PREFACE

Understanding how worker well-being is distributed across the population is of paramount importance. With such knowledge policy makers can devise efficient strategies to improve social welfare. This volume contains 13 chapters on topics enhancing our comprehension of inequality across workers. The issues addressed deal directly with the economic institutions that affect individual and family earnings distributions. The themes explored include job training, worker and firm mobility, minimum wages, wage arrears, unions, collective bargaining, unemployment insurance, and schooling. Among the questions answered are: To what extent do greater work hours of women mitigate the widening family earnings distribution? To what extent does deunionization widen the distribution of earnings? Do computers really cause a widening of the earnings distribution? How would the Russian wage distribution change if one accounted for wage arrears? How much of job creation and job destruction comes about because of business relocation? To what extent does maternal education increase children's education? Why do increases in the minimum wage fail to substantially decrease employment as economic theory would predict? And, to what extent do job skills matter for low-income workers?

The widening dispersion of earnings in the United States and other economies over the last 30 years is now well documented. Not only has this dispersion grown for individual wage earners, but family earnings has become more dispersed, as well. However, understanding family earnings dispersion is complicated because labor force participation decisions of husbands and wives are interrelated. In the first chapter, John Pencavel examines US family earnings inequality between 1926 and 1995. First, he shows that earnings inequality among all couples has increased over the sample period. Concomitant with this increased disparity is higher earnings inequality both among men and women, but women's higher labor hours have had a mitigating impact on inequality among couples. Pencavel studies to what extent changes in earnings inequality (for husbands and wives separately) are driven by changes in employment.

Decisions regarding where and how much to work are in part potentially related to job creation and destruction. In the second chapter, David Neumark, Junfu Zhang, and Brandon Wall present a new data source – the National Establishment Time Series (NETS) – which offer rich possibilities for studying employment dynamics by tracking business establishment relocations that contribute to regional job creation/destruction. The authors first assess the quality and the measurement accuracy of the data by comparing the California extract to alternative data sources along various dimensions. Then they decompose employment changes into components related to (i) changes in the size of existing firms; (ii) changes due to birth and death of establishments; and (iii) changes due to relocation of firms (into and out of California). The chapter provides evidence that the highly debated phenomenon of business relocation accounts only for a small share of the overall job creation/destruction process, and the chapter derives policy conclusions.

In part, earnings dispersion has been widening because of increased training. In the next chapter, Alison L. Booth Mark L. Bryan examine who pays for training. It is one of a new genre of articles to find that corporations finance general training, counter to the prediction of the commonly applied human capital model that assumes no fixed costs of job mobility. Booth and Bryan use the British Household Panel Survey (BHPS) to show that despite the most work-related training being general the preponderance of training is paid by the firm despite most work-related training being general. This result is consistent either with credit constraints or substantial fixed costs of mobility, and implies that general training is more specific than once thought.

Not widely studied is earnings dispersion in Russia. In the next chapter, Hartmut Lehmann and Jonathan Wadsworth use the Russian Longitudinal Monitoring Survey for the years 1994–1998 to assess the effects of wage arrears on wage inequality. Specifically, using various econometric techniques, Lehmann and Wadsworth estimate what the wage distribution would look like if all workers had been paid their full contractual wage on time, i.e., if there were no arrears. This counterfactual series suggests that wage inequality would have been some 30% larger if workers had been paid in full. Moreover, since wage arrears affect men more than women, the gender pay gap would have been around 10% higher than the observed gap. On the other hand, both regional pay differentials and sectoral differentials would have been narrower in the absence of arrears. In short, wage arrears widen the observed earnings distribution. Thus, one must take arrears into account when making policy recommendations based on the overall wage distribution.

Most of the current literature argues that one can attribute the widening of the earnings distribution over the last 30 years to skill-biased technological change (SBTC). Many have argued that in part SBTC comes about because computers have become particularly useful in the workplace. In the next chapter, Michael J. Handel examines four possible mechanisms by which computers can affect skill demand. However, he finds none of these potential causal links between computers and wages to be strong and that the individual computing wage premium is negligible. In addition, he argues the timing and magnitude of the increase in computer usage appear inconsistent with the rise in inequality. He concludes that computers have done little to change the US wage structure in the last 20–30 years.

Where migrants locate geographically is important not only to the migrants but also to policy makers seeking to control a particular area's economic growth. One commonly observed phenomenon regarding locational choice is immigrant clustering, whereby immigrants of a particular racial, ethnic, or religious ilk locate in areas populated by similar inhabitants. In other words, a location has significant externalities based on its "ethnic capital". In the next chapter, Thomas Bauer, Gil S. Epstein, and Ira N. Gang perform an empirical study of Mexican migration to various US locations. Their innovation is to get at a location's ethnic capital by showing how an area's migrant "stock" and migrant "flow" affect the probability of migration. The significance and size of the effects vary according to the migrant's legal status and whether the migrant is a "new" or a "repeat" mover.

Understanding low-skilled jobs is important for policy makers seeking to alleviate poverty. The next chapter by Rucker C. Johnson analyzes wage growth prospects of former and current welfare recipients. He finds job markets for these workers have many of the same features as typical labor markets for the mainstream population. As such, jobs differ in their prospects for wage growth. Some jobs allow for wage increases and further job advances over the course of employment, while others do not. Similarly, low-skilled workers differ in their abilities and skills. Using the Women's Employment Survey along with the Michigan Employer Survey containing data from 1997 to 2004, Johnson finds that even in low-skilled jobs, workers sort based on ability. Workers with greater relative skills (such as knowledge of the computer) gravitate toward jobs with greater skill requirements and achieve a larger wage growth. Those relatively skilled workers initially in less desirable jobs move to better ones, so that turnover is smaller when able workers initially attain relatively more skilled jobs with higher wage growth. From a policy perspective these results question welfare reform that concentrates solely on job placement rather than training because in the end skills are found to be important even for current and former welfare recipients.

Unemployment insurance (UI) is a mechanism of government's mandate to ease a workers downside risk of unemployment. Typically employers and/or employees are required to pay into a central fund from which workers can draw if they later become unemployed. Rates are set using the ''law of large numbers'' that implies that the reported losses will be based on the underlying probability of the loss. In the long run the premium for each worker and firm should reflect the expected loss equally across all the insured. However, in the short run or with imperfect rating schemes cross-subsidization can occur. In the next chapter, by using 1986–1996 Canadian data that link firms, workers and claimants, Miles Corak and Wen-Hao Chen compute cross-subsidization benefits across industries, provinces, and firms, as well as the dead-weight losses of the Canadian UI system. They find significant transfers from cyclical to non-cyclical industries and significant transfers to industries with high separation rates and low wages. Also there is significant cross-subsidization between firms in subsidizing as well as receiving industries.

The widening earnings dispersion observed in many developed countries is now well documented. Also well documented is the decline of union membership in Britain. Given that unions tend to equalize wages, one can ask how much of the increase in Britain's wage dispersion is caused by declining union representation. In the next chapter, John T. Addison, Ralph W. Bailey, and W. Stanley Siebert utilize the 1983 General Household Survey (GHS) data and the 1995 Labor Force Survey (LFS) to answer this question. They find that the large decline in union density accounts for little of the increase in earnings variation in the private sector, either for men or women. However, in the public sector, although union density declined less precipitously, earnings dispersion has more or less held steady. The difference, they argue, results because public sector unions organized relatively skilled workers. As such, changes in the composition of unionized workers are important in understanding earnings dispersion.

Of course, the future of any nation lies in the human capital acquisition of its children. But in the underdeveloped world, acquiring human capital often costs the household dearly, so that overall levels of education remain relatively low. This is particularly true for girls in Nepal where literacy rates are particularly depressed. Thus, understanding the factors affecting children's education is important to get these types of countries on a path to higher plateaus of development. Development economists often model household behavior and test their models with data, so they can ascertain the factors that enhance the probability children get more education. However, one problem with empirical work is the type sampling techniques used to gather data. In particular, most surveys in developing countries are two-stage stratified samples of households in which the first stage samples villages, and the second samples households from within each village. However, households within each village often have similar characteristics, so that ignoring these cluster fixed effects is likely to result in biased estimates. In the next chapter, Diane Dancer and Anu Rammohan utilize a household Nash bargaining model to obtain derived demand curves for children's education. They then employ a cluster fixed-effects model using the Nepal Demographic Household Survey. As might be expected, they find that boys receive more education than girls, and that higher maternal education (both primary and secondary) more greatly affects the schooling of girls. Greater household wealth equally increases education of male and female children.

One important and often debated question is the effect of raising the minimum wage. At least for Britain and the United States a number of studies found only a meager detrimental impact on employment. These weak employment effects have served to justify small increases in the minimum wage. In the next chapter, Sara Lemos uses monthly data for Brazil from 1982 to 2000 to show that increases in the minimum wage raise not only wages but also prices. This sets off a wage–price inflationary spiral, but with little effect on employment. One implication is such inflationary pressures mitigate the power of using minimum wage increases as a tool help alleviate poverty.

In the next chapter, Cary Deck and Amy Farmer present a series of experiments to test how final offer and conventional arbitration affect bargaining outcomes. They consider the impact that the choice of dispute–resolution mechanism, conventional or final offer arbitration, has on settlement. They formally show that final offer arbitration can favor the informed party by shifting the contract zone toward more profitable allocations. Laboratory results confirm this result. Nonetheless, settlement is positively correlated with the width of the contract zone, which suggests that the location of the contract zone in final offer arbitration generates more disputes.

The final paper is purely theoretical. It analyzes why productivity is only weakly correlated with the business cycle, contrary to the implications of real business cycle models. In RBC models, positive productivity shocks raise the demand for labor, leading to higher levels of employment. In the model here, firms reduce their hiring standards in order to achieve their desired level of employment. As a result, firms increase the proportion of low-ability workers in their workforce, which moderates the observed change in productivity.

As with past volumes, we aimed to focus on important issues and to maintain the highest levels of scholarship. We encourage readers who have prepared manuscripts that meet these stringent standards to submit them to *RLE* via the IZA website (http://www.iza.org/index_html?lang=en&mainframe=http%3A//www.iza.org/en/webcontent/index_html) for possible inclusion in future volumes. For insightful editorial advice in preparing this volume, we thank Paul G. Althaus, Ann Bartel, Andrea H Beller, Mike Bognanno, Holger Bonin, Marco Castillo, Ludo Cuyvers, Andy Dickerson, Bruce Fallick, Gary S. Fields, Belton M. Fleisher, Alessandra Guariglia, Peter Haan, Todd Idson, Murat F. Iyigun, Peter Kuhn, David MacPherson Lena Nekby, Trond Petersen, Patrick Puhani, Barbara Rossi, Shannon Seitz, Wendy Sigle-Rushton, Curtis Simon, Konstantinos Tatsiramos, and Phanindra V. Wunnava.

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EARNINGS INEQUALITY AND MARKET WORK IN HUSBAND–WIFE FAMILIES☆

John Pencavel

ABSTRACT

Constructing pseudo-panel data from successive Current Population Surveys, this paper analyzes earnings inequality in husband and wife families over the life cycle and over time. Particular attention is devoted to the role of labor supply in influencing measures of earnings inequality. Compact and accurate descriptions of earnings inequality are derived that facilitate the analysis of the effect of the changing market employment of wives on earnings inequality. The growing propensity of married women to work for pay has mitigated the increase in family earnings inequality. Alternative measures of earnings inequality covering people with different degrees of attachment to the labor market are constructed. Inferences about the extent and changes in earnings inequality are sensitive to alternative labor supply definitions especially in the case of wives.

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1. INTRODUCTION

To what extent do the increases in earnings inequality among individual American workers pose an issue for public policy? To answer this, we would want to know the extent to which changes in individual earnings translate into changes in income inequality in the households within which these earnings are pooled and shared. The link between the earnings of one household member and the income consumed of each household member depends not only on the magnitude of this individual's earnings but on whether other household members work for pay, and, if so, how many hours they work, on other sources of income, and on changing patterns of household formation and dissolution. Hence, the connection between the growth in inequality of individual pay and changes in income consumed by individuals (both those who work for pay and those who do not) is complex and involves a number of interrelated factors.

Some of these links are traced out in this paper which focuses on income in husband–wife families. First, we determine the extent to which changes in income inequality are attributable to changes in inequality in labor market earnings. Second, we examine changes in family earnings inequality and assess how increases in wives' employment have affected family earnings inequality. To address this, a simple and compact accounting framework is derived that describes the movements of family earnings inequality and that may be used to discriminate between the part played by husbands' earnings and that played by married women's employment in understanding movements in family earnings inequality.

We then turn to earnings inequality of wives and husbands separately and ascertain how changes in earnings inequality are affected by differences in the degree to which the husbands and wives work in the labor market. Again, a simple expression is derived that links earnings inequality to the employment–population ratio. This inspires the more general question: are inferences about differences and changes in earnings inequality sensitive to variations among people in their commitment to market work? Imagine the population being censored in increasing degrees by the extent of their market work: have the changes in earnings inequality for these groups in the population been the same?

In addressing these questions, the analysis will recognize that income inequality varies over the lifetime: husband–wife incomes are more unequal among older couples than among younger couples. Furthermore, the past 30 years has seen an aging of the typical husband–wife couple induced in part by the postponement of age of first marriage. In 1967–1969, in almost

14 percent of all couples, the wives were aged between 20 and 25 years; by 1998–2000, only 5.4 percent were in this category. In 1998–2000, there were almost 10 percent more couples with wives aged above 36 years than there were in 1967–1969. By organizing the data by years since leaving school, we differentiate between two time effects on income inequality: the increase in income inequality associated with the aging of a household and the increase in income inequality that has occurred over time even among households of the same age.[1]

At the outset, some important restrictions on the analysis need to be noted. First, the data used in this paper are drawn from successive March Current Population Surveys and they do not constitute genuine panel data, which can record changes in the marital status of a given population. On the other hand, panel data have serious problems of nonrandom attrition with changes in marital status constituting one of the key reasons for losing individuals from the panel survey. The CPS allows the construction of pseudo-panels and, as the principal source of information about the U.S. labor force, the CPS provides a large and accurate characterization of the U.S. population.

Second, over the past 30 years or so, the number and attributes of married people have changed: many fewer adults are now married with spouse present and those who are married tend to be better schooled and older (relative to unmarried people) than they were in the 1960s. So married people at the end of our period are a more select group of the adult population.

Third, this paper focuses on incomes generated by the market so government taxes and transfers will be ignored. Of course, the presence of such taxes and transfers may well affect the level and structure of market incomes but this is neglected here. At the same time, the movement of pre-tax household income has followed closely the movement of post-tax household income even though there have been nonnegligible changes in the tax structure as in the Tax Reform Act of 1986 and the reform of the welfare system in the 1990s.[2]

We turn first to a description of the data and the methods underlying this research.

2. CONSTRUCTION OF THE DATA

There are different ways of examining the evolution of people's earnings over time. In a companion paper (Pencavel, 2006), husband and wife couples are organized by their year of birth and by their age.[3] In this paper, people are "born" when they have completed their schooling so each cohort is defined as the calendar year in which the cohort members left school and could have started their market work careers. Their "age" is measured by the years that have elapsed since schooling completion. Years since completion of schooling is called "experience".[4]

When a husband and wife are born in the same year and complete the same schooling, the couple's cohort and experience are the same whether defined by the husband's characteristics or the wife's. However, when the wife's year of birth and schooling differ from the husband's, their cohort and experience may not be the same. Because cross-classifying husbands and wives by the cohort and experience of each individual consumes many degrees of freedom, we define cohorts by 5-year intervals so that some couples of the same age would have to have large differences in schooling not to be in the same cohort and we index a family's "experience" by the years since the wife has left school. We organize the family's data by the wife's experience and cohort because the relationship between the employment and earnings of wives and family earnings inequality plays a special role in this analysis.

The Annual Demographic Supplements of the March Current Population Surveys for 1968 through to 2001 are used to sort husband and wife couples into cohorts defined by the estimated year of schooling completion and by the years of experience of the wife. Each cohort covers a 5-year interval from 1926–1930 to 1991–1995. Table 1 lists the resulting 294 cohort-experience cells we use. Each cell consists of no less than 1,000 husband–wife pairs.

Three components of family income are distinguished: the husband's earnings; the wife's earnings; and the interest, dividends, and rent received by the husband and wife. These components are measured before tax and transfers – the purpose is to examine the differences across families in the incomes generated by the market, not by the adjustments that governments make to these incomes – and they neglect the incomes of any other family members. For any experience x and cohort c cell, let $y_{Hi}(x,c)$ denote the annual earnings of the husband in household i, $y_{Wi}(x,c)$ the annual earnings of the wife in household i, and $y_{Ni}(x,c)$ the annual nonlabor income (the sum of dividends, interest, and rent) of household i.[5] To be included, both husband and wife must be at least 20 years of age and not more than 60 years. To avoid the difficulties in measuring the labor returns to people who are self-employed, couples containing a self-employed worker are excluded.

For most husband–wife families, labor market earnings constitute the most important components of income and nonlabor income represents a

Table 1. Definitions of Cells by Cohort and Experience (Omitting Cells with Fewer than 1,000 Husband–Wife Pairs).

Cohort	Years of Schooling Completion	Minimum Years of Experience	Maximum Years of Experience	Number of Cells
1	1926–1930	39	44	6
2	1931–1935	33	44	12
3	1936–1940	28	44	17
4	1941–1945	23	44	22
5	1946–1950	18	43	26
6	1951–1955	13	42	30
7	1956–1960	8	40	33
8	1961–1965	3	37	35
9	1966–1970	2	32	31
10	1971–1975	2	28	27
11	1976–1980	2	23	22
12	1981–1985	2	18	17
13	1986–1990	3	13	11
14	1991–1995	3	7	5
All	1926–1995	2	44	294

An individual's experience is defined as the minimum of (1) her years of age minus her years of schooling minus 6 and (2) her years of age minus 17. Then an individual's cohort is defined as the calendar year in which her experience is zero.

relatively small part. Across these 294 cells, the average of the ratio of nonlabor income to total income is 0.045. Furthermore, for a study of income inequality across all husband–wife families, variations in nonlabor income are not important. This is illustrated in Fig. 1 where for two cohorts, cohorts 6 and 9, the Gini coefficients of income inequality are graphed: one Gini coefficient includes nonlabor income (this is marked as ''incl N'') and the other Gini coefficient excludes nonlabor income (marked as ''excl N''). For each cohort, income inequality rises with experience and the more recent cohort, cohort 9, exhibits greater income inequality than the earlier cohort, cohort 6. The values of the Gini coefficient that includes nonlabor income is slightly higher at low years of experience and slightly lower at high years of experience than the values of the Gini coefficient that excludes nonlabor income. However, the movements in the two Gini coefficients are close. Across all 294 experience-cohort cells, the correlation coefficient between the Gini coefficient including nonlabor income and the Gini coefficient excluding nonlabor income is 0.993. In view of this, we shall simplify our analysis of inequality by neglecting nonlabor income and by concentrating on labor

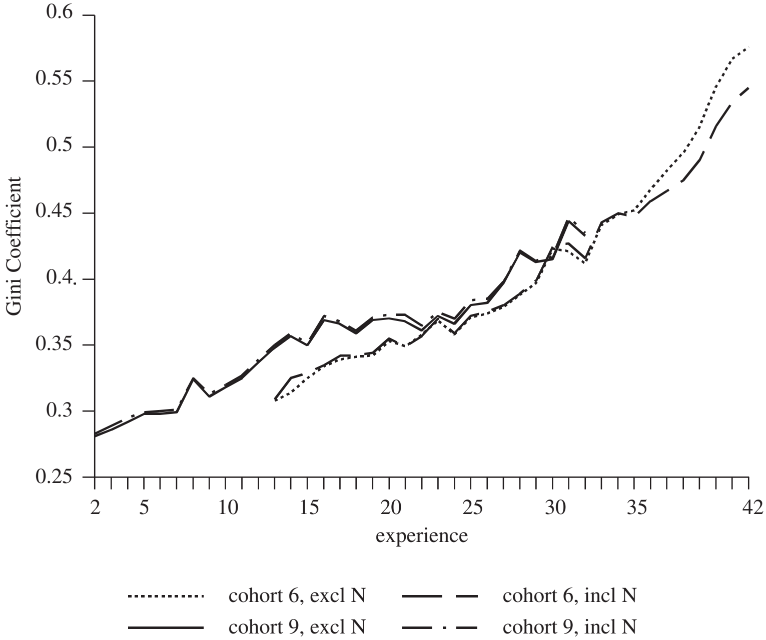

Fig. 1. Gini Coefficients for Cohorts 6 and 9: Including and Excluding Nonlabor Income. *Note:* "excl N" means excluding nonlabor income and "incl N" means including nonlabor income.

earnings. We shall call the sum of the husband's earnings and the wife's earnings "family" earnings: $y_i(x,c) = y_{Hi}(x,c) + y_{Wi}(x,c)$.[6]

3. AN EXPRESSION TO DESCRIBE MOVEMENTS IN FAMILY EARNINGS INEQUALITY

The purpose of this section is to derive an expression permitting reliable simulations of the movements of family earnings inequality. This expression is addressed to assessing the extent to which increases in wives' employment have affected family earnings inequality. The equation to be derived takes the following form:

$$G = \beta_0 + \beta_1 G_H + \beta_2 \frac{m_W E_W}{m_H E_H} + \beta_3 \left[\frac{m_W E_W}{m_H E_H}\right]^2 + u \tag{1}$$

where G stands for the Gini coefficient of family earnings inequality, G_H is the Gini coefficient of husbands' earnings inequality, E_H and E_W are, respectively, the employment–population ratios of husbands and wives, m_H and m_W are the mean earnings of husbands and the mean earnings of wives among those husbands and wives employed for pay, and u is a term that incorporates other factors. The β's are parameters to be estimated. This expression is an approximation to an accounting framework. It will be shown that a very large fraction of the variations in family earnings inequality is removed by this linear (in the parameters) approximation and that Eq. (1) provides a compact means of discriminating between the roles of husbands' earnings inequality and married women's employment to describe the movements in family earnings inequality. We proceed to deriving and rationalizing Eq. (1).

If $\sigma_H\,(x,c)$ is the standard deviation of the earnings of husbands, $\sigma_W\,(x,c)$ the standard deviation of the earnings of wives, and $\sigma\;(x,c)$ the standard deviation of family earnings, then

$$\sigma^2(x,c) = \sigma_H^2(x,c) + \sigma_W^2(x,c) + 2r(x,c)\sigma_H(x,c)\sigma_W(x,c)$$

where $r(x,c)$ is the correlation coefficient between the earnings of the spouses. To reduce needless notation, we drop the cohort, c, and experience, x, identifiers. Let V denote the coefficient of variation in family earnings (i.e., $V = \sigma/\mu$, where μ stands for the mean of family earnings) and let V_j represent the coefficient of variation in j's earnings (i.e., $V_j = \sigma_j/\mu_j$), where $j = H,\ W$. Then the previous equation may be written

$$V^2 = (B_H)^2(V_H)^2 + (B_W)^2(V_W)^2 + 2rB_HB_WV_HV_W \tag{2}$$

where $B_H = \mu_H/\mu$ and $B_W = \mu_W/\mu$. So B_H and B_W are, respectively, each cell's average values of the shares of the husband's earnings and of the wife's earnings in family earnings. In Section 5 of this paper, expressions will be derived for $(V_H)^2$ and $(V_W)^2$ that involve the employment–population ratios of husbands and wives, respectively, but for now we concentrate on family earnings inequality, V^2 in the previous equation.

Descriptive statistics on all elements of Eq. (2) are contained in Table 2. The values of these variables describe all husband–wife households regardless of their labor market status. People who do not work in the market report zero earnings and such people are included in the statistics in Table 2. Thus the coefficient of variation of wives' earnings, V_W, is higher than that of husbands', V_H, principally because the employment–population ratio of wives has been much lower than that of husbands and, therefore, the frequency distribution of wives' earnings has a much higher spike at zero.

Table 2. Descriptive Statistics on Variables for 294 Experience-Cohort Cells.

	Variable	Mean	S.D.	Minimum	Maximum
1	V^2	0.601	0.253	0.234	1.600
2	$(V_H)^2$	0.820	0.406	0.256	2.598
3	$(V_W)^2$	1.982	0.727	0.832	5.252
4	V_H	0.882	0.206	0.506	1.612
5	V_W	1.386	0.244	0.912	2.292
6	$(B_H)^2$	0.580	0.087	0.408	0.765
7	$(B_W)^2$	0.061	0.028	0.016	0.131
8	B_H	0.760	0.057	0.639	0.875
9	B_W	0.240	0.057	0.125	0.361
10	r	0.057	0.065	−0.065	0.327
11	$\ln V$	−0.293	0.190	−0.727	0.235
12	$\ln V_H$	−0.151	0.225	−0.681	0.477
13	$\ln B_H$	−0.278	0.076	−0.449	−0.134

Similarly, r measures the correlation coefficient between husbands' earnings and wives' earnings in each cohort-experience cell among all husbands and wives, not merely among working husbands and working wives. r tends to be higher in recent cohorts principally because, in recent cohorts, the employment–population ratio of wives is much higher than in earlier cohorts.[7] When the wives' employment–population ratio is low, the relatively large number of zero values for wives' earnings inclines r to be low. As the wives' employment–population ratio rises and more women record positive earnings, so higher values of r are recorded. The frequency distribution of r is graphed in Fig. 2. Ninety-two percent of cells have values of r in the range of ± 0.15. With such values of r, an approximation of Eq. (2) is

$$V^2 = (B_H)^2(V_H)^2 + (B_W)^2(V_W)^2 \tag{3}$$

Confirmation that this is a good approximation is provided by values of

$$H = \text{abs}\left\{\frac{V^2 - (B_H^2)(V_H^2) - (B_W^2)(V_W^2)}{V^2}\right\}$$

where abs denotes the absolute value of the term in braces. H is simply a rearrangement of Eq. (2) that neglects the third term on the right-hand side. Low values of H suggest that Eq. (3) provides a good approximation to Eq. (2). H is graphed for five cohorts in Fig. 3. The only cases in which H exceeds 0.15 are for a few cells corresponding to young couples in the

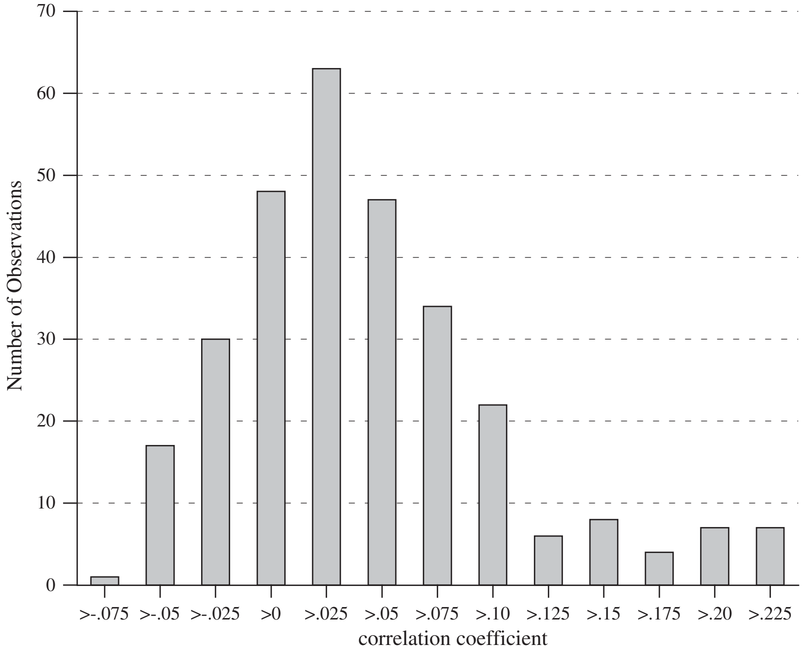

Fig. 2. Frequency Distribution of *r*.

most recent cohort. In most cases, H is less than 0.10. Hence, we shall proceed with the approximation given by Eq. (3).

After factoring $(B_H)^2(V_H)^2$ and taking logarithms, Eq. (3) can be rewritten as

$$\ln\ V = \ln\ V_H + \ln\ B_H + (0.5)\ln\left[1 + (B_W/B_H)^2(V_W/V_H)^2\right] \qquad (4)$$

The left-hand side of this equation, the logarithm of the coefficient of variation in family earnings, is an indicator of the inequality in family earnings. The broad movements in $\ln V$ are similar to those of the Gini coefficient of family earnings, G, as is evident from the smoothed values of $\ln V$ and G shown in Figs. 4 and 5. The dispersion of family earnings rises sharply with experience for each cohort: for instance, following the data for the 1956–1960 cohort, according to both $\ln V$ and G, inequality at 37 years is about twice that observed 30 years earlier.[8] In addition, each cohort's family earnings inequality tends to lie above the previous cohort's inequality at any experience level: at 10 years of experience, the 1986–1990 cohort's values of $\ln V$ are 1.5 times and its values of G are 1.3 times those for the cohort entering the labor market 30 years earlier.[9]

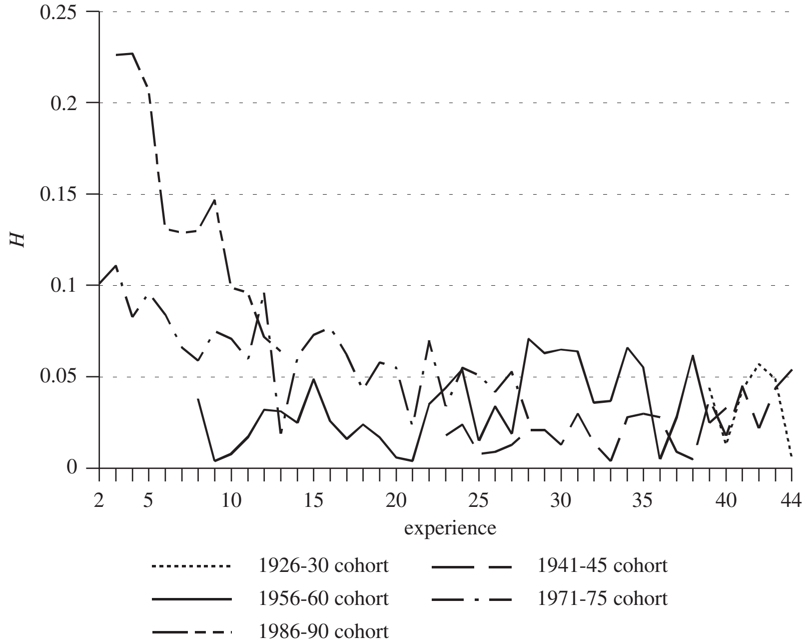

Fig. 3. Absolute Value of $\{V^2-[(B_H)^2(V_H)^2+(B_W)^2(V_W)^2]\}/V^2$ by Cohort and Experience.

Further approximations of Eq. (4) facilitate a better understanding of changes in family earnings inequality. First, given $B_H=\mu_H/\mu$, where μ_H is the mean of husbands' earnings and μ the mean of family earnings (including those not working for pay), if m_H and m_W denote, respectively, the mean earnings of husbands and the mean earnings of wives among those husbands and wives employed for pay and if E_H and E_W denote respectively the employment–population ratios of husbands and wives, then

$$\ln\ B_H = -\ln\left[1+(m_W E_W)/(m_H E_H)\right] = -(m_W E_W)/(m_H E_H) \qquad (5)$$

The last step is an approximation and to assess the quality of this approximation form

$$-\ln\left[1+(m_W E_W)/(m_H E_H)\right]+(m_W E_W)/(m_H E_H)$$

the frequency distribution of which is given in Fig. 6. All values are less than 0.10 and 95 percent are less than 0.06.

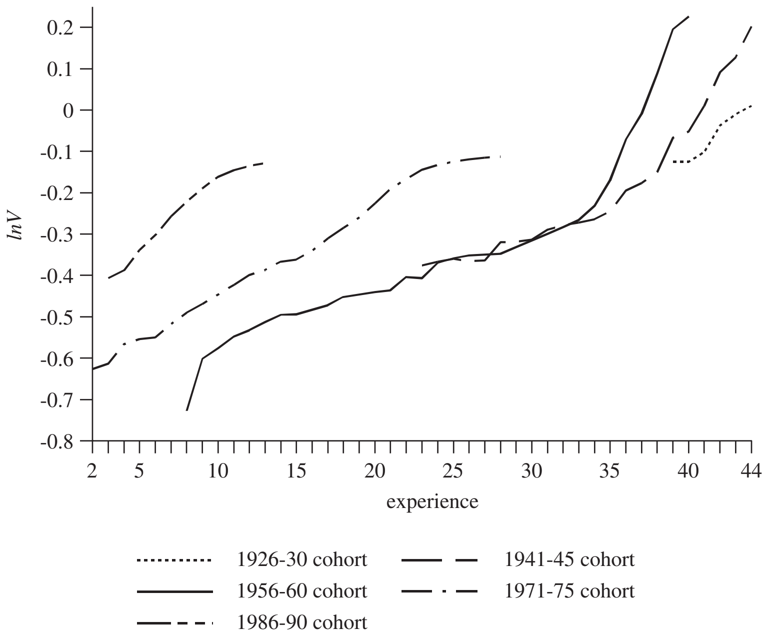

Fig. 4. Values of ln V by Cohort and Experience.

Now consider substituting $(B_W/B_H)^2(V_W/V_H)^2$ for $\ln[1+(B_W/B_H)^2(V_W/V_H)^2]$ in Eq. (4). To evaluate this, compute $\ln[1+(B_W/B_H)^2(V_W/V_H)^2]-(B_W/B_H)^2(V_W/V_H)^2$ whose values for all 294 cells are presented by the frequency distribution in Fig. 7. Over 90 percent of the cells have values between -0.075 and 0 with the mean being -0.032.

Replacing $\ln[1+(B_W/B_H)^2(V_W/V_H)^2]$ with $(B_W/B_H)^2(V_W/V_H)^2$ and using Eq. (5), Eq. (4) may be written approximately as

$$\ln V = \ln V_H - \frac{m_W E_W}{m_H E_H} + \frac{1}{2}\left[\frac{m_W E_W}{m_H E_H}\frac{V_W}{V_H}\right]^2 \tag{6}$$

Eq. (6) proposes a remarkably simple expression to describe movements in the dispersion of family earnings: approximately, the logarithm of the coefficient of variation of family earnings, ln V, equals the logarithm of the coefficient of variation of husbands' earnings, ln V_H, less a quadratic term involving $(m_W E_W)/(m_H E_H)$, the ratio of mean wives' earnings to mean husbands' earnings where these mean earnings are not conditional upon working for pay. The ratio of the coefficient of variation of wives' earnings

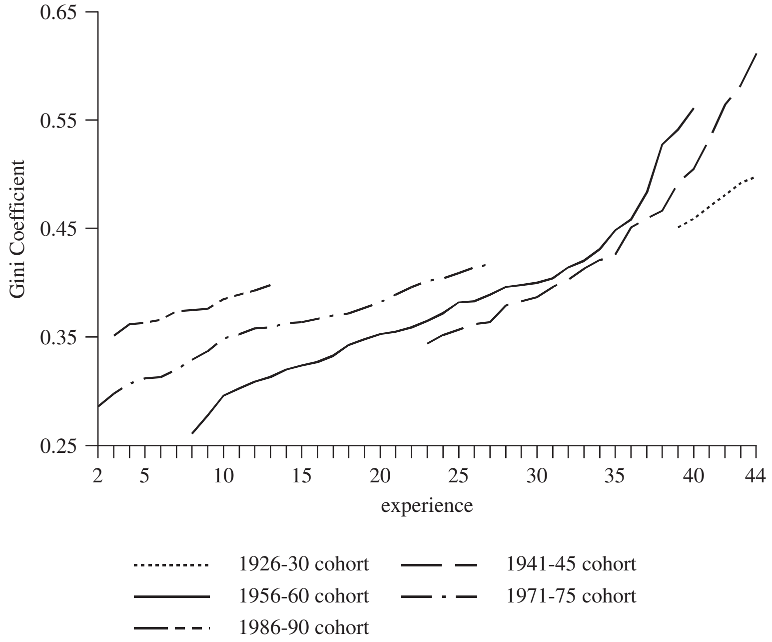

Fig. 5. Values of Gini Coefficients by Cohort and Experience.

to the coefficient of variation of husbands' earnings, V_W/V_H, also enters this expression, but the next step will involve treating this as parametric. Suppose $(V_W/V_H)^2 = k$ and, to move to the Gini coefficient as a more familiar indicator of inequality, suppose $\ln V = a_0 + a_1 G + u_1$ and $\ln V_H = b_0 + b_1 G_H + u_2$,[10] then Eq. (6) may be written as

$$G = \beta_0 + \beta_1 G_H + \beta_2 \frac{m_W E_W}{m_H E_H} + \beta_3 \left[\frac{m_W E_W}{m_H E_H}\right]^2 + u$$

where the stochastic term u incorporates the various approximations that have been made and the β's are parameters to be estimated. The above equation is Eq. (1), the expression introduced at the beginning of this section to describe variations in family earnings inequality in terms of variations in husbands' earnings inequality and in wives' relative employment and pay. Eq. (1) treats $(V_W/V_H)^2$ as parametric and incorporates it into the term β_3. Of course, $(V_W/V_H)^2$ is not fixed so the question is whether this assumption impedes an attempt to derive a useful compact description of the main empirical regularities in family earnings inequality.