elasticities (Kremers et al., 1992). We therefore provide additional evidence on cointegration by applying the autoregressive distributed lag (ARDL) approach developed by Pesaran et al. (2001). This procedure is applicable irrespective of whether the explanatory variables are $I(1)$ or $I(0)$. It is based on a conditional error correction model, which in our case is given by

$$\begin{aligned}\Delta LPOV_t = {} & b_1 + b_2 LPOV_{t-1} + b_2 LM_{t-1} + b_3 LHF_{t-1} + b_4 LPA_{t-1} + b_5 LW_{t-1} + b_6 LF_{t-1} \\ & + \sum_{i=1}^{k}\beta_i\Delta LPOV_{t-i} + \sum_{i=0}^{k}\gamma_i\Delta LM_{t-i} + \sum_{i=0}^{k}\lambda_i\Delta LHF_{t-i} + \sum_{i=0}^{k}\delta_i\Delta LPA_{t-i} \\ & + \sum_{i=0}^{k}\chi_i\Delta LW_{t-i} + \sum_{i=0}^{k}\sigma_i\Delta LF_{t-i} + u_t.\end{aligned} \tag{5}$$

[6] Critical values depend on number of regressors and the sample size.

In this model, which can be interpreted as an autoregressive distributed lag model, we test the absence of a cointegration relationship between $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t by calculating the F-statistic for the null of no cointegration

(6) $$H_0 : b_2 = b_3 = b_4 = b_5 = b_5 = 0$$

against the alternative

(7) $$H_1 : b_2 \neq b_3 \neq b_4 \neq b_5 \neq b_6 \neq 0 .$$

The distribution of the test statistic under the null depends on the order of integration of the variables. In the case where (a) all variables are $I(0)$, the asymptotic 1% critical value is 3.41 (see Pesaran et al., (2001), p. 300, Table CI(iii)). If the calculated F-statistic falls below this value, the null hypothesis cannot be rejected. In the case where (b) one or more series are $I(0)$ and one or more series are $I(1)$, the critical value falls in the interval [3.41, 4.68]. If the F-statistic falls within these bounds, the result is inconclusive; thus the order of integration must be known before any conclusion can be drawn. In the case where (c) $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t are $I(1)$, the 1% critical value is 4.68. If the F-statistic lies above 4.68, the null of no cointegration is rejected at the 1% level.

In order to determine the lag length, k, the Schwarz criterion is used. The Schwarz criterion has been shown to lead to consistent estimates in both stationary and nonstationary models, while the Akaike criterion is characterized by a positive limiting probability of overfitting (see, e.g., Pötscher, 1989; 1990). The Schwarz criterion suggests one lag for our model, $k = 1$; hence, we estimate the ARDL model with one lag. Here, the calculated F-statistic for the null of no cointegration amounts to 7.08. Since this value exceeds the upper bound of the critical value band

[3.41, 4.68], we reject the null of no cointegration at the 1% significance level. Note that this result confirms our earlier finding that $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t are $I(1)$, because the F-statistic (7.08) is higher than the 1% critical value, if all series are $I(1)$.

B. *Estimation of the Long-Run Poverty Function*

Having found that $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t, and LF_t are cointegrated, we proceed under the assumption that the relation

$$LPOV_t - \alpha_1 LM_t - \alpha_2 LHF_t - \alpha_3 LPA_t - \alpha_4 LW_t - \alpha_5 LF_t \tag{8}$$

is stationary. Because the business cycle is also stationary and because CY_t is expected to be an important explanatory variable in the fully specified equation, it is included it in the long-run relation. To this end, we follow Herzer and Nowak (forthcoming), who estimate models with $I(1)$ and $I(0)$ regressors making use of the Stock (1987) approach. This approach is based on the conditional error correction model (5), where the current and lagged values of the detrended GDP are included as explanatory variables. Accordingly, we regress $\Delta LPOV_t$ on $LPOV_{t\text{-}1}$, $LM_{t\text{-}1}$, $LHF_{t\text{-}1}$, $LPA_{t\text{-}1}$, $LW_{t\text{-}1}$, and $LF_{t\text{-}1}$ the differences of $LPOV_t$, LM_t, LHF_t, LPA_t, LW_t and LF_t up to lag order two, CY_t up to lag order two, the lagged differences of $LPOV_t$ also up to lag order two, and an intercept term. Moreover, we introduce an intervention dummy, *i*_81/82, in order to control for a large outlier in the empirical model. The dummy variable accounts for the poverty effects of the 1981–82 recession that are obviously not sufficiently captured by the business cycle variable, and takes the value of 1 in 1981 and -1 in 1982. After applying the general-to-specific model reduction procedure by successively eliminating the least significant variables, we obtain the following equation (*t*-statistics in parentheses beneath the estimated coefficients):

$$
\begin{aligned}
\Delta LPOV_t = & -3.735 - 0.678LPOV_{t-1} - 0.036LM_{t-1} - 0.099LHF_{t-1} - 0.136LPA_{t-1} \\
& \quad (-7.810) \quad (-12.509) \quad (-2.215) \quad (-6.294) \quad (-5.915) \\
& - 0.473LW_{t-1} + 0.703LF_{t-1} - 1.971CY_t - 0.205\Delta LPA_t + 1.118\Delta LF_t \\
& \quad (-3.221) \quad (8.615) \quad (-11.846) \quad (-3.732) \quad (5.858) \\
& + 0.647\Delta LF_{t-1} + 0.387\Delta LF_{t-2} - 0.025\Delta LM_{t-2} + 0.043i_81/82 \\
& \quad (3.428) \quad (2.011) \quad (-2.685) \quad (3.566)
\end{aligned} \tag{9}
$$

$$
\begin{aligned}
& \bar{R}^2 = 0.95 \quad SE = 0.015 \quad JB = 1.69(0.43) \quad RESET(1) = 0.21(0.65) \\
& LM(1) = 0.05(0.81) \quad LM(3) = 0.45(0.71) \quad LM(5) = 1.35(0.28) \\
& ARCH(1) = 0.21(0.65) \quad ARCH(2) = 0.17(0.85) \quad ARCH(4) = 1.16(0.35)
\end{aligned}
$$

The numbers in parentheses behind the values of the diagnostic test statistics are the corresponding *p*-values. *JB* is the Jarque-Bera test for normality, *RESET* is the usual test for general nonlinearity and misspecification, *LM*(*k*), *k* = 1, 3, 5 are Lagrange Multiplier (LM) tests for autocorrelation based on 1, 3, and 5 lags, and *ARCH*(*k*) is an LM test for autoregressive conditional heteroscedasticity of order *k*, *k* =1, 2, and 4. As can be seen, all *p*-values exceed the conventional significance levels. Hence, we conclude that neither obvious nonlinearity or misspecification is present, nor that the residuals show any signs of nonnormality, autocorrelation or autoregressive heteroscedasticity.

The stability of the estimated equation is checked using the CUSUM test and the CUSUM of squares test. Figure II shows the results along with the 5% critical lines. As can be observed, neither of the two tests indicate any instability of the estimated equation.

[Figure 2 around here]

A significant negative coefficient of the lagged dependent level variable indicates cointegration. Therefore, as the findings of Ericsson and MacKinnon (2002) suggest, this coefficient – which we denote here as b_2 – can be used to test for cointegration. Accordingly, the null to be tested is b_2 = 0. Critical values are provided by Ericsson and MacKinnon (2002). For 39

included observations and six variables in the cointegration relation, the finite sample critical value at the 1% level is –5.14. Since the absolute value of the estimated t-statistic of $\hat{b}_2$, $|12.509|$, is higher than the absolute value of the 1% critical value, $|5.14|$, we conclude (as in the previous section) that the null of no cointegration can be rejected. Normalizing on the coefficient of $POV_{t\text{-}1}$ yields the long-run relation

$$(10) \qquad LPOV_t = -0.053LM_t - 0.146LHF_t - 0.201LPA_t - 0.697LW_t + 1.037LF_t,$$

which may be interpreted as an essential part of our poverty function. Adding the (normalized) impact of the business cycle finally gives the following complete poverty function

$$(11) \qquad LPOV_t = -0.053LM_t - 0.146LHF_t - 0.201LPA_t - 0.697LW_t + 1.037LF_t - 2.907CY_t.$$

As can be seen, our results suggest that government transfer programs play an important poverty-reducing role. This is in sharp contrast to the earlier studies by Blank and Blinder (1986), Peterson and Rom (1989), Gottschalk and Danziger (1984), Balke and Slottje (1993), Formby et al. (2001), Vedder and Gallaway (2001), Enders and Hoover (2003), and Hoover et al. (2004) who found either no statistically significant poverty-reducing impact of government transfers, or even a statistically positive relationship between transfers and poverty. We infer from the estimated poverty function that the poverty rate decreases by 0.053 percent due to a one percent increase in medical care, by 0.146 percent due to a one percent increase in housing and food assistance, and by 0.201 percent due to a one percent increase in public assistance payments. From this we conclude that the work disincentive effects of government transfers on poverty, described at the beginning of the paper, are not dominant. This conclusion is indirectly supported by the studies of Winkler (1991), Moffit (1992), and Painter (2001), who indeed found that the labor supply is negatively affected by

government transfers such as ADF/TANF, Medicaid, and housing assistance, but that these negative effects are quite small.

As expected, the poverty rate is reduced by higher wages and increased by the number of female family heads. The estimated relationship suggests that a one percent increase in real wages is associated with a 0.697 percent decrease in poverty, while a one percent increase in female family heads is associated with a 1.037 percent increase in poverty. Consequently, as Freeman (2001, p. 7) points out, "*... the absence of a male breadwinner in families invariably increases poverty in a world where men earn more on average than women, and where many families need two earners to achieve a reasonable level of income*." This result is in line with the findings of Enders and Hoover (2003), who also conclude that an increase in female family heads is associated with an increase in the US poverty rate.

Looking at the coefficient of CY_t, it immediately becomes clear that the long-run poverty function is strongly dominated by the business cycle. A one percent upswing in the business cycle leads to a 2.907 percent decrease in the poverty rate, while business cycle troughs increase poverty to the same extent. Accordingly, the effects of the business cycle on poverty are larger in magnitude than the effects of all other relevant variables.

One may still wonder how robust these results are. It is well known that the cointegration vector and thus our long-run poverty function can only be estimated efficiently from the above conditional error correction model if the explanatory variables are weakly exogenous. For a robustness check, we therefore use the Dynamic OLS (DOLS) procedure advocated by Stock and Watson (1993), since DOLS generates unbiased and asymptotically efficient estimates for variables that cointegrate, even with endogenous regressors. It involves regressing any $I(1)$ variable on other $I(1)$ variables, any $I(0)$ variables, and leads and lags of the first differences of the $I(1)$ variables (for a practical example, see Herzer and Nowak, forthcoming). Hence, our DOLS regression is

$$
\begin{aligned}
LPOV_t &= a + \alpha_1 LM_t + \alpha_2 LHF_t + \alpha_3 LPA_t + \alpha_4 LW_t + \alpha_5 LF_t + \alpha_6 CY_t + i_81/82 \\
&+ \sum_{i=-k}^{i=k} \Phi_1 \Delta LM_{t+i} + \sum_{i=-k}^{i=k} \Phi_2 \Delta LHF_{t+i} + \sum_{i=-k}^{i=k} \Phi_3 \Delta LPA_{t+i} + \sum_{i=-k}^{i=k} \Phi_4 \Delta LW_{t+i} + \sum_{i=-k}^{i=k} \Phi_5 \Delta LF_{t+i} + \varepsilon_t,
\end{aligned} \tag{12}
$$

where α_1, α_2, α_3, α_4, α_5, α_6 are the long-run elasticities, and Φ_1, Φ_2 ,Φ_3, Φ_4, Φ_5 are coefficients of lead and lag differences of the $I(1)$ regressors. Note that Φ_1, Φ_2, Φ_3, Φ_4, Φ_5 are treated as nuisance parameters that serve to adjust for possible endogeneity, autocorrelation, and non-normal residuals. Like model (9), the DOLS equation is estimated with up to two leads and lags (k=2). The following equation results when applying the general-to-specific modeling approach (t-statistics are given in parentheses beneath the estimated coefficients):

$$
\begin{aligned}
LPOV_t &= -4.089 - 0.088 LM_t - 0.116 LHF_t - 0.177 LPA_t - 0.955 LW_t + 0.942 LF_t \\
&\quad (-6.31) \quad (-3.48) \quad (-7.79) \quad (-5.11) \quad (-6.04) \quad (10.30) \\
&- 2.929 CY_t + 1.689 \Delta LW_{t-1} + 0.174 \Delta LHF_{t-1} - 0.079 \Delta LHF_{t+1} + 0.050 i_81/82 \\
&\quad (-12.72) \quad (3.43) \quad (4.709) \quad (-2.07) \quad (3.09)
\end{aligned} \tag{13}
$$

$$
\begin{aligned}
&\bar{R}^2 = 0.96 \quad SE = 0.020 \quad JB = 1.37(0.50) \quad RESET(1) = 0.17(0.68) \\
&LM(1) = 0.71(0.41) \quad LM(3) = 1.52(0.24) \quad LM(5) = 0.87(0.52) \\
&ARCH(1) = 0.17(0.68) \quad ARCH(2) = 0.37(0.69) \quad ARCH(4) = 0.38(0.82)
\end{aligned}
$$

As can be seen, the diagnostic test statistics suggest that the model is well specified. The assumption of normally distributed residuals cannot be rejected (*JB*). The Lagrange multiplier (*LM*) tests for autocorrelation based on 1, 3 and 5 lags, respectively, do not indicate any problems concerning autocorrelated residuals. The model also passes the LM tests for autoregressive conditional heteroscedasticity (*ARCH*(*k*)) of order k = 1, 2, 4, and the *RESET* test does not suggest nonlinearity. Furthermore, the CUSUM and CUSUM of squares tests are presented in Figure III, indicating a stable relationship between poverty, government transfers to the poor, real wages,

female family heads, and the business cycle. Note that we also performed a series of Chow forecast tests which were not significant at the 10 percent level and are thus not reported to save space.

[Figure 3 around here]

The DOLS approach finally yields the following cointegrating relation and the following long-run poverty function respectively

(14) $$LPOV_t = -0.088LM_t - 0.116LHF_t - 0.177LPA_t - 0.955LW_t + 0.942LF_t + ect_t,$$

(15) $$LPOV_t = -0.088LM_t - 0.116LHF_t - 0.177LPA_t - 0.955LW_t + 0.943LF_t - 2.929CY_t,$$

which are very close to the results obtained from the Stock approach. From this we infer that the results are very robust to different estimation techniques. Consequently, the above qualitative conclusions about the poverty impacts of medical care expenditures, housing, food and public assistance expenditures, real wages, the number of female-headed households, and the business cycle remain unchanged.

For a more complete picture of the channels of poverty-reducing policies, we should model the dynamic interactions between these variables. Of course, a model which completely explains all our variables would theoretically require modeling the whole US economy. Because this is not feasible, we construct a seven-equation model.

C. *The Empirical Model*

Our modeling approach is similar to that used in Lütkepohl and Wolters' (2003) investigation of the German monetary policy. It involves treating the error correction term

(16) $$ect_t = LPOV_t + 0.088LM_t + 0.116LHF_t + 0.177LPA_t + 0.955LW_t - 0.942LF_t$$

from equation (14) as an additional stationary variable in specifying the seven-equation model. Recall that weak exogeneity is not required for the DOLS procedure. Therefore we continue our analysis using the cointegrating relation derived from the DOLS approach, rather than from the Stock procedure.

Our seven-equation model starts from a vector error correction model with $\Delta LPOV_t$, ΔLM_t, ΔLHF_t, ΔLPA_t, ΔLW_t and CY_t, as dependent variables, where all equations are in reduced form. Accordingly they initially contain as explanatory variables ect_{t-1}, $\Delta LPOV_{t-i}$, ΔLM_{t-i}, ΔLHF_{t-i}, ΔLPA_{t-i}, as well as ΔLW_{t-i} up to lag order two (i = 2), and CY_{t-i} also up to lag order two (i = 2). Notice that CY_t does not appear in first differences because the business cycle is already stationary.

As in the previous analysis, variables with insignificant coefficients are then eliminated successively according to the lowest t-values, while the error correction term in each equation is kept until the end. The error correction term is eliminated if it turns out to be insignificant in the model in which all other insignificant variables are already eliminated. This strategy results in the equations presented in the following.

Before interpreting the results, it should be noted that the modeling approach described above is justified if it results in a system without instantaneous correlation between the residuals. The residual correlation matrix of the estimated single equations (17) - (23) is

$$\begin{bmatrix} 1.00 & 0.30 & 0.05 & -0.30 & -0.11 & 0.02 & -0.39 \\ 0.30 & 1.00 & 0.14 & 0.16 & 0.25 & 0.14 & -0.35 \\ 0.05 & 0.14 & 1.00 & 0.09 & -0.21 & -0.31 & -0.07 \\ -0.29 & 0.16 & 0.09 & 1.00 & 0.23 & -0.06 & -0.21 \\ -0.11 & 0.25 & -0.21 & 0.23 & 1.00 & 0.02 & 0.06 \\ 0.02 & 0.14 & -0.31 & -0.06 & 0.02 & 1.00 & 0.10 \\ -0.39 & -0.35 & -0.07 & -0.21 & 0.06 & 0.10 & 1.00 \end{bmatrix} \begin{matrix} \Delta LPOV_t \\ \Delta LM_t \\ \Delta LHF_t \\ \Delta LPA_t \\ \Delta LW_t \\ \Delta LF_t \\ CY_t \end{matrix}$$

Because all off-diagonal elements are relatively small, we proceed under the assumption that there is no problem with autocorrelated residuals and that, hence, we have a recursive system as postulated for identification.

The estimated poverty equation is

$$
\begin{aligned}
\Delta LPOV_t = & -3.469 - 0.842 ect_{t-1} + 0.655 \Delta LPOV_{t-1} + 1.012 \Delta LF_{t-2} + 1.411 \Delta LW_{t-2} \\
& \quad (-4.56) \quad (-4.55) \quad (6.19) \quad (3.76) \quad (2.21) \\
(17) \qquad & -1.346 CY_{t-1} - 0.092 im_76 + 0.044 i_82/83 \\
& \quad (-2.10) \quad (-2.94) \quad (1.80)
\end{aligned}
$$

$$\bar{R}^2 = 0.73 \quad SE = 0.028 \quad JB = 1.73(0.42) \quad RESET(1) = 2.39(0.13)$$

$$LM(1) = 0.14(0.71) \quad LM(3) = 0.34(0.80) \quad LM(5) = 0.52(0.76)$$

$$ARCH(1) = 0.37(0.54) \quad ARCH(2) = 0.06(0.95) \quad ARCH(4) = 1.04(0.40)$$

Note that the deterministic terms are not the same as in equations (9) and (13). For example, an impulse dummy for 1976, *im*_76, was needed to achieve a normal distribution of the residuals.[7] A possible reason for the importance of *im*_76 is the fast economic recovery after the 1974-75 recession that caused a sharp decrease in the poverty rate in 1976. Furthermore, the intervention dummy *i*_82/83 had to be introduced in order to account for the poverty effects of the 1982-83 recession that are obviously not sufficiently captured in the detrended GDP.[8] The error correction term is statistically significant and correctly negatively signed. Accordingly, poverty shrinks if it exceeds its long-run equilibrium level, as one would expect in a stable model. The size of the coefficient of ect_{t-1} suggests that the speed of adjustment towards long-run equilibrium after a shock is remarkably high. More precisely, it indicates that around 85 percent of the deviation from the long-run equilibrium is corrected every year. Moreover, the business cycle is Granger-causal for

[7] *im*_76 is one in 1976 and zero otherwise.
[8] *i*_82/83 takes the value of 1 in 1982, -1 in 1983, and zero otherwise.

poverty, as indicated by the significance of the lagged business cycle variable, CY_{t-1}. Interestingly, the long-run and short-run effects of real wages on poverty differ. In the short run (as shown by ΔLW_{t-2}), real wages are positively related to poverty. This might indicate that poverty is driven by unemployment, and that unemployment, in turn, is caused by real wages rising faster than productivity.

The medical care expenditure equation turns out to be

$$
\begin{aligned}
\Delta LM_t = & -0.841 - 0.217 ect_{t-1} + 0.360 \Delta LM_{t-1} - 2.141 \Delta LW_{t-1} + 1.112 \Delta LW_{t-2} \\
& \quad (-2.52) \quad (-2.68) \quad (11.24) \quad (-5.17) \quad (2.13) \\
& + 0.245 \Delta POV_{t-2} + 0.780 im_67 + 0.019 im_72 \\
& \quad (2.03) \quad (35.25) \quad (4.56)
\end{aligned} \tag{18}
$$

$$\bar{R}^2 = 0.98 \quad SE = 0.021 \quad JB = 2.14(0.34) \quad RESET(1) = 0.17(0.69)$$

$$LM(1) = 0.02(0.89) \quad LM(3) = 0.52(0.67) \quad LM(5) = 0.70(0.63)$$

$$ARCH(1) = 2.14(0.15) \quad ARCH(2) = 1.22\ (0.31) \quad ARCH(4) = 0.89(0.48)$$

An impulse dummy for 1967, *im*_67, was needed to achieve a normal distribution of the residuals. It presumably captures the effects of the Vietnam War, which brought with it a sharp increase in medical care expenditures in 1967 (see Figure I). Moreover, an impulse dummy for 1972, *im*_73, had to be introduced in order to control for an unexplainable outlier in the model.[9] The business cycle variable turned out to be insignificant and, hence, was eliminated from the model. From this it can be concluded that the business cycle has no Granger-causal impact on medical care expenditure growth. The negative coefficient of the error correction term implies that "excess poverty" lowers the growth of medical care expenditures. The rationale for this finding will become apparent below. As equation (19) and (20) will show, if poverty overshoots its long-run level, the downward adjustment towards the long-run equilibrium does occur via increased housing and food assistance

as well as public assistance payments, while the growth of medical care expenditures decreases. Obviously there is a redistribution of resources from the medical care program to the housing, food and public assistance programs due to a "poverty shock". This point will be taken up again later on.

The equation for housing and food assistance was found to be

$$
\begin{aligned}
\Delta LHF_t &= \underset{(2.20)}{2.830} + \underset{(2.15)}{0.677} ect_{t-1} - \underset{(-2.43)}{0.718} \Delta LPOV_{t-1} - \underset{(-2.70)}{3.003} \Delta LW_{t-1} \\
&+ \underset{(3.16)}{2.567} CY_{t-1} + \underset{(5.31)}{0.326} im_70 + \underset{(9.31)}{0.566} im_71 + \underset{(5.14)}{0.312} im_72
\end{aligned} \tag{19}
$$

$$\bar{R}^2 = 0.85 \quad SE = 0.058 \quad JB = 0.22(0.90) \quad RESET(1) = 1.830(0.19)$$

$$LM(1) = 2.28(0.14) \qquad LM(3) = 0.92(0.44) \qquad LM(5) = 0.72(0.62)$$

$$ARCH(1) = 0.66(0.42) \quad ARCH(2) = 0.25\ (0.78) \quad ARCH(4) = 0.23(0.92)$$

Three impulse dummy variables (*im*_70, *im*_71, *im*_71) were needed to obtain a well-specified equation.[10] The positive coefficient of the error correction term ect_{t-1} suggests that the downward adjustment towards the long-run poverty equilibrium takes place through increased housing and food payments, as already noted. Consequently, housing and food – as well as medical care payments – are not weakly exogenous to the system. Moreover, the positive coefficient of the lagged business cycle variable indicates that business cycle downswings (upswings) lower (stimulate) the growth of housing and food benefits. From this we conclude that business cycle fluctuations tend to affect poverty through their impact on housing and food payments. It should also be noted that equation (19) includes one lag of real wages. The negative sign of this variable suggests that the demand of the poor for public housing and food assistance programs – and hence the growth of public housing and food expenditures – is decreased by the income effect of the wage

[9] *im*_67 (*im*_72) is one in 1967 (1972) and zero elsewhere.
[10] *im*_70 (*im*_71, *im*_72) is one in 1970 (1971, 1972) and zero elsewhere.

change. On the other hand, because of the various interactions between the variables, the exact reason for the negative impact of $\Delta LPOV_{t-1}$ on ΔLHF_t is not clear. One possible explanation could be that poverty affects the business cycle (as the discussion of equation (23) will show), and poverty-related business cycle downswings, in turn, tend to dampen the increase in housing and food assistance.

The public assistance equation is

$$\Delta LPA_t = \underset{(3.31)}{2.409} + \underset{(3.24)}{0.578} ect_{t-1} + \underset{(4.36)}{1.950} CY_{t-2} - \underset{(-4.52)}{0.210} im_73 - \underset{(-3.22)}{0.147} im_82 \tag{20}$$

$$\bar{R}^2 = 0.54 \quad SE = 0.044 \quad JB = 3.22(0.20) \quad RESET(1) = 0.51(0.48)$$

$$LM(1) = 0.20(0.65) \qquad LM(3) = 1.38(0.27) \qquad LM(5) = 0.96(0.46)$$

$$ARCH(1) = 0.11(0.74) \quad ARCH(2) = 1.77\ (0.19) \quad ARCH(4) = 1.10(0.38)$$

Two impulse dummies for the years 1973 and 1982 were introduced to avoid the effects of outlying observations. As in the equations above, the public assistance equation includes the error correction term ect_{t-1}. Its positive sign indicates that "excess poverty" stimulates the growth of public assistance payments. Since the growth of government expenditures on both public assistance as well as housing and food responds positively, while the growth of expenditures on medical care responds negatively to excess poverty, we conclude (as already noted): a "poverty shock" appears to cause a redistribution of resources from the medical care program to the housing, food and public assistance programs. Moreover, similar to equation (19), the positive sign of the business cycle variable suggests that the US government tends to increase (decrease) public assistance payments when the business cycle is up (down).

For real wages, we found the following autoregressive model

$$\Delta LW_t = 0.003 + 0.957\Delta LW_{t-1} - 0.384\Delta LW_{t-2} \tag{21}$$

$$\quad (1.61) \qquad (7.06) \qquad (-2.95)$$

$$\bar{R}^2 = 0.65 \quad SE = 0.007 \quad JB = 0.66(0.72) \quad RESET(1) = 0.00(0.99)$$

$$LM(1) = 0.04(0.83) \qquad LM(3) = 0.43(0.73) \qquad LM(5) = 0.33(0.89)$$

$$ARCH(1) = 0.01(0.91) \quad ARCH(2) = 0.49\ (0.62) \quad ARCH(4) = 0.44(0.78)$$

The error correction term turned out to be insignificant. Hence, real wages are weakly exogenous. Since the wage equation contains own lags only, real wages can actually be treated as strictly exogenous. The absence of the business cycle variable indicates that business cycle fluctuations have no statistically significant (Granger-causal) impact on the growth of real wages, which may be due to wage rigidities.[11] We can therefore conclude that the US business cycle is not related to poverty through the wage channel. This conclusion is indirectly supported by the studies of Solon et al. (1994) and Kandil and Woods (2002). The former found for low-skilled workers that business cycle adjustments result in a significant change in labor hours, not in hourly wages. Kandi and Woods (2002) obtained a similar result for workers age 25 and older, who make up the largest group of workers in the United States. This might explain our statistically insignificant relationship between changes in (aggregate) real wages and the business cycle. If, however, the growth of hourly earnings is independent of business cycle fluctuations, we can conclude that the business cycle does not influence poverty through real wage changes (measured by growth in hourly earnings). Other plausible mechanisms by which business cycle fluctuations might affect poverty in the US include, of course, fluctuations in employment and income from work ─ that is, the product of hourly wages *and* the number of hours worked.

The equation for the number of female-headed households turns out to be

$$\Delta LF_t = 0.666 + 0.159 ect_{t-1} + 0.374 \Delta LF_{t-2} + 0.509 CY_{t-2} - 0.036 im_83 \tag{23}$$

$$(2.334) \quad (2.28) \quad (-2.65) \quad (2.88) \quad (-1.95)$$

$$\bar{R}^2 = 0.27 \quad SE = 0.017 \quad JB = 0.63(0.73) \quad RESET(1) = 2.67(0.11)$$

$$LM(1) = 0.01(0.90) \quad LM(3) = 0.21(0.89) \quad LM(5) = 0.81(0.55)$$

$$ARCH(1) = 0.81(0.37) \quad ARCH(2) = 0.81\ (0.45) \quad ARCH(4) = 0.66(0.62)$$

where an impulse dummy for 1983 was needed to achieve a normal distribution of the residuals.[12] The positive coefficient of the error correction term ect_{t-1} implies that "excess poverty" stimulates growth in the number of female-headed households. Because these families are created through divorce and the birth of children to as yet unmarried women, we interpret this finding as evidence that poverty erodes family stability, reducing the likelihood that individuals will marry and increasing the likelihood that their marriages will deteriorate. Consequently, poverty is a cause and a consequence of non-marriage and marital disruption. Interestingly, the business cycle appears to be positively related to an increased number of female-headed households. This finding is not surprising given that divorce rates tend to fluctuate procyclically in many countries (see, e.g., Becker, 1988; Huang, 2003). As already explained by Ogburn and Thomas (1922), one reason for more divorces in times of economic prosperity is that divorces are expensive, involving lawyer and court fees and perhaps alimony. Furthermore, the economic theory of marriage suggests that increasing women's wages in times of economic growth may reduce the gains from staying married (or marrying) by diminishing the benefits of household specialization (Becker, 1981). Since business cycle downswings increase poverty, which, in turn, raises the number of female-headed households, business cycle fluctuations obviously may have two opposing effects: (*i*) an indirect effect on those families living close to the poverty line by pushing them into poverty in times of

[11] Note that the available empirical evidence of the cyclicality of the real wages in the US is inconclusive about the direction as well as about the degree of cyclical movement in response to business cycle fluctuations (see, for example, Bodkin 1969; Abraham and Haltiwanger 1995; Kandil and Woods 2002).
[12] *im*_83 is one in 1983 and zero elsewhere.

business cycle downturns, undermining family cohesion, and thus *increasing* the number of female-headed households; and (*i*) a direct effect on families (who are not vulnerable to poverty) by increasing the financial incentives of marriage and raising the financial burden of divorce or separation in business cycle downswings, and hence *decreasing* the number of female-headed households.

The business cycle equation is

$$
\begin{aligned}
CY_t = & -1.082 - 0.263ect_{t-1} - 0.088\Delta LPOV_{t-2} + 0.051\Delta LHF_{t-2} \\
& \quad (-4.52) \quad (-4.50) \qquad (-1.81) \qquad\quad (2.93) \\
& + 0.825\Delta LW_{t-1} - 0.480CY_{t-2} - 0.038im_70 \\
& \quad (4.00) \qquad\quad (-3.34) \qquad (-2.71)
\end{aligned} \tag{23}
$$

$$
\begin{aligned}
& \bar{R}^2 = 0.60 \quad SE = 0.013 \quad JB = 0.81(0.67) \quad RESET(1) = 0.67(0.42) \\
& LM(1) = 0.17(0.68) \qquad LM(3) = 0.08(0.97) \qquad LM(5) = 0.78(0.57) \\
& ARCH(1) = 0.57(0.47) \quad ARCH(2) = 0.43\ (0.65) \quad ARCH(4) = 0.45(0.77)
\end{aligned}
$$

where one impulse dummy variable (*im*_70) was needed to obtain a well-specified equation.[13] The equation includes the error correction ect_{t-1} with a negative sign so that "excess poverty" lowers economic activity around its log-run trend. In addition to the error correction term and the own lag CY_{t-2}, equation (23) includes lags of $\Delta LPOV_t$, ΔLHF_t, and ΔLW_t, indicating that the business cycle is caused by demand-related factors such as poverty, real wages, and housing and food payments. Thus, poverty is affected by the business cycle, which is in turn affected by poverty.

[13] *im*_70 is one in 1970 and zero elsewhere.

IV. Summary and Conclusions

The objectives of this paper were threefold. First, we reexamined the impact of government transfers on US poverty empirically by applying cointegration techniques to aggregate time series data over the period 1964-2004. In sharp contrast to most previous studies, we found that government transfers (cash transfers, medical care as well as food and housing assistance) play a significant role in reducing poverty. Second, we investigated the impact of the business cycle on US poverty and found its effect to be not only statistically significant but also larger in magnitude than any of the other relevant poverty determinants. Third, we empirically analyzed the dynamic interactions between poverty, government transfers, and the business cycle. Our estimations showed that the overall amount and composition of government transfers changes over the business cycle. Moreover, we found significant feedback effects of poverty on government transfers, the business cycle and household structure. Summing up, our results demonstrate how modern techniques of time series analysis can be used to shed more light on the determinants of poverty in an industrialized society and their patterns of interaction.

The implications for economic and social policy are obvious and far-reaching. The dominant influence of the business cycle on changes in poverty clearly calls for improved macroeconomic stabilization policies that reduce the vulnerability of low-income people and households to poverty. Even if it is not clear whether these improvements can be achieved by pure demand management or pure supply-side policies – or an intelligent mixture of both – a successful dampening of GDP fluctuations around the trend seems to be an effective way to fight poverty. In addition, the cyclical development of public transfers to the poor could be reduced in order to eliminate one of channels through which GDP fluctuations affect poverty. And finally, strengthening two-parent household structures also seems to be a promising way to reduce the negative effects of the business cycle on poverty. None of these conclusions is totally new, but they have never been brought together in the context of a comprehensive and empirically well-grounded study of poverty.

Potential areas for future research are clear. The results for the US should be compared to similar investigations for other industrialized and developing countries. Here, we can expect to find different patterns of dynamic interaction in developing countries where government transfers still play a minor role. For industrialized countries, future research should focus much more closely on the interaction between real wages, the business cycle, and poverty, in order to clarify this relationship further than we have been able to do in the present study.

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TABLE I

ADF TEST

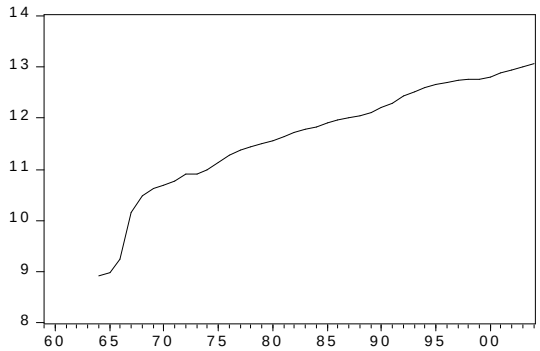
Variable	Deterministic terms[a]	Lag length	Value of test statistic	Probability[b]
Levels				
$LGDP_t$	$c, t\ (4.93^{***})^c$	1	-4.95	0.001
$LPOV_t$	C	5	-2.54	0.115
LM_t	c, t	6	-3.25	0.092
LHF_t	c, t	1	-2.20	0.479
LPA_t	c, t	0	-1.86	0.656
LW_t	c, t	4	-2.48	0.337
LF_t	c, t	0	-0.06	0.993
CY_t	-	1	-5.06	0.000
First Differences				
$\Delta LPOV_t$	C	1	-4.22	0.002
ΔLM_t	C	0	-4.87	0.000
ΔLHF_t	c, t	1	-4.08	0.014
ΔLPA_t	C	0	-5.82	0.000
ΔLW_t	C	1	-3.63	0.010
ΔLF_t	C	0	-5.60	0.000

[a] c = constant; t = linear time trend; [b] MacKinnon (1996) one-sided p-values. [c] t-value of the time trend in parentheses, *** denotes the 1% level of significance.

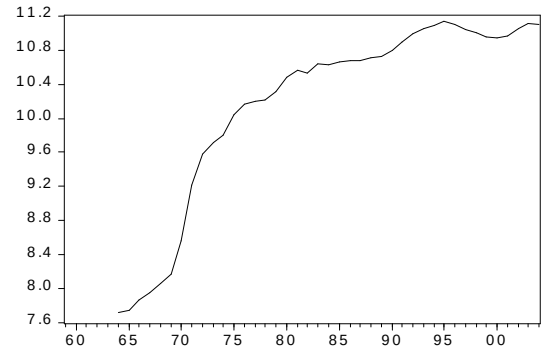
FIGURE I

TIME SERIES USED

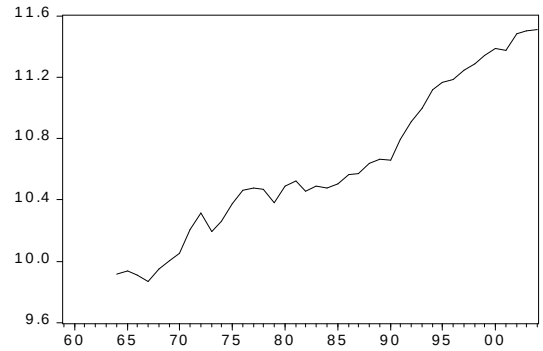
Logs of poverty rate, $LPOV_t$



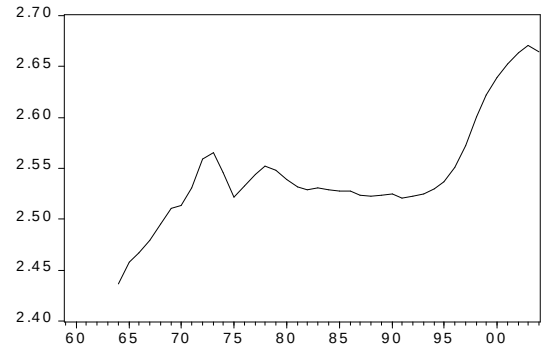
Logs of real medical care expenditures, LM_t



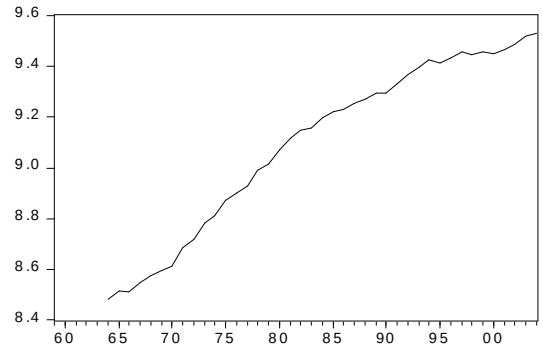
Logs of real housing and food assistance, LHF_t



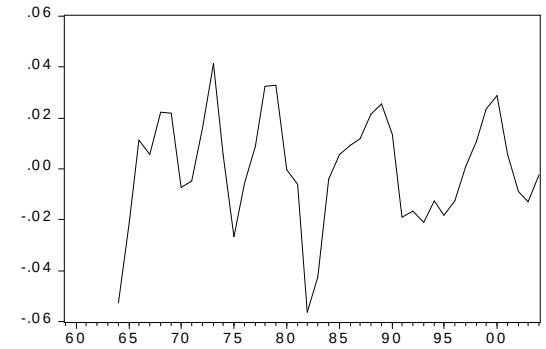
Logs of real public assistance, LPA_t



Logs of real wages (average hourly earnings), LW_t



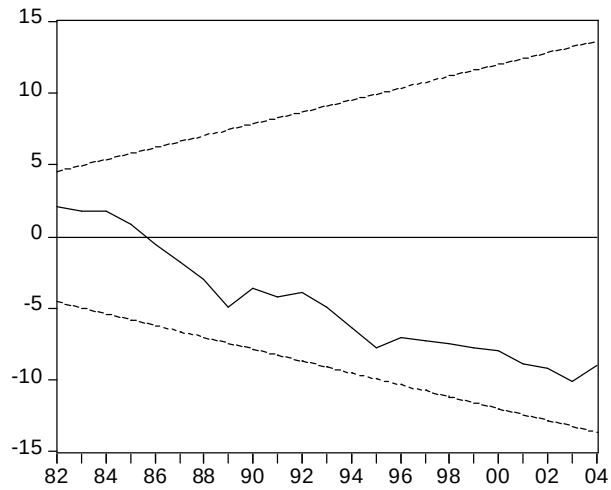
Logs of female family heads, LF_t



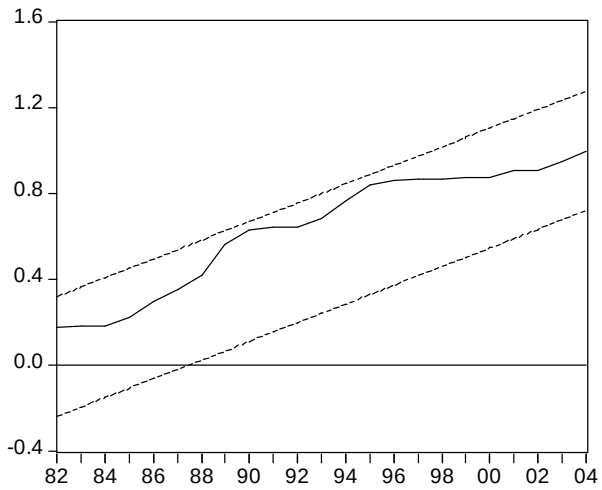
Business cycle (detrended logs of real GDP), CY_t

FIGURE II

STABILITY ANALYSIS FOR MODEL (9)



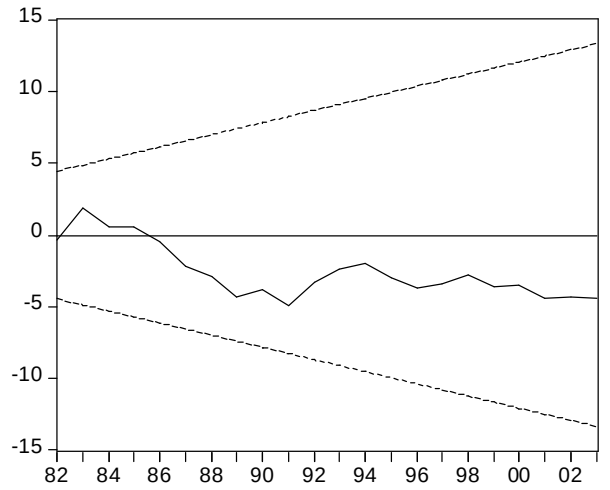
CUSUMs and 5% significance bounds



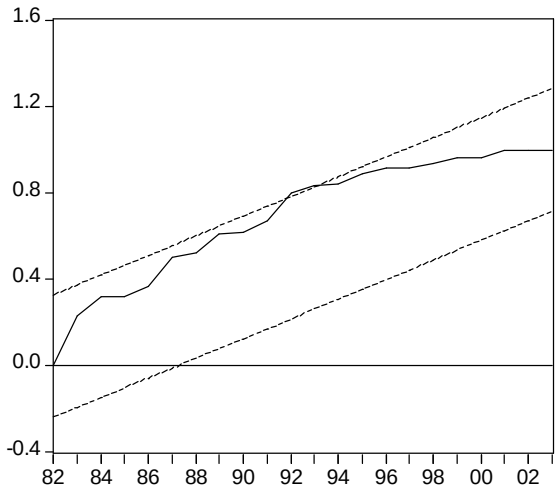
CUSUM of squares and 5% significance bounds

FIGURE III

STABILITY ANALYSIS FOR MODEL (13)



CUSUMs and 5% significance bounds



CUSUM of squares and 5% significance bounds