INTERTEMPORAL LABOR SUPPLY AND THE DISTRIBUTION OF FAMILY INCOME

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Abstract—The earnings of married women have a more equalizing effect on the distribution of *lifetime* family earnings (or the expected present value of earnings) than on the distribution of annual family earnings, using PSID longitudinal data. The intertemporal variability of wives' labor supply causes the correlation between the lifetime earnings of husbands and wives to weaken relative to the correlation between their annual incomes, resulting in lower lifetime inequality. The inequality of potential income (full employment earnings) is found to be much greater for lifetime earnings than average annual earnings, based on alternative endogenous wage-hours models.

I. Introduction

A NUMBER of recent empirical studies have focused on the effect of female earnings on family income inequality, concluding that wives' earnings have had a small equalizing effect on the income of two-headed households.[1] These studies omit several features of income determination which suggest that this issue needs to be reexamined.

Though the earnings of married women have risen sharply over the last twenty years, their labor supply and wage rates continue to exhibit pronounced lifecycle patterns. Many married women continue to reduce their labor supply during the child-rearing years, reflecting intertemporal changes in the value of household production. Intertemporal variation in nonlabor income and wage rates, arising from lifecycle changes in human capital investment, also induce labor supply changes.

As a result of the intertemporal variation of labor supply and wages, the contribution of the wife's income to total family income can vary considerably over her lifecycle. Consider, for example, the labor supply of "wealthier" women, or those whose husbands earn above average income. If wealthier women are more likely to reduce their labor supply during the child-rearing years, due to the larger value of the husbands' negative income effect, then the income distribution will appear much more equally distributed during those years than before or after. An accurate assessment of income inequality requires that these stages of the lifecycle be linked together—thus the appropriate measure of income inequality is the distribution of the present value of income, not annual income.[2] The importance of a lifetime focus has been emphasized by Lillard (1977) and Parsons (1978), who analyze the effects of human capital investment on male income inequality.[3]

Previous researchers have recognized the lifecycle variation in the effect of female earnings on family income inequality, but their work examines stages of the lifecycle like cross-sectional snapshots, omitting the links between the stages of the lifecycle.[4] As described in the example above, the

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[1] Only Layard and Zabalza (1979) find an unequalizing effect, for Britain, 1975, based on the *CV*. The early study by Mincer (1974) found the first equalizing effect, while Smith (1979) found the effect to be particularly large for younger women, as did Lehrer and Nerlove (1981, 1984), and Blau (1984). Gronau (1982) finds an equalizing effect for Israel, while Winegarden's (1987) cross-country analysis shows an equalizing effect at higher participation rates, and Danziger (1980) finds an equalizing effect using Gini coefficients. All but Danziger use coefficients of variation for their inequality index. In all cases, the analysis is restricted to two-headed households. Researchers are now beginning to recognize the importance of single-headed households (Blank (1985)), but the data for longitudinal analysis are quite limited.

[2] The present value of income may not be the preferred measure of individual welfare for low income families that are severely liquidity constrained. For example, policymakers would be concerned with current income if poverty households are unable to meet their current needs, regardless of their expected future income. Nevertheless, for the majority of the population, who may choose to vary their income from one year to the next, the appropriate measure of welfare is lifetime income not current income.

[3] See also Friesen and Miller (1983) and Eden and Pakes (1981) for analyses of lifetime inequality.

[4] Both Lehrer and Nerlove (1981, 1984) and Blau (1984) have focused on the lifecycle changes. However, Lehrer and Nerlove do a purely cross-sectional analysis of annual income, while Blau uses only NLS Young Women, in their twenties and thirties, which limits the lifecycle analysis, and neither exploit the panel nature of his data by looking for interperiod correlations.

linkages can produce very different pictures of inequality, if, for example, wives move to different points in the income distribution at each stage.[5] To assume that the stages of the lifecycle are independent, as previously done, is to misrepresent lifetime income inequality.

The theoretical framework of lifecycle income inequality is developed in the next section, with the empirical results following in section III. The Panel Study of Income Dynamics for 1966–1981 is used for the estimation. The results are summaized in the concluding section IV.

II. Theoretical Framework

I adopt the convention of using the coefficient of variation (CV) of the expected present value of family earned income as the measure of income inequality (the absence of wealth data precludes its inclusion). The objective of this paper is to analyze the effect of wives' incomes on the CV of family incomes, relative to the CV of husbands' incomes were men the sole earners.

The expected present value of lifetime earnings is defined as

$$EPV \equiv \sum_{t=1}^{T} \beta^t E(Y_t) \qquad (1)$$

where Y_t is the sum of the wife's and husband's annual earnings, r is the rate of time preference, for $\beta = 1/(1+r)$, T is the maximum number of years in the labor force, and $E(Y_t)$ is the mean value of family income for all families currently in year t. The family unit is most conveniently indexed by the husband's labor market experience, years $1 \ldots T$, because husbands' earnings considerably exceed their wives' earnings on average (and retirement years are excluded from the calculation, due to lack of data).

The variance of the present value of earnings is

$$VPV = \sum_{t=1}^{T} \beta^{2t} \operatorname{var} Y_t + 2\sum_{j=1}^{T-1}\sum_{k=2}^{T} \beta^{j+k} \operatorname{cov}(Y_j, Y_k), \quad k > j \qquad (2)$$

where

$$\begin{aligned}\operatorname{cov}(Y_j, Y_k) &= \operatorname{cov}(Y_j^w + Y_j^h, Y_k^w + Y_k^h)\\ &= \operatorname{cov}(Y_j^h, Y_k^h) + \operatorname{cov}(Y_j^w, Y_k^h)\\ &\quad + \operatorname{cov}(Y_j^h, Y_k^w) + \operatorname{cov}(Y_j^w, Y_k^w)\end{aligned}$$

for variances and covariances calculated across individuals, where $Y_t = Y_t^h + Y_t^w$, for Y_t^h equal to the husband's annual income and Y_t^w equal to the wife's income.

Combining (2) and (1), greater inequality is reflected in a larger coefficient of variation, defined as $CV = (VPV)^{1/2}/EPV$. No data set contains a complete lifetime work history for individuals—the PSID used below has 14 years of longitudinal data for each individual. To calculate the CV with limited longitudinal data, the VPV sums variances and covariances calculated by cohort; annual variances and covariances are calculated across individuals in each experience year, while covariances between current and lagged income for each spouse and between spouses are calculated using the longitudinal data for individuals in each experience year. These calculated variances and covariances are then combined to form one lifetime VPV for the sample. The EPV is calculated in a similar manner. The resulting coefficient of variation represents the CV of lifetime earnings for the population. Possible biases in this measure are discussed and tested below. This method was chosen in lieu of forecasting future income for each individual, because income forecasts omit the stochastic shocks that shape income distribution.[6]

[5] Is this a realistic example? Heckman and Willis (1977) show that individual female labor supply is very stable over time, due either to individual heterogeneity or to state dependence. But stability may be very great from one year to the next, but considerably weaker across longer lifecycle segments. If there are demand side constraints on hours of work or high fixed costs associated with work, reactions to persistent changes in the value of home time may result in one major shift in labor supply, as depicted in figure 1. Cogan (1981) demonstrates that changes in fixed costs associated with employment have a very substantial effect on female labor supply.

[6] Lillard (1977) also focuses on the distribution of the present value of income, of men only, using the alternative technique of calculating the expected present value. Using a very rich individual data set, he runs income regressions, then predicts income for each individual for each year in the labor force and takes present values. The drawback with his approach is that the use of predicted income rather than actual income eliminates shocks to income which alter its distribution. Parsons (1978) and I use the same methodology (described further in section II)—his use is for men only and he does not analyze the CV.

To isolate the effect of wives' earnings on the distribution of family incomes, the squared coefficient of variation can be decomposed into the components representing male and female contributions:

$$CV^2 = \alpha^2(CV^h)^2 + (1-\alpha)^2(CV^w)^2 + 2\alpha(1-\alpha)\rho CV^h CV^w \quad (3)$$

where $(CV^i)^2$, for $i = h, w$, are the squared values of husbands' and wives' coefficients of variation of the present value of lifetime earnings; α is the husbands' share of lifetime earnings, $\alpha \equiv EPV^h/EPV$; and ρ is the correlation between husbands' and wives' lifetime earnings. The values for CV, CV^h, CV^w, and α can be calculated from equations (1) and (2) above and comparable equations for male and female earnings. Given these values, the value of ρ in the sample can be derived from equation (3). Given estimates of all components of (3), it is then possible to isolate the components of (3) that cause CV^h to differ from CV.

Equation (3) identifies the ways wives' incomes affect family income inequality, but obscures the underlying effects of variation in wages and labor supply. For example, a positive covariance ρ between husbands' and wives' incomes may reflect a positive correlation between either their wage rates or their labor supply (an analytical derivation of the determinants of ρ is uninformative using present values). To examine the wage rate correlation, equation (3) is also calculated for potential income, defined as full-time labor supply times the expected wage rate. If the wage rates or potential incomes of spouses are highly correlated, then individuals of like ability marry and "assortative mating" is uncovered. If assortative mating is present yet actual spousal incomes are weakly correlated, income effects in labor supply must account for the weaker income correlations and reduced income inequality.

To estimate potential income, wages must be predicted for those wives who do not work. The basic wage equation is

$$\ln W_{it}^w = BX_{it}^w + DZ_{it}^h + a_1 W_{it}^h + \mu_i + e_{it} \quad (4)$$

where X^w is the vector of the wife's background variables, including education, experience, and the number of children; Z^h is the vector of the husband's background variables; and W^h is the husband's wage. Given the sole objective of estimating (4) to predict the wife's wages, the husband's variables are included to increase predictive power on the assumption that they may be correlated with the wife's unobserved ability or investment (making the common assumption that the wife's wage has no causal effect on his wage). The error term e_{it} is i.i.d., while μ_i is an individual-specific effect assumed to be distributed i.i.d. normal across individuals independent of the right-hand-side variables, so (4) is estimated as a random effects model.[7] For ease in forecasting wages, it is assumed that the random effect μ_t is the only form of unobserved correlation in wages, omitting other forms of serial correlation. This wage equation is also subject to the selectivity bias arising from conditioning observed wages on labor force participation. This bias is controlled for by estimating a participation probit using the standard Heckman procedure.[8]

One primary problem with filling in missing wages with predicted wages is that the variance of predicted wages will be less than the variance of actual wages. Given the estimated parameters of the distributions of e_{it} and μ_i, random draws from these distributions are added to the predicted wages (see Blau (1984)). Alternatively, for those women who have three or more years of observed wage rates, an individual fixed effect is calculated from their available earnings data, as $\hat{\mu}_i = \Sigma_t^T(W_{it}^w - \hat{W}_{it}^w)/T$. This estimated fixed effect is likely to be more accurate than the random draw from the distribution of individual effects.

Given these wage estimates, the distribution of actual income is compared to the distribution of potential income, where the latter equals the expected wage rate times 2000 annual hours of work. A strong positive correlation between spouses' po-

[7] The random effects model assumes that the individual-specific effect μ_t is distributed independently of the observed right-hand-side variables in the regression. This assumption would be violated if, for example, unmeasured ability differences are correlated with education. The alternative estimation method, first-differencing to eliminate fixed effects, is, however, not useful here because the purpose of the wage estimates is to predict wage *levels* not their rates of growth. Furthermore, predictive power is the objective here, not coefficient consistency.

[8] The probit, for participation greater than 100 hours versus non-participation ($\leq$ 100 hours), contains the following variables for identification: all variables in the wage equation excluding *SMSA* and *SOUTH* (see table A1), plus husband's hours, income, education, experience, and their interactions. The probit error was assumed to be i.i.d. normal.

tential incomes would suggest the presence of assortative mating.

III. Empirical Results

Fourteen years, 1968–1981, of the longitudinal Panel Study of Income Dynamics (PSID) are used to estimate the distribution of real earnings. In the process of surveying households, the PSID introduces new households into the survey as children leave their parents' homes, so unlike other panels, the PSID approximates a random sample suitable for the analysis of income distribution. After dropping the low income subsample, there are a total of 18,655 family-years for 2,316 families.

Income inequality is measured as the coefficient of variation, defined as $CV = (VPV)^{1/2}/EPV$, where the variance of the present value, VPV, is defined in equation (2) and the expected present value, EPV, is defined in equation (1). Clearly this method of estimating the CV combines the earnings of younger and older cohorts into one lifetime CV (described in section II). The lagged covariances are calculated using individual longitudinal data, but the discounted sum of covariances sums the longitudinal covariances across different cohorts (equation (2)), introducing cohort bias into the lifetime measures of VPV and EPV. This is a necessary drawback of doing complete lifecycle analysis—in order to forecast the future earnings of young men and women we must use the current earnings of older cohorts. However, because the current younger cohorts are likely to behave differently when they age relative to the current older

TABLE 1.—COEFFICIENTS OF VARIATION

Experience	CV	CV^h	CV^w	α	ρ	$\%\Delta(CV - CV^h)$
			A. Actual Income			
			CV of Present Value of Income			
1. Lifetime earnings	0.327	0.369	0.676	0.802	0.016	11.3
2. Cross-sectional earnings[a]	0.098	0.106	0.218	0.802	0.075	7.3
			CV of Annual Income			
3. 1–5	0.53	0.58	1.03	0.71	0.10	9.4
4. 6–10	0.56	0.59	1.26	0.78	0.10	5.4
5. 11–15	0.58	0.62	1.46	0.84	0.02[b]	6.9
6. 16–20	0.65	0.70	1.53	0.86	0.06[b]	7.7
7. 21–25	0.72	0.78	1.46	0.85	0.09	8.3
8. 26–30	0.71	0.78	1.32	0.83	0.13	9.9
9. 31–35	0.65	0.69	1.45	0.83	0.11	6.2
10. 36–40	0.66	0.69	1.57	0.82	0.11	4.5
11. mean	0.65	0.70	1.40	0.81	0.083	7.3
			B. Potential Income			
			CV of Present Value of Potential Income			
12. Lifetime earnings	0.285	0.331	0.361	0.631	0.363	14.
13. Cross-sectional earnings[a]	0.088	0.108	0.122	0.631	0.175	18.
			CV of Annual Potential Income			
14. 1–5	0.48	0.58	0.70	0.58	0.17	20.
15. 6–10	0.48	0.58	0.70	0.61	0.19	19.
16. 11–15	0.53	0.68	0.69	0.64	0.16	27.
17. 16–20	0.59	0.71	0.78	0.65	0.21	20.
18. 21–25	0.63	0.77	0.79	0.66	0.24	22.
19. 26–30	0.64	0.79	0.76	0.66	0.25	24.
20. 31–35	0.57	0.70	0.70	0.67	0.25	21.
21. 36–40	0.55	0.67	0.71	0.65	0.21	22.
22. mean	0.55	0.68	0.73	0.66	0.18	19.

[a] Sets all lagged covariances equal to zero, to mimic standard cross-sectional results.
[b] The correlation between spouses' incomes is actually negative (−0.017 to −0.027) in experience years 13–16, but when added to adjacent years' positive values the averages turn positive.

cohorts, sensitivity analysis is used below to explore the variation in income inequality resulting from different expected future earnings patterns.

The calculated coefficients of variation of the present value of income, presented in table 1 (row 1), indicate that the distribution of wives' incomes lowers family earnings inequality moderately. However, keep in mind that one property of the *CV* is that, by construction, the calculated family *CV* will decline relative to the husbands' *CV* when wives' earnings are distributed identically to husbands'.[9] Therefore, the primary objective herein is to compare the relative impact of wives' earnings on the lifetime *CV* versus the impact on the commonly calculated annual earnings *CV*, and then to assess the determinants of these effects.

To compare the present value *CV* results to the annual earnings *CV*, one could average the annual *CV*s over the lifetime, but unfortunately the average annual *CV* and present value *CV* are not directly comparable.[10] Since the essence of the annual cross-sectional *CV*s is that they assume zero income correlation from one year to the next, an alternative to averaging the annual *CV*s is to calculate a *CV* using equation (2) but setting all lagged covariances of income equal to zero. This *CV*, which I will call the "cross-sectional *CV*" compared to the present value "lifetime *CV*", (or "lifetime inequality"), is presented in line 2 of table 1 (for comparison, lines 3–11 contain the annual *CV*s, which are averaged over 5-year experience intervals to compress the presentation). Note first that lifetime inequality (row 1) is greater than cross-sectional inequality (row 2). The reason for this is that individual income is persistent from year to year, due to the distribution of education and the well-known importance of individual fixed effects which represent either ability or highly correlated luck. As a result, lifetime inequality is greater than what it would be if income were randomly redistributed every year, as is assumed in the cross-sectional *CV* (though inequality is considerably less than it would be if incomes were perfectly persistent over time).

Comparing the lifetime *CV* to the cross-sectional *CV*, the distribution of wives' incomes lowers lifetime family inequality by 11.3%, relative to a decline of 7.3% for cross-sectional income inequality. There are two reasons for this difference. First, wives' lifetime earnings are more equally distributed than are cross-sectional earnings, as reflected in a reduced lifetime CV^w relative to the corresponding husbands' CV^h. This decline in inequality arises from the weaker persistence of the wife's income—women are more likely than men to change their position in the income distribution from year to year, due to either lifecycle variation in labor supply or to pure stochastic shocks.[11] The second reason for the reduced inequality of family lifetime earnings relative to men's is that the correlation between spouses' lifetime incomes (at 0.016) is considerably weaker than the correlation between spouses' average annual incomes (at 0.075). A weaker correlation between spouses' incomes will reduce the variance of family income (equation (3)). Thus, I turn to an exploration of the causes of the weaker correlation.

As described above, the correlation between husbands' and wives' incomes reflects both the lifecycle correlation between their wage rates, or potential incomes, and the correlation between their labor supply. Row 12 of table 1 presents the lifetime *CV* estimates in which the actual incomes of wives and of husbands is replaced by their potential incomes, defined as their wage rate times 2000 hours per year. For those women who do not work, the calculation of the expected wage is described in section II.[12] (Note that the *CV* of

[9] Looking at equation (3), it is apparent that even if wives' and husbands' incomes are identically distributed, having equal means and variances, family incomes will be more equally distributed than husbands' incomes. The reason is that the *CV* has the convexity property, such that the CV^2 of a weighted sum is always less than the squared weighted sum of the spouses' *CV*s. The only time adding spousal income will not be equalizing is if the incomes of the spouses are perfectly correlated. This feature has been noted but not emphasized in this literature, which consistently uses *CV*.

[10] The average annual *CV* will be larger than the *CV* calculated for present values of income, for the reasons described in the above footnote. The present value *CV* is smaller because it takes the square root of the sum of future variances, which must be less than the sum of the square roots of all future variances (equal to the average annual *CV*).

[11] The correlation matrices for men and for women are in Shaw (1987). One reason why female income may be more persistent than male is that if women invest less in on-the-job training, their wages will vary less over their lifecycle.

[12] Note that the wives' labor force participation rate is 60%, requiring wage estimates for 40% of the sample. Of these wage estimates, 17% of the sample had worked at some time, resulting in estimated individual fixed effects. For the remaining 23%, fixed effects were drawn from a normal distribution with

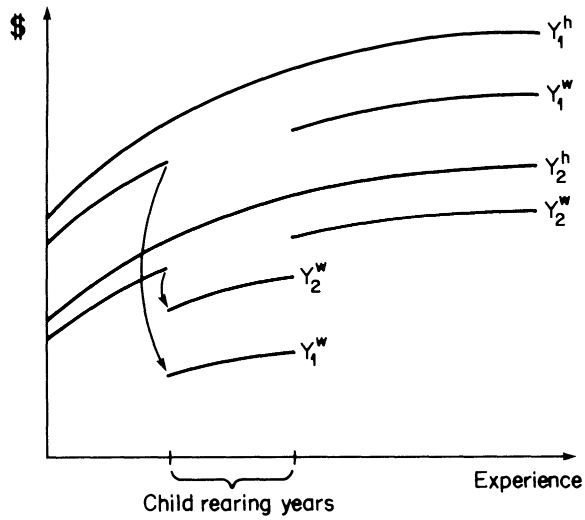
potential income must fall relative to the actual income CV because the variance of hours is zero for potential income.)

The results uncover dramatic differences between the distributions of lifetime potential incomes and cross-sectional potential incomes. The correlation between the potential lifetime incomes of the spouses is 0.363, much greater than the correlation between actual lifetime incomes, at 0.016. In contrast, the correlation between cross-sectional potential incomes is only 0.175 (row 13 of table 1), relative to a correlation between cross-sectional actual incomes of 0.075. Thus, previous cross-sectional estimates of income inequality strongly underestimate the role of assortative mating.

The obvious question is, what causes actual lifetime incomes to diverge so much from potential lifetime incomes, but causes less discrepancy between actual and potential average annual incomes?[13] This issue is addressed in figure 1. The difference between the actual and potential incomes of wives is determined solely by female labor supply. Figure 1 assumes that labor supply declines during the child-bearing years, lowering earnings. During this decline the correlation between spouses' actual incomes falls relative to their potential income correlation. But this alone cannot explain why spouses' income correlations for potential and actual lifetime incomes diverge more than their correlations for potential and actual average annual incomes. This pattern can occur only if the decline in the wife's labor supply results from the dominance of the husband's negative income effect. That is, during the child-rearing years, the "wealthier" wife, with greater husband's income, reduces her labor supply *by more* than does the "poorer" wife, as depicted in figure 1. As a result, the correlation between the husbands' and wives' actual incomes become negative during these years. This will clearly reduce the average correlation between their annual incomes. However, it will reduce the correlation between their lifetime incomes by more. The reason is that it introduces negative persistence into the model. That is, wives that initially earned above average income will later earn below average, creating an equalizing effect on lifetime earnings as the lagged correlations between spouses' lifetime incomes turn negative. Purely cross-sectional estimates omit this intertemporal variation in female labor supply, by setting all lagged income covariances to zero, and therefore dramatically underestimate the discrepancy between potential and actual income inequality.

FIGURE 1.—INCOME PROFILES FOR SPOUSES IN TWO FAMILIES

[INCOMES (Y_1^h, Y_1^w) AND (Y_2^h, Y_2^w)]



The scenario described in figure 1 is the only scenario consistent with the calculated differences in the lifetime and annual potential income correlations, but there is also other empirical evidence supporting this scenario. Most important, the spouses' income correlations do turn negative in experience years 13 through 16 (see table 1, rows 5–6). Furthermore, the lagged covariances between husbands' and wives' incomes are negative for a very wide band of years during their early to mid-career.[14] Lastly, the literature on labor supply elasticities supports the scenario in figure 1. Schultz

a variance equal to that of the estimated random effect. Wage estimates are required for only 2.2% of men who report no earnings in some year.

[13] One issue not addressed in the text is why the potential incomes of spouses are more highly correlated for the entire lifecycle (0.363) than on average (0.175). The likely reason is that there is intertemporal variation in wages due to the investment in human capital. If more able men invest more early in their career than do their wives, and the cost of investment is lower current wages, then the presence of assortative mating will appear weaker in the early years, but surface more strongly over the entire lifecycle after men earn returns to their early investment.

[14] The correlation matrix of husband's and wives' incomes is in Shaw (1987).

(1980) estimates wives' labor supply elasticities by age group, demonstrating that during the child-rearing years the husband's negative income effect rises and the wife's own wage elasticity falls:

Ages	Own Wage Elasticity	Husband's Wage Elasticity
14–24	1.66	− 0.33
25–34	1.06	−1.62
35–44	0.18	−1.33
45–54	0.84	−1.24
55–64	2.00	−0.49

(from Schultz, table 1.6, p. 66, averaging columns 3–5.) Thus, female labor supply reductions during the child-rearing years have a strong equalizing effect on family income.

Sensitivity Analysis

As described at the outset of this section, the results herein depict lifetime inequality as it existed in 1968–81, but may be subject to a cohort bias when predicting the lifetime inequality that today's young people will eventually experience over the courses of their lifetimes. A series of wage simulations are constructed to examine the impact on inequality of alternative assumptions about the distribution of future wages.

In the first set, potential future wages are hypothesized to be a simultaneous function of hours of work due to the investment in human capital. Current hours of work increase future wages via on-the-job training, and conversely, high expected future wages (associated with greater ability) may increase current investment and hours. Assuming that hours at work increase investment, the increase in the labor force participation rates of young married women over the last two decades should increase their future wages relative to the current wages of older women. This effect is simulated by making hours endogenous in the wage equation (4), or by instrumenting the wife's hours with the husband's income, hours, and background variables. Thus, the wife's endogenous hours equation is identified in the standard fashion: nonlabor income affects her hours but not her wages, while regional and urban variables determine wages but not hours.[15]

Three different measures of the wife's hours of work are tested in her wage equation. The first measure is past hours representing past on-the-job training.[16] The PSID lacks this retrospective variable, so I use the sum of lagged hours for the past six years, assuming a 10% depreciation rate (zero depreciation does not alter the results). Using this variable arbitrarily eliminates the first six years of panel data from the wage regression, so an alternative hours variable is current hours of work. However, this is a poor proxy for human capital investment for women with highly variable hours. The last measure is average observed hours over the 14 years of the survey (or as few as 4 years given missing data). While simply averaging future and past hours is theoretically questionable, this variable picks up the effects that both past and future expected hours have on the decision to invest in human capital, and there is no loss of panel years for the wage regression.[17] These are admittedly crude attempts to merely examine the sensitivity of income inequality to reasonable predictions of future wage profiles; the models should

[15] For variable lists identifying the model, see table A1. For a more complete description of this identification in labor supply models, see Schultz (1980) or Cogan (1980), where the latter presents the model used herein with the sample selection bias correction. This identification strategy assumes that hours have a separable effect on wages, and that instrumenting hours will produce an estimated hours coefficient which reflects the causality running from hours to wages, not vice versa. Assuming that the individual-specific effect in wages represents ability or unobserved productivity, hours should be positively correlated with the individual-specific effect and the hours coefficient in the wage equation will be biased upward. Since the individual effect is estimated as a random effect, the strategy is to acknowledge that the estimated impact of hours is an upward bound on the true impact. The approach of other researchers, to ignore the impact of hours on wages, clearly sets a lower bound on its effect!

[16] For models in which past hours affect wages via investment, see Ellwood (1982) and Mincer and Polachek (1974).

[17] The models described in footnote 16 are too short-sighted: in a rational expectations model, expectations of future hours of work will increase current investment and wages—see Eckstein and Wolpin (1987). So the wife's average panel hours are tested in her wage equation. The husband's average panel wage, average hours, and average income are also likely to be better variables in the wife's hours equation than current values of these variables that contain transitory influences. The reasoning is that in a lifecycle model, the husband's current income or hours may play a minor role. Considering his income effect, if households are not liquidity constrained, the wife's labor supply should be a function of the total lifetime income of her husband. Holding constant lifetime income, short-run changes in the husband's income would alter the intertemporal allocation of the wife's labor supply, but would not alter her long-run labor supply. Thus, the wife's labor supply is specified as a function of the husband's current and average sample labor supply and income.

TABLE 2.—COEFFICIENTS OF VARIATION FOR EXPECTED PRESENT VALUE OF INCOME

	CV	CV^h	CV^w	α	ρ	Description
1[a]	0.327	0.369	0.676	0.802	0.016	Actual income
2[b]	0.285	0.331	0.361	0.631	0.363	$Y^h = \hat{w}^h \cdot 2000, Y^w = \hat{w}^w \cdot 2000$
3	0.305	0.369	0.361	0.645	0.325	Actual Y^h, $Y^w = \hat{w} \cdot 2000$
4	0.337	0.369	0.406	0.480	0.500	Actual Y^h, $Y^w = \hat{w}^w \cdot 2000$; $\hat{w}^w$ for endogenous lagged hours
5	0.313	0.369	0.373	0.560	0.414	Actual Y^h, $Y^w = \hat{w}^w \cdot 2000$; $\hat{w}^w$ for endogenous lifetime hours
6	0.305	0.369	0.363	0.645	0.322	Actual Y^h, $Y^w = \hat{w}^w \cdot 2000$; $\hat{w}^w$ for endogenous annual hours
7	0.317	0.369	0.386	0.550	0.415	Actual Y^h, $Y^w = \hat{w}^w \cdot 2000$; $\hat{w}^w$ using male wage coefficients
8	0.341	0.377	0.742	0.784	0.035	Same as row 1, but discount rate = 10%
9	0.360	0.389	0.788	0.766	0.062	Same as row 1, but discount rate = 15%

Note: Rows 1–7 assume a discount rate of 5%. Results comparable to row 1 for higher discount rates are in rows 8, 9.
[a] Same as row 1, table 1.
[b] Same as row 12, table 1.

not be construed as careful tests of endogenous wage–hours models (see the appendix for regression results).

The final wage simulation predicts the wife's future wages by replacing female wage coefficients with male wage coefficients (see appendix for male regression results). This simulation is based on the hypothesis that the structure of female wages may eventually resemble that of men's, as discrimination lessens and female hours rise.

The CVs of potential incomes based on these four wage simulations (rows 4–7, table 2) can be compared to the CV for potential income calculated in the standard way for this literature, which omits endogenous hours in wages (row 3, table 2). The new wage simulations increase the earnings of some women, resulting in: a higher lifetime CV for women; considerably higher correlations between husbands' and wives' lifetime incomes;[18] and a lower share of male earnings as a fraction of potential household earnings. The bottom line is that in the future there may be much greater inequality of potential household income than would be suggested using the actual 1968–81 wage patterns.

IV. Summary and Conclusion

The primary conclusions of this analysis are:

1. Wives' earnings have a slight equalizing effect on the distribution of lifetime family earnings, as measured by the coefficient of variation (CV). However, the CV is not a metric-free measure of inequality—due to its convexity, the family CV will decline relative to the husbands' if wives' incomes are distributed identically to husbands'. Lack of a better measure of inequality, and the ability to decompose CV^2, accounts for its extremely widespread use in this literature.[19]

2. Wives' earnings have a more equalizing effect on lifetime earnings (the expected present value of earnings) than on annual earnings, largely because the correlation between spouses' lifetime earnings is weaker than the correlation between spouses' annual earnings. The weaker correlation arises from the intertemporal variation of female labor supply: wealthier wives, whose husbands earn above average, have above average earnings before and after the child-rearing years, but below average earnings during the child-rearing years. This intertemporal variation in female labor supply and

[18] Based only on predicted wages with no stochastic effects added, the correlation of the lifetime earnings of spouses would rise to 0.748. The weaker correlation of 0.414 in row 5 is due to unobserved effects and random shocks to wages.

[19] The drawbacks of alternative measures of inequality are: they are usually not decomposable (e.g., Gini coefficient is not, see Bourguignon (1979)); they take logs of income, which are not meaningful for wives with zero income; they have the same convexity property as the CV; or they cannot be simplified to calculate the inequality of present values, as in (2).

thus earnings, moving from above average to below average and back above, tends to equalize the distribution of lifetime female earnings relative to annual earnings and to weaken the correlation between spouses' lifetime earnings.

3. Spouses' potential lifetime earnings, or their wage rates, are very highly correlated, and this correlation is at least twice that typically estimated for annual earnings. This result is particularly important in forecasting future trends in inequality. The longitudinal data used above pertain to the 1968–81 years, when the participation rates of women in the child-rearing years were lower than they are today. If women increase their attachment to the labor force in the future, and actual income approaches potential income, the very high correlation between spouses' potential lifetime incomes could well increase the inequality of lifetime family income much more than previously estimated.

4. If potential income is viewed as a measure of family welfare, because women choosing not to work must value their leisure as highly as their potential market income, then women have a stronger unequalizing effect on family welfare than previously realized (Blau, 1984).

Of course, a number of caveats apply to these conclusions. First, as stated above, these results pertain only to the period 1968–81, though numerous attempts have been made to indicate how the results may be changing. Secondly, this study does not analyze the impact of rising female labor force participation on the increase in single-headed households. To the extent that female participation has increased the number of female headed households, it is clear that the total effect of female earnings on income inequality is not addressed here.

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APPENDIX TABLE A1.—SIMULTANEOUS WAGE–HOURS ESTIMATION

	Dependent Variable:			
	Wife's Wage		Husband's Wage	
	(1)	(2)	(3)	(4)
EDUC	−1.34	−0.79	0.504	−0.067
	(−2.75)	(−5.72)	(1.75)	(−0.37)
EDUC^2	0.75	0.65	0.158	0.291
	(5.42)	(15.32)	(1.97)	(5.04)
EXPER	−0.11	0.22	0.377	0.213
	(−0.88)	(3.46)	(4.08)	(4.20)
EXPER^2	0.018	−0.029	−0.041	−0.022
	(1.19)	(−3.04)	(−3.61)	(−2.86)
EDUC · EXPER	0.019	−0.057	−0.06	−0.02
	(0.30)	(−2.46)	(−1.57)	(−0.83)
HWAGE	0.16	0.18	0.035	−0.009
	(1.56)	(3.39)	(1.65)	(−0.14)
HWAGE · EDUC	−0.04	−0.05	−0.015	0.067
	(0.67)	(−1.54)	(−1.31)	(1.67)
HWAGE · EXPER	−0.001	0.0004	0.001	0.070
	(−0.09)	(0.06)	(0.44)	(6.73)
SUMW	0.023	0.013	−0.004	0.0016
	(4.69)	(4.57)	(−0.64)	(0.42)
HOURS[a]	0.0015	0.00032	0.0011	0.0011
	(4.40)	(2.95)	(2.61)	(8.13)
CHILD	0.026	−0.089	0.223	0.265
	(0.36)	(−2.96)	(4.22)	(7.88)
CHILD^2	−0.014	0.004	−0.017	−0.008
	(−2.66)	(1.68)	(−4.65)	(−3.17)
CHILD · EDUC	0.082	0.046	−0.097	−0.154
	(1.71)	(2.52)	(−3.35)	(−6.77)
CHILD · EXPER	−0.003	−0.007	−0.028	−0.034
	(−0.25)	(−1.30)	(−3.27)	(−6.63)
LAMDA	−0.196	0.066	—	—
	(−1.16)	(1.30)		
System Weighted R^2	0.171	0.154	0.156	0.178
N	4052	11570	6647	18493
Correlations across equations	−0.436	−0.126	−0.475	−0.286

Note: Variable definitions: *EDUC* is years of education; *EXPER* is years of experience; *CHILD* is number of children under age 18; *HWAGE* is spouse's wage; *SUMW* is the panel average of spouse's wage; *LAMDA* is Heckman's lamda from the probability of working probit (see footnote 8—results available on request). *SMSA* and *SOUTH* dummies are also in the regressions. The dependent variable is the natural log of wages. Equations are estimated with limited information maximum likelihood. *t*-statistics are in parentheses.

[a] *HOURS* is the endogenous hours variable, where it is the average of all panel hours in columns 2 and 4, and it is the sum of 6 years of lagged hours depreciated at 10% in columns 1 and 3. The variables in all *HOURS* regressions are those in the wage equation (excluding *SMSA* and *SOUTH*) plus husband's; hours, average panel hours, average panel income, education, experience, and their interactions and squares. The husband's hours and income variables are highly significant.