INCOME INEQUALITY AND THE BUSINESS CYCLE: A THRESHOLD COINTEGRATION APPROACH ♣

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Abstract:
This paper investigates the impact of various socio-economic variables on various cohorts of the income distribution. We use asymmetric cointegration tests to show that unemployment and immigration shocks have real impacts on income inequality. In addition, using threshold test results we are able to show that positive and negative shocks to the economy do not have symmetric effects nor do the impacts of these shocks impact income quintiles uniformly.

Keywords: Income inequality, Granger Causality, Asymmetric Cointegration

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1. INTRODUCTION

Beginning with the seminal work of Kuznets (1955) many researchers have endeavored to investigate the nature of the relationship between economic growth and income inequality. The Kuznets hypothesis posited that the functional relationship between inequality and economic development had an inverted "U" shape. Kuznets speculated that inequality would initially be positively correlated with economic development but that the relationship between economic growth and inequality would become negative at higher levels of development. Results supporting this hypothesis typically come from the use of cross-sectional country-specific data. Some recent researchers dispute the Kuznets hypothesis such as Bruno et al. (1998). Still others, such as Blinder and Esaki (1978), have found results that support the basic premise of the Kuznets hypothesis but expand on how inflation and unemployment factor into inequality.

What makes this area of research so inviting is that key to the debate over the relationship between growth and inequality is the question of what impact growth has on citizens throughout the entire income distribution. Most research in this area investigates the impact that economic development, namely GDP, has on some standard measure of income inequality, such as the Gini coefficient. What cannot be gleaned from these endeavors is whether a growing economy is helping all segments of society or is just helping certain subsets of society.

If economic growth is found to be positively correlated with income inequality it is not clear if the increase in income inequality is being caused by an increase in the incomes of those in the highest quintile of the income distribution while those in the bottom quintile have incomes that are stagnant or falling. It could also be the case that while incomes are growing for all income quintiles, the income growth of the top quintile is greater than the income growth for other quintiles. These are empirical questions that can not be answered by simply regressing a standard Gini coefficient against GDP.

Our paper will go beyond what has been done previously in that we will be able to investigate the various degrees of impact that economic growth, unemployment, and to a lesser extent, immigration have on different cohorts of the income distribution. This paper has the advantage of using a time-series that has nearly 60 years of reliable U.S. data. Specifically, we consider whether economic upturns have a different impact on income inequality than economic downturns.

Asymmetric behavior over the business cycle has attracted considerable attention in the last decades. Neftci (1984) showed that several measures of U.S. unemployment display asymmetric adjustment over the course of the business cycle. Focusing on the asymmetric behavior of unemployment rates over the business cycle, Rothman (1992) showed that the primary source of asymmetry is the cyclical behavior of the unemployment rate in the manufacturing sector. Acemoglu and Scott (1994) have also shown asymmetries in the cyclical behavior of UK labor markets. Harris and Silverstone (1999) and Silvapulle et al. (2004) tested asymmetric adjustment in specifications of Okun's law. They found that the short-run effects of positive cyclical output on cyclical unemployment are quantitatively different from those of negative ones; as such, the relationship between labor market indicators and aggregate income is asymmetric.

Previous Research and Our Model

Typically there have been two approaches to this type of research. One approach uses a cross-section of countries with varying levels of economic growth and income inequality to investigate the impact of economic growth on country level inequality. Another approach is to take a consistent time series for one country (typically the United States) to analyze how growth over time has impacted income inequality without regard to redistributive policy measures such as taxes or social programs. What we propose in this paper is more akin to the latter methodology.

Our model is similar to that of Blinder and Esaki (1978) and Bishop et al. (1994) with some key differences. Both papers use an extensive time series, although the one used in our paper is the longest, by far, and covers the period from 1948 to 2003. (See Perman and Stern (2003) for an excellent review of the issues and techniques related to this type of investigation.) Blinder and Esaki (1978) used income quintiles as left hand side variables with a time series of unemployment and inflation as explanatory variables. Their finding that inflation is progressive along the income distribution has been supported others such as Blank and Blinder (1986).

Later work by Bishop et al. (1994) includes several controls for demographic, structural, and economic variables that might also affect movements along the income distribution. They also recognized that the possibility of random walks and cointegration should be addressed. The time series they used is relatively short and they did not include a measure of income inequality, such as the Gini coefficient to test the validity of the Kuznets hypothesis.

Research, such as that done by Chen (2003), Gomez and Foot (2002), and Adams (2003), does test the Kuznets hypothesis with fairly reliable country-level cross-sectional data. Their results are complementary to Kuznets but fail to account for the variance in responses of the different quintiles along the income distribution. Income is being impacted by growth in their model but they can not say whether those in the higher quintiles are being impacted more, less, or the same as those income earners in the lowest quintile.

There has been some research on the impact of growth on after-tax inequality. Hayes et al. (1991) examines impacts on the income distribution after policy initiatives, such as redistributive taxes, have been implemented. More recent work by Lundberg and Squire (2003) points out that the impact of policy initiatives on inequality and on growth should share some common characteristics and as such should be studied simultaneously. They report that by doing so it is shown that the determinants of growth and inequality are not mutually exclusive.

Theoretical work on the relationship between business cycles and income inequality fails to account for the increase in inequality and wealth concentration in the United States. Castaneda, Diaz-Gimenez and Rios-Rull (1998) examined the extent to which unemployment spells and cyclically-moving factor shares account for the behavior of income inequality over the business cycle. While their model somewhat accounts for income inequality business cycle dynamics, it does not account for wealth concentration. Dolmas, Huffman, and Wynne (2000), and Albanesi (2007) model inflation in a public choice framework whereby political conflicts lead to inflation; as such, agent heterogeneity allows for the modeling of monetary policy as a function of inequality. The results will depend on the political powers of agents. Heer and Sussmuth (2003) analyze the effects of a permanent change in inflation on the distribution of wealth and find a significant relationship between inequality and inflation for the U.S. economy. Specifically, higher inflation leads to higher nominal interest rates and a higher real tax burden on interest income. An increase in inflation results in a lower stock market participation rate and an increase in wealth inequality. Focusing on cross-country correlations between inflation unemployment and income inequality, Romer and Romer (1999) find a strong relationship between unemployment and poverty, and no clear relationship between inflation and poverty.

Even though the literature is suggestive of potential variables that are associated with worsening of income inequality, the dynamic interaction between movement in the income distribution and the business cycle have not been explored in the literature. The primary objective of this paper is to investigate the dynamic interactions between income inequality and measures of the business cycle. We also consider a host of socio-economic variables such as immigration, imports from less developed countries, annual inflation, female headed households, labor force participation rate by females, total transfers, the share of services in GDP, service employment as share of total employment, and productivity. After identifying significant variables, we test whether the relationship between business cycles and income inequality is asymmetric. This issue is germane since the relationship between labor market indicators and aggregate income has been found to be asymmetric. Since the principal sources of income, particularly for persons in the lower quintiles of the income distribution, are wages and salaries, it is natural to examine whether the relationship between business cycles and the income distribution is asymmetric. Using threshold and momentum models of cointegration developed by Enders and Granger (1998) and Enders and Siklos (2001), we test whether economic expansions have a different impact on the income distribution than economic contractions. Since income inequality also can affect the business cycle via the propensity to spend at the lower quintiles of the income distribution, there can be feedback effects between the income distribution and the business cycle. Impulse response functions based on the Vector Error Correction Model are suitable to analyze such feedback effects.

To preview our results, we find asymmetric adjustment between the quintiles comprising the U.S. income distribution and business cycle measures over the last 50 years. Particularly, increases in unemployment cause increases in income inequality, but negative shocks to unemployment have only short-lived positive benefits on income inequality. In what follows, we spell out our methodology and data. Section 3 presents empirical results and section 4 concludes the paper with a discussion of policy implications.

2. METHODOLOGY AND DATA

Consider the relationship between an income distribution measure, y_t, and a set of conditioning variables, x_{it}:

$$y_t = \beta_0 + \beta_1 x_{1t} + \ldots + \beta_k x_{kt} + \mu_t \tag{1}$$

where μ_t is a stationary random variable that represents the deviation from the long run equilibrium, if any. As in Enders and Siklos (2001), a formal way to introduce asymmetric adjustment to the model is to let the deviation from the long-run equilibrium (i.e. μ_t) in Equation (1) behave as a Threshold Autoregressive (TAR) process.

$$\Delta\mu_t = I_t \rho_1 \mu_{t-1} + (1 - I_t)\rho_2 \mu_{t-1} + \sum_{i=1}^{p} \beta_i \Delta\mu_{t-i} + \varepsilon_t \tag{2}$$

where I_t is the Heaviside indicator such that

$$I_t = \begin{cases} 1 \text{ if } \mu_{\text{t-1}} \geq \tau \\ 0 \text{ if } \mu_{\text{t-1}} < \tau \end{cases} \tag{3}$$

where τ is the value of a threshold.

Since the exact nature of the non-linearity may not be known, it is also possible to allow the adjustment to depend on the change in $\mu_{\text{t-1}}$ (i.e., $\Delta\mu_{\text{t-1}}$) instead of the level of μ_{t}. In this case, the Heaviside indicator in equation (3) becomes:

$$I_t = \begin{cases} 1 \text{ if } \Delta\mu_{\text{t-1}} \geq \tau \\ 0 \text{ if } \Delta\mu_{\text{t-1}} < \tau \end{cases} \tag{4}$$

Enders and Granger (1998) and Enders and Siklos (2001) show that this specification is especially relevant when the adjustment is such that the series exhibits more "momentum" in one direction than the other; the resulting model is called a momentum-threshold autoregressive (M-TAR) model.

A sufficient condition for stationarity of $\{\mu_t\}$ is -2 < (ρ_1, ρ_2) < 0. Tong (1983) shows that the least squares estimates of ρ_1 and ρ_2 have an asymptotic multivariate normal distribution when the $\{\mu_t\}$ sequence is stationary. Thus, it is possible to test for symmetric adjustment (i.e. $\rho_1 = \rho_2$) using a standard *F*-test when the null hypothesis of non-cointegration is rejected.

The critical values for the statistics needed to test the null hypothesis, $\rho_1 = \rho_2 = 0$, depend on the number of variables used in the co-integrating vector. Enders and Siklos (2001) report critical values for the TAR and M-TAR models containing two variables, called the Φ (for TAR adjustment), $\Phi*$ (for the M-TAR adjustment). Critical values for the multivariate case are derived by Wane, Gilbert and Dibooglu (2004). As there is generally no presumption as to whether to use the TAR or M-TAR model, the recommendation is to select the adjustment mechanism by a model selection criterion such as the Akaike Information Criterion (AIC) or Schwarz's Bayesian Information Criterion (BIC). Similarly, the lag length can also be selected by AIC or BIC.

This framework presumes that the value of the threshold τ is known; however in practice one has to estimate the value of the threshold. As in Chan (1993), and Enders and Siklos (2001), we find a consistent value of the threshold by a grid search. First, we sort the $\{\mu_t\}$ sequence (or the in case of the M-TAR model, $\{\Delta\mu_t\}$ the sequence) in an ascending order. In order to have a reasonable number of observations in each regime we consider each μ_t between the lowest 20 percent and the highest 80 percent values of the series as a potential threshold. We then estimate regressions in the form of (1) using each μ_t (or $\Delta\mu_t$) as a potential value of the threshold. The value resulting in the lowest residual sum of squares is a consistent estimate of the threshold.

To examine the effect of the business cycle on income inequality, we examine two types of variables related to income distribution: the Gini coefficient and conditional mean family income by quintile. The Gini ratio for the United States has varied over the time period of our analysis (1948-2003). In 1948 the Gini ratio was 0.376 and for the next two decades it declined, somewhat unsteadily, until it reached a low of 0.348 in 1968; then, for the next thirty-five years, it mostly steadily increased, reaching 0.436 in 2003. Following Bishop et al. (1994), we define conditional mean family income for each quintile group as the share of total income received by that quintile group times overall mean family income (measured in 2003 dollars). As can be seen in Figure 1, the conditional mean incomes for all quintile groups increased over the period of our analysis, with overall increases ranging from a 128% increase for the second quintile to a 213% increase for the top quintile. Other key variables of interest in our analysis are overall median family income, the annual unemployment rate, and immigration as a percent of total population.[1]

3. EMPIRICAL RESULTS

In this section we pretest the variables for stationarity using Augmented Dickey Fuller (Dickey and Fuller 1981) and KPSS tests based on Kwiatkowski et al. (1992). The results are given in Table 1.[2] The ADF test statistics fail to reject a unit root for all series in levels at the 5 percent level except unemployment and immigration which are on the borderline. The KPSS statistics reject the null hypothesis of stationarity except for unemployment which is on the borderline. Both tests confirm that the series are all stationary in first differences. In what follows we assume the variables are unit root processes in levels and stationary in first differences.

3.1. The Business Cycle and Gini

In order to examine any non-linear behavior of the income distribution over the business cycle, we estimate regressions in the form of equation (1) where *gini* is the left hand side variable and unemployment or GDP is the right hand side variable. In addition, we consider a host of socio-economic variables as conditioning variables. These include, annual immigration as a share of population, aggregate imports as a share of GDP, imports from less

[1] Data for the Gini ratio comes from the U.S. Census Bureau, Historical Income Tables – Families: Table F-4: Gini ratios for Families, All Families 1947 to 2003. Conditional Mean Incomes are calculated from data given by the U.S. Census Bureau, Historical Income Tables – Families: Table F-2: Share of Aggregate Income Received by Each Fifth and Top 5 Percent of Families (All Races): 1947 to 2003; and Table F-5: Race and Hispanic Origin of Householder--Families by Median and Mean Income: 1947 to 2003. Immigration figures come from the U.S. Department of Homeland Security: Yearbook of Immigration Statistics, 2003, Table 1: Immigrant Aliens Admitted for Permanent Residence. The Unemployment Rate comes from the Bureau of Labor Statistics. All data are annual.

[2] The Gini ratio, unemployment and immigration are in levels while conditional mean family incomes by quintile and overall median family income are in logs.

developed countries, annual inflation, female headed households, labor force participation rate by females, total transfers, the share of services in GDP, service employment as share of total employment, and output per worker.

In addition, we consider the proportion of white population, the proportion of married "adult population", a measure of average education level, the proportion of the population aged over 25 with a high school degree, and a Gini coefficient of education as in Thomas, Wang, and Fan (2001). We then test the null hypothesis of non-cointegration between the income distribution and socio-economic indicators against the alternative of cointegration with asymmetric adjustment.

Test statistics reveal that none of the variables other than unemployment and immigration as a share of total population are cointegrated with the Gini. This does not mean that the rest of the variables do not affect the distribution of income. Such effects, if any, must be confined to the short run. Table 2 reveals that *gini*, unemployment, and immigration are indeed cointegrated. The Bayesian Information Criterion (BIC) selects TAR adjustment over M-TAR adjustment. Note that the null hypothesis of symmetric adjustment can be rejected in favor of asymmetric adjustment. Of further note, the point estimates of ρ_1 and ρ_2 suggest substantially faster convergence for below threshold deviations from long run equilibrium (below threshold being ρ_2) than above threshold deviations (above threshold being ρ_1). For example, the point estimates of ρ_1 and ρ_2 suggest that negative deviations from the long run equilibrium resulting from decreases in *gini* or decreases in unemployment or increases in immigration (such that $\mu_{t-1} <$ -0.0213) are eliminated at a rate of 60.3 percent per year while positive deviations are not eliminated at all. In that sense, disequilibria caused by decreases in *gini* (improvements in the income inequality), economic expansions (decreases in unemployment) or increases in immigration are reversed quickly whereas disequilibria represented by worsening of income inequality, increases in unemployment, or reductions in immigration seem to be persistent. Note that the coefficients in the estimated long run relationship cannot be interpreted as elasticities, which would be standard in simple OLS regression analysis, because the *ceteris paribus* assumption may not hold (Lutkepohl 1994). The relationships between any pair of variables can be examined by estimating the impulse response functions based on an error correction model.

3.2. Dynamic adjustment of income distribution

In this section we examine the dynamic adjustment of the income distribution to various shocks using an asymmetric vector error correction model. To that end, we estimate equations of the form:

$$\Delta gini_t = A_{11}^{+}(L)\Delta gini_{t-1}^{+} + A_{11}^{-}(L)gini_{t-1}^{-} + A_{12}^{+}(L)\Delta u_{t-1}^{+} + A_{12}^{-}(L)\Delta u_{t-1}^{-} + A_{13}^{+}(L)\Delta im_{t-1}^{+} + A_{13}^{-}(L)\Delta im_{t-1}^{-} - \alpha_1^{+} z_{t-1}^{+} - \alpha_1^{-} z_{t-1}^{-} + \mathrm{e}_{1t} \quad (5)$$

$$\Delta u_t = A_{21}^{+}(L)\Delta gini_{t-1}^{+} + A_{21}^{-}(L)gini_{t-1}^{-} + A_{22}^{+}(L)\Delta u_{t-1}^{+} + A_{22}^{-}(L)\Delta u_{t-1}^{-} + A_{23}^{+}(L)\Delta im_{t-1}^{+} + A_{23}^{-}(L)\Delta im_{t-1}^{-} - \alpha_2^{+} z_{t-1}^{+} - \alpha_2^{-} z_{t-1}^{-} + \mathrm{e}_{2t} \quad (6)$$

$$\Delta im_t = A_{31}^{+}(L)\Delta gini_{t-1}^{+} + A_{31}^{-}(L)gini_{t-1}^{-} + A_{32}^{+}(L)\Delta u_{t-1}^{+} + A_{32}^{-}(L)\Delta u_{t-1}^{-} + A_{33}^{+}(L)\Delta im_{t-1}^{+} + A_{33}^{-}(L)\Delta im_{t-1}^{-} - \alpha_3^{+} z_{t-1}^{+} - \alpha_3^{-} z_{t-1}^{-} + \mathrm{e}_{2t} \quad (7)$$

$$z_t^{+} = I_t(\mathrm{gini}_t\text{-}\beta_0 - \beta_1\, u_t - \beta_2\, im_t)$$

$$z_t^{-} = (1 - I_t)\,(\mathrm{gini}_t\text{-}\beta_0 - \beta_1\, u_t - \beta_2\, im_t).$$

where the Heaviside indicator is set in accord with TAR adjustment, $A_{ij}^{+}(L)$ are p-th order lag polynomials, $\Delta gini_t^{+} = max(\Delta gini_t, 0)$, $\Delta gini_t^{-} = min(\Delta gini_t^{-}, 0)$; $\Delta u_t^{+}, \Delta u_t^{+}$, $\Delta im_t^{+}, \Delta im_t^{+}$ are similarly defined. We then test for weak exogeneity, Granger causality, and symmetry based on the representations in (5)-(7). The results are given in Table 3.

The point estimates of the error correction terms indicate that immigration does not adjust to eliminate deviations from long run equilibrium that are below threshold. However, the rest of the error correction terms adjust to eliminate deviations from long run equilibrium. The error correction terms for unemployment are not significant, indicating that unemployment is exogenous with respect to the long run equilibrium. The results indicate that unemployment and income inequality do not Granger cause immigration, implying that immigrants do not take into account the business cycle or the state of income distribution in the long run when they immigrate. This result is not surprising since for most immigrants it is not the absolute state of the US economy that matters, but rather their expected well-being in the US relative to their native countries.

It is interesting to note that immigration does not Granger cause unemployment but income inequality, as measured by the Gini, does. This finding is not at all surprising given that wage earners are disproportionately congregated at the lower end of the income distribution. Increases in inequality would be firstly manifested in job losses through the labor market. Note also that immigration significantly Granger causes income inequality. This is an interesting finding, suggesting that immigrants are not evenly distributed through the income distribution but are disproportionately congregated below the mean.

The test statistics for symmetric adjustment can be rejected for immigration, unemployment, and the *gini;* however, the p-values for unemployment and the *gini* are 8.1

and 11.3 percent respectively, indicating weak asymmetry. Overall, there is evidence that unemployment, immigration and the *gini* respond to above threshold deviations from long run equilibrium differently than positive deviations.

The dynamic interaction of income inequality, unemployment, and immigration can best be understood by examining impulse response functions (IRF). We assume that the system is in long-run equilibrium and consider the responses to 1-standard deviation shocks. We orthogonalize innovations using the ordering, immigration → unemployment → *gini*. Figure 2 presents the IRFs based on the dynamic models given in (5)-(7). The figure gives the changes in *gini* in standard deviations as a result of a positive and negative shock of one standard deviation in size.

In Panel A of Figure 2 we note that a negative shock to immigration has an initial one-period reduction in income inequality which is not sustained and after four periods the adjustment is positive and sustained. In other words, there is an immediate reduction in income inequality due to a decrease in immigration (which would be expected if a major portion of immigrants entered the economy at lower income levels cohorts) but as they assimilate to the economic environment, their impact is dispersed over the entire range of incomes. However, a positive immigration shock worsens income the distribution (except for the second year); the worsening income distribution peaks after four years and declines thereafter.

The pattern of a positive shock to unemployment on income inequality meets our *a priori* expectations as illustrated in Panel B of Figure 2. It can be seen here that initially income inequality is increased by a positive shock to unemployment (partially due to the fact that those persons in the lower quintiles of the income distribution are more likely to derive a significant portion of their income from wages), but after four years returns to normal. However, in response to a decrease in unemployment, income inequality improves for only one year and deteriorates thereafter. In other words, economic expansions seem to have only short-lived improvements on income inequality. Since the typical expansion in the postwar period lasted for almost five years, this is an indication that the benefits of economic expansions did not spread out evenly over the entire population. Since higher income groups tend to be less affected by unemployment and derive a non-trivial portion of their income from non-labor sources, the asymmetric behavior of unemployment is but one source of asymmetric behavior of the income distribution over the business cycle and there may be other factors at play.[3] In addition, Blank (1997) shows that those persons in the lowest quintile of the income distribution were adversely effected by increases globalization and technical innovation that were also happening during the last two periods of expansion.

3.3. The Real Mean Family Income in Different Cohorts and Unemployment

In this section we examine the relationship between real mean family income in different cohorts and socio-economic indicators. Of the socio-economic and demographic indicators mentioned earlier, only unemployment seems to have any bearing on mean incomes in the long run. Therefore we estimate long run relationships of the form:

$$y_{it} = \beta_0 + \beta_i u_t + \mu_t \tag{8}$$

where y_i is the log of real mean income in cohort i, i =1…5. Here y_1 is the log of real mean family income in the bottom fifth of the income distribution.[4] We also estimate a model for

[3] As is common in the business cycle literature, we are assuming that real wages are acyclical and do not have a tendency to decline in recessions.
[4] Each y_i represents conditional mean income equal to the quintile income share (the share of total income times mean family income) in that income quintile. Conditional mean incomes are measured in logs.

overall real median family income in the U.S., denoted $\bar{y}$, and unemployment. Table 4 presents threshold cointegration test statistics assuming TAR and M-TAR adjustments.

The results presented in Table 4 show that mean income in each income group and overall median income are cointegrated with unemployment. The Bayesian Information Criterion (BIC) selects TAR adjustment over M-TAR adjustment except for mean income in Group 5 (the highest income bracket) and overall median income. In what follows, we will consider the TAR model for y_1 through y_4, and the M-TAR model for y_5 and $\bar{y}$. The null hypothesis of no cointegration can be rejected in favor of cointegration with asymmetric adjustment. The null hypothesis of symmetric adjustment ($\rho_1 = \rho_2$) is soundly rejected in favor of asymmetric adjustment for all mean incomes in all income brackets.

As before, the point estimates of ρ_1 and ρ_2 suggest faster convergence for negative (below threshold being ρ_2) deviations from long run equilibrium than positive (above threshold being ρ_1) deviations. The point estimates of ρ_1 and ρ_2 suggest that negative deviations from the long run equilibrium stemming from decreases in y_i or increases in unemployment (such that $\mu_{t-1} <$ threshold) are eliminated faster than positive deviations.

In some cases the point estimates of ρ_1 suggest that positive deviations from long run equilibrium are not eliminated at all as the point estimates of ρ_1 are positive. This is true for y_2 through y_5 when the adjustment is set to the TAR flag. Moreover, all adjustment coefficients for above threshold deviations seem to be insignificant. Note that all income groups have similar adjustment speeds for below threshold deviations from equilibrium except Group 1, where the adjustment speed is substantially slower. For this group, below threshold deviations are eliminated at only 2.7 percent per year whereas the corresponding adjustment coefficient for y_2 is 23.2 percent per year. In that sense, below threshold deviations caused by decreases in y_1 or increases in unemployment are eliminated much slower for a typical family in the lowest 20 percent income bracket as compared to other income brackets. The data demonstrate that for the poorest people in society, their ability to recover from unemployment shocks is slower and limited. As mentioned earlier, this group derives the greatest percentage of household income from wages. In addition, this group has a difficult time recovering from even the smallest losses of income.

3.4. The Dynamic Adjustment Real Mean Family Income in Different Cohorts and Unemployment

In this section, we evaluate the dynamic adjustment of real mean family income in different income quintiles and unemployment. To that end, we estimate a bivariate error correction model similar to that in equations (5)-(7). Table 5 presents tests of exogeneity, Granger causality and symmetry based on this model. The error correction terms for unemployment are insignificant for all mean incomes and overall median income, indicating unemployment is exogenous with respect to the long run relationships. Therefore, unemployment does not seem to be responsive to deviations from long run equilibrium. The error correction terms indicate substantially faster speed of adjustment for below threshold deviations from long run equilibrium. Notice also that the adjustment speed is higher for lower income groups. For example, below threshold deviations are corrected at 8.8 percent per year at the lowest income group but at 3.5 percent per year at the real mean income in Group 4. Even though the adjustment speed is higher for the highest income group, the adjustment conforms to M-TAR as opposed to the TAR specification so comparisons are not appropriate.

The Granger causality tests indicate that unemployment fails to Granger cause income for mean incomes in all groups. On the other hand, mean income Granger causes unemployment for Group 4, Group 5, and overall median real income. Symmetry tests are conducted to see whether positive and negative polynomials in the error correction equations have different coefficients and the error correction terms are equal. The test statistics in Table 5 regarding symmetry are weak for income groups 1 through 4 as the p-values are between 13-17 percent. However, symmetric adjustment can be rejected for unemployment at conventional significance levels.

Next, we present the dynamic interaction of mean incomes and unemployment using impulse response functions. Again, we assume that the system is in long-run equilibrium and consider the responses to 1-standard deviation shocks. We orthogonalize innovations using the ordering, unemployment $\rightarrow y_i$. Figure 3 presents the IRFs based on the bivariate error correction model of mean income and unemployment. The figure gives the changes in mean income as a result of a positive and negative shock of one standard deviation.

In support of our earlier results we see from Figure 3 that the mean income of all groups and overall median income have an initial increase in response to a negative shock to unemployment. In other words, mean income in all groups increases in economic expansions represented by a decline in the unemployment rate. However, the impact of a decline in unemployment is not spread uniformly over the entire population. Lower income groups tend to benefit more from an economic expansion but mean incomes return to their original level faster. For example, comparing Group 1 to Group 4 shows that in response to an economic expansion (represented by a decline of unemployment equal to 1 standard deviation) Group 1 has an initial increase of mean income of approximately 3 standard deviations while Group 4 only experiences a slightly more than 1 standard deviation. For Group 1 (the poorest segment of the population) the benefits of an economic expansion seem to last 6.5 years, whereas this is 11 years for Group 4.

In response to an increase in the unemployment rate, mean incomes decline initially but recover after two years. The initial decline is largest for lower income groups, but these groups seem to recover faster. The magnitude of the impact again seems to be due to the heavy reliance on wage income for lower income groups. The fact that lower income groups recover faster after an economic contraction may be due to the presence of transfer programs and reliance on labor income. In an absolute sense these results are not surprising. If income fell the farthest in the lower quintile cohorts, it should be expected that recovery would have to be greater for them. In addition, it should be noted that these groups are not static, meaning that people shift between groups. Those individuals dropping to lower groups will in turn speed the recovery of the lower group by having above-mean incomes of that lower group. What must also be mentioned is that for the middle and upper cohorts of the income distribution, employment shocks will lead to stagnant wages that will be slower to recover than the new employment that occurs for the lowest group.

4. CONCLUSIONS AND POLICY IMPLICATIONS

The interaction of the business cycle and income inequality is of great importance to academics and policy makers alike. If it is true that "a rising tide lifts all boats" then policies designed to grow the economy as fast and as vigorously as possible may be viewed as desirable. This type of policy ensures that all segments of the income distribution are enhanced. However, if different cohorts along the income distribution do not behave uniformly to shocks to economy it may be necessary to derive a more extensive policy instrument.

In this paper we show that asymmetries do exist among the quintiles comprising the U.S. income distribution over the last fifty years. Of particular note, this paper finds that increases in unemployment causes increases in income inequality but that negative shocks to unemployment have only short-lived positive benefits to income inequality. This is a new and important finding.

In addition, this work shows that shocks to unemployment have impacts that are not uniform to cohorts along the income distribution. In particular, those individuals with the lowest mean family income (sorted by quintile) are most adversely affected by shocks to unemployment but are quickest to return to the steady state.

The paper also shows that immigration is an important factor in explaining changes in inequality. Increases in immigration lead to significant increases inequality but it should be noted that we do not distinguish between country of origin of incoming groups.

What is principally important to note in this work is that policies designed to increase the well-being of the entire range along the income distribution should be tailored and exact since it is clear that persons in different income quintiles have distinctly different reactions to business cycle changes.

REFERENCES

Acemoglu, D., and Scott, A. "Asymmetries in the Cyclical Behaviour of UK Labor Markets." *The Economic Journal* **104** (November, 1994): 1303-1323.

Adams, R., (2003), "Economic Growth, Inequality, and Poverty: Findings from a New Data Set," World Bank Policy Research Working Paper # 2972.

Albanesi, S. (2007), "Inflation and Inequality," *Journal of Monetary Economics* 54,

pp. 1088-1114.

Bishop, J., J. Formby, and R. Sakano, (1994), "Evaluating Changes in the Distribution of Income in the United States," *Journal of Income Distribution*, 4(1), pp. 79 – 105.

Blank, R., (1997), "Why Has Economic Growth Been Such an Ineffective Tool Against Poverty In Recent Years?" in Jon Neil (Ed.). *Poverty and Inequality: The Political Economy of Redistribution*, Kalamazoo MI: W.E. UpJohn Institute.

Blinder, A. and Esaki H., (1978), "Macroeconomic Activity and Income Distribution in the Postwar United States," *The Review of Economics and Statistics*, Vol. 60(4), pp. 604 – 609.

Bruno, M., M. Ravallion, and L. Squire, (1998), "Equity and Growth in Developing Countries: Old and New Perspectives on the Policy Issues, in *Income Distribution and High Growth*, Vito Tani and Ke-Young Chu editors, MIT Press, Cambridge, MA.

Castañeda, A., J. Díaz-Giménez and J. Rios-Rull, (1998), "Exploring the Income Distribution Business Cycle Dynamics," Journal of Monetary Economics, Volume 42(1), June 1998, pp. 93-130.

Chan, K. S. (1993). Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model. *The Annals of Statistics* 21, pp. 520 - 533.

Chen, B., (2003), "An Inverted-U Relationship Between Inequality and Long-Run Growth," *Economics Letters*, Vol. 78, pp. 205 – 212.

Dolmas, J., G.E. Huffman, and M.A. Wynne (2000), "Inequality, Inflation, and Central Bank Independence," *Canadian Journal of Economics* 33, pp. 271-287

Enders, Walter and Clive W. J Granger (1998). "Unit-Root Tests and Asymmetric Adjustment With an Example Using the Term Structure of Interest Rates." *Journal of Business & Economic Statistics*, 1998, 16, pp. 304-11.

Enders, Walter and Pierre Siklos (2001). Cointegration and Threshold Adjustment. *Journal of Business & Economic Statistics*, April 2001, Vol. 19 (2), pp. 166-76.

Gomez, R., and D. Foot, (2002), “Age Structure, Income Distribution and Economic Growth,” European University Institute Working Paper RSC 2002/36.

Harris, R. and Silverstone, B. “Testing for Asymmetry in Okun’s Law: A Cross-Country Comparison.” *Economics Bulletin* **5** (July, 2001): 1-13.

Hayes, K.; D. Slottje and S. Porter-Hudak, (1991), “US Federal Redistributive Income Policies,” *Applied Economics*, Vol. 23, pp. 1193 – 1200.

Heer, B. and B. Sussmuth (2003), “Effects of inflation on wealth distribution: Do stock market participation fees and capital income taxation matter?,” *Journal of Economic Dynamics and Control* Volume 31(1), January 2007, pp. 277-303.

Kuznets, S. (1955), “Economic Growth and Income Inequality,” *American Economic Review*, Vol. 34(1), pp. 1 – 28.

Kwiatkowski, Denis and Peter C.B. Philips, Peter Schmidt, Yongcheol Shin (1992). Testing the Null Hypothesis of Stationary Against the Alternative of a Unit Root. *Journal of Econometrics*, vol. 54, pp. 158-178.

Lundberg, M., and L. Squire, (2003), “The Simultaneous Evolution of Growth and Inequality,” *The Economic Journal*, Vol. 113, pp. 326 – 344.

Lutkepohl, Helmut (1994). Interpretation of Cointegration Relations. *Econometric Reviews,* vol. 13 (3), pp. 391-394.

Neftci, S. “Are Economic Time Series Asymmetric Over the Business Cycle?” *Journal of Political Economy* **92** (1984): 307-328.

Perman, R., and D. Stern, (2003), “Evidence from Panel Unit Root and Cointegration Tests that the Environmental Kuznets Curve does not exist,” *The Australian Journal of Agricultural and Resource Economics*, Vol. 47(3), pp. 325 – 347.

Romer, C.D. and D.H. Romer (1999), “Monetary Policy and the Well-Being of the Poor,” *Federal Reserve Bank of Kansas City Economic Review* QI, pp. 21-49.

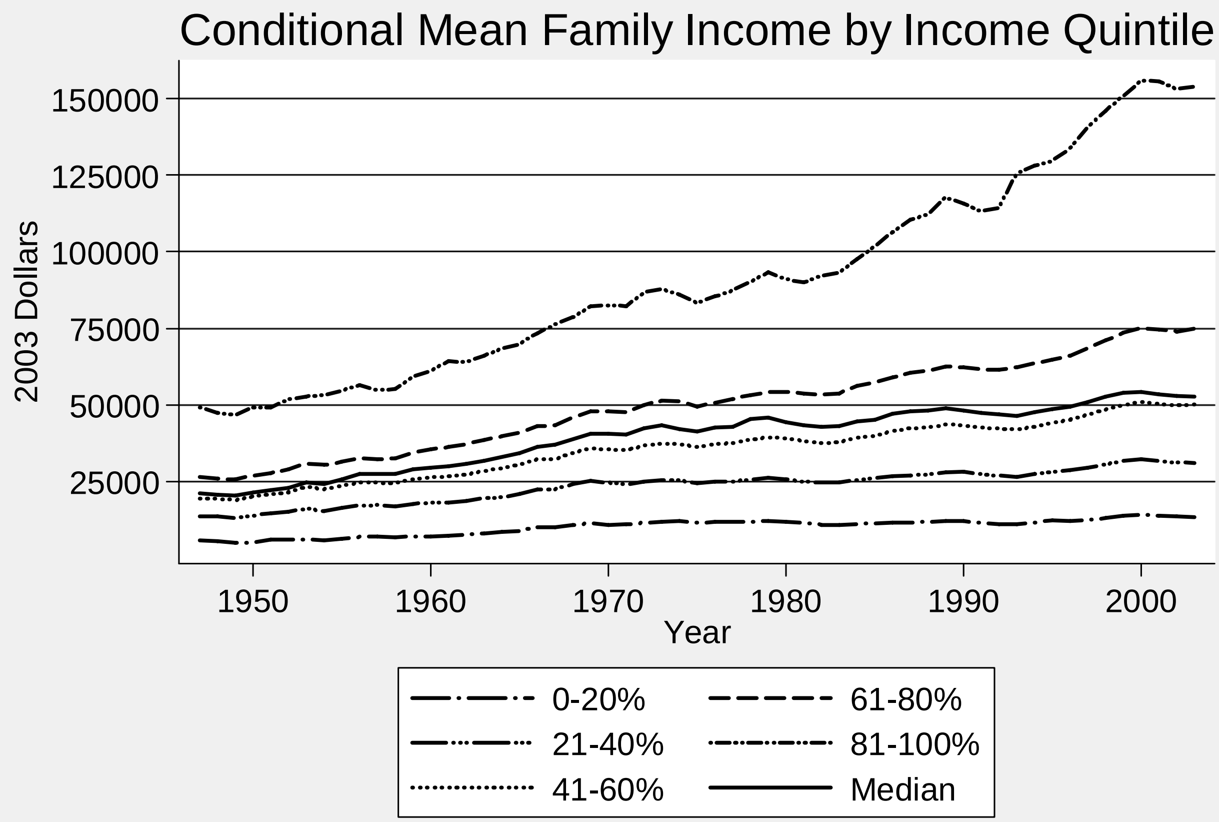
Silvapulle, Paramsothy, Imad A. Moosa and Mervyn J. Silvapulle (2004). Asymmetry in Okun's law, *Canadian Journal of Economics*, 37 (2)و May 2004, pp. 353 – 374.

Tong, Howell. *Threshold Models in Non-Linear Time Series Analysis*, New York: Springer-Verlag, 1983.

Thomas, Vinod; Wang, Yan; Fan, Xibo (2001). "Measuring Educational Inequality: Gini Coefficients of Education." Policy Research Working Report No. 2525, World Bank, Washington, DC.

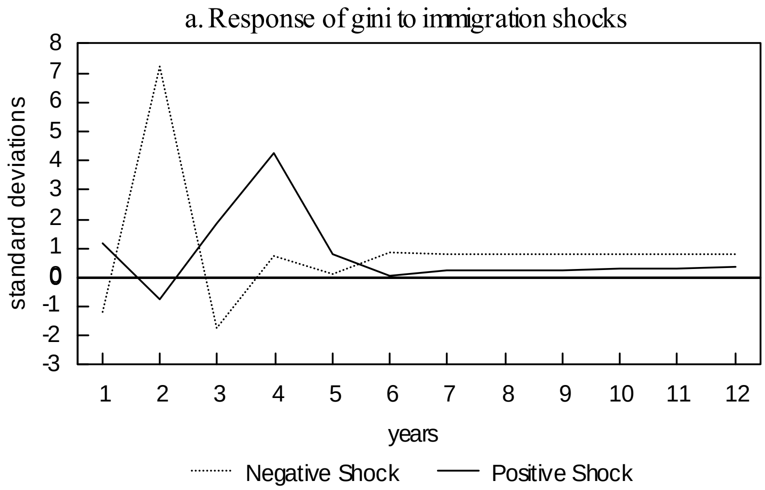
Wane, A., S. Gilbert and S. Dibooglu (2004). Critical Values of the Empirical F-Distribution for Threshold Autoregressive and Momentum Threshold Autoregressive Models. Unpublished Working Paper No. 13, Southern Illinois University at Carbondale.

Figure 1



Source: U.S. Census Bureau, Historical Income Tables F-2 and F-5

Figure 2. Response of Gini to immigration, unemployment, and own shocks



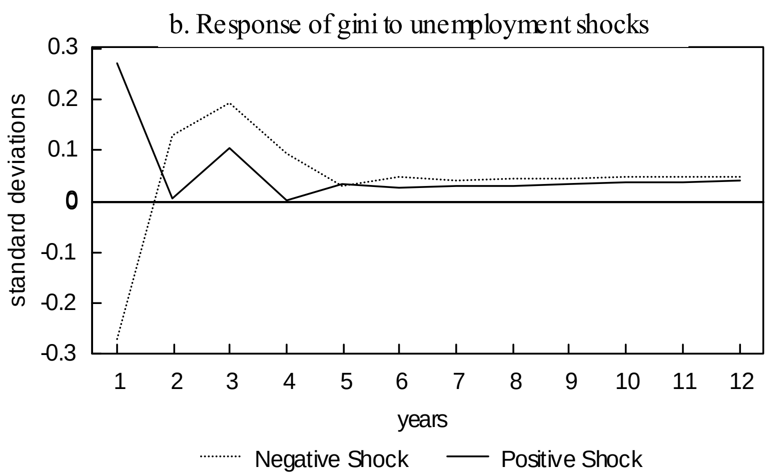
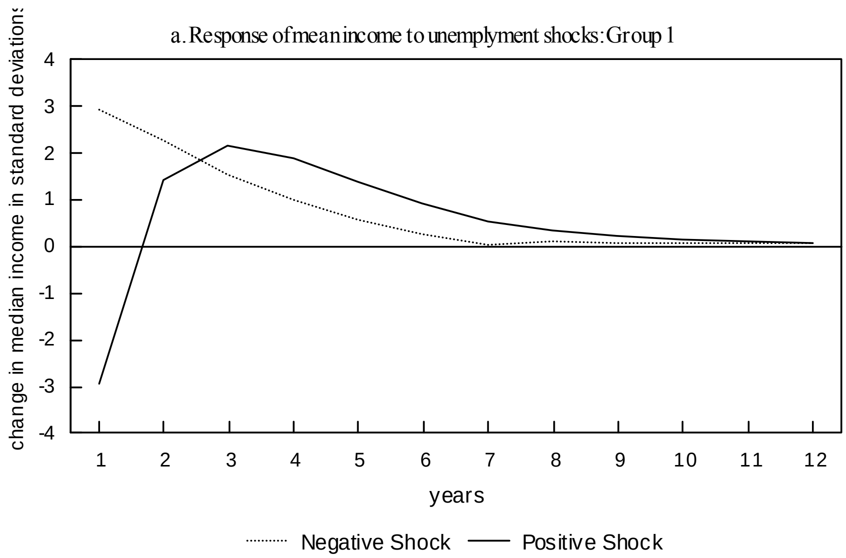
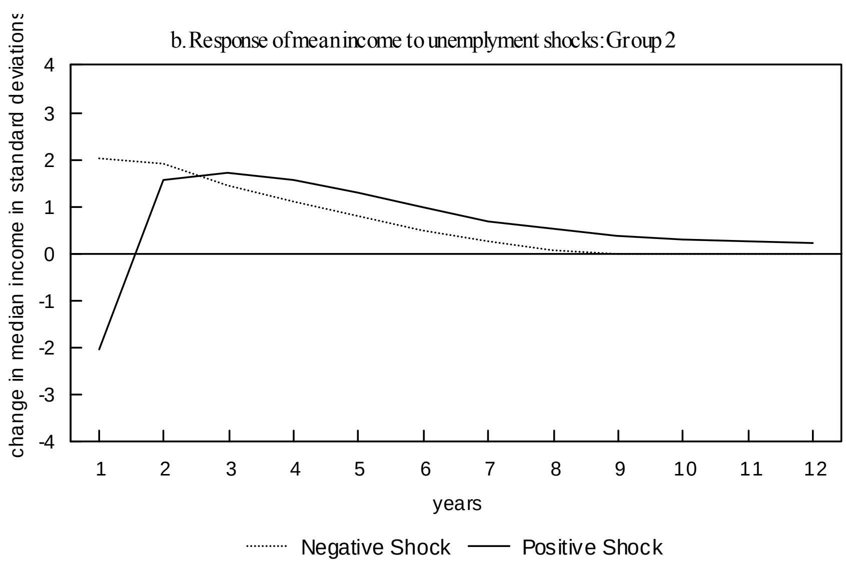
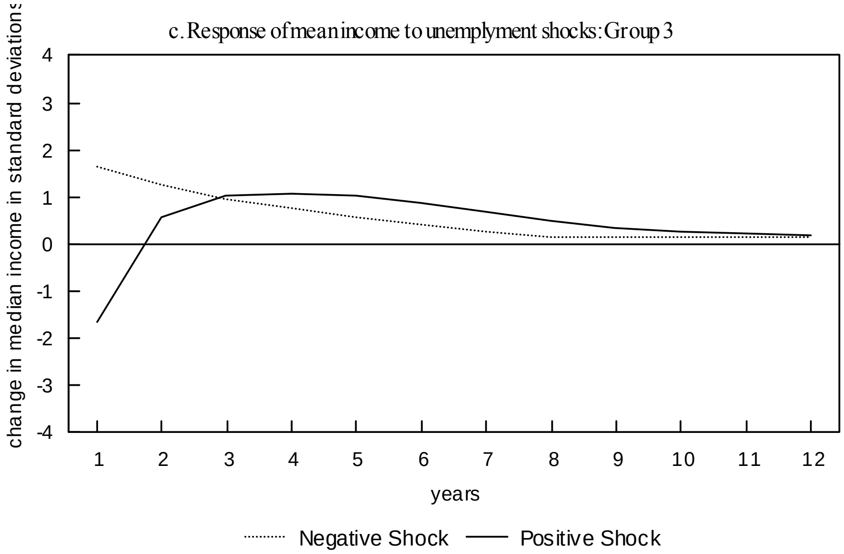
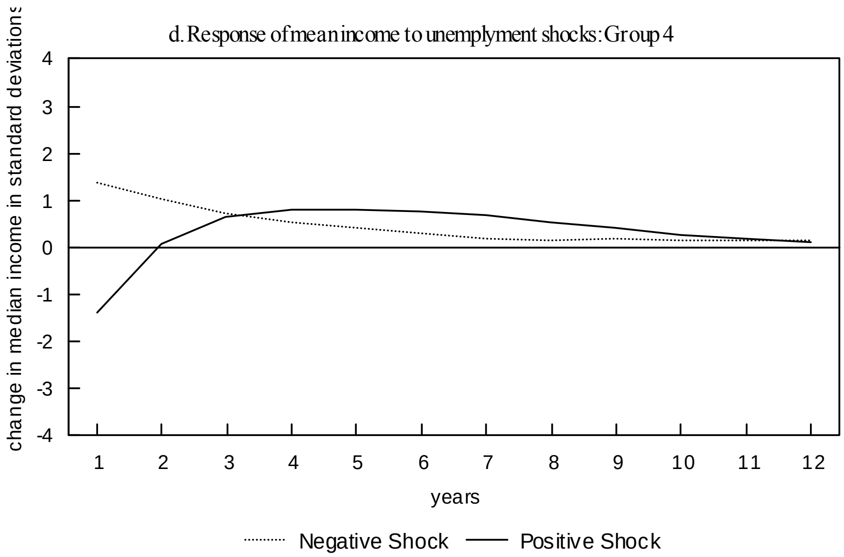


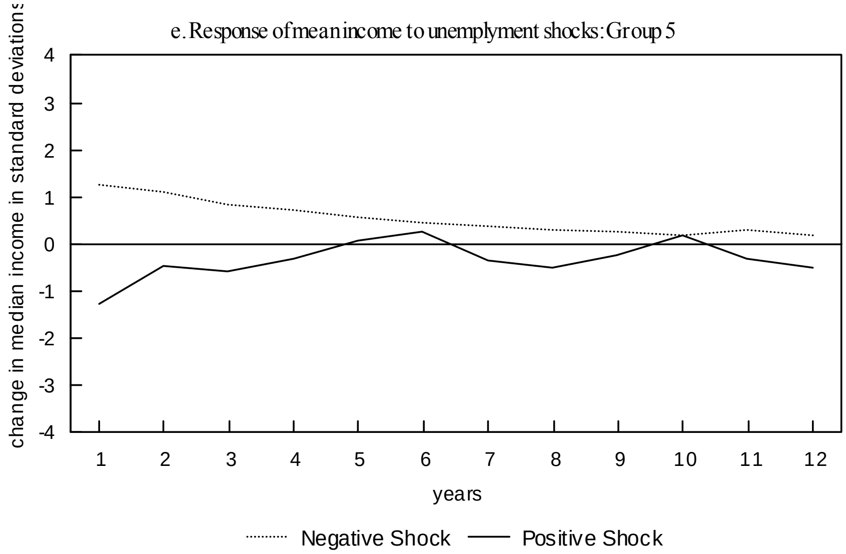
Figure 3. The response of median income to unemployment shocks






c. Response of mean income to unemplyment shocks: Group 3
change in median income in standard deviations
4
3
2
1
0
-1
-2
-3
-4
1
2
3
4
5
6
7
8
9
10
11
12
years
Negative Shock
Positive Shock


d. Response of mean income to unemplyment shocks: Group 4
change in median income in standard deviations
4
3
2
1
0
-1
-2
-3
-4
1
2
3
4
5
6
7
8
9
10
11
12
years
Negative Shock
Positive Shock


e. Response of mean income to unemplyment shocks: Group 5
change in median income in standard deviations
4
3
2
1
0
-1
-2
-3
-4
1
2
3
4
5
6
7
8
9
10
11
12
years
Negative Shock
Positive Shock

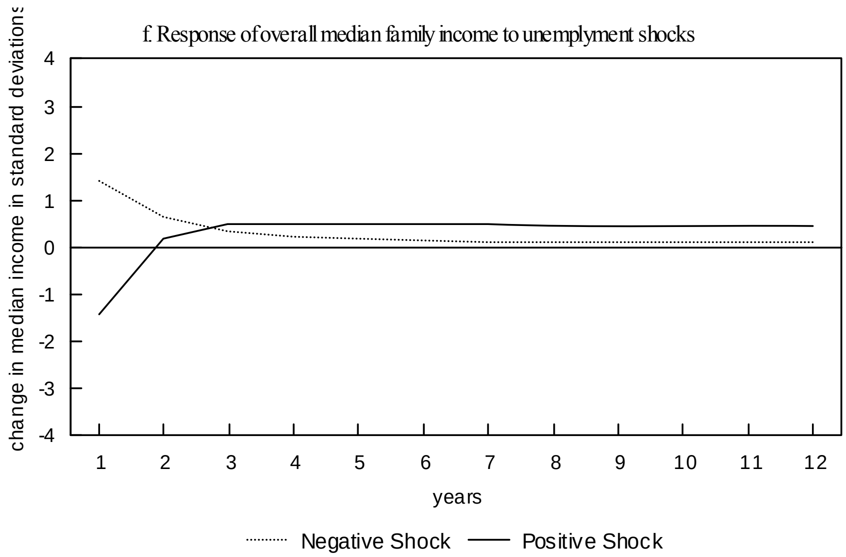

f. Response of overall median family income to unemplyment shocks
change in median income in standard deviations
4
3
2
1
0
-1
-2
-3
-4
1
2
3
4
5
6
7
8
9
10
11
12
years
Negative Shock
Positive Shock

Table 1. Unit Root and Stationarity Tests

	KPSS Statistics	*ADF Statistics*
Levels		
gini	1.46	0.29
y_1	1.61	-1.47
y_2	1.76	-1.97
y_3	1.83	-1.93
y_4	1.88	-1.54
y_5	1.91	-0.50
$\bar{y}$	1.77	-2.40
im	1.16	-2.80
u	0.48	-2.85
First Differences		
$\Delta gini$	0.52	-8.53
Δy_1	0.21	-6.25
Δy_2	0.29	-6.26
Δy_3	0.31	-6.48
Δy_4	0.24	-6.25
Δy_5	0.06	-6.58
$\Delta \bar{y}$	0.47	-5.98
Δim	0.05	-6.46
Δu	0.04	-7.11

Notes: Both ADF and KPSS tests include an intercept. The critical value of the ADF test at the 5 percent level is -2.89. The maximum lag for the ADF test is selected by the BIC. The lag truncation for the KPSS test is set at 2. The KPSS critical value at the 5 percent level is 0.46.

Table 2: Asymmetric Cointegration Test Statistics for Income Distribution (GINI)

	GINI	
	TAR	M-TAR
ρ_1	0.003 (0.04)	-0.029 (-0.38)
ρ_2	-0.603 (-4.80)	-0.612 (-4.24)
$\rho_1 = \rho_2 = 0$ (Φ_μ or Φ^*_μ)	11.59**	9.01*
$\rho_1 = \rho_2$ (F-Test)	18.13***	13.33***
Estimated threshold	-0.0213	-0.0075
Estimated long run relationship	$gini = 0.35 - 0.08\ u + 14.03\ im + \mu$	
Number of lags	1	1
BIC	-274.93	-271.04

Notes: Lag length is determined by the BIC. The t-statistics are given in parenthesis. (*) indicates significance at 10%; (**) at 5 %; (***) at 1 %.

Table 3. Some Estimates and Test Statistics Based on the Asymmetric Error Correction Model for GINI

	Δim	Δu_t	$\Delta gini_t$
$\alpha^{+\,a}$	-0.004 (-0.81)	-0.075 (-1.02)	-0.001 (-0.025)
$\alpha^{-\,a}$	0.040 (4.54)	-0.095 (-0.067)	-0.013 (-1.68)
$A_{im}(L)^{+} = A_{im}(L)^{-} = 0$ [b]	3.48 (0.038)	0.02 (0.978)	11.62 (0.000)
$A_{u}(L)^{+} = A_{u}(L)^{-} = 0$ [b]	0.51 (0.598)	4.42 (0.017)	0.27 (0.762)
$A_{gini}(L)^{+} = A_{gini}(L)^{-} = 0$ [b]	0.97 (0.383)	2.61 (0.083)	1.18 (0.316)
Symmetry [c]	4.96 (0.002)	2.22 (0.081)	1.97 (0.113)
Number of lags [d]	1	1	1

Notes:

[a] The entries are estimated error correction terms given TAR adjustment with t-statistics in parentheses.

[b] The entries are estimated F-statistics that the parameters in the corresponding polynomials are zero with the p-values in parentheses.

[c] The entries are estimated F-statistics that $A_{ij}(L)^{+} = A_{ij}(L)^{-}$ and $\alpha^{+} = \alpha^{-}$ with the p-values in parentheses.

[d] Lag length is selected by the multivariate version of the BIC.

Table 4: Asymmetric Cointegration Test Statistics for Median Income and Various Income Groups

	Flag	ρ_1	ρ_2	$\rho_1 = \rho_2 = 0$ (Φ_μ or Φ^*_μ)	$\rho_1 = \rho_2$ (F-test)	Estimated threshold	Estimated long run relationship	BIC
y_1	TAR	-0.005 (-0.09)	-0.027 (-4.24)	9.02***	9.98***	-0.3251	$y_1 = 8.86 + 5.81$ u	- 41.24
	M-TAR	-0.035 (-0.62)	-0.267 (-3.63)	6.83**	6.11**	-0.0094		- 37.70
y_2	TAR	0.064 (-0.12)	-0.232 (-3.99)	8.01**	9.22***	-0.2504	$y_2 = 9.77 + 4.60$ u	-70.59
	M-TAR	-0.019 (-0.39)	-0.264 (-3.81)	7.38**	8.10***	-0.0142		-69.58
y_3	TAR	0.011 (0.21)	-0.238 (-3.96)	7.88**	10.33***	-0.2798	$y_3 = 10.12 + 5.64$ u	-61.32
	M-TAR	-0.004 (-0.08)	-0.250 (-3.74)	7.02**	8.74***	-0.0139		-59.91
y_4	TAR	0.016 (0.35)	-0.217 (-3.71)	6.95**	9.71***	0.3244	$y_4 = 10.1 + 6.49$ u	- 52.52
	M-TAR	-0.022 (-0.54)	-0.331 (-3.43)	6.15*	8.21**	-0.0862		- 51.18
y_5	TAR	0.024 (0.57)	-0.121 (-2.69)	5.67*	5.62**	0.0766	$y_5 = 11.04 + 5.81$ u	-56.26
	M-TAR	0.002 (0.06)	-0.316 (-4.05)	8.21**	14.15***	-0.0928		-63.84
$\bar{y}$	TAR	-0.001 (-0.02)	-0.236 (-3.82)	7.29**	7.83***	-0.2681	$\bar{y} = 10.19 + 6.43$ u	- 49.62
	M-TAR	-0.018 (-0.36)	-0.283 (-3.90)	7.72**	8.59***	-0.0164		- 50.32

Notes: Lag length is determined by the BIC. The t-statistics are given in parenthesis. (*) indicates significance at 10%; (**) at 5 %; (***) at 1 %. Critical values are based on Enders and Siklos (2001).

Table 5. Tests of Exogeneity, Granger Causality, and Symmetry for Median Income and Various Income Groups

Model	Equation	α^{+a}	α^{-a}	$A_u(L)^+ = A_u(L)^- = 0$ [b]	$A_y(L)^+ = A_y(L)^- = 0$ [c]	Sym. [d]	Flag
Group 1	Δu	-0.002 (-0.34)	0.012 (1.31)	2.12 (0.131)	0.187 (0.830)	2.17 (0.100)	TAR
	Δy_1	-0.003 (-0.09)	-0.088 (-2.16)	1.43 (0.251)	1.13 (0.331)	1.91 (0.130)	
Group 2	Δu	0.005 (-0.61)	0.009 (0.91)	2.28 (0.113)	0.22 (0.804)	2.32 (0.086)	TAR
	Δy_2	-0.005 (-.020)	-0.057 (-2.01)	1.18 (0.317)	0.47 (0.625)	1.87 (0.147)	
Group 3	Δu	-0.007 (-0.94)	0.009 (1.02)	3.92 (0.026)	1.66 (0.201)	3.57 (0.020)	TAR
	Δy_3	-0.005 (-2.74)	-0.049 (-2.20)	1.23 (0.301)	0.58 (0.562)	2.24 (0.141)	
Group 4	Δu	-0.004 (-0.073)	0.008 (0.95)	4.08 (0.022)	2.74 (0.074)	3.93 (0.013)	TAR
	Δy_4	-0.007 (-0.055)	-0.035 (-1.96)	1.14 (0.328)	1.26 (0.291)	1.75 (0.168)	
Group 5	Δu	0.003 (0.39)	-0.001 (-0.14)	6.74 (0.002)	10.80 (0.000)	4.72 (0.005)	M-TAR
	Δy_5	0.014 (0.64)	-0.125 (-1.01)	1.59 (0.214)	2.91 (0.064)	3.55 (0.021)	
Median Income	Δu	-0.002 (-0.33)	0.015 (1.50)	2.79 (0.071)	4.17 (0.021)	6.61 (0.000)	M-TAR
	$\Delta \bar{y}$	-0.027 (-1.79)	-0.069 (-2.82)	0.094 (0.556)	3.22 (0.049)	3.86 (0.014)	

Notes:
[a] The entries are estimated error correction terms with t-statistics in parentheses.
[b] The entries are estimated F-statistics that unemployment Granger causes the corresponding row variable with the p-values in parentheses.
[c] The entries are estimated F-statistics that median income Granger causes the corresponding row variable with the p-values in parentheses.
[d] The entries are estimated F-statistics that $A_i(L)^+ = A_i(L)^-$ and $\alpha^+ = \alpha^-$ with the p-values in parentheses. Lag length is selected by the multivariate version of the BIC.