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DEMOGRAPHIC CHANGE AND INEQUALITY IN THE SIZE DISTRIBUTIONS OF LABOR AND NONLABOR INCOME

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This paper utilizes a joint distribution model of labor and nonlabor income that allows us to analyze the impact of demographic change in the U.S. on the marginal distributions of these two income components over time. The beta distribution of the second kind is the hypothetical statistical distribution used in this study to approximate the observed income graduation. This distribution is sum stable which allows us to compare and contrast the marginal distributions in a consistent manner, a property most hypothesized functional forms of income distribution do not possess. We are in effect using a hyperparameter model to do our estimation. We examined the impact of changes over time in labor force participation and population on the marginal distributions of labor and nonlabor income. We disaggregated the variables by sex and age cohorts and found that changes in the age distribution and in the labor supply behavior of women in particular has had a significant effect on the marginal income distributions over time. We also found that the results vary when we examined overall changes in the labor force participation rate vis a vis changes in women's labor force participation separately. The findings are consistent for both income components.

I. INTRODUCTION

Ricardo (1817) long ago realized the importance of questions concerning the functional distribution of income. He was concerned with the distribution of income among the factors of production that produced final output. Beginning with Pareto (1897), primary interest shifted to concern with how a particular observed distribution was generated. In the 1960s and 1970s, Atkinson (1970), Sen (1973), Theil (1967) and others began to realize the major limitations of only looking at income when overall economic well-being was really the topic of concern. In the late 1970s and 1980s Cowell (1977), Shorrocks (1982, 1983) and others began a careful discussion of appropriate decomposition and aggregation properties of these so-called "multi-dimensional attribute" distributions. Finally, a synthesis of all this work began as Basmann *et al.* (1983, 1984), Jorgenson and Slesnick (1984a, b), Maasoumi (1986) and Slottje (1987) among others have actually attempted to measure inequality in multi-dimensional distributions.

One dimension that has not been modelled specifically into the multi-dimensional analyses is how demographic changes in the population have impacted the observed multi-dimensional distributions. While Jorgenson and

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Slesnick (1984a, 1985) include the âge of the consumer as one demographic characteristic influencing individual welfare, here we use a joint distribution approach to examine this question. Focusing on labor and nonlabor income, we empirically examine in our model how changes in the various age cohorts and in labor market activity of these groups (manifested through their respective labor force participation rates) affect the marginal distributions of labor and nonlabor income.

In section II we discuss a model for jointly analyzing the labor and nonlabor income distributions in a consistent manner. In the third section we analyze the empirical axpects of a changing age distribution and examine how changes in labor force participation rates impact the distribution of these sources of income. The innovation here is the presentation of a multidimensional model that uses a multivariate joint distribution. By selecting a flexible functional form of the joint distribution, meaningful comparisons can be made between the two marginal distributions (labor and nonlabor), and we are able to analyze the effect of demographic change on these marginal distributions. In section IV we summarize our findings.

II. Measuring Inequality: The Joint Distribution Approach

As Jorgenson and Slesnick (1984a) pointed out in their study, it was Dalton who long ago noted that,

> The economist is primarily interested, not in the distribution of income as such, but in the effects of the distribution of income upon the distribution and total amount of economic welfare. (Dalton, 1920).

Basmann *et al.* (1984), Jorgenson and Slesnick (1984a, b) and Slottje (1984, 1987) have all attempted to measure a multidimensional aspect of economic inequality by incorporating other information into their analysis. As Maasoumi (1986) points out, one approach to doing this is to take a multivariate distribution of various components of income and expenditures on various commodities. Basmann *et al.* (1984) noted that the selection of initial forms of theoretical models of the multivariate personal distribution of components of income and expenditures should be guided by the following criteria:

1. The first criterion calls for minimization of the number of *ad hoc* parameters in the theoretical multivariate personal distribution.
2. The second criterion calls for the selection of a multivariate form such that derived marginal distributions of the sums of one or more components of income and expenditures shall have the same form as the multivariate personal distribution.
3. The third criterion is that the form selected should be a good approximation to the data in the sense that the errors from the difference between observed and predicted frequencies are small.
4. The last criterion calls for the form selected to satisfy the weak Pareto law (see Dagum, 1977).

The first criterion is essentially one of research economy, if the number of parameters necessary to describe a distribution is large, then the value of modeling the data is obviously diminished. The third criterion simply says that the form should be a reasonable approximation of the actual data keeping in mind criterion number one. The fourth criterion is based on the tail behavior of the empirical distribution following the Pareto law as the number of observations gets large. It is the second criterion that concerns us here. In order to make meaningful comparisons between the multivariate distribution and (say) the marginal distribution of one of the income components, then criterion number two is desirable. For example, selection of a lognormal form of multivariate distribution is ruled out since the sums of lognormal variables are not lognormally distributed.

This second criterion is particularly important here since we want to examine the relationship between the marginal distribution of total income and the marginal distributions of labor and non-labor income. As we noted above, the functional distribution of income has been extensively analyzed since Ricardo first broached the subject two hundred years ago. Our aim is to compare the marginal distributions of labor and non-labor income to the marginal distribution of total income so that we can get a better approximation to Dalton's notion, but still keep the analysis in a positive framework. We now present the multivariate distribution of expenditures and income that satisfies the criteria discussed above and allows us to make meaningful comparisons between these various marginal distributions.

All of our criteria are met by the theoretical Beta II multivariate distribution characterized by the following density function:

$$f(m_1, \ldots, m_n; w_1, \ldots, w_q)$$

$$= \frac{K^{b^*} m_1^{a_1-1} \ldots m_n^{a_n-1} w_1^{c_1-1} \ldots w_q^{c_q-1}}{B(a_1, \ldots, a_n; c_1, \ldots, c_q; b^*)[K+m+w]^b} \quad m_i > 0;\ w_k > 0 \tag{2.1a}$$

$$= 0 \quad \text{otherwise,} \tag{2.1b}$$

where all of the parameters a_i $(i = 1, 2, \ldots, n)$, c_k $(k = 1, 2, \ldots, q)$, b^*, b, and k are positive, and where expenditure on commodity group i is m_i, $i = 1, \ldots, n$. Total expenditure on all commodities is m,

$$m = m_1 + \ldots + m_n. \tag{2.1c}$$

We define w_k as income of the kth income source $k = 1, \ldots, q$. Total income W is defined as

$$W = w_1 + \ldots + w_q. \tag{2.1d}$$

$$b^* = b - \sum_{i=1}^{n} a_i - \sum_{k=1}^{n} c_k. \tag{2.1e}$$

Parameters a_i, c_k, b^*, K, and b are population parameters. They should bear time-period subscripts t, which are suppressed here for convenience. Slottje (1987, 1989) has studied the intertemporal dependence of income component parameter c_k on commodity prices and several economic growth variables in the United States for the period 1952–81 and across states. We mention this empirical work here only to emphasize that the parameters of the personal multivariate distribution of components of income and expenditures on commodities are not fixed constants.

Let y designate the sum of one or more of the expenditures $m_1, \ldots, m_n$ and components of income $w_1, \ldots, w_q$ and let α designate the sum of the corresponding exponents in (2.1a). The marginal distribution function of y derived from (2.1a–d) is

$$H(y;\alpha,b^*,K)=0 \qquad (y<0) \tag{2.2a}$$

$$=1-\left[\left(\frac{K}{K+y}\right)^{b^*}\Big/ b^*B(\alpha,b^*)\right]$$

$$\times {}_2F_1\left[b^*;1-\alpha;b^*+1;\frac{K}{K+y}\right] \qquad (y\geq 0), \tag{2.2b}$$

where the symbol ${}_2F_1\ (A;B;C;Z)$ stands for the ordinary hypergeometric function. Notice that for $\alpha=1$, Equation (2.1a–b) becomes the ordinary Pareto distribution function with parameter b^* and lower terminal K. As $y\to\infty$, the hypergeometric function in (2.2a–b) converges to unity; consequently for any α the marginal distribution function (2.2a–b) satisfies the weak Pareto law. For this reason we call b^* the generalized Pareto paremter. In the special case for which y is the sum of income components we have $\alpha = c$, where c is the sum of $c_1, \ldots, c_q$, so that the marginal personal distribution of total income $H(w; c, b^*, K)$ that is deductively implied by (2.1a–d) satisfies the weak Pareto law as required.

Inequality in the empirical multivariate distribution of components of income and expenditures on commodities described above and inequality in its theoretical counterpart (2.1a–d) have many diverse aspects for which there are a number of different inequality measures. For purposes of this paper we can make do with only one aspect of economic inequality and its corresponding inequality measure based on (2.1a–d). Referring to the marginal distribution function (2.2a–b), we note that the Gini concentration ratio for the sum y is

$$g(\alpha,b^*)=\frac{\Gamma(\alpha+b^*)\Gamma(\alpha+1/2)\Gamma(b^*+1/2)}{\Gamma(1/2)\Gamma(\alpha+1)\Gamma(b^*)\Gamma(\alpha+b^*+1/2)}$$

$$\times 1+\frac{2a}{2b^*-1}, \qquad b^*>1. \tag{2.3}$$

As $\alpha\to 0$, $g(\alpha,b^*)\to 1$; as $b^*\to 1$, $g(\alpha,b^*)\to 1$. Formula (2.3) holds for all sums y of one or more components of income and expenditures on commodities.

The estimates $g(\alpha, b^*)$ in (2.3) can then be specified to look at only labor income $w_l\ (=w_1)$ with parameter $c_l\ (=c_1)$ or non-labor income $w_{nl}=(w_2+\ldots+w_q)$ with parameter c_{nl}. To find the marginal distribution of labor income, we simply integrate out all other components in the joint distribution. The same procedure is of course followed to find the marginal distribution of non-labor income. The marginal distributions of labor and non-labor income have the same form as (2.2a–b) and the same inequality measure as (2.3). The estimate of $g(\alpha, b^*)$ is based on the generalized variance method of moments. This simply means that the estimates of $g(\alpha, b^*)$ are computed from the joint statistical estimates of parameters of (2.1a–d) and are functions of survey components of both income and commodity expenditures. If we estimated the inequality measure $g(\alpha, b^*)$

for (say) total income from the marginal distribution of total income alone, ignoring the interdependence of income and expenditures, we would be using the single variance method of moments (SVMM). The generalized variance method of moments is used because it incorporates more sample information into estimation of $g(\alpha, b^*)$. It is in this sense that our analysis is multidimensional. We now proceed to the empirical section.

III. The Empirical Results

Use of the model described in section 2 requires cross-section data on consumer expenditures as well as data on various income components in frequency form. The Bureau of the Census collects expenditure data every few years at tremendous cost on behalf of the Bureau of Labor Statistics. The data is collected in survey form. The survey we used is the Consumer Expenditure Survey, 1972–73. This survey provides comprehensive expenditure and income data for the year specified. As noted above, one of the primary features of analyzing the distribution of total income utilizing the multivariate distribution (2.1a–b) is that expenditure as well as income data is incorporated into the estimates of income inequality by using the Beta II multivariate distribution. The expenditure information is incorporated into the analysis through the lower terminal k [see Slottje (1987) for details]. The actual empirical data in frequency form for labor and non-labor income is from the Internal Revenue Service: Statistics of Income. Utilizing (2.3), we report the Gini coefficients for the years 1952–81 in Table 1.

The results are of course only meaningful if the Beta II distribution is a good approximation of the actual empirical multivariate distribution in question. Slottje (1984, 1987, 1988), Porter and Slottje (1985) and Shackett and Slottje (1987) have found the Beta II form to be in excellent agreement with the data. A result consistent with the findings of McDonald and Ransom (1979) and McDonald (1984). The hypothetical distribution is said to be in good agreement with the data if the residuals from subtracting the predicted frequencies from the observed frequencies are small.

Utilizing the IRS data and CES survey, we estimated (2.3) for total income, for non-labor income and for labor income. We report these estimates in Table 1 below. Labor income is the IRS's definition of labor income, i.e. wage and salary income. Non-labor income includes dividend income, interest income, rents and all other reported non-wage and salary income. As can be seen from Table 1, the Gini coefficient for the marginal distribution of labor income indicates less inequality than does the Gini coefficient for the marginal distribution of no-labor income. This result is not unexpected since [as Ehrenberg and Smith (1985) point out] the owners of financial capital (stocks, bonds, real estate) probably are people whose assets grow as these individuals age over time. Thus, the distribution of non-labor income is becoming more concentrated. Ehrenberg and Smith also predict that the distribution of total income will be less equal than the distribution of labor earnings since people with many financial assets also generally have high earnings. As Table 1 indicates, the empirical evidence does not bear this out. This result is not surprising if it is recalled that many

TABLE 1

GINI COEFFICIENTS OF INEQUALITY FOR THE MARGINAL DISTRIBUTIONS OF LABOR EARNINGS, NON-LABOR INCOME AND TOTAL INCOME

Year	Labor Earnings	Non-labor Income	Total Income
1952	0·315984	0·417565	0·308228
1953	0·308689	0·415573	0·301865
1954	0·314139	0·414786	0·306825
1955	0·292814	0·383159	0·286143
1956	0·309093	0·400836	0·302263
1957	0·304369	0·399035	0·297942
1958	0·328202	0·426538	0·321043
1959	0·328636	0·425430	0·321852
1960	0·324847	0·424995	0·318466
1961	0·327761	0·422926	0·321165
1962	0·327357	0·421785	0·320973
1963	0·331319	0·422219	0·324817
1964	0·334521	0·422931	0·328128
1965	0·336319	0·420617	0·329817
1966	0·354057	0·442451	0·347503
1967	0·357665	0·445950	0·351236
1968	0·359180	0·445534	0·352791
1969	0·350569	0·447051	0·345054
1970	0·352415	0·447873	0·347007
1971	0·349765	0·444327	0·344480
1972	0·347857	0·437317	0·342563
1973	0·346091	0·433483	0·340735
1974	0·345076	0·429350	0·339255
1975	0·343290	0·437048	0·337841
1976	0·339111	0·429775	0·333742
1977	0·355421	0·446047	0·349723
1978	0·319399	0·402100	0·314278
1979	0·351257	0·435840	0·345278
1980	0·341018	0·438637	0·336195
1981	0·338273	0·443703	0·333119

Note: The Gini coefficient is defined as,

$$\text{Gini Coefficient} = \left[1+\frac{2c}{2b^*-1}\right] \cdot \frac{\Gamma(c+b^*)\Gamma(c+0{\cdot}5)\Gamma(b^*+0{\cdot}5)}{\Gamma(c+b^*+0{\cdot}5)\Gamma(b^*)(\Gamma(0{\cdot}5)\Gamma(c+1)}.$$

individuals (such as retirees) may have low labor earnings, but high incomes. Thus, when the marginal distribution of total income is analyzed, inequality as indicated by the Gini coefficient is not as great. Another explanation, of course, is that much income at the upper tail of the distribution is not reported so the observed distribution is actually truncated with a bias indicating less inequality than is actually the case.

Our study indicates that the marginal distribution of total income has less inequality than the marginal distribution of labor income, a result not consistent with the findings of many labor economists. We do find, however, that the marginal distribution of non-labor income has more inequality (as indicated by the Gini coefficient) than dose the marginal distribution of labor income, a result consistent with other research.

We now wish to examine the impact of changing age distributions and labor force participation rates on these two marginal distributions of income. In order to examine the impact of changes in various demographic characteristics on the level of income inequality (as measured by the Gini coefficient), we proceed in the following manner. We follow the Bureau of the Census and divide the population into several categories. We look at the percent of the population less than or equal to seventeen years of age. We also examine the 18–64 age cohort (the usual "economically active" designation), the 18–24 age cohort, the 25–44 age cohort, the 45–64 age cohort and those in the over age 65 cohort. We refer to the population variables as POP. Our labor force participation rate cohorts include those 16–19 years of age, the 20–24 year old group, those 25–44 years old and those 45 and over. These variables are designated as LFP16, LFP20, LFPMID and LFPOLD respectively. We will examine each of these population variables by male/female classification as well, this will allow us to obtain information about how recent trends in women in the labor force and earlier retirement by men (to name just a few) have affected the different income distributions. We also use a constructed variable, earnings, which represents the average hours worked per week for manufacturing workers multiplied times their average hourly wage rate multiplied times the average weeks worked per year. This variable is obviously crucial in explaining the shape of the earnings distribution and thereby affecting the total income distribution as well. We also include a transfer variable (public assistance) that consists of the share of the U.S. budget which is targeted to transfer programs. These programs include AFDC, school lunch and school milk, food stamps and other welfare programs. Finally, we also include GNP to capture any gains from increases in the "size of the pie." We note at the outset that earnings and GNP were not found to be collinear, which was of some concern to us.

Given these variables our model is then,

$$c, c_l, c_{nl}, b^* = F(\text{Earnings, LFP, Public Assistance, POP, GNP}) + \varepsilon \tag{3.1}$$

where ε is assumed to follow an AR(1) process, LFP (POP) represents the relevant labor force participation (population) cohort variable.

Since we are interested in analyzing the impact of changes in these various demographic characteristics on the various marginal income distributions, we adopt the following research strategy. We will undergo a sensitivity analysis to determine the sensitivity of the inequality parameters to different specifications of populations subgroups and labor force participant cohorts jointly with the earnings, transfer and growth variables to attempt to track how changes in population and labor force participation by age cohort impact the inequality parameters. Space constraints preclude us presenting all the specifications here. We refer to the interested reader to a longer working paper by Black *et al.* (1988) and summarize our results here. Similar analysis by sex cohort was also done and the results are included in the aforementioned working paper. We begin with the discussion of the earnings distributions. We then examine total income inequality and finish with a discussion of nonlabor income distributions. We discuss b^* jointly with each of the three distributions because of the relation (2.3).

Since theory doesn't strongly suggest which population and/or labor force participation rate is appropriate to be specified as the regressors of our model, we present several alternatives. Since we need to jointly test each c_i (and c) with b^* we present each specification (c_l, c_{nl}, c) with b^* in one table.

Our discussion of the results begins with the results for labor earnings. We consider only those coefficients which are jointly significant with the comparable ones for b^*. We then proceed to discuss the same inequality measures nonlabor income and total income. We then disaggregate the data and look at the same analysis for women and then men.

Turning to Table 2 we give the results for the impact of the less than 17 population cohort and the various labor force participation rate cohorts, on the inequality parameter c_1 (the parameter for the marginal distribution of earnings).

TABLE 2

COEFFICIENT ESTIMATES OF THE IMPACT OF VARIOUS DEMOGRAPHIC, MACROECONOMIC AND EARNINGS VARIABLES ON EARNINGS INEQUALITY

Dependent Variable: c_l

W.R.T. Intercept	Earnings	LFP16–19	Public Assistance	Population Age 0–17	GNP	
17·52	0·10	−54·54	25·77	−18·47	−0·00003	0·53
(0·0001)	(0·0032)	(0·0320)	(0·8336)	(0·0395)	(0·0037)	
		LFP20				
17·91	0·011	−41·94	78·07	−20·54	−0·00004	0·51
(0·0001)	(0·0076)	(0·0610)	(0·5541)	(0·0266)	(0·0074)	
		LFPMID				
0·31	0·09	20·99	3·54	−15·90	−0·00003	0·49
(0·9772)	(0·0108)	(0·0937)	(0·9785)	(0·1084)	(0·0113)	
		KFPOLD				
2·53	0·07	109·18	266·25	−42·18	−0·00003	0·48
(0·7996)	(0·0129)	(0·1144)	(0·1996)	(0·0115)	(0·0176)	

Dependent Variable: b^*

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Total Population Aged 0–17	GNP	$\bar{R}^2$
11·54	0·01	−37·95	47·96	−13·40	−0·00001	0·87
(0·0001)	(0·3734)	(0·0001)	(0·0001)	(0·2213)	(0·1103)	
		LFP20				
11·85	0·02	−32·50	−14·78	88·53	−0·00001	0·88
(0·0001)	(0·1073)	(0·0001)	(0·0001)	(0·0287)	(0·0367)	
		LFPMID				
−4·15	0·01	18·45	−10·65	30·77	−0·00001	0·88
(0·1793)	(0·2305)	(0·0001)	(0·0005)	(0·3979)	(0·0631)	
		LFPOLD				
11·52	−0·02	−3·34	−13·95	18·85	0·000005	0·78
(0·0098)	(0·0548)	(0·8993)	(0·0336)	(0·8068)	(0·2921)	

Note: $\bar{R}^2$ is the adjusted coefficient of determination· Numbers in parentheses represent the $\Pr[\hat{t} > t_{\alpha/2}/ H_0\colon \beta_j = 0]$.

As can be seen, irregardless of LFP variable, the earnings coefficients are positive and statistically significant and the GNP coefficients are negative and statistically significant (at $\alpha = 0{\cdot}05$ level). These results indicate that as earnings increase (ceteris parivus) the level of inequality as measured by the Gini coefficient decreases. This result is robust across the different specifications of population variable and labor force participation rate variable. Joint significance tests of c_1 and b^* (see Table 3) corroborate these results. A plausible explanation is that the earnings variable is representative of a middle class income indicator (recall our construction), and since the Gini coefficient is generally recognized as being more sensitive to transfers in the middle of a given distribution, the empirical finding is not surprising. On the other hand, when GNP increases, the result appears to be that inequality in the marginal distribution of earnings increases (as measured by the Gini coefficient), ceteris paribus. As the economic pie increases, the gains appear to be greater for those at the upper end of the earnings

TABLE 3

COEFFICIENT ESTIMATES OF THE IMPACT OF VARIOUS DEMOGRAPHIC, MACROECONOMIC AND EARNINGS VARIABLES ON EARNINGS UNEQUALITY

Dependent Variable: c_l

W.R.T. Intercept	Earnings	LFP16–19	Public Assistance	Population Aged 18–24	GNP	$\bar{R}^2$
9·36	0·13	−162·69	91·48	82·37	−0·00004	0·52
(0·0001)	(0·0013)	(0·0045)	(0·4425)	(0·0456)	(0·0019)	
		LFP20				
9·09	0·14	−121·84	262·25	71·49	−0·00005	0·45
(0·0003)	(0·0187)	(0·0629)	(0·1186)	(0·2027)	(0·0248)	
		LFPMID				
30·21	0·11	50·41	14·15	44·49	0·00004	0·47
(0·1020)	(0·0068)	(0·0252)	(0·9169)	(0·2252)	(0·0101)	
		LFPOLD				
20·52	0·05	−41·05	−23·74	−29·52	−0·00001	0·36
(0·0423)	(0·1425)	(0·3856)	(0·9079)	(0·2204)	(0·1825)	

Dependent Variable: b^*

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Total Population Aged 18–24	GNP	$\bar{R}^2$
6·25	0·02	−86·71	82·41	36·32	−0·00001	0·79
(0·0001)	(0·2747)	(0·0009)	(0·1333)	(0·0468)	(0·1556)	
		LFP20				
6·04	0·02	−67·73	163·86	34·49	−0·00001	0·76
(0·0001)	(0·2187)	(0·0067)	(0·0202)	(0·1143)	(0·2132)	
		LFPMID				
27·71	0·03	42·23	31·21	38·01	−0·00001	0·88
(0·0001)	(0·0118)	(0·0001)	(0·3852)	(0·0005)	(0·0030)	
		LFPOLD				
18·89	0·02	−55·61	−56·29	−25·55	0·00001	0·78
(0·0001)	(0·0371)	(0·0031)	(0·4223)	(0·0119)	(0·1351)	

Note: $\bar{R}^2$ is the adjusted coefficient of determination· Numbers in parentheses represent the $\Pr[\hat{t} > t_{\alpha/2}/H_0\colon \beta_j = 0]$.

distribution relative to those at the lower end. This result also appears to be robust, regardless of specification of demographic factors. The joint tests of significance of c_1 and b^* for the public assistance variable indicate statistical insignificance in all except one case. Unfortunately, this is probably due more to the nature of our data than to an interesting economical result. Since the IRS data is only made up of taxable income, the poor at the lower end of the distribution are censored out so the transfer variable shouldn't be expected to pick up a significant effect. Out data should be very informative as a description of earned, reported income, but are not very good for picking up the impact of transfers.

Our results indicate that as the labor force participation rates of 16–19 year olds and 20–24 year olds increases due to growth in the population of any of our age cohorts, inequality in the marginal distribution of earnings increases. This is hardly a surprising result. When teenagers enter the labor force, they are employed in low skill jobs and have lower education levels and will have lower wages. The cohort in their early twenties will also be at the preliminary stage of their life-cycle of earnings. Thus, we would again expect an increasing inequality bias *relative* to similar individuals that are in the labor force longer. As those in 25–44 age group increase in number, the level of inequality should decrease as this cohort ascends to the top of their respective earnings profiles. This can be seen in Table 4.

The results for changes in the labor force participation rate of those over 45 is more difficult to predict. On one hand, workers in the over 45 year old age group are at a relatively high earnings stage of their careers, but those over sixty may be undergoing a transformation from earnings to dependence on non-labor income sources. We might expect mixed results, and this is what is observed in Table 5. The results are statistically insignificant in almost every case, ceteris paribus. When the result is statistically significant, the sign is positive, indicating the distributional effects of the sheer numbers of the younger workers are outweighing number of older workers.

We now flip around our analysis to check for consistency, i.e., we now look at how the population change impacts on the distributions. The inequality parameter for the labor earnings distribution appears to be very sensitive to population cohort specification. An increase in young people (less than 17 years old) in the population ceteris paribus increases inequality in every case. However, the joint test with b^* fail in every instance. The same holds true in Table 6 for those over 65 years of age as that group increases. Only for the 25–44 and 45–64 years of age cohorts do we find a jointly significant, but decreasing impact on inequality, cf. Tables 4 and 5. We should also state that collinearity fears were not realized which indicates that the distribution of labor force entry is somewhat different from the distribution of population cohort growth. Overall, the results seem to indicate that as workers enter their prime working years the life-cycle of earnings is a reasonable hypothesis and inequality falls.

A similar analysis can be discussed for the level of nonlabor income inequality. For each population and labor force participation cohort we examine the regression coefficients for the c_{nl} and b^* regressors. The parameter estimates are reported in Black *et al.* (1988). In nearly every instance, the joint significance

TABLE 4

COEFFICIENT ESTIMATES OF THEIMPACT OF VARIOUS DEMOGRAPHIC, MACROECONOMIC AND EARNINGS VARIABLES ON EARNINGS INEQUALITY

Dependent Variable: c_I

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Population Aged 25-44	GNP	$\bar{R}^2$
3·09	0·10	−25·22	22·73	22·00	−0·00003	0·51
(0·5014)	(0·0034)	(0·4277)	(0·8574)	(0·0598)	(0·0047)	
		LFP20				
1·82	0·10	−12·02	31·25	24·85	−0·00003	0·50
(0·6706)	(0·0107)	(0·6469)	(0·8215)	(0·0281)	(0·0101)	
		LFPMID				
0·64	0·09	2·38	7·12	26·11	−0·00003	0·50
(0·9515)	(0·0104)	(0·8975)	(0·9585)	(0·0872)	(0·0112)	
		LFPOLD				
−30·49	0·15	116·98	286·45	48·61	−0·00005	0·61
(0·0292)	(0·0002)	(0·0246)	(00·826)	(0·0002)	(0·0002)	

Dependent Variable: b^*

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Population Aged 25-44	GNP	$\bar{R}^2$
−0·07	0·01	−11·77	38·04	18·84	−0·00001	0·90
(0·9547)	(0·1587)	(0·1505)	(0·2406)	(0·0001)	(0·0371)	
		·LFP20				
−0·26	0·01	−9·66	50·32	19·24	−0·00002	0·90
(0·8026)	(0·1230)	−(0·1437)	(0·1507)	(0·0001)	(0·0312)	
		LFPMID				
−4·23	0·01	5·60	32·48	17·93	−0·00001	0·90
(0·1207)	(0·2024)	(0·2385)	(0·3212)	(0·0001)	0·0507)	
		LFPOLD				
0·903	0·02	29·49	100·18	26·73	−0·00001	0·91
(0·0162)	(0·0354)	(0·0315)	(0·0250)	(0·001)	(0·0080)	

Note: $\bar{R}^2$ is the adjusted coefficient of determination· Numbers in parentheses represent the $\Pr[\hat{t} > t_{\alpha/2}/H_0\colon \beta_j = 0]$.

tests were identical to those results previously discussed. In those cases which did not yield similar results, labor force participation rates were not jointly significant, but parameter estimates for earnings were jointly significant. This suggests, that earnings levels are more inportant than changes in labor force participation over time in determing inequality in the marginal distribution of non-labor income.

We again found almost identical results for our analysis on total income inequality. These results are not surprising since, as we noted earlier, earnings comprise between $\frac{3}{4}$ and $\frac{2}{3}$ of total income for the sample period of 1952-81. We also observed similarity in the inequality measures for total income and earnings in Table 1. GNP has a decreasing inequality bias on total income inequality as measured by the Gini coefficient, which is particularly strong when considering population change in the 25-44 and 45-64 cohorts, cf. Black *et al.* (1988).

We repeated the same analysis of women in the population and women in the labor force. These results are also given in our working paper and quite

TABLE 5

COEFFICIENT ESTIMATES OF THE IMPACT OF VARIOUS DEMOGRAPHIC, MACROECONOMIC AND EARNINGS VARIABLES ON EARNINGS INEQUALITY

Dependent Variable: c_l

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Population Aged 45–64	GNP	$\bar{R}^2$
−9·62	0·09	−76·89	78·21	110·72	−0·00003	0·52
(0·3668)	(0·0119)	(0·0058)	(0·5313)	(0·0506)	(0·0316)	
		LFP20				
−13·26	0·10	−64·19	166·07	127·79	−0·00003	0·50
(0·2522)	(0·0177)	(0·0130)	(0·2229)	(0·0381)	(0·0423)	
		LFPMID				
−34·40	0·09	32·50	29·25	103·14	−0·00003	0·51
(0·0328)	(0·0160)	(0·0093)	(0·8213)	(0·709)	(0·0368)	
		LFPOLD				
−2·22	0·01	−12·32	44·80	79·64	−0·00002	0·35
(0·9081)	(0·6941)	(0·8112)	(0·8372)	(0·2607)	(0·8531)	

Dependent Variable: b^*

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Total Population Aged 45–64	GNP	$\bar{R}^2$
0·99	0·0003	−49·16	67·01	42·49	−0·000001	0·80
(0·8100)	(0·7997)	(0·0007)	(0·2515)	(0·0519)	(0·8252)	
		LFP20				
−2·17	0·01	−39·82	113·85	47·96	−0·000001	0·79
(0·6083)	(0·6122)	(0·0011)	(0·0713)	(0·0354)	(0·8242)	
		LFPMID				
−21·11	0·01	25·11	48·93	43·11	−0·000003	0·85
(0·0004)	(0·3893)	(0·0001)	(0·2880)	(0·0211)	(0·3961)	
		LFPOLD				
10·30	−0·04	−39·92	−33·75	19·57	0·00001	0·74
(0·1475)	(0·0026)	(0·0707)	(0·6694)	(0·4115)	(0·0341)	

Note: $\bar{R}^2$ is the adjusted coefficient of determination· Numbers in parentheses represent the $\Pr[\hat{t} > t_{\alpha/2}/ H_0: \beta_j = 0]$.

similar to the results for the total population with few exceptions. The results for males are also given in the working paper and are remarkably similar to those reported in Tables 2–6. This would suggest that the inequality parameters for total income and earnings are not very sensitive to changes in the highly aggregated demographic variables.

IV. CONCLUSION

In this paper we develop a joint distribution approach to analyzing the marginal distributions of labor and non-labor income simultaneously. Based on labor and non-labor income data as reported by the IRS, we calculate Gini coefficients assuming a Beta II joint distribution of income. Since the sum of the maginal distributions yields the joint Beta II distribution, we can compare the marginal labor and marginal non-labor income distributions in a consistent manner. Based on regression analysis we find that demographic change in terms

TABLE 6

COEFFICIENT ESTIMATES OF THE IMPACT OF VARIOUS DEMOGRAPHIC, MACROECONOMIC AND EARNINGS VARIABLES ON EARNINGS INEQUALITY

Dependent Variable: c_l

W.R.T. Intercept	Earnings	LFP16–19	Public Assistance	Population Age 65≥	GNP	$\bar{R}^2$
21·94	0·15	−73·00	133·64	−143·33	−0·00004	0·50
(0·0013)	(0·0034)	(0·0076)	(0·2953)	(0·0978)	(0·0043)	
		LFP20				
20·39	0·14	−52·06	202·38	−126·40	−0·00004	0·44
(0·0045)	(0·0148)	(0·0393)	(0·1686)	(0·1754)	(0·0182)	
		LFPMID				
−4·31	0·13	28·91	77·69	−102·72	−0·00004	0·46
(0·6891)	(0·0092)	(0·0201)	(0·5668)	(0·2442)	(0·0110)	
		LFPOLD				
18·98	0·04	−18·93	55·93	−61·51	−0·00001	0·33
(0·0782)	(0·3590)	(0·7286)	(0·8132)	(0·5956)	(0·3395)	

Dependent Variable: b^*

W.R.T. Intercept	Earnings	LFP16	Public Assistance	Total Population Age 65≥	GNP	$\bar{R}^2$
12·98	0·03	−48·67	110·74	−79·35	−0·00001	0·80
(0·0001)	(0·0723)	(0·0001)	(0·0374)	(0·0159)	(0·1037)	
		LFP20				
11·88	0·03	−36·06	144·94	−66·68	−0·00001	0·77
(0·0001)	(0·1470)	(0·0013)	(0·0229)	(0·0566)	(0·2331)	
		LFPMID				
−6·99	0·03	23·52	76·49	−63·45	−0·00001	0·84
(0·0532)	(0·0276)	(0·0001)	(·0881)	(0·0237)	(0·0331)	
		LFPOLD				
16·02	0·03	−39·07	−23·81	−28·41	0·00001	0·74
(0·0017)	(0·0823)	(0·0816)	(0·7698)	(0·4532)	(0·1333)	

Note: $\bar{R}^2$ is the adjusted coefficient of determination· Numbers in parentheses represent the $\Pr[\hat{t} > t_{\alpha/2}/ H_0: \beta_j = 0]$.

of population and labor force participation do affect the marginal and joint distributions of income. Unfortunately, we were unable to identify strong differences in the parameter estimates across the different marginal distributions. This leads us to conclude that demographic changes have the same impact on both sources of income. As the age distribution grows older, ceteris paribus, we anticipate a more equal income distribution. As the labor force participation of women increases, the level of inequality increases, a result consistent with others findings, cf. Shackett and Slottje (1987).

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