RELATIONSHIPS AMONG THE FAMILY INCOMES AND LABOR MARKET OUTCOMES OF RELATIVES

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I. INTRODUCTION

This paper quantifies the links between the labor market experiences and economic outcomes of individuals who are related by blood or by marriage using panel data on siblings, their parents, and their spouses from the four original cohorts of the National Longitudinal Surveys (NLS) of Labor Market Experience. Our main objectives are (1) to provide better estimates of intra- and intergenerational correlations in family income and earnings, (2) to estimate earnings correlations among individuals who are related by marriage, (3) to examine intergenerational links among a broad set of labor market outcomes, and (4) to show how intergenerational labor market data can be used to examine the sources of labor supply variation, theories of labor turnover, and theories of wage structure.

The first purpose of the paper is simply to provide better estimates of the correlations of permanent income and earnings levels between parents and children

Research in Labor Economics, Volume 12, pages 269–310.

ISBN: 1-55938-381-X

and among siblings. Many studies have examined sibling correlations, and a small number have examined intergenerational family income correlations in the United States.[1] As Solon (1989a,b) points out, previous U.S. studies finding weak intergenerational correlations (see Becker and Tomes, 1986) are plagued by homogeneous samples and lack of attention to downward biases caused by measurement error and transitory variation in income or earnings observations drawn from a single year.[2] We use the NLS data, which is a broad-based sample, and compute correlations using two alternative approaches that should be less sensitive to transitory variations in the data. The first is a method-of-moments estimator that is constructed to be insensitive to transitory variation. The second approach uses time averages of the data for individuals. We also use an instrumental-variables technique to estimate the regression coefficients relating the permanent components of parents' income, earnings, wage rates and other labor market variables to those of their sons and daughters.[3]

The second purpose of this paper is to provide evidence on the correlations in earnings among those individuals who are related by marriage. Specifically, we present evidence on covariances and correlations between the labor market outcomes of husbands and wives, fathers- and sons-in-law, mothers- and daughters-in-law, brothers-in-law, and so forth. While a number of researchers have examined the role of assortative mating patterns in marriage in the determination of inequality, we know of very few previous studies that have examined the relationships between parental and sibling earnings and the earnings of spouses.[4] We produce a set of correlation matrices relating the labor market outcomes of individuals who are related by blood or by marriage that can be used by other researchers. The covariances and correlations are quite large in many cases.

The third purpose is to examine family relationships among a broad set of labor market outcomes. While a large number of studies have examined intra- and intergenerational links in family income or occupational status, few have attempted to examine family links in the main components that influence earnings. Is the link between the economic success of fathers and sons primarily due to work effort or to wage levels? Is the propensity to change jobs a personal characteristic that is correlated among family members?

The fact that little is known about intergenerational links in unemployment experience, work hours, or labor turnover is one motivation for our examination of these topics in this report.[5] Additionally, we show how evidence on the relationships among labor market outcomes of family members may be used to address broader questions about labor supply, turnover behavior, and even the industry structure of wages that are normally studied using cross-sectional data on unrelated individuals.

One obvious application is to labor supply determination. Economists have not been very successful in explaining hours differences among males using wage rates, nonlabor income, and observed personal characteristics. [See, for example, Pencavel's (1986) survey.] It is possible that hours choices are influenced by

differences in preferences that are hard to measure but depend upon genetic and environmental factors that are correlated among family members. Indeed, it is common to say that an individual is from a "hard-working family." While ultimately we would like to have a structural model of the determinants of labor supply preferences, it is useful to start by examining whether or not a common family component plays an important role in hours determination. In this paper we present descriptive evidence on hours links, and in Altonji and Dunn (1990) we use a factor model to measure the importance of parental and sibling preference factors in the variance of hours worked and of earnings for young men and young women. In that paper, we find preferences play a large role in hours linkages.

This paper proceeds as follows. In Section II we discuss the NLS data used in the study. In Section III we discuss the statistical methods used in the paper. In Section IV we quantify the links among family members in family income, earnings, hourly wage rates, and work hours. Section V presents evidence on links among individuals who are related by marriage. In Section VI we present evidence on the relationship between the turnover behavior of pairs of related family members. We also discuss the implications of these relationships for studies of the role of individual heterogeneity and job match heterogeneity in the turnover process. In Section VII we show that young men whose fathers work in high-wage industries (controlling for human capital characteristics) tend themselves to work in high-wage industries. We argue that the results are consistent with non-market-clearing explanations for industry wage premiums (such as efficiency wages) only if family connections play a key role in gaining access to high wage firms. Section VIII concludes the paper.

II. DATA

The data used in this report are from the four original cohorts of the National Longitudinal Surveys (NLS) of Labor Market Experience. Specifically, we work with the sample of young men who were 14 to 24 years old in 1966 and were followed through 1981, the samples of young women who were 14 to 24 in 1968 and mature women who were 30 to 44 in 1967 and continue to be followed, and the sample of older men who were 45 to 59 years old in 1966 and were last surveyed in 1983. We use data only through 1981 in the case of mature men because after that only a very few of the men meet the screening criteria described below. We use data through 1982 in the case of the young women and through 1984 in the case of mature women. Some of the households contributed more than one person to the young men and young women surveys, and in some cases the households contributed to both the youth surveys and older men and mature women surveys. Consequently, it is possible to match data on sibling pairs and parent–child pairs. For some of our analysis, we have also matched data on husbands and wives who were members of the older men's and mature women's surveys. Appendix Tables

A1 and A2 summarize information on the mean values of the labor market variables and sample sizes of the original cohorts, the numbers of sibling pairs, and the number of parent–child pairs. It is important to emphasize that the sample sizes used in the analyses vary, depending upon the particular variables and type of family member match being considered.[6]

Because sample members are asked questions about the labor market outcomes of their spouses, we are also able to examine the relationships among the labor market outcomes of individuals related by marriage. For example, we report the covariance between the earnings of fathers- and sons-in-law using the reports of spouse's earnings provided by members of the young women's cohort who could be matched to their fathers in the older men's cohort.

Many of our analyses exploit the availability of panel data on the individuals in the sample. However, data on a particular question may be missing either because the individual left the sample prior to that survey or because the response is invalid for some reason. In the case of the young men and young women, our basic approach is to restrict the sample to individuals who were at least 24 years old prior to leaving the survey. We chose this age cutoff to reduce transitory variation in labor market outcomes associated with the transition between school and work. We use labor market data (wages, hours, unemployment, and so forth) from a particular year only if the individual was at least 24 and was out of school and did not return to school in a subsequent year.

The fact that many of the older men in the sample approach retirement age during the course of the survey raises additional complications. Earnings, work hours, and wage rates of such individuals after retirement may not be closely related to the typical or "permanent" values for these individuals over the course of their careers. To minimize this problem, we only use data on family income and labor market variables for older men and women who had not yet retired, and who were less than 61 years old when the data were collected. Since the age in 1966 of the older men ranges from 45 to 59, there is substantial variation across sample members in the number of years of labor market data available.[7] Retirement is a concern for the mature women's sample only in the last few years that we study, and even then only a handful of women report being retired.

For all four cohorts we excluded wage observations of less than $0.40 per hour, earnings of less than $100 per year, and family income of less than $200 per year (all in 1967 dollars). Wages greater than $100 per hour were capped at $100 per hour. Additionally, hours worked per week were capped at 96 hours. This restriction forces annual hours (constructed as reported number of weeks worked times reported number of hours worked per week) to range between 0 and 5000 hours per year.

As a job turnover measure, we use the number of different employers the individual reports from the first to the last survey (or the year that he or she left the sample) divided by the number of valid reports he or she provides. We count only those reports made after age 24 and after schooling has ended for the younger

cohorts, and before age 61 and before retirement for the older cohorts. Multiple spells with the same employer are counted only once. For example, a young man who remained with the same employer through eight surveys would have a value of 0.125, while one who switched employers every survey would have a value of 1.0. There are a few problems with this turnover measure. The most serious is that the elapsed time between surveys and between a respondent's reports can vary, so that we do not have a consistent measure of employers per calendar year. Also, those individuals with short work histories will tend to have a larger number of employers per survey. For these reasons, we view this measure as only a rough indicator of turnover rates.

III. OVERVIEW OF ECONOMETRIC MODELS AND METHODS

In this section we begin by discussing the covariances and correlations among a variety of labor market outcomes for family members. Our aim is to estimate the correlations among the permanent components of the labor market outcomes of family members, and so it is necessary to compute the correlations using an approach that reduces the downward bias introduced by transitory variation and measurement error. We implement two different estimation procedures.

The first approach, which we will refer to as the time average approach, computes the covariances and the correlations among the time averages of the adjusted labor market outcomes of matched family members. We remove year and age effects by regressing each labor market outcome for each cohort on a set of year dummies and a cubic specification of the individual's age. We then calculate each individual's time average using the residuals from the appropriate regression.

The sample used to compute the brother correlations consists of all unique brother pairs for whom valid data are available for the particular labor market outcome. The samples for the other family relationships also consist of the unique pairs of individuals who are in that relationship. For example, a family with four brothers who have valid data on a particular labor market variable will contribute six observations to the sample used to compute the brother pair covariances. A family contributing one father to the NLS older men's cohort and three daughters to the young women's cohort will contribute three observations to the father–daughter sample, and three to the sisters sample. Appendix Table A2 provides frequency distributions for the number of multiple sibling and parent–child matches from the same family.

The second approach, which we refer to as the method-of-moments approach, is to compute family covariances of a particular labor market outcome by first adjusting the data to have zero mean. Next, we compute the unique set of cross products of the elements of the vector of labor market outcomes in different years for one family member with the elements of the vector of labor market outcomes of the other family member. Then, we take the mean of all the cross products for all of the pairs of family members. We estimate the variance of the permanent component of labor market outcomes for young men by first computing the cross products of all unique pairs of yearly observations on a labor market outcome that are for the same individual and that are separated by more than two years in time and then taking the average of all of the cross products for all individuals.[8] We do the same for young women's, mature women's, and older men's variables.

The specific formula for the covariances, variances, and correlations are as follows. Let $Y_{ik(j)t}$ be the adjusted[9] labor market outcome of an individual, where i denotes a set of related individuals (say, mother–son pairs), k is the type of individual (for example, young man, young woman, older man, or mature woman), j indicates the particular individual of type k from family i, and t indexes time. (The index j may exceed 1 when k refers to young men or young women and there is more than one young man or young woman from a given family.) Then the method-of-moments estimator of the covariance of variable Y cross the family pairs of type kk' is

$$\mathrm{Cov}(Y_{ik}, Y_{ik'}) = \sum_i \left(\sum_j \sum_{j'} \sum_t \sum_{t'} Y_{ik(j)t} Y_{ik'(j')t'} \right) / N_{YYkk'}. \tag{1}$$

When $k = k'$, as is the case for brother pairs and for sister pairs, then the covariance estimator is

$$\mathrm{Cov}(Y_{ik}, Y_{ik}) = \sum_i \left(\sum_j \sum_{j' \neq j} \sum_t \sum_{t'} Y_{ik(j)t} Y_{ik(j')t'} \right) / N_{YYkk}. \tag{2}$$

The method-of-moments variance estimator for the variable Y for the person of type k is

$$\mathrm{Var}(Y_{ik}) = \sum_i \left(\sum_j \sum_t \sum_{t' > t+2} Y_{ik(j)t} Y_{ik(j)t'} \right) / N_{Yk}. \tag{3}$$

In the above equations, $N_{YYkk'}$, N_{YYkk}, and N_{Yk} are the number of terms in the sums taken in (1), (2), and (3), respectively.

The correlation coefficient for the family pairs of type kk', $k \neq k'$, is

$$\mathrm{Corr}(Y_{ik}, Y_{ik'}) = \mathrm{Cov}(Y_{ik}, Y_{ik'}) / [\mathrm{Var}(Y_{ik}) \ \mathrm{Var}(Y_{ik'})]^{0.5}. \tag{4}$$

The correlation coefficient for family pairs of type kk (that is, brother–brother or sister–sister) is

$$\mathrm{Corr}(Y_{ik}, Y_{ik}) = \mathrm{Cov}(Y_{ik}, Y_{ik}) / \mathrm{Var}(Y_{ik}). \tag{5}$$

Note that we use the full-cohort samples—rather than matched samples—of young men, young women, older men, and mature women to compute the variances $\mathrm{Var}(Y_{ik})$ for each type.

We prefer the correlation estimates based upon the method-of-moments approach because we believe that the method-of-moments estimates of the variance for each type of family member are less likely to suffer from downward bias due to transitory variation in labor market outcomes and measurement error than the variance estimates based on the time averages. However, the method-of-moments estimator may be more sensitive to heterogeneity in variances and covariances of the labor market outcomes that is related to (a) whether or not particular individuals have a relative in the sample, and to (b) the number of years of data on a particular family member. The estimates of the covariances based upon the time averages give each pair of individuals the same weight, while the estimates based upon unique pairs of observations across individuals and over time (that is, the method-of-moments estimators) give proportionately more weight to pairs of individuals who contribute many time series observations.[10] In most cases, the covariance estimates based on (1) and (2) are reasonably close to the covariances based on the time average estimators. (If the expected value of the covariance is unrelated to the amount of valid labor market data available, then the method-of-moments estimator is probably more efficient.) In most cases, the estimates of the correlations are larger using the method-of-moments estimation procedure than the time average procedure. The difference is almost always due to somewhat lower estimates of the variances of the labor market outcome [the denominator in (4) or (5)], rather than to higher estimates of the covariances.

A. Regression Equations

Regression equations relating the labor market outcomes of children to those of their parents provide a third way of summarizing family relationships in labor market outcomes. Since it is easy to incorporate control variables into the analysis, this approach provides a convenient way to assess the extent to which the links among family members are due to particular factors, such as education, race, or location. For example, part of the positive correlation between the separation rates of fathers and sons may be due to correlation between the educational levels of fathers and sons.

Here we estimate equations of the following form:

$$\mathrm{WAGE}_{is} = A_1 X_{is} + A_2 X_{if} + \gamma_{sf} \mathrm{WAGE}_{if} + e_{is}, \tag{6a}$$

$$\mathrm{WAGE}_{id} = B_1 X_{id} + B_2 X_{if} + \gamma_{df} \mathrm{WAGE}_{if} + e_{id}, \tag{6b}$$

$$\mathrm{WAGE}_{is} = C_1 X_{is} + C_2 X_{im} + \gamma_{sm} \mathrm{WAGE}_{im} + \varepsilon_{is}, \tag{6c}$$

$$\mathrm{WAGE}_{id} = D_1 X_{id} + D_2 X_{im} + \gamma_{dm} \mathrm{WAGE}_{im} + \varepsilon_{id}. \tag{6d}$$

In the above equations, WAGE_{ik} is the time average of the log wage rate and X_{ik} are personal characteristics, where k = d in the case of young women, s for young men, f for fathers, and m for mothers. The key parameters of interest are γ_{df}, γ_{dm}, γ_{sf}, and γ_{sm}, which reflect the effect of a one-unit change in the parent's outcome on the labor market outcome of the son or daughter. In the empirical work we estimate similar equations for log earnings, log family income, log annual hours, and other labor market variables.

We use two estimation methods. The first is ordinary least squares (OLS). The problem with this is that transitory variation and measurement error in particular years may affect the time average of the labor market variable. This is likely to lead to downward bias in the γ estimates.

As an alternative, we use an instrumental-variables (IV) procedure. Specifically, we regress the first observation on WAGE_{ikt} (which equals the permanent component of the wage of parent *ik* plus a time *t* transitory component) on the parent's and child's personal characteristics and $\text{WAGE}_{ik(t)}$. We construct $\text{WAGE}_{ik(t)}$ as the mean of the parent's wage observation over *t excluding* the first observation from the computation. The "pseudomean" $\text{WAGE}_{ik(t)}$ will then be correlated with the permanent component of WAGE_{ikt}, and it will be uncorrelated with the transitory component if the transitory component is white noise.[11] Consequently, in the second-stage regression we may estimate the response of WAGE_{id} (or WAGE_{is}) to the instrumented WAGE_{ikt} and the family members' personal characteristics, X_{id} (or X_{is}) and X_{ik}, k = f or m.[12]

We now turn to estimates of the correlations, covariances, and regression coefficients relating the labor market outcomes of relatives.

IV. INTRA- AND INTERGENERATIONAL LINKS IN FAMILY INCOME, WAGE RATES, EARNINGS, AND WORK HOURS

In this section we present the estimates of the covariances and correlations among log family income, log earnings, log hourly wage rate, and log work hours for family member pairs. In Section IV.A we discuss the results for family income. In Section IV.B we discuss earnings, wages, and work hours. In the remainder of this introduction we describe the organization of the tables to follow.

In the text we emphasize the covariances and correlations across family member pairs of the *same* labor market variables (for example, son's wages with father's wages), though we have computed the covariances and correlations of different labor market variables (for example, son's hours with father's wages) as well.[13] The results using the time average approach are summarized in Table 1. The column headings report the type of family relationship. The row headings report the labor market variable involved. For example, we find that the correlation of the mean of log family income among brothers is .30. The correlations in the number of employers per survey year they have had is .25. The correlations in family income and log earnings between sons and fathers are .32 and .22, respectively. The number of observations used to compute a given correlation depends upon the labor market variable under consideration and the number of family member matches for the particular relationship. Beneath each correlation we report the number of sample observations. At the foot of each column we report the number of unique family

Table 1. Summary of the Covariances and Correlations of the Time Averages of Selected Labor Market Variables for Matched Family Members

Labor market variable	*Brother–brother*	*Sister–sister*	*Brother–sister*	*Father–son*	*Father–daughter*	*Mother–son*	*Mother–daughter*	*Father–mother*	*Husband–wife*
Log family income	.097	.215	.116	.112	.143	.153	.163	.303	.323
	.30	.45	.28	.32	.30	.36	.36	.79	.84
	264	354	905	680	723	931	1276	323	462
Log earnings	.130	.206	.089	.119	.173	.091	.134	.185	.167
	.32	.26	.14	.22	21	.14	.16	.30	.25
	390	322	1060	735	596	912	1014	228	339
Log hourly wage	.052	.058	.047	.071	.072	.045	.409	.085	.072
	.33	.38	.27	.34	.31	.27	.25	.43	.37
	376	333	1054	675	551	873	1013	215	314
Log hours worked per week	.006	.010	−.007	.005	−.001	−.002	.005	.005	−.000
	.22	.06	−.09	.12	−.01	−.02	.03	.04	−.00
	406	354	1121	835	700	1002	1118	264	386
Log weeks worked per year	.009	.057	.012	.006	.007	.000	.048	.011	.013
	.12	.17	.06	.09	.04	.00	.13	.08	.09
	352	312	1002	790	655	923	1085	277	400
Weeks unemployed per year	9.818	.742	2.705	2.317	1.049	−.097	1.896	3.836	3.354
	.20	.02	.07	.08	.05	−.00	.11	.19	.21
	368	413	1152	815	764	1120	1409	340	488
Log annual hours	.017	.098	.008	.014	.019	.002	.055	.027	.021
	.13	.15	.02	.10	.05	.00	.08	.08	.07
	351	311	998	781	650	888	1042	257	377
Number of employers per year	.022	.010	−.000	.004	.001	.004	.007	.017	.012
	.25	.10	−.00	.07	.02	.04	.08	.27	.21
	399	303	1022	825	638	929	985	253	368
Potential number of matches	621	646	1921	1099	988	1671	1848	345	492

Note: The covariance is given first, with the correlation next, followed by the number of matching pairs.

Table 2. Summary of the Means and Variances of Time Averages of Selected Labor Market Variables for All Young Men, Young Women, Older Men, and Mature Women

Labor market variable	*All young men*	*All young women*	*All older men*	*All mature women*
Log family income	8.95	8.74	8.85	8.83
	.337	.430	.557	.460
	3423	3855	4884	4845
Log earnings	8.58	7.61	8.56	7.59
	.456	.880	.679	.834
	4030	3673	4274	3973
Log hourly wage	1.10	0.63	1.05	0.57
	.179	.156	.271	.181
	4003	3681	4052	3996
Log hours worked per week	3.76	3.46	3.74	3.42
	.037	.177	.065	.197
	4130	3797	4767	4275
Log weeks worked per year	3.83	3.50	3.83	3.52
	.087	.386	.091	.334
	3888	3581	4782	4284
Weeks unemployed per year	2.51	2.19	1.58	1.11
	39.058	29.661	22.430	8.211
	3939	4044	5017	5083
Log annual hours	7.60	6.97	7.57	6.99
	.157	.724	.204	.657
	3872	3562	4756	4155
Number of employers per year	.51	.65	.51	.44
	.090	.095	.057	.091
	4084	3519	4691	4116
Potential sample size	5225	5159	5020	5083

Note: The mean is given first, with the variance next, followed by the sample size.

pairs for each type of family relationship.[14] In Table 2 we present the means, variances, and number of observations on the various labor market outcomes for the full samples of young men, young women, older men, and mature women in the four NLS cohorts. Appendix Table A3 presents the percentage distributions of individuals by the number of observations entering into the time average calculations. The distributions are shown for each labor market variable for each cohort.

Table 3 provides estimated family covariances and correlations based on the method-of-moments procedure for log family income, log earnings, log wage rates, and log annual work hours. Table 4 presents the estimated method-of-moments variances for the various labor market outcomes for each of the four cohorts.

We present evidence on both the covariance and correlation because the correlation depends on both the covariance of the common component of the labor market outcome and the variances of the components affecting only the individuals, while the covariance does not depend on the individual specific variance components. It is important to keep this in mind when assessing the relative strength of

Table 3. Summary of the Covariances and Correlations of Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method-of-Moments Estimators for Matched Family Members

Labor market variable	*Brother–brother*	*Sister–sister*	*Brother–sister*	*Father–son*	*Father–daughter*	*Mother–son*	*Mother–daughter*	*Father–mother*
Log family	.071	.178	.119	.087	.133	.142	.163	.262
income	.38	.73	.56	.36	.48	.56	.56	.80
Log earnings	.091	.097	.097	.106	.145	.096	.104	.114
	.37	.26	.32	.39	.42	.32	.28	.34
Log hourly	.058	.045	.050	.068	.062	.045	.039	.053
wage	.42	.42	.41	.42	.43	.35	.35	.35
Log annual	.011	.076	.007	.012	.011	.010	.028	.024
hours	.36	.34	.08	.34	.12	.15	.15	.32

Note: The covariance is followed by the correlation.

the different family relationships for a particular labor market outcome. For example, although the correlation in log earnings is .26 for sister pairs and .32 for brother–sister pairs, the covariance of log earnings is exactly the same (.097) for the two sibling pair types. The larger correlation for brother–sister pairs reflects a smaller variance of log earnings for young men.

In addition to the covariances and the correlations, we report estimates of the regression equations (6) in Table 5. These associate a unit change in the parent's labor market outcome and the change in the expected value of the son's or daughter's outcome.

Table 4. Summary of the Variances of Permanent Components of Log Real Earnings, Log Real Wages, and Log Annual Hours for All Young Men, Young Women, Older Men, and Mature Women

Labor market variable	*All young men*	*All young women*	*All older men*	*All mature women*
Log family income	.188	.243	.310	.345
	6,496	9,618	5,244	15,718
Log earnings	.245	.378	.310	.367
	37,158	17,708	7,252	18,169
Log hourly wage	.137	.108	.192	.120
	32,162	17,383	4,056	27,265
Log annual hours	.030	.226	.039	.149
	12,680	6,593	9,617	11,594

Note: The variance is followed by the sample size.

Table 5. Regression Analysis of the Relationships between the Time Averages of the Child's Labor Market Outcomes and the Parent's Labor Market Outcomes[a]

	Labor Market Outcome							
	Log family income	*Log earnings*	*Log wage rate*	*Log hours per week*	*Log weeks worked*	*Number of weeks unemployed*	*Log annual hours*	*Number of employers*
A. Sons and fathers[e]								
Ordinary least squares: Time mean of father's corresponding labor market outcome								
With control	.267	.180	.263	.095	.107	.104	.095	.149
variable set I[b]	(.030)	(.028)	(.028)	(.031)	(.046)	(.048)	(.040)	(.057)
With control	.110	.024	.077	.067	.081	.072	.058	.133
variable set II[c]	(.040)	(.032)	(.035)	(.031)	(.047)	(.048)	(.041)	(.057)
Sample size	684	739	678	841	796	821	787	825
Instrumental variables:[d] Father's corresponding labor market outcome								
With control	.279	.218	.282	.068	.326	.198	.190	
variable set I[b]	(.040)	(.037)	(.034)	(.058)	(.131)	(.111)	(.128)	
With control	.102	−.001	.100	.032	.252	.129	.080	
variable set II[c]	(.059)	(.048)	(.047)	(.059)	(.140)	(.112)	(.140)	
Sample size	530	654	597	767	758	790	715	
B. Daughters and fathers[f]								
Ordinary least squares: Time mean of father's corresponding labor market outcome								
With control	.265	.219	.227	.008	.103	.057	.103	.055
variable set I[b]	(.032)	(.044)	(.030)	(.061)	(.084)	(.045)	(.072)	(.062)
With control	.077	.053	.083	.046	.187	.011	.172	.049
variable set II[c]	(.046)	(.050)	(.037)	(.063)	(.103)	(.044)	(.080)	(.063)
Sample size	728	600	555	705	659	769	654	638
Instrumental variables:[d] Father's corresponding labor market outcome								
With control	.287	.330	.210	−.012	.250	.097	.177	
variable set I[b]	(.042)	(.067)	(.036)	(.128)	(.281)	(.056)	(.242)	
With control	.150	.151	.088	.063	.316	.055	.378	
variable set II[c]	(.070)	(.088)	(.047)	(.137)	(.312)	(.057)	(.286)	
Sample size	549	517	455	635	616	726	581	

Table 5. Regression Analysis of the Relationships between the Time Averages of the Child's Labor Market Outcomes and the Parent's Labor Market Outcomes[a] (continued)

	Labor Market Outcome							
	Log family income	*Log earnings*	*Log wage rate*	*Log hours per week*	*Log weeks worked*	*Number of weeks unemployed*	*Log annual hours*	*Number of employers*
C. Sons and mothers[g]								
Ordinary least squares: Time mean of mother's corresponding labor market outcome								
With control	.308	.098	.257	−.006	.002	−.049	.003	.043
variable set I[b]	(.028)	(.023)	(.033)	(.014)	(.020)	(0.085)	(.017)	(.033)
With control	.135	.003	.058	−.014	−.018	−.135	−.013	.032
variable set II[c]	(.034)	(.024)	(.037)	(.014)	(.020)	(.083)	(.017)	(.033)
Sample size	931	912	873	1002	923	1120	888	929
Instrumental variables:[d] Mother's corresponding labor market outcome								
With control	.368	.167	.355	.025	.048	−.215	.022	
variable set I[b]	(.041)	(.043)	(.056)	(.031)	(.067)	(.302)	(.058)	
With control	.170	−.025	.120	−.005	−.036	−.575	−.074	
variable set II[c]	(.067)	(.050)	(.081)	(.033)	(.073)	(.318)	(.063)	
Sample size	768	545	531	627	646	1096	534	
D. Daughters and mothers[h]								
Ordinary least squares: Time mean of mother's corresponding labor market outcome								
With control	.369	.172	.227	.036	.142	.229	.091	.080
variable set I[b]	(.027)	(.032)	(.028)	(.029)	(.033)	(.054)	(.033)	(.033)
With control	.121	.072	.075	.040	.108	.162	.063	.066
variable set II[c]	(.034)	(.032)	(.031)	(.029)	(.033)	(.054)	(.033)	(.034)
Sample size	1276	1014	1013	1118	1085	1409	1042	985
Instrumental variables:[d] Mother's corresponding labor market outcome								
With control	.443	.341	.314	.068	.522	.608	.128	
variable set I[b]	(.041)	(.069)	(.051)	(.100)	(.124)	(.150)	(.139)	
With control	.147	.278	.175	.137	.467	.460	.120	
variable set II[c]	(.075)	(.094)	(.078)	(.117)	(.131)	(.149)	(.144)	
Sample size	1035	636	607	715	769	1390	645	

Table 5. Regression Analysis of the Relationships between the Time Averages of the Child's Labor Market Outcomes and the Parent's Labor Market Outcomes[a] (continued)

Notes: [a]Standard errors are in parentheses.

[b]All equations contain the following set of control variables: child's age (in 1966 for sons, in 1968 for daughters), age squared, age cubed, and parent's age in 1966, age squared, and age cubed.

[c]All equations contain controls for child's race, child's education, education squared, education cubed, child's age (in 1966 for sons, in 1968 for daughters), age squared, age cubed, child's mean residence in the South and in an SMSA, and parent's education, education squared, parent's age in 1966, age squared, and age cubed.

[d]In the IV equations, the following variables were used as measures of the father's/mother's labor market outcomes: the log wage in 1966/1967, log wage and salary income in 1965/1966, log family income in 1965/1967, log average hours worked per week in 1965/1967, log weeks worked in 1965/1967, number of weeks unemployed in 1965/1967, and log annual hours worked in 1965/1967. The instrumental variables consist of all the control variables in the corresponding labor market outcome equations (see notes *b* and *c*) plus the father's/mother's time average of the particular outcome variable constructed from all later years: for example, in the family income equation we use the average of log family income reports for the father/mother for years after 1965/1967.

[e]Potential sample size = 1099.

[f]Potential sample size = 988.

[g]Potential sample size = 1671.

[h]Potential sample size = 1848.

A. Family Income

The first row of Table 1 provides time average estimates of log family income covariances and correlations for various pairs of family members. The sibling correlations are .30 for brothers, .45 for sisters, and .28 for brothers and sisters. The covariance of sisters' family incomes is more than double the covariance of brothers'. The effect of the higher covariance on the family income correlation is partially offset by the fact that among the sets of all young men and all young women, the variance of log family income is much larger for young women. It is interesting to speculate on whether this higher variance is a reflection of a large number of young-female-headed households with children.

The method-of-moments estimates in Table 3 imply substantially higher sibling correlations in family income. The correlations are .38 for brothers, .73 for sisters, and .56 for brothers and sisters. We view the estimates for sisters and for brother–sister pairs as very large relative to those in the existing literature. The estimate for brothers is in the same range as Solon et al.'s (1987) estimate of .342. However, their estimate for sisters' earnings is much smaller at .276. (See note 25 for further comparisons to Solon et al.'s work.)

The intergenerational correlations of family income based upon the time averages are .32 for sons and fathers, .30 for daughters and fathers, .36 for daughters and mothers, and .36 for sons and mothers. Again, the method-of-moments estimates are larger: .36 for son–father pairs, .48 for daughter–father pairs, .56 for daughter–mother pairs, and .56 for son–mother pairs. Our results based on the time averages are on the low end of those reported by Solon (1989b) and by Altonji (1988), who use data on fathers and sons from the PSID.[15] At the same time, the method-of-moments estimates for all intergenerational pairs except son–father are higher than any previous estimates for the United States in the literature.[16]

There are some potential problems with the family income variables that require discussion. In the older men's and mature women's cohorts, family income is the sum of incomes from various sources of all the family members residing in the household. The parents' family income reports may thereby include their children's earnings. In most years, the young men's and young women's family income counts the incomes of only the respondent and spouse who live alone (with children younger than 13 years old). However, the 1981 measure of family income for young men (the 1982 measure for young women) sums the incomes of all the members of the household—possibly including the incomes of their parents or siblings. Both of these accounting procedures may upward bias our sibling and parent–child covariances and correlations.

We recalculated our method-of-moments covariances and correlations after making the following adjustments. First, we subtracted from the total family income amount all income attributable to family members other than the respondent and spouse in the two older cohorts. Second, we omitted 1967 observations for the older men and 1981 for the mature women because information on the incomes of other family members is not available. Third, we excluded the 1981 reports for young men (and the 1982 reports for young women) who coreside with a parent, parent-in-law, sibling, or other adult (excepting a spouse or partner). Other family member income accounts for about 20% of total family income for those households reporting such income. In the younger cohorts, coresidence described above is rare, occurring in about 12% of the younger households.

Overall these adjustments make little difference in our estimated moments. The young men's and young women's family income variances fall slightly, while the older men's rises from .310 to .330 and the mature women's from .345 to .426. The sibling and parent–child family income covariances are slightly larger than those reported in Table 3, but the correlations are nearly identical: .35 for brothers, .77 for sisters, .49 for brothers and sisters, .36 for fathers and sons, .53 for mothers and sons, .48 for fathers and daughters, .56 for mothers and daughters, and .77 for fathers and mothers.

Regression Results for Family Income

Table 5A–5D reports OLS and IV estimates of the regression equations (6a) – (6d) relating the labor market outcomes of fathers and sons, fathers and daughters, mothers and sons, and mothers and daughters (respectively). We report results for two sets of control variables. Control set I consists only of the child's age in 1966 (1968 for young women), age squared, and age cubed, and the parent's age in 1966, age squared, and age cubed. Control set II consists of control set I plus controls for the child's race, residence in the South, residence in a standard metropolitan statistical area (SMSA), a cubic in the child's education, and a cubic in parent's education. To save space, we focus on the IV estimates in the text. We wish to emphasize that since the variances of family income are higher for fathers and mothers than for sons and daughters, the regression coefficient estimates are likely to be smaller than the correlation coefficients even when no controls are added.[17] This is especially true for fathers and sons.

Using control set I, the coefficients on father's family income is .279 for sons and .287 for daughters. Since the variables are in logs, the result for family income implies that the elasticity of son's income with respect to father's income is .279. For sons, much of the relationship in incomes appears to operate through education and, to a lesser extent, race. To see this, note first that when we use control set II, we obtain .102 as the coefficient on father's family income. By adding the son's race, son's education, and father's education one at time to control set I, we have determined that including the son's education as a regressor has the largest negative impact on the magnitude of the father's family income coefficient, which is what we would have expected a priori.[18]

The estimates of the relationship between family income of the mother and family income of sons and daughters are typically stronger than the corresponding results for the father–son and father–daughter samples. The IV estimate for mother–son pairs with controls for their ages only (control set I) is .368. The estimate for mother–daughter pairs is .443. The estimates for mother–son and mother–daughter pairs fall to .170 and .147 (respectively) when control set II is used.

Since in the case of two-parent households the family income of mothers and fathers is the *same*, the larger estimates when using the mother–daughter and mother–son samples merit some discussion. We suspect that the difference in father–child and mother–child regression coefficients arises for two reasons. First, because of the design of the NLS, the parent's family income data in the father–son and father–daughter sample are obtained when the father is somewhat older than in the mother–son and mother–daughter sample. To the extent that family income is subject to permanent shifts that occur after children leave the household, then parental income in later years may have a weaker relationship with children's permanent income.[19] For this reason we suspect that our estimates based on the father–son and father–daughter samples understate intergenerational links in family income. Also, the mother–son and mother–daughter samples include female-headed, single-parent families, while the father–son and father–daughter samples do not. It is possible that family income has larger effects in the case of single-parent families than two-parent families, although we found little evidence to support this.[20]

In summary, we find very strong intra- and intergenerational correlations in family incomes. The sibling correlations are stronger for sisters than for brothers, even though the young women's incomes have a larger variance. The regression analysis suggests that a 1% increase in the permanent family income of the parents raises the conditional mean of children's family income by .28% to .37% for sons and .29% to .44% for daughters. A substantial part of this effect is found to operate through the child's education and race.

B. Earnings, Wage Rates, and Work Hours

When we use time averages, the estimated correlations of log earnings are .32 for brothers, .26 for sisters, and .14 for brother–sister pairs. The corresponding estimates are .37, .26, and .32 when we use the method-of-moments procedure to isolate the correlation of the permanent components of earnings. The intergenerational correlation coefficients for earnings are also sensitive to the estimation method. We prefer the estimates based on the method-of-moments procedure, which are .39 for fathers and sons, .32 for mothers and sons, .42 for fathers and daughters, and .28 for mothers and daughters.[21] The method-of-moments estimates of the earnings correlation between fathers and sons are large relative to the estimates summarized in Becker and Tomes (1986), but are comparable to Solon's (1989b) results using the PSID. Atkinson et al. obtain an estimate of .45 for fathers and sons using English data.[22]

It is interesting to look separately at the components of earnings: hourly wage rates and annual hours. Using the method-of-moments approach we obtain log wage correlations of .42 for brothers, .42 for sisters, .41 for brother–sister pairs, .42 for father–son pairs, .43 for father–daughter pairs, .35 for mother–son pairs, and .35 for mother–daughter pairs. (The corresponding estimates based on time averages are typically a bit smaller.) Thus, we find somewhat stronger family relationships in log wages than in log earnings.[23]

Given this fact and the fact that earnings depend upon work hours as well as upon wages, it is not surprising that the correlations in annual hours are usually smaller than the correlations in wages. However, the method-of-moments estimates are substantial in all cases involving family members of the *same sex*. For example, the annual hours correlation is .36 for brothers, .34 for sisters, .34 for fathers and sons, and .15 for mothers and daughters.[24,25] The large correlations between brothers and between fathers and sons are particularly striking in light of the fact that hundreds of studies of male labor supply have examined the effects of family characteristics, wages, and income on hours worked and have met with little success in explaining hours worked for males.[26] [See Killingsworth (1983) and Pencavel (1986) for surveys of the literature.] The findings in Table 3 suggest that factors common to family members explain a substantial part of the permanent variation in work hours among males. In Altonji and Dunn (1990), we show that the similarity in the wage rates of brothers plays only a small role in the similarity in their annual hours worked.

Part of the relationship in annual hours, then, may be due to correlations in labor market constraints that lead to unemployment, and the results for unemployment in Table 1 indicate that the unemployment rates of family members are correlated. The correlations based on time averages of the number of weeks of unemployment are .08 for fathers and sons, .20 for brothers, .07 for brothers and sisters, and .11 for mothers and daughters.[27] The correlations between fathers and daughters, mothers and sons, and sisters are weaker.[28] Though not reported in Table 1, we found the strongest correlations in the level of weeks *worked* for sister pairs (.25), brother pairs (.21), and mother–son, mother–daughter, and brother–sister pairs (all three are .10). The *level* of annual hours correlation for father–son pairs is .17 (compared to .10 for the correlation of the log of annual hours). Similarly, for brothers the correlation is higher: .23 versus .13 using the level of annual hours.

In contrast to the strong method-of-moments annual hours correlations for fathers and sons, for brothers, and for sisters, the correlations of the annual hours of brother–sister pairs (.08) and father–daughter pairs (.12) are weaker. (The correlation for mothers matched to children of either sex is .15.) Why do hours tend to be more strongly correlated among family members of the same sex? The results suggest that family factors influencing work hours are different for males and females. We speculate that preferences for leisure and correlations in labor market constraints are a key factor among men, most of whom choose to work more or less full time, while preferences and incentives for market work versus nonmarket work play a key role in the sisters' and mother–daughter correlations and in the total variance in the work hours of women. With data on hours spent on housework and child care, one could examine the correlation between leisure time of female and male family members. We conjecture that one would find larger mother–son and father–daughter correlations in hours if such a measure were used.[29]

Regression Results for Earnings, Hours, and Wages

As noted above, Table 5 contains IV estimates of the regressions relating the earnings, hours, and wages of sons and daughters to the earnings, hours, and wages of fathers and mothers. The IV estimate of the effect of father's earnings on son's earnings is .218. However, the coefficient falls to –.001 (not significant) after we control for race, educations of the father and son, and location variables.[30] The corresponding results for daughters are .330 and .151.

For wages we obtain a coefficient of .282 with control set I and .100 with control set II for fathers and sons, and .210 and .088 for fathers and daughters. Overall, the regression relationship between the wages and earnings of fathers and sons and fathers and daughters are similar to the relationships for family income. As before, we find that a substantial part of the intergenerational relationship operates through education and race, particularly for sons.

The regression results for annual hours show a weaker relationship between annual hours of the father and the son. The OLS results are in line with the correlations between the time averages discussed earlier, and in view of the large variability in the time averages of father's annual hours, the small regression coefficient does not come as surprise. However, the IV estimates are much weaker than we would have expected given the method-of-moments results. The IV estimate with control set I is only .190. In contrast, the regression coefficient implied by dividing the method-of moments estimate of the covariance of hours of fathers and sons by the method-of-moments estimate of the variance of the hours of older men is .35. Since the time average of father's hours has a coefficient of .260 in the first-stage IV equation for father's hours in 1965, we would have expected the second-stage estimates to be roughly 3.85 (=1/.260) times larger than the OLS estimate (of .095), which would be roughly consistent with the method-of-moments "regression coefficient" of .35. We are puzzled by the discrepancy. We have shown that it does not result from the fact that a smaller sample is available to compute the IV estimates.[31,32]

The father–son relationship for log hours per week is statistically significant under OLS for control set I and for control set II, but the IV estimates are not statistically significant for either set of explanatory variables. The regression results for fathers and daughters do not show a relationship in annual or weekly hours worked, nor in weeks worked. This is fully consistent with the small correlations discussed earlier.

Mother's earnings has only a moderate influence on son's earnings (.167), despite the fact that the mother's wage has a relatively strong link to the son's wage

(.355 with control set I). This reflects the facts that (1) hours of work of mothers and sons are only weakly related, and (2) the variance across women in work hours has a large effect on the variance in female earnings. The results for daughters and mothers are an interesting contrast: the coefficients on earnings, the wage rate, log weeks worked, and weeks unemployed are all strong at .341, .314, .522, and .608, respectively. The strong link between the earnings of mothers and daughters reflects the fact that both weeks worked and the wage rates of mothers and daughters are strongly related, though annual hours are not. The coefficient for annual work hours is .128 but the t-statistic is 0.92.

In summary, we find strong family links in earnings and in wages for all sibling and parent–child pairs. We also find fairly strong correlations (but weak regression relationships) in the work hours of family members of the same sex. For father–son and mother–daughter pairs, we also find strong regression relationships in log weeks worked. Much of the effect of parental background on earnings and wage rates, particularly in the case of fathers and sons, operates through education and race.

V. CORRELATIONS BETWEEN LABOR MARKET OUTCOMES OF INDIVIDUALS RELATED BY MARRIAGE

In this section we discuss the correlations among the earnings and hours worked of individuals related by marriage. Tables 6 and 7 report covariances and correlations based on time averages of earnings, hours worked per week, weeks worked per year, and weeks unemployed per year for husbands and wives, fathers- and sons-in-law, mothers- and sons-in-law, brothers-in-law, fathers- and daughters-in-law, mothers- and daughters-in-law, and siblings-in-law.[33] The main focus of our discussion is on the relationships in earnings.

As an aid to interpreting the results, consider the following simple model of the relationship between an individual's earnings and spouse's earnings. Suppose that one's value in the labor market is related both to one's own earnings potential and to the earnings potential of one's blood relatives. To be specific, let the permanent earnings E_{ij} of child j from family i be determined by

$$E_{ij} = c_0 + u_i + u_{ij}, \tag{7}$$

where E_{ij} are the permanent earnings of a young woman j from family i, c_0 is a constant, u_i are parental and sibling influences that have a common effect on the earnings of siblings, and u_{ij} is a child-specific earnings factor that is uncorrelated across families and across children from family i.

Assume also that one's value in the marriage market depends on one's own earnings capacity and on the earnings capacity of one's siblings and parents. This assumption plus competition in the marriage market suggest that spouse's earnings capacity (and other traits that are valued in the marriage market) tend to be

Table 6. Summary of the Covariances and Correlations of Time Averages of Selected Labor Market Variables for Young Women's Reports of Their Husbands and Other Matched Family Members

Labor market variable	*Husband–wife*	*Husband–father-in-law*	*Husband–mother-in-law*	*Husband–brother-in-law*
Log earnings	.074	.135	.087	.095
	.14	.26	.18	.23
	2875	561	927	962
Log hours worked	–.003	.002	.006	.004
per week	–.03	.04	.07	.11
	3026	639	1002	1010
Log weeks worked	.003	–.001	.004	.008
per year	.02	–.02	.03	.11
	2890	639	1022	943
Weeks unemployed	2.195	–.175	–.067	.067
per year	.10	–.01	–.00	.00
	3198	640	1189	953
Log annual hours	–.001	.002	.025	.019
	–.00	.01	.09	.13
	2907	647	1010	958

Note: The covariance is given first, with the correlation next, followed by the sample size

Table 7. Summary of the Covariances and Correlations of Time Averages of Selected Labor Market Variables for Young Men's Reports of Their Wives and Other Matched Family Members

Labor market variable	*Wife–husband*	*Wife–father-in-law*	*Wife–mother-in-law*	*Wife–sister-in-law*
Log earnings	.055	.056	.058	.106
	.11	.07	.07	.12
	2319	433	554	595
Log hours worked	–.002	–.003	.013	.011
per week	–.03	–.05	.07	.07
	2645	520	664	686
Log weeks worked	.002	.006	.010	.041
per year	.02	.04	.03	.09
	2563	535	694	680
Log annual hours	–.006	.005	.048	.070
	–.02	.02	.07	.09
	2507	518	651	658

Note: The covariance is given first, with the correlation next, followed by the sample size.

positively related to one's own earnings capacity and those of one's relatives. Let the regression equation relating the earnings of the spouse of woman ij to the family i earnings component u_i and to her earnings E_{ij} be

$$E_{ij}^{S} = b_0 + b_1 u_i + b_2 E_{ij} + e_{ij}^{S}, \tag{8}$$

where the error term e_{ij}^{S} is uncorrelated with u_i and E_{ij}.

Using (7) and (8) the covariances of the earnings of spouses, siblings, and in-laws can be derived easily. For instance, the covariance between the earnings of spouses, E_{ij}^{S} and E_{ij} is $(b_1 + b_2)$ Var(u_i) + b_2 Var(u_{ij}). The covariance between the earnings of siblings ij and ij' implied by (7) is equal to Var(u_i), where to keep the discussion simple we have ignored the potentially important possibility that the factor loading on the family component u_i may be different for young men than for young women. The covariance between brothers-in-laws' earnings E_{ij}^{S} and $E_{ij'}$ is $(b_1 + b_2)$ Var(u_i).

If $b_1 = 0$, then the family effect u_i has no direct influence on spouse's earnings, and the covariance between the in-laws earnings arises simply because u_i affects E_{ij}^{S} through E_{ij}. On the other hand, if only the income of the family matters ($b_2 = 0$), then the brothers-in-law and spouse covariances are both equal to b_1 Var(u_i), and both are less than the sibling covariance Var(u_i) when $b_1 < 1$. An increase in b_1 holding b_2 fixed raises the value of the in-law covariance relative to the sibling covariance, and relative to the spouse covariance. Consequently, the larger the value of the brothers-in-law covariance relative to the sibling covariance and relative to the spouse covariance, the more likely it is that the family has influence on the permanent earnings of the spouse.[34]

The time average earnings covariance is .135 for father–son-in-law pairs and .119 for father–son pairs. The correlation of their earnings is .26, which is actually larger than the corresponding estimate (.22) for fathers and sons. The earnings covariance (correlation) for brothers-in-law is .095 (.23), which compares to .130 (.32) for brothers. The earnings covariance for sisters-in-law is .106, which compares to .206 for sisters. The corresponding correlations are .12 and .26. All of these correlations are based on time averages and we suspect that they are substantially understated as a result of transitory variation and measurement error.

The in-law correlations of some of the other labor market variables deserve mention. Brothers-in-law have a log weeks worked correlation that is similar to that of brothers, .11 versus .12. The same is true for the annual hours worked correlation, which is .13 for brothers and for brothers-in-law. The brothers-in-law hours worked per week correlation is about one-half of the brothers. In general, the sisters-in-law correlations are smaller than the corresponding sisters correlations. When we look at the number of weeks worked (not shown in Table 7), rather than the its logarithm, the wife–mother-in-law correlation jumps from .03 to .12, and the sisters-in-law correlation from .09 to .13.

Thus, we find that siblings-in-law covariances and correlations in earnings are somewhat weaker than the corresponding figures for sibling pairs. However, they seem large enough, particularly in light of the strong father–son-in-law covariance, to suggest that a family earnings component has an effect on the earnings capacity of spouses. The brothers-in-law and sisters-in-law covariances are also large relative to the covariance of spouses' earnings,[35] which, in the context of the simple model sketched above, also points to an important direct effect of the family earnings component on the expected earnings capacity of the spouse. As a cautionary note, we do not wish to make too much of this interpretation, because the framework presented above ignores differences between men and women in family linkages, substitution in labor supply between husbands and wives, selectivity in who gets married, and other factors. In future work we plan to explore the issues systematically by combining a more elaborate version of the factor model sketched above with the factor model of earnings, hours, and wages estimated in Altonji and Dunn (1990).

VI. FAMILY CORRELATIONS IN TURNOVER BEHAVIOR

Table 1 also provide estimates of the correlations across family members of the number of employers the individuals have worked for over the years of the survey. In the literature on wages and job mobility there has been considerable discussion of the importance of observed and unobserved personal characteristics in explaining the large differences found across individuals in the propensity to change jobs. A positive correlation in the separation rates of family members would arise if the desire and ability to "hold a job" has an important effect on turnover behavior and is correlated among family members. That is, mobility costs and personality traits that influence quits and layoffs may be correlated among family members. A number of authors have argued that personal characteristics related to turnover are negatively related to productivity. As a result, ex post measures of turnover behavior, such as job seniority, are endogenous in a wage equation. We can investigate whether individual heterogeneity in turnover behavior is negatively related to productivity by examining the sign of the correlation between the turnover behavior of one family member with the wage rate of another. Job instability has been featured prominently in discussions of low-income workers.[36] It is natural to ask if job instability is in part a family characteristic and whether the common family component of turnover behavior is negatively related to the family component of wages.

Before turning to the evidence, it is also important to point out that other theories of job mobility imply that variation across firms in wage offers as well as differences across specific firm–worker matches in productivity will lead to ex post differences in turnover even if the propensity of all workers to quit or induce a layoff or discharge is the same.[37] Some of the differences (such as initial wage offers) are readily observable, and workers may switch jobs in response to a higher wage offer. Other differences can be observed only after a trial period on the job, and will also lead to ex post differences in separation rates even if the expected values of separation rates are the same for all workers. What are the implications of wage offer and job match heterogeneity for family correlations among turnover and wages? If the expected values of separation rates are the same for all workers, then one would not expect job mobility to be correlated across family members. Also, simple matching models do not have a clear implication for the relationship between actual separation rates and productivity. Consequently, matching models in which differences in workers are unrelated to differences in expected mobility do not lead us to expect a correlation between the wages and mobility of one family member with the mobility patterns of another.

Unfortunately, the implications of matching and job search models of labor turnover for family correlations are less clear if the optimal amount of turnover associated with finding a good job match is related to occupation, ability, education, or other worker characteristics that are correlated among family members. In this case one might also find positive family correlations in turnover behavior even if matching and job search provide a complete explanation for turnover. The family correlations could also arise if the number and strength of personal contacts are correlated among family members and are an important determinant of turnover.

Table 1 reports the correlations in number of employers per survey year for sibling pairs and parent–child pairs. The largest correlations are found for same-sex pairs. For example, the correlation is .25 for brother pairs and .10 for sister pairs, .08 for daughter–mother and .07 for father–son pairs. In contrast, the correlation is .00 for brother–sister pairs, .02 for fathers and daughters, and .04 for sons and mothers. Altonji (1988) also finds a significant correlation between the separation rates of fathers and sons and between brothers. (This is the only other evidence on intra- and intergenerational links in turnover behavior of which we are aware.)

Table 5 presents OLS estimates of the relationship between the number of employers for matched family members. As noted above, a positive sibling correlation or intergenerational correlation in turnover rates is unlikely to arise from a simple job-matching model. Not much should be made of the specific values of the regression coefficients given that turnover behavior is highly dependent on years of labor market experience. However, we find a significant, positive relationship between the turnover rates of fathers and sons.[38] We also find a statistically significant relationship between the turnover rates of mothers and daughters; however, we do not find a relationship between the turnover rates of fathers and daughters or mothers and sons.

Thus, intra- and intergenerational links in turnover behavior appear to be stronger for persons of the same sex. We do not have a theory to explain this finding. One possibility is that individual differences in labor supply behavior play a larger role in the turnover behavior of women. Recall from Section IV.B that correlations in hours worked and weeks worked were also much stronger for individuals of the same sex.

We do find that the wage rates of one family member are negatively correlated with the turnover behavior of other family members. (To save space we have not included the tables showing these results.) The correlations are almost always negative in sign, but are frequently insignificant for sibling pairs.[39] For example, the number of employers the father worked for from 1966 until retirement or age 60 has a correlation of –.06 with the son's log wage rate (p-value .08) and –.08 (.05) with daughter's wage rate. The corresponding correlation for brother pairs is –.05 (p-value .29) and for sister pairs is .002 (.76). Daughters' wages and mothers' number of employers has a correlation of –.11 and is significant at the .0005 level. The mother–son correlation is –.11 with a p-value of .001. Consequently, there is modest evidence in the NLS data that the (intergenerational) family component of turnover behavior is negatively related to wages rates.[40] These results corroborate those of Altonji (1988) for a sample of fathers and sons and brother pairs from the PSID. He finds a significant negative correlation between the separation rates of fathers and the wages of sons. He also finds that the separation rates of young men are negatively correlated with the wage rates of their brothers.

In summary, there is consistent evidence from the NLS and PSID that turnover behavior depends on family characteristics. There is also evidence in both data sets that the family component of turnover behavior is negatively related to labor market productivity. However, the evidence does not suggest that turnover behavior plays a major role in the intra- and intergenerational links in wages.

VII. ARE "INDUSTRY WAGE PREMIUMS" CORRELATED ACROSS GENERATIONS?

In this section we ask whether the sons of men who work in industries that pay high wages (controlling for occupation and human capital) also tend to work in industries that pay high wages. We examine this correlation in part because we are interested in the magnitude of the link in the "industry component" of wages relative to the overall link. However, under certain assumptions, this correlation provides information about the extent to which industry wage differentials are market-clearing differentials that compensate for differences across industries in worker quality or job characteristics, and the extent to which they are non-market-clearing differentials that arise because firms choose to pay efficiency wages (or for other reasons.)

Assume first that employers select workers, and that family connections play an insignificant role in the allocation of workers across jobs. If industry differentials reflect differentials in worker quality, then one would expect the relation between the industry components of the father's and the son's wage rates to be similar to the relationship between the wages of the father and the son. On the other hand, if industry wage premiums are rents that are unrelated to worker quality, and employers select workers without regard to family connections, then the industry wage effects of the father and the son should be unrelated. However, if family connections are important in the rationing of jobs, then fathers who are in industries that pay rents may be able get jobs for their children in the industry. In this case, both neoclassical and efficiency wage explanations for industry differentials would predict a positive relationship between the industry wage effects of fathers and sons.[41]

To investigate the issue empirically, we first constructed estimates of industry wage components. We pooled the panel data on young men and older men and estimated a set of 18 coefficients on industry dummies using a regression equation that also included controls for education, experience, residence in the South, year dummies, residence in an SMSA, and a set of 11 dummy variables for occupation. Let λ_I denote the (18 × 1) vector of estimated industry coefficients and D_{ikt} the (18 × 1) vector of industry dummies for person k from family i in year t. We define D_{ik} (k = s,f) to be the average of D_{ikt} taken over the years in which the person meets the age, schooling, and retirement criteria for inclusion in the analysis and has valid reports of his wage and industry. D_{ik} then is the average time each young man (k = s) or older man (k = f) spends in each of the 18 industries over his working history. We use the time average as a simple way of dealing with the fact that industry classifications vary from year to year due to measurement error and industry switches. We then form the time average of the industry wage premiums as $I_{ik} = \lambda_I' D_{ik}$ for each young man and his father.

We use matched data on father–son pairs to estimate the following regression relating the industry wage component of sons, I_{is}, to the industry wage component of their fathers, I_{if}:

$$I_{is} = \gamma_I I_{if} + B_1 X_{is} + B_2 X_{if} + \text{error},$$

where X_{is} and X_{if} are control variables. The regression results are presented in Table 8. The simple regression coefficient of the father's average industry premium is .179 with a t-value of 5.1.[42] Not surprisingly (given the way the industry coefficients are constructed) this estimate is relatively insensitive to adding controls for the father's and son's mean occupation coefficients (constructed in the same way as I_{if} and I_{is}) and to the addition of other control variables.[43] The estimate of .179 can be compared to the OLS and IV estimates of .263 and .282 relating the son's wage rate and the father's wage rate [see equation (6) and Table 5A]. However, the latter estimates fall to .077 and .100 when one includes controls for race, educations of the son and father, region and SMSA, and ages of the son and the father. Only when we include additional controls for the collective-bargaining status and occupation coefficients of both the father and the son does the father's industry coefficient fall by about two-thirds to .060 with a t-statistic of 1.2 (column 6 of Table 8).[44]

These results are largely consistent with the hypothesis that unobserved ability differences may play a substantial role in industry wage differentials (see Murphy

Table 8. Regression Analysis of the Relationship between Father's and Son's Industry Wage Components

Independent variable	*Dependent variable: Son's mean industry wage component* (1)	(2)	(3)	(4)	(5)	(6)
Father's mean industry wage component	.179 (5.1)	.185 (5.2)	.185 (5.2)	.182 (5.1)	.169 (4.6)	.060 (1.2)
Son's mean occupation component			−.028 (−0.7)	−.033 (−0.9)	−.025 (−0.6)	−.024 (−0.5)
Father's mean occupation component				.078 (2.1)	.091 (2.4)	.164 (3.4)
Son's mean collective bargaining status					.068 (5.4)	.064 (4.3)
Father's mean collective bargaining status						.027 (1.9)
Controls included?	No	Yes	Yes	Yes	Yes	Yes
R^2	.03	.07	.07	.08	.13	.16
N	734	729	727	726	629	454

Notes: 1. t-statistics are in parentheses.
2. Control variables are the following: son's education, father's education, son's age, father's age (all in cubic specifications), indicators for race, for residence in the South, and for residence in an SMSA.
3. The dependent variable has mean equal to .16 with a standard error of .125. The father's corresponding variable has mean equal to .17 and standard error of .131.

and Topel, 1987), or the joint hypothesis that (a) industry differences are not market clearing and (b) family ties are important in gaining access to jobs in high wage industries.[45] However, they are inconsistent with a non-market-clearing model in which the family does not play a role in the allocation of jobs, where one would not expect industry wage premiums of sons and fathers to be related.

We have also examined intergenerational links in collective-bargaining status.[46] For fathers and sons, we computed the time averages of dummy variables indicating membership in a collective bargaining unit. Table 9 reports the results of various regression specifications. The simple regression coefficient is .194 with a t-value of 5.2.[47] Since the mean of the collective-bargaining variable for the young men in the matched sample is .31, this indicates that whether or not the father was covered by collective bargaining has a quantitatively large effect on the son's collective-bargaining probability. The coefficient falls to .129 when controls for father's age and education, son's age and education, residence in the South and in an SMSA, and race are added. The coefficient on father's collective-bargaining status ranges between .089 and .110 and remains significant as controls for I_{is}, I_{if}, and the mean occupation coefficients of the father and the son are added.

Although the results are not reported, a series of regressions relating the son's

Table 9. Regression Analysis of the Relationship between Father's and Son's Collective Bargaining Status

Independent variable	Dependent variable: Son's mean collective-bargaining status					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Father's mean collective bargaining status	.194	.129	.089	.110	.106	.104
	(5.2)	(3.4)	(2.2)	(2.5)	(2.5)	(2.3)
Son's mean industry component			.649	.666		.657
			(4.3)	(4.4)		(4.3)
Son's mean occupation component					–.595	–.566
					(–3.8)	(–3.7)
Father's mean industry component				–.225		–.232
				(–1.4)		(–1.4)
Father's mean occupation component					–.037	–.107
					(–0.2)	(–0.7)
Controls Included?	No	Yes	Yes	Yes	Yes	Yes
R^2	.05	.16	.19	.19	.18	.22
N	548	547	457	457	454	454

Notes: 1. t-statistics are in parentheses.
2. Control variables are the following: son's education, father's education, son's age, father's age (all in cubic specifications), indicators for race, for residence in the South, and for residence in an SMSA.
3. The dependent variable has mean equal to .31 with a standard error of .410. The father's corresponding variable has mean .38 with a standard error of .457.

mean occupation component of wages to his father's were also run. When one controls for education, age, residence, and race, the regression coefficient relating the son's occupation coefficient to the father's mean occupation coefficient (t-statistic) is .060 (1.7). (The simple regression coefficient is .304 with a t-value of 9.2, and the simple correlation is .32.) The positive relationship in the occupations ranked by wage rates is consistent with the literature on intergenerational links in the SES scores of occupation.[48]

In short, we find a large positive and significant relationship between the industry wage premiums of fathers and sons. Furthermore, we also find a substantial positive relationship between fathers' and sons' collective-bargaining coverage.

VIII. CONCLUSIONS

In this paper we examine the links between the labor market outcomes and family incomes of individuals who are related by blood or by marriage using panel data on siblings, their parents, and their spouses from the four original cohorts of the National Longitudinal Surveys of Labor Market Experience. We provide better estimates of intra- and intergenerational correlations in family income and earn-

ings, estimate labor market correlations among in-laws, examine intergenerational links among a broad set of labor market outcomes, and show how intergenerational labor market data can be used to examine the sources of labor supply variation, theories of labor turnover, and theories of wage structure. We use a wide range of econometric methods in attempting to deal with problems associated with transitory variation and measurement error.

Our main empirical findings are as follows. First, we find very strong intra- and intergenerational correlations in family incomes. The sibling correlations are stronger for sisters than for brothers. Our preferred estimates are based upon the method-of-moments procedure. The correlations are .38 for brothers, .73 for sisters, and .56 for brothers and sisters, which are very large relative to most of the existing literature. The method-of-moments estimates of the intergenerational correlations of family income are .36 for son–father pairs, .48 for daughter–father pairs, and .56 for daughter–mother and for son–mother pairs. The method-of-moments estimates for all intergenerational pairs except son–father are very large relative to the literature for the United States. The regression analysis suggests that a 1% increase in the permanent family income of the parents raises the conditional mean of children's family income by .28% to .36% for sons and .29% to .44% for daughters. A substantial part of this effect operates through the child's education and race.

Second, we find strong family links in earnings and in wages. The method-of-moments wage correlations for the various family member pairs vary around .40. The earnings correlations vary around .35. Much of the effect of parental background on earnings and wage rates, particularly in the case of fathers and sons, operates through education and race.

Third, we also find fairly strong correlations in the annual work hours of family members of the same sex. We also find strong regression relationships in weeks worked for parent–child pairs of the same sex. Overall our results suggest that family components play an important role in work hours determination. They suggest that genetic and environmental, and cultural factors common to family members may play an important role in labor supply decisions. There is also some weak evidence that hours constraints (as measured by unemployment) are correlated among family members.

The correlation in family members' earnings appears to be due to strong wage correlations and weaker hours correlations. The results in Altonji and Dunn (1990) support this conclusion. They also indicate that very little of the correlation in work hours is induced by labor supply responses to correlated wage rates.

Fourth, we find substantial covariances in the earnings of in-laws. Some of the time average correlations rival those of blood relatives. Developing a marital sorting model to explain these correlations is an exciting project for the future.

Fifth, we have shown that it is possible to examine theories of labor turnover and theories of wage structure by exploiting intergenerational linkages. There is consistent evidence from the NLS [and the PSID reported in Altonji (1988)] that turnover behavior depends on family characteristics. Additionally, there is evidence that the family component of turnover behavior is negatively related to labor market productivity. We also show that young men whose fathers work in high-wage industries (controlling for human capital characteristics) tend themselves to work in high-wage industries. We argue that the results are consistent with non-market-clearing explanations for industry wage premiums (such as efficiency wages) only if family connections play a key role in gaining access to high-wage firms. We also show that there is a strong, positive, and significant relationship between fathers' and sons' collective-bargaining coverage.

APPENDIX

Table A2 shows the distribution of the number of siblings and matched family pairs by the number of persons from a given family. For example, there are 3 families each having 4 sons. Together they contribute 18 brother pairs, 6 per family, to the brothers data set.

Comparison of the Matched Samples and the Full-Cohort Samples

The older men in the father–son sample are on average 1 year younger than the full sample of older men. The men who could be matched to children of either sex have somewhat higher family income (17%), earnings (7%), wages (6%), hours worked per week (4%), and hours worked per year (4%). They also have 0.33 more years of education than the mature men's sample as a whole. (These differences may reflect differences between older men who had children and older men who did not, rather than differences in the NLS matched sample from the population of older men with children.) The fraction of black men remains constant at about 28% for the father–child samples and the entire older men's cohort. Finally, the men in the father–child samples have slightly lower job turnover rates (as measured by the number of different employers per year surveyed): 0.45 versus 0.51 for the whole men's sample.

The mature women in the matched samples are about 2 years older than the sample of all mature women and have family income, earnings, wages, hours worked per week, and annual hours worked that are lower by 5, 15, 9, 1, and 3%, respectively. They also have 0.70 fewer years of education than the sample of all mature women (10.3 versus 11.0 years). Thirty-five percent of the women in the mother–child samples are black, compared to 28% for all mature women. Job turnover rates are the same for the whole women's cohort and the samples of women matched to children.

The young men matched to fathers are almost three-quarters of a year younger than the sample of all young men, but they have higher family incomes (5%) and about 0.5 additional years of education. Earnings, wages, hours worked per week, and annual hours worked are about equal for the two groups. Young men who are matched to mothers are about two years younger than the entire sample of young

Table A1. Summary Statistics for the Young Men, Young Women, Older Men, and Mature Women Cohorts

Variable	*Observations*	*Mean*	*S.D.*	*Mean observations entering time average*
		Young men		
Age in 1966	5225	18.09	3.16	—
Highest grade	5225	12.87	2.86	—
Black?	5225	.28	.45	—
Log family income	3423	8.95	.58	2.3
Log earnings	4030	8.58	.68	4.7
Log hourly wage	4003	1.10	.42	4.5
Log hours/week	4130	3.76	.19	4.9
Log weeks worked	3888	3.83	.29	3.3
Weeks unemployed	3939	2.51	6.25	3.3
Log annual hours	3872	7.60	.40	3.2
Employers/year	4084	.51	.30	5.0
Collective barg.	3713	.32	.41	3.5
		Young women		
Age in 1968	5159	18.72	3.02	—
Highest grade	5159	12.50	2.61	—
Black?	5159	.28	.45	—
Log family income	3855	8.74	.66	2.6
Log earnings	3673	7.61	.94	3.7
Log hourly wage	3681	.63	.39	3.7
Log hours/week	3797	3.46	.42	3.8
Log weeks worked	3581	3.50	.62	2.6
Weeks unemployed	4044	2.19	5.45	3.1
Log annual hours	3562	6.97	.85	2.7
Employers/year	3519	.65	.31	3.5
Collective barg.	3560	.21	.34	3.1
		Older men		
Age in 1966	4986	52.28	4.29	—
Highest grade	4987	9.30	3.95	—
Black?	5020	.28	.45	—
Log family income	4884	8.85	.75	3.8
Log earnings	4274	8.56	.82	3.9
Log hourly wage	4052	1.05	.52	3.3
Log hours/week	4767	3.74	.25	4.8
Log weeks worked	4782	3.83	.30	4.6
Weeks unemployed	5017	1.58	4.74	4.6
Log annual hours	4756	7.57	.45	4.2
Employers/year	4691	.51	.24	5.1
Collective barg.	3005	.40	.47	2.0
		Mature women		
Age in 1966	5083	37.28	4.36	—
Highest grade	5066	10.96	2.84	—
Black?	5083	.28	.45	—
Log family income	4845	8.83	.68	4.4
Log earnings	3973	7.59	.91	4.9
Log hourly wage	3996	.57	.42	6.0
Log hours/week	4275	3.42	.44	6.3
Log weeks worked	4284	3.52	.58	4.8
Weeks unemployed	4891	1.11	2.87	5.8
Log annual hours	4155	6.99	.81	4.1
Employers/year	4116	.44	.30	6.6
Collective barg.	3205	.19	.34	2.6

Table A2. Distributions of the Number of Siblings and Family Member Matches per Family

Brother pairs: 621 pairs from 492 families						
Young men per family:	1	2	3	4	6	
Families	4181	438	50	3	1	
Brother pairs	0	438	150	18	15	
Sister pairs: 646 pairs from 466 families						
Young women per family:	1	2	3	4	5	
Families	4143	392	66	6	2	
Sister pairs	0	392	198	36	20	
Brother–sister pairs: 1921 pairs from 1213 families						
Siblings per family:	2	3	4	5	6	7
Families	747	341	101	19	4	1
Brother–sister pairs	747	682	352	104	30	6
Father–son pairs: 1099 pairs from 878 families						
Sons per family	1	2	3	4	6	
Families	687	167	20	3	1	
Father–son pairs	687	334	60	12	6	
Father–daughter pairs: 988 pairs from 779 families						
Daughters per family	1	2	3	4	5	
Families	607	142	25	3	2	
Father–daughter pairs	607	284	75	12	10	
Mother–son pairs: 1671 pairs from 1320 families						
Sons per family	1	2	3	4	6	
Families	1008	278	31	2	1	
Mother–son pairs	1008	556	93	8	6	
Mother–daughter pairs: 1848 pairs from 1423 families						
Daughters per family	1	2	3	4	5	
Families	1070	292	53	5	3	
Mother–daughter pairs	1070	584	159	20	15	

men and have nearly identical family incomes, wages, and hours worked per week. Annual hours are lower by 3% and earnings are lower by 10%. Years of education are similar for the two groups.

The young women follow the same general pattern as the young men. Those whose fathers are in the mature men cohort are somewhat younger, better educated (by 0.5 years in each case), and slightly more successful than the young women's cohort as a whole (earnings are higher by 12%). Young women matched to mothers are 1.5 years younger than young women as a whole and have somewhat lower family income (by 6%). Average education (at 12.5 years), wages, earnings, and hours worked for the young women in the mother–daughter sample are the same as for the full sample of young women.

Fourteen percent of the young men report belonging to a female-headed household at age 14, the same percentage as in the mother–son sample. The figures are the same for young women. The fraction of black young men is 28% in the whole sample, 26% for those matched to fathers, and 35% for those matched to mothers. For young women, the figures are 28, 28, and 35%, respectively.

It should be noted with regard to sibling pair analysis that the restrictions we imposed on the sample (out of school and over 24 years old) may imply that we are looking at siblings who are somewhat closer in age and from somewhat larger families than would be the case from a representative sample. However, we suspect that this problem is minor given that the initial age range of the young men and women was 14 to 24 years.

Distributions of the Number of Observations Entering the Time Average Calculations

Table A3 reports the percentage distribution of individuals by the number of observations used to compute the time averages for the various labor market variables used in the analyses. The number of yearly observations ranges from 1 to 12 and varies according to the number of years in which reports on the particular variable were collected, and on the number of valid reports the individual supplies after our age, schooling, and retirement screens are applied. For example, in the case of young men, only 1 observation on family income was available for 42% of the sample. The corresponding figure for young women is 24%.

ACKNOWLEDGMENTS

This research was funded by the United States Department of Labor, Bureau of Labor Statistics, under Contract Number J-9-J-7-0094. Opinions stated in the paper do not necessarily represent the official position or policy of the U.S. Department of Labor. Extensive research support from the Center for Urban Affairs and Policy Research, Northwestern University, is also gratefully acknowledged. Avner Greif, Alex Idichandy, Michele Borsetti, Yasuyo Abe, and James Spletzer provided skillful research assistance. Gary Solon provided a number of useful suggestions. Blame us for the shortcomings of the paper.

NOTES

1. See Becker and Tomes (1986) for references. Solon (1989a,b) provides a critique of the previous intergenerational studies and provides new evidence based on the Panel Study of Income Dynamics (PSID). His results are discussed below. Bielby and Hauser (1981) use *Current Population Survey* (CPS) data to analyze the relationship between son's earnings and the son's report of parental income and attempt to correct for biases that arise from response error. They obtain a correlation of .161. (See their Table 8.) Other prominent references in the literature include Brittain (1977), Griliches (1979), Solon et al. (1987), Corcoran and Jencks (1979), Kearl and Pope (1986), Olneck (1977),

Table A3. Percentage Distribution of Individuals by Number of Observations Used to Compute Time Averages

Variable	Sample Size	*Number of yearly observations entering time average* 1	2	3	4	5	6	7	8	9	10	11	12
Young men													
Log family income	3423	42	31	7	7	5	4	3	1				
Log earnings	4030	12	12	12	14	16	12	5	4	4	4	3	2
Log hourly wage	4003	14	13	13	14	16	10	6	4	3	3	2	2
Log hours/week	4130	11	10	10	14	18	13	7	5	4	4	4	
Log weeks worked	3888	14	22	22	24	6	5	4	3				
Weeks unemployed	3939	14	22	22	24	6	5	4	3				
Log annual hours	3872	15	23	23	23	6	5	5					
Employers/year	4084	11	10	12	14	17	12	6	4	4	4	3	3
Collective barg.	3713	14	15	18	32	6	6	9					
Union status	1642	32	19	17	21	4	3	4					
Young women													
Log family income	3855	24	43	10	8	7	4	3	1				
Log earnings	3673	19	15	16	21	11	6	5	3	2	1	1	
Log hourly wage	3681	18	15	17	20	13	6	4	3	2	1	1	
Log hours/week	3797	17	14	16	22	13	6	5	3	2	1	1	
Log weeks worked	3581	23	24	26	23	3	1						
Weeks unemployed	4044	13	18	31	31	4	3						
Log annual hours	3562	23	24	27	23	2	1						
Employers/year	3519	21	16	17	19	11	5	5	3	1	1	1	
Collective barg.	3560	23	18	18	25	6	4	3	3				
Union status	1226	52	20	11	12	2	1	1	1				
Older men													
Log family income	4884	8	12	18	25	24	12	1					
Log earnings	4274	11	18	19	15	14	13	7	3				
Log hourly wage	4052	14	20	17	30	9	7	2	1				
Log hours/week	4767	11	11	11	15	13	12	8	9	6	3	1	
Log weeks worked	4782	9	9	12	26	13	8	10	8	4	1		
Weeks unemployed	5017	9	10	11	25	13	8	11	9	4	1		
Log annual hours	4756	12	13	13	22	11	8	11	6	3	1		
Employers/year	4691	10	8	11	15	14	14	7	10	7	3	1	
Collective barg.	3005	27	45	27	1								
Union status	1175	59	30	10	1								
Mature women													
Log family income	4845	10	9	12	16	18	21	14					
Log earnings	3973	17	8	11	11	11	8	8	12	13			
Log hourly wage	3996	13	8	8	10	8	8	7	7	9	11	11	
Log hours/week	4275	12	8	7	7	8	8	7	8	8	10	15	
Log weeks worked	4284	11	10	14	11	11	10	14	18				
Weeks unemployed	4891	5	8	5	16	19	22	25					
Log annual hours	4155	15	15	12	13	14	14	17					
Employers/year	4116	10	8	8	8	8	7	8	8	7	7	9	12
Collective barg.	3205	21	27	18	34								
Union status	868	43	29	13	15								

Behrman and Taubman, (1985), and Taubman (1977). Atkinson et al. (1983) find large intergenerational correlations using an English sample. We discuss several other related studies below.

2. Becker and Tomes mention the problems of measurement error and transitory variation in income, and several of the studies they cite use time averages to try to reduce the problem. The problems posed by homogeneous samples are not well known, although Corcoran and Jencks (Chapter 3, Section 1) mention it in the context of studies of sibling correlations.

3. Why focus on the correlation in permanent income rather than total income? The answer is that we view the inequality of lifetime income rather than inequality of income in a given year as the key variable of interest, and transitory variation in income that is weakly correlated across years has little effect on the cross-sectional variance in income over a lifetime. Consider the case in which income in a given year for a particular person is the sum of a fixed or permanent component and a serial uncorrelated transitory component. Suppose that the variance in the transitory component is twice as large as the variance of the permanent component. Then the contribution of the permanent component to the cross-sectional variance in the undiscounted sum of income over a 40-year period is 1600/(40·2) or 20 times larger than the contribution of the transitory component. Discounting increases the relative importance of the transitory component, but for realistic interest rates, the permanent component dominates the income variance. The relative importance of transitory factors does increase if they are correlated over time. However, even if the transitory components were a series of disturbances that took on the same value for four years, then the contribution of the permanent component would be 1600/(4·4·10·2) or 5 times larger than the contribution of the transitory components.

It should be pointed out that the term *permanent component* is used in the paper to refer to a component that is fixed over time for a given individual. In fact, it is more realistic to consider income as the result of an initial condition that remains fixed, a random-walk component that accumulates over time, and a transitory component that is uncorrelated across periods of more than a year or two. In this circumstance parental income and earnings in a given year reflect not only their earnings capacity at the time they entered the labor market but also the accumulated effect of changes in fortune that have occurred over many years, some of which may have occurred long after their children left the household. Our estimates of the variance of parental income will reflect not only the variance of initial parental income but also the variance of the accumulated random-walk component. (Note that below we report that the variances of father's family income, earnings, and wage rates are larger than the corresponding values for sons.)

Our estimates of the covariance between parents and children will reflect covariances of the child's income with the parents' fixed income component and with the parents' random-walk component. Assuming that most of the intergenerational correlation is in the fixed components of income rather than in the stochastic variation that occurs after entry in the labor market, then the correlation between a parent's income at age 50 and the child's income at age 30 may be greater (less) than the correlation between the parent's income at age 50 (30) and the child's income at age 50 (30). This is because as the child and parent age, the importance of the child's and the parent's random-walk components of income increases, lowering the correlation coefficient. In future work, it would interesting to estimate family correlations in discounted lifetime income using a statistical model of income that allows for random-walk components and serially uncorrelated components. See Jenkins (1987) for a more detailed analysis of some of the issues associated with using data on fathers and sons from only a portion of the life cycle.

4. Behrman and Taubman (1989) report education correlations for a variety of family relationships, including sisters-in-law. Blau and Duncan (1967) analyze evidence from the "Occupational Changes in a Generation" supplement to the 1962 CPS, indicating that there is a substantial correlation between the occupational status of father-in-law and sons-in-law and between fathers-in-law.

5. The gap in our knowledge is due in part to the fact that analysis of these questions requires detailed panel data for a representative sample on the labor market experience of mothers and fathers and sons and daughters. Until recently, the necessary data have been unavailable. Altonji (1988) and Corcoran et al. (1989) are among the few studies that provide data that can be used to address the question of whether the strong relationship between an individual's income and that of his parents is due to

common work effort, to hours worked, to unemployment experiences, to common wage levels at the time of entry into the labor market, or to common returns to education and experience.

6. It also should be noted that although the NLS provides yearly sampling weights for each member of each cohort, we do not employ a weighting scheme in our analyses. Because we work with a large number of family relationships and rely on unbalanced panel designs, it is difficult to formulate an appropriate weighting procedure. Furthermore, it is not clear how to apply the sampling weights for individuals to the family matches that we create. The original NLS samples were designed to be representative of the civilian noninstitutionalized population at the time of the first survey. Black and low-income households were oversampled to insure their representation in the samples.

7. There is always a concern in an analysis of sibling or intergenerational data that the very fact that it was possible to collect data on several family members makes the data unrepresentative. For example, it is necessary for more than one sibling to remain in our sample past the age of 24 in order for the sibling pair to contribute to our analysis. In the case of the NLS, two special problems come to mind. First, both the father and the child must satisfy the age restrictions of the sample design in the base year of the survey. Since a substantial number of children leave the household by age 24, one might expect that the matched sample would overrepresent individuals who are still living with their parents when they are in their early twenties. This problem is mitigated to some extent by the fact that the young men in the father–son sample are about 0.7 years younger than the entire young men's sample: 17.4 versus 18.1 years in 1966. Young women in the father–daughter sample are also younger on average than the entire young women's cohort: 18.2 versus 18.7 years in 1968.

We have computed descriptive statistics for the matched parent–child samples and compared them to the corresponding full-cohort samples. A summary is presented in the appendix section "A Comparison of the Matched Samples and the Full-Cohort Samples."

8. If a labor market variable such as the wage rate is equal to a fixed component and a transitory component that can be represented by a moving-average process of order 2 or less [MA(2) process], then the transitory component will not bias our variance estimates. Abowd and Card (1989) develop a three-components-of-variance model to describe the covariances of hours changes and earnings changes for adult males in the NLS, the PSID, and the Denver Income Maintenance Experiment/Seattle Income Maintenance Experiment data sets. The components are as follows: a stationary serially uncorrelated measurement error, a shared component of hours and earnings that follows a nonstationary MA(2) process, and a time-varying component that affects only the variances of earnings and hours and their contemporaneous covariance. They show that such a representation fits the estimated covariances of hours and earnings quite well. They find in all three data sets that changes in the experience-adjusted log earnings and log hours are uncorrelated with their own lagged changes at more than two periods. Since differencing increases the order of an MA term by 1, their results indicate that the MA error component in the level of earnings and hours is of order less than 2.

9. We work with the residuals of a regression of each of the labor market outcomes against a cubic in age and a set of year dummies.

10. It would probably be possible to improve upon the efficiency of our method-of-moments and time average estimates through a reweighting of the data, but we have not attempted to do so.

11. In estimating our equations, we also calculated $WAGE_{ik(t)}$ variously by omitting the first two, three, and then four observations from the pseudomean calculations. In these instances, we need not require that the transitory error be white noise. We can allow the error to be a moving-average process of order 1, 2, or 3, respectively. Any differences in the estimation results using the various pseudomeans are noted in the discussion of the empirical results in Section IV. By way of summary, the coefficients on the parent's variables more often than not are larger as more years are dropped from the pseudomean instrument. This may indicate that the IV estimates in Table 5 are downward biased due to persistence in transitory shocks. However, in most cases, the standard error grows as a result of the shrinking sample size.

12. The standard errors we report for the OLS and IV equations ignore heteroscedasticity and

correlation among the observations on young men and women who are from the same family. We suspect they are understated by a small amount.

13. Complete sets of tables reporting the mean values, variances, correlations, and covariances of all the labor market outcomes for each type of matched family member pair and for each of the original cohorts can be found in Altonji and Dunn (1991) for slightly different samples. Tables are provided for both the time average and the method-of-moments approaches.

14. The reported figure is the number of potential matches *before* the cohorts were screened for minimum age and completed schooling or maximum age and retirement.

15. Solon runs OLS regressions of the son's earnings in 1984 on various constructions of the father's earnings variable, and age controls. Using a single-year measure of father's earnings, the father's variable coefficient ranges from .247 to .386, depending on the year of the father's report. When a five year average of father's earnings is used, its coefficient is .413. In an equation with son's 1984 log wage as the dependent variable, father's log wage in 1967 appears with a coefficient of .294. In an analogous equation for family income, father's log family income in 1967 enters with a coefficient of .483. Altonji works with the time average of the level rather than the log of family income and obtains a correlation of .37 between fathers and sons.

16. Solon also presents a set of estimates in which the intergenerational relationship is estimated from an instrumental variables estimate of the relationship between son's income in 1984 and father's income in 1967, using father's education as an instrument for father's income to reduce the effects of transitory variation in income. He obtains a regression coefficient of .530. For similarly constructed equations for wages and earnings, the IV coefficients are .449 and .526, respectively. However, he points out that the regression coefficient is an estimate of the intergenerational correlation coefficient only if the variances of the family income of father and son are equal. [As we note, this comment also applies to our OLS and IV estimates of Equations (6).] Second, he points out that this estimate is likely to be upward biased even if the family income variances are equal because father's education should probably appear as an independent variable in the son's family income equation.

When we repeat this IV estimation technique with son's log family income in 1981 as the dependent variable using father's reported education and age controls as instruments for his mean log family income, we find a coefficient of .381 on the father's variable. (Our corresponding OLS coefficient is .312.) For log wages, we find an IV coefficient of .431 (and an OLS coefficient of .315) on father's mean log wages. For log earnings, the IV coefficient is .404 (and the OLS coefficient is .233) on father's mean log earnings. In summary, our estimated IV coefficients are smaller than Solon's for the intergenerational income, earnings, and wage equations.

17. When control variables are excluded, the probability limit of the correlation coefficient is equal to the probability limit of the regression coefficient times the probability limit of the standard deviation of the father's outcome variable divided by the standard deviation of the son's outcome variable.

18. The coefficient on father's mean wage when control set I is used is .282. When we add controls separately for father's education, son's race, then son's education, the coefficient falls to .253, .226, then to .167. Repeating the procedure with log earnings, the father's coefficient begins at .218, then falls to .148, then to .142, and then to .067. Finally, race plays a slightly more important role in the annual hours relationship. With control set I, father's mean log annual hours enters with a coefficient of .190, which falls to .163 when controls for father's education are added separately. When only the son's education is controlled for, the father's coefficient drops to .124. When race is added by itself the coefficient is even lower at .085. Clearly, race and son's education are important in the relationship between the labor market variables of fathers and sons.

19. Also see our discussion in note 3. A number of studies, such as MaCurdy (1982) and Altonji et al. (1987), provide evidence that family income and earnings are subject to highly persistent shocks.

20. We investigated this hypothesis by including an indicator for "female-headed household at age 14" and the indicator interacted with the mother's average family income in the equations for the matched mother–child samples. Both the indicator and the interaction term enter insignificantly for both young men and young women using both sets of control variables. In a similarly constructed earnings

equation, the results are the same for young women. For young men, however, the indicator has a negative coefficient, the interaction term has a positive coefficient, and both are significantly different from zero. In summary, growing up in a female-headed household only alters the link between mother's earnings and son's earnings. See Peters (1990) for more detailed evidence from the NLS on the sensitivity of intergenerational links in income to family structure and parental education.

21. A comparison of the covariances reported in Tables 1 and 3 and the variance estimates reported in Tables 2 and 4 suggests that in most cases the larger correlations obtained with method-of-moments procedure result from smaller estimates of the variances for family member type rather than larger estimates of the covariances across family members of the various labor market outcomes.

22. Zimmerman (1990) has recently performed a similar analysis of earnings of fathers and sons using the NLS but employing somewhat different econometric methods. He concludes that the earnings correlation is between .35 and .40.

23. Bound et al. (1986) report cross-sibling wage correlations of .11 for brothers, .34 for sisters, and .07 for brothers–sisters. (See the results for LW2 in their Table 5.) However, these estimates are based upon only one wage observation for each individual and will be downward biased by measurement error or transitory variation.

24. The lower correlation for sisters masks the fact that the covariance in annual hours is much larger for sister pairs than brother pairs.

25. Solon et al. (1987), using data from the PSID and analysis of variance estimators, find the correlations of brothers' log earnings, log annual hours, and log wages to be .448, .410, and .534 . All are larger than our corresponding method-of-moments estimates, which are .37, .36, and .42. Corcoran and Jencks (1979) provide estimates from several survey data sets and pick .17 as the best available point estimate of the earnings correlation between brothers. They pick .12 as a minimum estimate and .28 as the maximum. We believe their estimates are downward biased as a result of an inadequate correction for measurement error and transitory earnings components.

26. Table 1 also presents family covariances and correlations for the time averages of the log of hours worked *per week* and the log of weeks worked per year. (We have not produced separate estimates of weekly hours and yearly weeks worked using the method-of-moments approach.) For brothers, the correlation based upon the time averages for hours per week is .22, for weeks per year is .12, and for annual hours is .13. For sisters, the hours per week correlation is .06, weeks worked .17, and annual hours .15. In light of the strong method-of-moments correlations for annual hours, we believe that these correlations are substantially reduced by the effects of measurement error and transitory variation in the time averages of hours worked per week and weeks worked per year.

The corresponding hours per week and weeks per year estimates for father–son pairs are .12 and .09, which are in line with the father–son correlation in the time average of annual hours of .10. We find weaker correlations in log weeks worked and log hours per week (occasionally some negative) for opposite-sex pairs.

27. Altonji (1988) obtains correlations of .171 for brothers and .151 for fathers and sons using the PSID and hours of unemployment during the year. Part of the correlation in both the NLS and PSID might arise from regional variation in labor market conditions that affects family members living in the same geographic area.

28. When we condition on having positive weeks of unemployment in at least one year (by taking time average of *log* weeks unemployed) the correlations are much larger: .34 for brothers, .39 for sister, .19 for brother–sister, .23 for father–son, and .15 for mother–daughter pairs. The sample sizes on which these correlations are estimated are dramatically smaller than those in Table 1.

29. The young women and mature women NLS data sets do provide some limited information on time spent on child care and household chores, which would make such an investigation possible. The PSID also contains the necessary data.

30. Using the PSID, Behrman and Taubman (1990) regress child's average log earnings over 1975–1984 on parent's average log income over the same period, interacted with child's age and race and gender indicators. Their preferred intergenerational regression coefficient is .60.

31. The IV sample is smaller because either log annual hours in 1965 or the average of the log of father's hours in years other than 1965 is missing in a few cases. (A similar explanation underlies the discrepancy in the OLS and IV sample sizes for the other variables in Table 5.) We do obtain strong and statistically significant IV estimates of the link between log weeks worked by the father and log weeks worked by the son. The IV and method-of-moments estimates of the regression coefficients are quite close in the case of mothers and daughters.

32. Altonji (1988) uses a small sample of father–son pairs from the PSID to estimate separate regressions for son's average values (over the years in which he works positive hours) of annual work hours, annual hours of unemployment, the log of the real hourly wage rate, the log of real earnings, and the job separation probability against the corresponding variable for the father and controls for the son's education, experience, and race, and the father's education and experience. His results show that virtually all of the father's labor market variables have a strong positive association with the corresponding labor market variable of the son. His results also suggest that race and father's education have independent influences on the labor market outcomes.

33. To be precise, Table 6 reports covariances and correlations of a young woman's reports of her husband's variables with the variables of the father, mother, and brother to whom the young woman can be matched. Similarly, young men supply the reports of their wives' variables for the covariances and correlations shown in Table 7. The spouses' reports were screened in much the same way as the young men's and young women's reports were: only reports made after age 24 and after schooling was completed were counted in the time averages.

It turns out that the time averages and number of yearly reports entering the average calculations of the young women's reports of her husband's labor market variables match very closely the time averages and number of valid reports for the corresponding variables for the whole young men sample. Similarly, the time averages of the young man's reports of his wife's variables match very closely those of the young women's cohort, as do the average number of yearly reports entering the time average calculations. Note that it is possible that a young woman's husband (or young man's wife) in fact may be included in the young men's (or young women's) cohort.

34. It is not difficult to fit the estimated earnings covariances to our simple model of family earnings relationships. First note that when $\mathrm{Var}(u_i) = \frac{1}{2}\mathrm{Var}(u_{ij})$, the implied siblings earnings correlation is .33, which is typical of the estimated siblings earnings covariances reported in Tables 1 and 3. [The siblings earnings correlation is

$$\mathrm{Corr}(E_{ij}, E_{ij'}) = \mathrm{Var}(u_i) / [\mathrm{Var}(u_i) + \mathrm{Var}(u_{ij})],$$

which equals .33 when $\mathrm{Var}(u_i) = \frac{1}{2}\mathrm{Var}(u_{ij})$.]

Simply dividing the brothers-in-law covariance (.095) by the brothers earnings covariance (.130) suggests $(b_1 + b_2) = .731$. Also, when the spouses' estimated earnings covariance—the average of which is .065 (see note 35)—is fitted into the model, the brothers-in-law covariance indicates that $b_2\ \mathrm{Var}(u_{ij}) = -.030$. Working through a few more steps produces estimates of $b_1 = .846$ and $b_2 = -.115$. When we use the sisters and sisters-in-law covariances to fit the model, the estimates are $b_1 = .615$ and $b_2 = -.100$.

The rough indications are that the family effect is substantial. A richer earnings model that allows sex differences in the influences of spouses might be able to explain the differences in the moments implied by the brothers and the sisters estimates. Such a model is currently being developed.

35. From Table 6 the covariance and correlation of spouses' earnings are .074 and .14 when the young woman supplies both reports. In Table 7, when the young man supplies reports on himself and his wife, the results are similar: the covariance is .055 and the correlation is .11. As for the other labor market variables, the spouse covariances and correlations are very similar whether a young man supplies both reports or a young woman does. For example, the spouse covariance of log hours worked per week is –.003 according to the young women's reports and –.002 according to the young men's reports, and the correlation is –.03 in both cases.

36. See, for example, Ballen and Freeman (1986) and Jackson and Montgomery (1986).

37. Garen (1988) provides a recent survey of the literature.

38. The estimated coefficient does not change much when we add controls for education of the son and the father, race, residence in the South, and residence in an SMSA.

39. Tables depicting these results are available form the authors.

40. For each of the four cohorts, the correlation of our turnover measure and the log wage rate is negative and significant. For young men the correlation is –.17, for young women –.26, for older men –.07, and for older women –.31. All have *p*-values of .0001.

41. It is interesting to note that whether or not one believes in noncompetitive wage differentials has implications for how one views the role of networks in the labor market. If wage differentials are competitive, and one views personal connections as important, then one must view them as important because they convey information about job openings and the characteristics of workers and jobs. If differentials are noncompetitive, then connections may be important because they provide access to rents.

42. The simple correlation between I_{is} and I_{if} is .19.

43. The set of control variables includes son's age and education, father's age and education (all in cubic specifications), son's race, residence in the South, and residence in an SMSA.

44. In another set of specifications we replaced the son's mean occupation premium with controls for son's mean time spent in each occupation. The coefficient on the father's mean industry premium was estimated to be .125 (t = 3.8) under specification (2) of Table 8. The coefficient fell to .096 (t = 2.5) when both the son's and the father's mean time in each occupation were added. Finally, when son's mean collective-bargaining status was added, the coefficient fell to .114 (t = 2.8) and then to .021 (t = 0.4) when father's collective-bargaining status was added. Overall, mean time in each occupation steals more explanatory power from the father's mean industry premium than do the mean occupation premium measures. It is not at all clear that one wishes to control for parental or son's occupation, since these may be related to unobserved differences in labor quality that in turn are related to industry.

45. If one assumes that the father is able to help his son get a job in his own industry but not in another industry, then in principle one can try to discriminate between the two hypotheses by examining the sample of sons who do not work in the same industries as their fathers. The fact that individuals hold jobs in more than one industry over a period of years complicates selection of the appropriate subsample of fathers and sons. However, one can take the inner product of the vector of time means of the industry dummies of the fathers and sons, and reestimate over the sample for which the inner product is zero or below a certain threshold.

Unfortunately, a second problem is introduced. By eliminating fathers and sons who are in the same industry, one induces a systematic *negative* correlation between their industry coefficients. Thus far, we have not found a simple econometric procedure to eliminate this bias. If one ignores the bias and estimates the industry effects on the sample of fathers and sons who rarely work in the same industry, one obtains (unsurprisingly) a negative relationship between the average industry premiums. In future work, we plan to provide a descriptive analysis of the links between industries of fathers and sons and an estimation procedure that provides consistent estimates of the effects of the father's industry wage effect on the son's when they are not in the same industry.

As a further test, we added the square of the father's industry premium to our regression specifications on the grounds that if family connections provide a young man the option to work in the father's industry, the option would only be exercised if the father worked in a high-wage industry. This line of reasoning would lead one to expect a positive coefficient on the quadratic term. In fact, we obtained a positive and large (.311) but statistically insignificant coefficient on the father's squared industry component.

46. Blakemore, Hunt, and Kiker (1986) using a sample of fathers and sons from the NLS estimate the wage effect of collective-bargaining coverage to be 4.8% and the union membership effect to be 9.7% for young men.

47. The simple correlation of father's and son's mean collective-bargaining status is .22.

48. See for example, Blau and Duncan (1967).

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