Inter-Age and Intra-Age Income Inequality: A Cross-Sectional Analysis*

I. Introduction

A number of studies have used the Gini concentration ratio to examine differences in family income inequality across states and metropolitan areas.¹ Despite the extensive amount of research in this area, results have not been completely satisfactory. In large part this occurs because most of the research lacks a unified theoretical framework from which to develop and interpret empirical work.² In addition, a sizable portion of income inequality measured by the Gini coefficient is age related, due to a parabolic age-income profile. Thus, interarea differences in income inequality result, in part, from differences in the age structure of populations. Age-related differences in measured inequality, however, are not generally regarded as a cause for concern, nor are they subject to policy control. For these reasons, removal of age-related inequality from cross-sectional studies seems conceptually desirable.

Morton Paglin [22] recently developed a concentration ratio which attempts to measure intra-age or within-cohort inequality but excludes inter-age inequality. In this study Paglin concentration ratios are calculated for 124 Standard Metropolitan Statistical Areas (SMSAs) and a regression model is estimated to examine inter-age and intra-age income inequality. The calculated Paglin ratios provide evidence on the degree of intra-age income inequality within U. S. labor markets and the extent to which this inequality varies across areas. The regression analysis allows a comparison of the qualitative and quantitative results generated with alternative inequality measures.

II. The Paglin Measure of Inequality

Prior to Paglin there existed no simple way to calculate a concentration ratio which would correct for age related income differences. Paglin’s contribution was his construction of a new reference curve which allowed a decomposition of the standard Gini ratio into two parts: inequality due to inter-age differences in mean incomes and inequality due to intra-

* A longer version of this paper is available from the authors.

1. Interstate studies include Aigner and Heins [1], Conlisk [6], Al-Samarrie and Miller [2], Sale [26], Ruben-berg and Stano [25], and Formby and Seaks [10]. Frech and Burns [11], Farbman [9], Danziger [7], and Long, Ras-mussen, and Haworth [19] use SMSA data. Farbman [8] utilizes county data within twelve southern states. The Paglin ratio is estimated for states in [25] and used as a dependent variable; however, only a sketchy discussion of results is provided.

age income dispersion. Inter-age inequality is measured by the Age-Gini, while the Paglin ratio, measuring intra-age inequality, is simply the standard Gini minus the Age-Gini. While the Paglin ratio is not an ideal measure, it is the most widely available summary measure of intra-age income inequality.3

Paglin concentration ratios (and Age-Ginis) are calculated for the 124 SMSAs with populations greater than 250,000 in 1970.4 We find, as did Paglin, that about a third of the income inequality measured by the standard Gini is age related. The unweighted mean across SMSAs of the Paglin ratio is .232, as compared to .341 for the Gini. Intercity dispersion in intra-age inequality is found to be relatively greater than the dispersion in total inequality, the coefficient of variation of the Paglin measure being .119, as compared to .079 for the Gini. The coefficient of variation of the Age-Gini is .101. The lower relative variation of the Gini than either the Paglin or Age-Gini indicates that there is some tendency for inter-age and intra-age inequality differences across SMSAs to offset each other. The simple correlation coefficient between the Paglin ratio and the Age-Gini is −.27. Although it has not been emphasized or explained, an even stronger offsetting tendency between inter-age and intra-age inequality can be shown to exist over time [22, Table 3, p. 604]. Despite differences across labor markets in the shape of cross-sectional income profiles and in age structure the Paglin and Gini concentration ratios are highly correlated due to this offsetting tendency.5

III. The Determinants of Family Income Inequality

In lieu of developing a full scale theory of family income determination and deriving from that a model of interarea income inequality, we attempt to integrate the findings of previous research in this area.6 We employ a regression model in which income inequality, as measured by the Gini and Paglin concentration ratios, is related to personal characteristics such as schooling, occupation, age, race, and sex; and to labor market characteristics such as income level, city size, region, unemployment and industrial structure. Obviously a single equation regression model does not allow us to identify supply side and demand side determinants of the income generating process.

Personal Characteristics: Schooling, Occupation, Age, Race, and Sex.

The inequality studies generally use a median years of schooling variable and find that inequality decreases as the level of schooling increases [1; 2; 9; 25; 26], or employ schooling

3. Although the Paglin measure makes a correction for the age-income profile of the population, it is not an ideal correction. Nelson [21] shows that if age-income distributions overlap, Paglin’s measure of intra-cohort inequality is affected by each cohort’s mean income and population weight. The Paglin measure also fails to exactly measure the inequality in lifetime incomes since the shape of longitudinal age-income profiles can not be precisely estimated with cross-sectional data. Paglin [23] argues that these impressions are minor. A second problem with the Paglin measure of inequality is that it does not lead to unambiguous policy conclusions. While society does not generally regard inter-age inequality as a cause for concern, this need not be the case: witness the tradition of either the family or the state supporting children and the aged poor. Further, some intra-age inequality results from the exercise of free choice (e.g., human capital investment and labor-leisure choice) and may be regarded as just by society.

4. See [22] for details. Paglin recommends the cubic spline technique because it achieves very accurate results with few data points. We utilize a published routine by Greville [13], similar to Paglin’s own program, to carry out the calculations.

5. The Spearman rank correlation coefficient between the Paglin and Gini ratios is .92. They are also highly correlated across states, our calculations again indicating a Spearman rank correlation coefficient of .92.

6. See those studies referenced in footnote 1. The use of largely ad hoc regression models in this area is not due primarily to difficulties in modeling an appropriate framework, but rather results because of the tremendous data requirements for even the simplest models of income determination. For instance, Hirsch [16] shows the importance of using individual data within SMSAs in order to test a simple version of the human capital model.
inequality variables which are positively related to inequality [6; 7; 25]. The simple human capital model predicts that inequality in earnings will be positively related to the dispersion in years of schooling, to the rate of return to schooling, to the level of schooling, and to the covariance between schooling and age [4; 5; 16]. Unfortunately, estimation of within-area rates of return and the covariance between schooling and age requires the use of microdata within each labor market [16; 17]. The finding from previous studies of a strong negative relationship between inequality and schooling level is misleading, resulting because higher schooling levels are associated generally with more equal distributions of schooling, lower rates of return, and a stronger (more negative) covariance with age.

In this study we expect income inequality to be positively related to the inequality in schooling, as measured by the percentage of an area's adult population with less than one year of high school (HIGHSCHOOL) and with at least four years of college (COLLEGE). The relationship between inequality and schooling level, as measured by an area's median years of schooling (MEDSCHOOL), is also expected to be positive, unless unmeasured rates of return exhibit a strong negative correlation with MEDSCHOOL.

The distribution of schooling is, of course, an important determinant of the occupational distribution. Long, Rasmussen, and Haworth [19] omit an education variable and find intra-SMSA inequality to be greater the higher the percentage of white-collar workers. Similarly, Farbman [8; 9] finds inequality to be less in SMSAs and in southern counties with greater percentages of clerical and blue-collar workers. Other studies [2; 26] use similar occupational variables, but generally find them insignificant, probably because of high multicollinearity with the schooling variable and fewer degrees of freedom with state data. Both theoretical and empirical analysis indicates that intra-earnings dispersion increases with skill level [20; 27], as well as inter-age dispersion due to steeper income profiles. We include an occupational variable, the percentage of employment in white-collar jobs (WC), which is expected to be positively related to income inequality. We expect the coefficient of WC to decrease when the Paglin ratio is used as the dependent variable since the Paglin measure will not capture income dispersion due to a steeper lifetime profile among white-collar workers.

Because incomes vary systematically over the life cycle, a population's age structure is an important determinant of its distribution of income. Surprisingly, previous interarea inequality studies have used at most only a single age variable in their regression models. Family income inequality has been found positively (but weakly) related to median age [1; 25], the percent of the population over 65 [26], the percentage of the population under 35 and over 65 [2; 6], and under 25 and over 65 [7]. In this study we examine the relationship between inequality and six age groups which include all families within an SMSA: the percentage of families with head of household less than 25 (AGE25), between 25 and 34 (AGE25-34), between 35 and 44 (AGE35-44), between 45 and 54 (AGE45-54), between 55 and 64 (AGE55-64), and over 65 (AGE65). Use of a detailed age breakdown should provide more information than can be gleaned from previous interarea studies.

Income inequality results from life-cycle differences in average incomes, from within-cohort income dispersion, and, of course, from differences in age structure. Inequality as

7. Interarea differences in rates of return may be partially captured by detailed regional dummies or the median income variable, since rates of return are inversely related to income level (see Chiswick [4] and Hirsch [17]).

8. AGE45-54 is used as the reference group since families in this group have the highest average income in a cross-section. A concave cross-sectional income profile results from vintage effects and a secular increase in schooling, as well as from life-cycle (age and investment) effects. A decreasing income profile does not imply falling income for any single cohort (prior to retirement). See Ruggles and Ruggles [24].
measured by the Gini is expected to be greater the larger the percentage of families in age groups with average incomes significantly different from the mean, and the larger the percentage of families in age groups with large intra-age dispersion in income. However, inequality as measured by the Paglin ratio should vary only with the age structure according to the amount of income dispersion within age groups. Even though the Paglin measure excludes inter-age inequality which is life-cycle related, it is affected by a population's age structure if intra-cohort dispersion varies across age groups. And, both theory and evidence indicate that income dispersion varies with the accumulation of human investment over the life cycle and with changes in labor force participation and hours worked.

All of the inequality studies find income inequality to be significantly greater in areas with higher percentages of nonwhites. However, evidence in [19] indicates that the significance of the nonwhite variable is due in part to its high correlation with the number of female-headed households. Inequality among blacks is somewhat greater than among whites, and the disproportionate concentration of black and female-headed families in the lower end of the income distribution acts to increase significantly within-age inequality for an SMSA's population as a whole. We include a race variable, BLACK, representing the percentage of nonwhites in an area's population, and FEMHEAD, which measures the percentage of female-headed households.


Most of the studies examine the relationship between income inequality and the level of income, arguing that a negative relationship supports Kuznets' hypothesis that inequality decreases during later stages of economic development. While the theoretical basis for Kuznets' hypothesis is not well developed, all studies find income inequality to be negatively related to median family income [1; 6; 8; 9; 11; 19; 25; 26]. We follow others in including median family income (INCOME) as an explanatory variable.

Several studies [7; 9; 19] find that inequality increases with city size. Neither [7] nor [9] find population density to be significant, after accounting for size. We include the variable LOGPOP, representing the natural log of population size, in order to examine the city size relationship. It is probable that LOGPOP captures supply side or human capital differences not measured by other variables. Larger cities will tend to attract not only the most able, motivated, and best trained workers, but will also attract large numbers of low-skill and displaced workers, particularly in those SMSAs with large central cities. The structure of demand within larger SMSAs probably induces and reinforces this supply response. Long, Rasmussen, and Haworth [19] also include a population growth variable to help adjust for any disequilibrium effects, and find this variable significantly related to inequality. High rates of population growth may also be associated with disproportionate in-migration of high

9. Ruthenberg and Stano [25] mistakenly expect the Paglin measure of inequality not to be related to their age variable. Finding otherwise, they conclude that the Paglin measure does not correctly adjust for life-cycle influences.

10. The Gini coefficient of black family income is .397, while that for whites is .353 (U.S. Census [28], Table 252.)

11. Danziger [7] omits median income, arguing that it is simply a function of the model's other variables. Also see Hirsch [16]. We also estimated our model with median income excluded. Coefficients on the model's other variables were quite similar; however, explanatory power was significantly reduced.
and low skill workers. We also include a growth variable, defining $\%\Delta POP$ as the percentage change in population between 1960 and 1970.

None of the state studies include regional variables. Among the SMSA studies, [19] finds inequality to be greater in southern cities, while [7] and [9] include regional dummies which appear to add moderate explanatory power to their equations. We also account for regional differences by use of dummy variables broken down by the nine census regions. Earnings function parameters are not particularly stable across labor markets [15; 17], and regional dummies should account, at least in part, for these differences.

An SMSA's unemployment rate (UNEMP) is expected to be positively related to its inequality of income, though few studies have found a statistically significant relationship. UNEMP may not be an ideal measure of variations in employment or accurately measure relative differences in labor market conditions. Studies utilizing a human capital framework [4; 16] find a strong positive relationship between individual earnings inequality and the dispersion in weeks worked. However, the relationship between family income inequality and employment dispersion is more complex.\(^{12}\)

None of the studies have systematically analyzed the relationship between industrial structure and the income distribution or attempted to separate empirically the effects on incomes by the demand side from those on the supply side. Danziger [7] accounts for 12 industry groupings in his regression model and concludes that industrial structure is important, while several studies [1; 11; 19; 25; 26] find inequality to be less in those areas with higher percentages of employment in manufacturing. Differences in the structure of labor demand due to differences in skill requirements and capital intensity will generate interarea differences in income structures. However, if labor is highly mobile and we are in equilibrium, all income differences may be captured by supply side or human capital variables. Because supply side characteristics cannot be completely accounted for, it may be appropriate to include industry variables in the regression. We cannot, however, distinguish between supply and demand effects on the income distribution. We include variables measuring the percentage of employment in 12 industry categories.

Previous studies have not examined the relationship between unionization and family income inequality. A priori, the effects of wage differentials between union and non-union workers on the dispersion in income is indeterminate, since some workers will have earnings pushed closer to the mean while others further away. However, empirical evidence in Borjas [3] shows that unionization is associated with flatter earnings profiles and less earnings dispersion. A recent study by Freeman and Medoff [12] makes available for the first time data on union membership by SMSA, which they calculate from the 1973-1975 Current Population Surveys for 98 SMSAs. We estimated our model using the Freeman-Medoff sample of SMSAs, but find that the percentage of private sector workers who are union members is not significantly related to family income inequality.\(^{13}\) In order to preserve our larger sample size of 124 SMSAs, we do not include a unionization variable in our model.\(^{14}\)

\(^{12}\) Neither male nor female labor force participation rates were found to be significant determinants in our analysis, nor have they generally been found significant in other studies. We also constructed variables measuring the variance in weeks worked by males and by females; however, neither measure was significantly related to family income inequality.

\(^{13}\) These results are available from the authors on request. The coefficient on the percent union variable is negative and very small, with a t statistic of $-0.76$. It is even closer to zero when industry variables are not included. Measurement error in the union membership variable (sample size in some SMSAs is not large) may bias the regression coefficient towards zero.

\(^{14}\) We do not include any variables in our model specifically intended to measure non-labor incomes. Several
IV. Empirical Results

Data are from the 1970 Census of Population and include SMSAs (124) with populations of 250,000 or greater.15 In this section, we summarize regression results using the Gini and Paglin concentration ratios as dependent variables. Empirical results are presented in Table I. Using independent variables discussed above, close to 90 percent of intercity differences in family income inequality are accounted for and most coefficients are significant at conventional levels. Comparison of results utilizing the Paglin and Gini inequality measures provides evidence on the determination of inter-age and intra-age income inequality.

Consistent with the human capital model, inequality is found to be positively related to the inequality in educational attainment, as seen by the highly significant coefficients on HIGHSCHOOL and COLLEGE, and to be positively related to MEDSCHOOL, the level of schooling, holding constant its dispersion and other variables of the model. Rates of return are not directly accounted for here, but are captured in part by INCOME and the regional variables. The coefficients on the educational variables are significant despite multicollinearity among these variables and with WC, the percentage of white-collar workers. Our results are also consistent with recent work indicating that comparative advantage among individuals will generate greater earnings dispersion among more skilled workers [27]. Further, they are consistent with the existence of capital-skill complementarity ([14] provides a survey of empirical evidence), whereby technological development and increased capital intensity complement higher-skilled (schooled) workers, thus increasing the dispersion in earnings.

Income inequality is found to be positively related to WC, the percentage of white-collar workers. Of course, occupational attainment and mobility is simply a major medium by which investment in schooling is translated into higher earnings and the effects of each cannot be separated easily. The coefficient on WC is reduced sharply when the Paglin measure is used as the dependent variable. The decrease implies that much of the inequality associated with white-collar workers is due more to steeper age-income profiles than from greater inequality among skilled workers within age (experience) groups. Steeper income profiles among white-collar workers likely result from a greater intensity in on-the-job training investments which lowers net earnings during early years and increases earnings in later years. The coefficient on MEDSCHOOL, unlike that on WC, does not decrease, suggesting that, ceteris paribus, higher schooling levels are associated more with intra-age than with inter-age income inequality.

The Gini concentration ratio is associated not only with inter-cohort difference in average incomes, but also with differences in intra-cohort income dispersion. The positive and significant coefficients on AGE25 and AGE65 primarily reflect the significantly lower average incomes for very young and very old families and is consistent with previous findings. The positive coefficients on AGE35–44 and AGE55–64 (relative to the reference group, AGE45–54) can not be explained adequately by differences in average earnings. Rather, it

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15. Income data cross-classified by age group is available only for SMSAs with populations 250,000 or greater (U.S. Census, [28], Table 202). Some of the SMSA data were kindly furnished by Sheldon Danziger of the University of Wisconsin. All data, including the Gini coefficients, are from the 1970 U.S. Census of Population, except for the industry variables which are from the Brown University Urban Analysis group.
Table I. Regression Results, Inter-Age and Intra-Age Income Inequality (t ratios in parentheses)

<table>
<thead>
<tr>
<th></th>
<th>Gini Concentration Ratio</th>
<th>Paglin Concentration Ratio</th>
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<tr>
<td></td>
<td>(1G)</td>
<td>(2G)</td>
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<tr>
<td>CONSTANT</td>
<td>- .245</td>
<td>- .074</td>
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<td></td>
<td>(-2.09)***</td>
<td>(-.54)</td>
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<td>INCOME</td>
<td>- .0012</td>
<td>- .0011</td>
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<td>(-8.13)***</td>
<td>(5.88)***</td>
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<td>HIGHSCHOOL</td>
<td>.184</td>
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<td></td>
<td>(4.98)***</td>
<td>(4.54)***</td>
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<td>COLLEGE</td>
<td>.284</td>
<td>.349</td>
</tr>
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<td></td>
<td>(4.67)***</td>
<td>(4.50)***</td>
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<tr>
<td>MESCHOOL</td>
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<td>1.181</td>
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<td></td>
<td>(2.81)***</td>
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<td>WC</td>
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<td>.099</td>
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<td>(2.57)***</td>
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<td>BLACK</td>
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<td>(6.95)***</td>
<td>(4.61)***</td>
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<td>FEMHEAD</td>
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<td>.220</td>
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<td>(2.17)***</td>
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<td>%ΔPOP</td>
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<td>(5.54)***</td>
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<td>.152</td>
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<td>(3.00)***</td>
<td>(1.74)***</td>
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<tr>
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<td>AGE55-64</td>
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<td>(1.51)***</td>
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<tr>
<td></td>
<td>(4.11)***</td>
<td>(3.44)***</td>
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<tr>
<td>INDUSTRY DUMMIES (Fb)</td>
<td>--</td>
<td>3.84**</td>
</tr>
<tr>
<td>REGIONAL DUMMIES (Fa)</td>
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</tr>
<tr>
<td>R²</td>
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<td>.900</td>
</tr>
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a test for joint significance of industry variables.  * Significant at .05 level (2-tailed test)
b test for joint significance of regional variables.  ** Significant at .01 level (2-tailed test)
All variables defined in text, each multiplied by 10^-2.  N = 124.
indicates that, ceteris paribus, intra-cohort income dispersion is relatively greater among families in these age groups than among families ages 25 to 34 and 45 to 54. The $AGE55-64$ may show relatively greater dispersion due to variation in employment resulting from retirements prior to age 65, reduced hours or weeks worked, or changes in labor force participation by other family members. The reason for greater intra-cohort dispersion in the $AGE35-44$ group than in the ages 25–34 or 45–54 groups is not so obvious. Neither of these variables are significant when industry and regional variables are included.\textsuperscript{16}

The Paglin measure should be affected by a population's age structure only if age cohorts differ in the amount of within-group income dispersion. We find, as expected, that $AGE25$ is not significantly related to intra-cohort inequality, while the size and significance of the coefficient on $AGE65$ is sharply reduced. Our earlier argument that $AGE55-64$ is associated with greater inequality due to larger intra-age dispersion in incomes rather than to life-cycle differences in average income is borne out by our results (1P and 2P), $AGE55-64$ being positively and significantly related to intra-cohort income inequality.

As expected, income inequality is found to be positively related to $BLACK$, the percentage of non-white families, and $FEMHEAD$, the percentage of female-headed households. The coefficient on $FEMHEAD$ increases sharply when the Paglin ratio is used as the dependent variable, indicating that its importance results from large variations between the incomes of male and female-headed households within similar age groups.

Several labor market characteristics are found to be significantly related to family income inequality. As in other studies, inequality varies inversely with median income. Income inequality is positively associated with both city size and the percentage change in population between 1960 and 1970 in specification (1G). However, the coefficient on $\%\Delta POP$ becomes insignificant and close to zero when industry dummy variables are included, while the coefficient of $LOGPOP$ increases slightly. This result implies that $\%\Delta POP$ captures differences in industry structure which are associated with greater inequality. Addition of the regional dummy variables adds only trivial explanatory power to the model, increasing the $R^2$ between specifications (2G) and (3G) from .921 to .926. We cannot reject the hypothesis that the regional variables are jointly insignificant determinants of income inequality ($F_{8,89} = .81$).

Income inequality is positively related to an area's unemployment rate in (1G), despite the imprecision with which local unemployment rates measure the dispersion in employment. The coefficient on $UNEMP$ does decrease however when industry variables are included, indicating that some of the effects of industry structure on inequality (specification 2G) result from inter-industry differences in employment stability. Inclusion of regional dummies reduces further the coefficient on $UNEMP$. The sharply lower coefficient on $UNEMP$ in specification (1P) reflects the age specificity of unemployment. That is, unemployment increases income inequality primarily through its effect on the incomes of young households relative to older households, but is not associated with greater intra-age income dispersion.

Inclusion of industry variables in the model (specification 2G) adds a moderate, but statistically significant amount to its explanatory power. The F statistic testing for joint significance of $INDUSTRY$ (comparing 1G and 2G) is 3.84. Regression analysis does not permit a precise measurement of the contribution of industry structure to inequality since demand

\textsuperscript{16} The age variables taken jointly add significant explanatory power to the model. For instance comparison of specification (1G) to an identical regression without age variables yields $F_{5,108} = 10.14$.
and supply effects cannot be separated. However, we obtained a relatively high $\hat{R}^2 (.540)$ when only industry dummies were included as regressors (these results not shown), suggesting that demand factors varying systematically across industries are important.

V. Summary and Conclusion

This study provides a relatively complete examination of interarea family income inequality. As predicted, income inequality is found to be positively related to the dispersion in schooling, the level of schooling, and the percent of white collar workers. Inequality is greater in labor markets with a higher proportion of nonwhites and female headed households, in low income areas, and in larger SMSAs. After controlling for differences in industry mix, it is found that a labor market's rate of growth and its unemployment rate are not significantly related to income inequality. Industry mix is an important determinant of the income distribution; however, we are unable to separate empirically causal forces on the demand side from those on the supply side. Region makes relatively little difference, ceteris paribus.

By utilizing several age variables and alternative measures of inequality—the Gini and Paglin concentration ratios—we have attempted to distinguish between those factors associated with inter-age and intra-age income inequality. Income inequality in a labor market is affected by its age structure because of life-cycle differences in mean incomes and because intra-age income dispersion varies among different cohorts. We find that variables such as unemployment and white-collar employment are associated with greater life-cycle differences in income, but not greater intra-age dispersion. On the other hand, the percentage of female-headed households and families with heads ages 55 to 64 are associated primarily with greater intra-age, rather than inter-age, dispersion in income.

While regression results from the use of the Paglin measure are generally similar to results from the use of the Gini, the differences we find have clear economic explanations. Our results indicate that distinguishing between inter-age and intra-age inequality provides insight into the income generating process, and also suggest that use of the Paglin concentration ratio will prove valuable in future research.

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References