

THE RELATIONSHIP BETWEEN WAGES  
AND WEEKLY HOURS OF WORK:  
THE ROLE OF DIVISION BIAS\*

*I. INTRODUCTION*

The estimation of the wage effect in the labor-supply function has received intensive attention by labor economists in the past two decades.<sup>1</sup> Most of this research has used the static neoclassical model of labor-leisure choices as the analytical framework. Despite the many estimates presented in the literature, there is little agreement on a point estimate of the gross effect of the wage rate on weekly hours of work, except that it is generally negative (i.e., the income effect dominates).<sup>2</sup> The fact that the wage elasticity is negative has been used to explain the secular decline of hours of work and is important in calculating the labor-supply effects of income-maintenance programs. As the study by DaVanzo, DeTray, and Greenberg [4] shows, if the emphasis is shifted from weekly hours of work to weeks worked per year, wage elasticities become positive and significant. Finally, if annual hours of work is the focus of the analysis, the inverse relationship between weekly hours and wage rates tends to dominate, creating a negative elasticity of annual hours with respect to wage rates.

This paper presents new evidence strongly questioning the result that the elasticity of weekly hours of work with respect to the wage rate is negative. It will be seen that one important factor, acknowledged to exist by most analysts but ignored in much empirical research, may be responsible for the overwhelming number of negative estimates presented in the literature.<sup>3</sup> In particular, most of the estimates are based on a measure of the

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\* I am grateful to James Heckman and Jacob Mincer for comments on previous drafts of this paper. [Manuscript submitted November 1978; accepted March 1979.]

- 1 For example, see the excellent collection of labor-supply studies contained in Cain and Watts [3]; a more recent analysis is contained in Masters and Garfinkel [9]. These studies, and others, are summarized in a detailed survey by Killingsworth [7].
- 2 However, see the Borjas and Heckman [1] review of the estimation procedures in the literature. They show that by using a few reasonable criteria in the interpretation of existing empirical work, the diversity in estimates is narrowed substantially.
- 3 One exception is the analysis by Lillard [8] which decomposes the variance of hours worked into a systematic component and errors in measurement.

wage rate calculated by dividing weekly (or annual) earnings by weekly (or annual) hours. The appearance of hours on both sides of the equation leads to downward biases in the estimates as long as there are errors of measurement in the observed measures of labor supply. Although this problem has been recognized in the literature, this is the first study specifically geared to a systematic analysis of the “division bias.” This paper will present (1) evidence on the importance of this bias in yielding the negative wage elasticities found in the literature; (2) a simple methodology for avoiding division bias that can be applied to most of the longitudinal data sets currently in use; and (3) substantial evidence that the correction for division bias leads to nonnegative (and often significant) elasticities of weekly hours of work with respect to the wage rate in the data analyzed in this paper, the 1971 National Longitudinal Survey of Mature Men.

## II. THE LABOR-SUPPLY FUNCTION

The static neoclassical theory underlying the determinants of hours of work is well known. Its basic prediction is that an increase in the wage rate creates two opposing effects on the individual’s supply of labor: the income effect, if leisure is normal, increases the demand for leisure, thus decreasing hours supplied to the market, while the substitution effect makes the individual substitute away from leisure and toward hours of work. Given an interior solution to the utility-maximization problem, we can write this relationship as:<sup>4</sup>

$$(1) \quad \ln H = \alpha + \beta \ln W + \gamma Z + \eta$$

where  $H$  = weekly hours of work,  $W$  = the wage rate,  $Z$  = a vector of other variables affecting hours of work, and  $\eta$  = a statistical residual. Since  $Z$  includes measures of the individual’s nonwage income,  $\beta$  provides an estimate of the gross elasticity of hours with respect to the wage rate. If it is negative, this would, of course, imply that the income effect outweighs the substitution effect.

The problem analyzed in this paper arises because of the *empirical* definition of the wage-rate variable.<sup>5</sup> We immediately must face up to the fact that most data sets do not contain a measure of the wage rate measured “independently” from hours of work. This, of course, may lead to a spurious

4 A constant elasticity form is used in order to facilitate the proof considered later in this section.

5 Note that the proper wage to use in (1) is the marginal wage rate. This, of course, raises problems on how to deal with individuals who work overtime. For simplicity, assume initially that we are dealing with a sample of workers who work only straight-time hours. The estimation of labor-supply functions correctly accounting for nonlinearities in the budget constraint creates substantial new problems; see Burtless and Hausman [2].

correlation between the variables. Specifically, the wage rate is often defined as:

$$(2) \quad W = E/H$$

where  $E$  is weekly earnings. As long as hours of work are correctly measured (and  $E$  also has no errors of measurement), no problem would arise in the estimation of (1) using (2). If, however, hours of work are incorrectly measured, the estimated coefficient of  $\beta$  in (1) will be biased toward minus one. For example, in a bivariate model, the observed equation can be written as:

$$(3) \quad \ln H^* = \alpha + \beta \ln W^* + \eta^*$$

where  $H^*$  is measured with error and this error is assumed to be uncorrelated with  $H$ ,  $E$ , and  $\eta$ . If  $H^* = H\nu$ , it can be easily shown that:<sup>6</sup>

$$(4) \quad \text{plim } \hat{\beta} = [\sigma_w^2/(\sigma_w^2 + \sigma_v^2)]\beta - [\sigma_v^2/(\sigma_w^2 + \sigma_v^2)]$$

where  $\sigma_w^2$  is the variance of the true log wage rate and  $\sigma_v^2$  is the variance of the errors in the log of hours worked. It can be seen from (4) that the probability limit of  $\hat{\beta}$  is a weighted average of the true  $\beta$  and minus one; the greater the proportion of the variance in the observed wage rate that is due to error, the more likely the estimated coefficient will be closer to minus one.<sup>7</sup> The next section of the paper presents strong evidence that the division of earnings by hours is a serious problem in estimating labor-supply functions and suggests several methods of obtaining relatively bias-free estimates of the wage elasticity.

### III. EMPIRICAL EVIDENCE

The sample used in the empirical analysis is the 1971 National Longitudinal Survey (NLS) of Mature Men. Since the wage coefficient is sensitive to the definition of the variables, it is useful to explain the construction of the variables in detail. We are given two measures of hours worked weekly on the main job: hours worked last week,  $H_w$ , and usual hours worked weekly,  $H_u$ .

6 Note that the disturbance in the observed regression equation is defined as  $\eta^* = \eta + (1 + \beta)\ln\nu$ .

7 To avoid the division bias, it has been proposed that we substitute for  $W$  in equation (1) and solve for  $\ln H$ . This transformation yields:

$$(4a) \quad \ln H = \alpha/(1 + \beta) + \beta/(1 + \beta)\ln E + \gamma/(1 + \beta)Z + 1/(1 + \beta)\eta$$

Since presumably  $E$  is free of measurement error, and the error in  $H$  appears on the left-hand side of (4a), it can be argued that a regression of this type yields consistent estimates of  $\beta/(1 + \beta)$  and hence of  $\beta$ . This method, however, ignores the fact that if (1) is the true behavioral relation,  $\ln E$ , on the right-hand side of (4a), is endogenous, and simultaneous-equation techniques must be used. In fact, it is easy to show that if one applies ordinary least squares to (4a), it yields upward biased estimates of the wage elasticity.

Presumably, the usual hours measure gets rid of transitory components in labor supply such as holidays, vacation, and sick days. It is possible, however, to adjust last week's hours for time lost due to these transitory variations, and this adjustment was carried out on the measure of last week's hours used in this paper.<sup>8</sup>

The 1971 survey also provides explicit information on overtime hours worked. It first tells us whether the current job pays an overtime premium for overtime hours. Information is then given on the number of straight-time hours the individual must work before getting an overtime premium. From these data, it is possible to construct overtime hours for last week and for the usual week.

Finally, we are given only one piece of information on wages. The question asked was:<sup>9</sup>

Q: How much do you usually earn at this job before deductions?

A: \$\_\_\_\_\_ per\_\_\_\_\_.

Since the time period was left up to the individual, we have answers in terms of three major categories: people who reported hourly wage rates, weekly wages, or annual earnings. The significance of this breakdown should not be overlooked. It gives (for a sizable subsample of the survey) an independent measure of wage rates: those individuals who answered the question in terms of hourly wage rates have wage rates and hours that are measured independently of each other.<sup>10</sup>

Our sample is composed of white, salaried men who reported all the key information in the 1971 survey; it contains 1908 observations. Initially, to avoid the problems that arise due to the nonlinearity of the budget constraint when overtime hours are worked, we will study the labor supply (as measured by hours worked weekly) of straight-time workers. This group is defined as men who did not work overtime hours either in the last week or usually. This subsample contains 1561 men out of a possible 1908 observations, or about 82 percent of the sample. There are two additional reasons which make an analysis of the straight-time sample useful. First, we are clearly interested in what determined hours of work for a group that makes up four-fifths of the population. Second, it is easier to illustrate the techniques used to tackle the division bias in a subsample where a constant wage rate is earned over all hours worked.<sup>11</sup>

8 Actually, due to the format of the questionnaire, the adjustment can only be carried out in the sample which reported between 35 hours and 49 hours worked last week.

9 Question 7a of the 1971 questionnaire.

10 There may be a problem in using this information if a selection bias exists. That is, workers who are paid per hour may differ significantly in their labor-supply behavior from workers who are paid per year. A detailed discussion of sample-selection bias is given by Heckman [6].

11 Two important qualifications must be made. First, such segmentation of the sample raises a serious risk of selection bias. As will be seen below, however, including the overtime

TABLE 1  
 SELECTED WAGE COEFFICIENTS  
 DEPENDENT =  $\ln(H_u)$

Measure of	Sample			
	Pooled	Hourly	Weekly	Annual
Wage (in logs)				
Usual wage rate	-.0383 (-2.37)	.0664 (1.51)	-.1040 (-3.81)	-.0256 (-1.11)
Predicted wage rate	.0269 (.59)	.1562 (1.47)	.0596 (.22)	.0863 (1.30)
Sample size	1561	278	449	834

Note: *t*-ratios are given in parentheses in all tables of this paper. Held constant in the regression are: other nonwage income in the family, expected number of years until retirement, years of labor force experience, number of children, whether job information refers to current or last (if not currently working) job, marital status, health status, and education.

The estimated wage-elasticity coefficients are given in Table 1. Held constant in the vector *Z* were: other nonwage income in the family,<sup>12</sup> expected number of years until retirement, years of labor-force experience, number of children, whether job information refers to current or last (if not currently working) job, marital status, health status, and education. The wage rate used in the regressions on the top row of the table is defined as the usual wage rate ( $=E/H_u$ ).<sup>13</sup> As shown earlier, there is a bias in the estimated wage coefficient toward minus one if there are errors of measurement in usual hours of work. We find that the elasticity of weekly hours with respect to the wage rate is  $-.038$  and significantly different from zero.

However, we can make use of the unique ways individuals responded to the wage question to get a preliminary view of the importance of the division

workers in the sample does not change the conclusion that division bias leads to a negative estimated wage elasticity when, in fact, the “true” elasticity may be nonnegative. Second, note that having a constant wage rate over all hours actually worked need not imply that the wage rate obtained by working one more hour equals the individual’s average wage rate. It may be that additional hours worked by these individuals would change both the marginal and average wage rates. Unfortunately, the NLS is ambiguous on this empirical problem. For example, it is impossible to ascertain whether individuals who do not usually work overtime would receive straight-time pay for additional hours or no pay at all.

- 12 Other nonwage income in the family is used so as to net out the influences of the wife’s income on the husband’s labor supply. Clearly, in a model of family labor supply, all the wife-participation and earnings variables would be endogenous.
- 13 That is, individuals who responded in weekly earnings were given a wage rate equal to weekly earnings divided by usual hours worked weekly. Individuals responding in other time units (e.g., monthly, annually) were first computed weekly earnings and then the usual wage rate was calculated.

bias. One way to do this is by segmenting the sample into three categories: individuals who answered in terms of hourly earnings, those who answered in terms of weekly earnings, and those who answered in terms of annual earnings.<sup>14</sup> The estimated elasticity for each of these three subsamples is shown in the remaining columns of the top row in Table 1. The results are striking. If the wage is measured independently of hours, as in the “hourly” sample, the wage elasticity is positive and approaching significance. The estimated coefficient is .066, with a *t*-ratio of approximately 1.5. Once division is necessary, as in the weekly sample, the estimated wage elasticity is  $-.104$  and significant. Finally, in the “annual” sample, the estimate is  $-.026$ , with a *t* of 1.1. Apparently the errors in hours affect the “weekly” sample the most.

Therefore the results can be interpreted as strongly suggesting that errors are indeed an important factor in obtaining negative wage-elasticity estimates in the cross section. One criticism can be made: namely, the results may simply indicate a different labor-supply structure among the subsamples. In fact, the average characteristics of these groups are quite different. The men who answered in terms of annual earnings are the most educated and have the highest wage rates. One rough method that can be used to test this hypothesis, a method which has acquired some popularity in the labor supply literature (see Hall [5]), is to use an instrument for the wage rate. The method involves the estimation of a wage equation:

$$(5) \quad \ln W = f(X)$$

From the estimated earnings function, we can predict wages for each individual. The important property of these predicted wages is that, theoretically, they are free of measurement error and are not related to hours of work, thus eliminating the spurious correlation.

A wage equation was estimated in the NLS.<sup>15</sup> This equation was used to obtain a predicted wage,  $\widehat{\ln W}$ , for each individual, and this predicted wage was used in the regressions as an instrument for the observed wage rate.<sup>16</sup> The wage coefficients are shown in the second row of Table 1 for the pooled sample and for the three “pay-unit” groups. The most important result is that the use of a predicted wage turns the elasticity in the pooled sample from negative and significant to positive and insignificant. Within the three

14 The “annual” group also includes individuals who answered in terms of bi-weekly, semimonthly, or monthly wages.

15 The variables used to predict wages were: education, experience, experience squared, tenure, tenure squared, SMSA dummy, health status, marital status, regional dummies, years of residence in present locality, years of formal postschool training, and unionization dummy.

16 Strictly speaking, this is not the technique of instrumental variables; what we are doing is using a “clean” proxy, the predicted wage, for a variable measured with error.

subsamples, we find that for both the weekly and annual samples, where the division bias is a potential problem, the use of a predicted wage makes the wage elasticity more positive, although in all three subsamples the predicted wage coefficient is not significant.<sup>17</sup>

There is, however, one serious problem with using predicted wage rates as an instrument for the wage rate. As has been noted in the analysis of DaVanzo, DeTray, and Greenberg [4], the estimated elasticity is very sensitive to the introduction or deletion of variables from the hours-of-work equation. In particular, it is very unstable when variables that are important in the prediction of  $\ln W$  (such as education) are omitted from or included in the hours-of-work equation. In fact, omitting education from the hours-of-work function would substantially *increase* all the elasticities reported in Row 2 of Table 1. This problem is particularly serious since there is little prior information that can be used to sort out which variables belong in each of the equations.

A more promising approach is to find a wage variable that is unrelated to hours for the whole sample (not simply for the hourly subsample) and that is not too sensitive to the introduction of other variables in the hours equation. One such measure can be obtained from the NLS by studying the data closely. We have a measure of usual earnings, which was divided by usual hours to obtain a *usual* wage rate ( $E/H_u$ ). Clearly, this measure of the usual wage rate will be spuriously correlated with usual hours of work. However, we also have an alternative hours variable: hours worked last week ( $H_w$ ). If hours worked last week vary sufficiently from usual hours, then clearly we can construct a wage measure,  $E/H_w$ , or usual earnings divided by hours worked last week, which is “independent” from usual hours worked. In other words, we “cross-divide” the earnings variable by the hours measure which is *not* the dependent variable. This wage measure is then used as an instrument for the true wage rate. In other words, the hours equation would be:

$$(6) \quad \ln H_u = \alpha + \beta \ln(E/H_w) + \gamma Z + \eta$$

Alternatively, we can “cross-divide” in the opposite way:

$$(7) \quad \ln H_w = \alpha + \beta \ln(E/H_u) + \gamma Z + \eta$$

The wage coefficients estimated from equations (6) and (7) are shown in Table 2. The remarkable result in Table 2 is that when one allows for spurious correlation between hours and wages, the estimated wage elasticities

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17 In a strict statistical sense, since all three wage elasticities are not different from zero, the results would suggest little difference in the structure of labor supply across the three groups. As will be seen below, whether there are structural differences or not is irrelevant in showing the importance of division bias in the estimation of labor-supply functions.

TABLE 2  
 “CROSS-DIVIDED” WAGE COEFFICIENTS

Measure of Wage	Measure of Hours	
	$\ln(H_u)$	$\ln(H_w)$
$\ln(E/H_u)$	-.0383 (-2.37)	.0099 (.63)
$\ln(E/H_w)$	.0163 (.09)	-.0743 (-4.30)

Note: See notes to Table 1 for a listing of variables held constant in the regression.

ties are strongly negative. If cross-division is used to eliminate the division bias, both estimates turn positive, although insignificant.<sup>18</sup> The important point is that we have obtained nonnegative wage elasticities without resorting to predicted wage variables computed from arbitrary specifications of an earnings function. Furthermore, note that since there are likely to be measurement errors in hours, there will also be errors in the cross-divided wage rate. These errors will not be spuriously related to the hours variable; thus the coefficient of the wage rate will, in general, be biased toward zero. Therefore, our positive wage elasticities are *underestimates* of the true parameters.<sup>19</sup>

An interesting exercise can be carried out with our results in order to estimate the proportion of the variance of usual hours that is explained by measurement errors. It can be shown that the bias caused by errors of measurement is given by:

$$(8) \quad \text{plim}(\hat{\beta} - \beta) = [-\sigma_v^2(1 + \beta)]/\sigma_w^{2*}$$

where  $\sigma_w^{2*}$  is the variance of the observed wage measure. Assuming that our (underestimated) elasticity of usual hours with respect to  $(E/H_w)$  in Table 2 is the “true” elasticity, and that the  $\hat{\beta}$  is obtained when we ignore the cross-division methodology, we can then solve for  $\sigma_v^2$  in equation (8). After performing the calculations, it can be shown that:<sup>20</sup>

18 The result is even more remarkable when one notes that the correlation coefficient between  $\ln(E/H_u)$  and  $\ln(E/H_w)$  is over .9.

19 This fact helps to explain why the estimates obtained by using the predicted wage are larger than those obtained from the cross-division method.

20 This calculation is only an approximation since the bias expression was derived for a bivariate regression and the coefficient was calculated in a multivariate setting. It is easy to show that division bias, even in a multivariate regression, imparts a negative bias in the wage elasticity when the only variable measured with error is hours of work. In any case, calculation of the error proportion in hours using coefficients estimated from a bivariate regression does not significantly change the results. Two necessary statistics needed for the calculations are:  $\sigma^2(\ln H_u) = .073$  and  $\sigma^2[\ln(E/H_u)] = .245$ .

TABLE 3  
WAGE ELASTICITIES, STRAIGHT-TIME SAMPLE

Step	Dependent = $\ln(H_u)$		Dependent = $\ln(H_w)$	
	$\ln(E/H_u)$	$\ln(E/H_w)$	$\ln(E/H_u)$	$\ln(E/H_w)$
1	.0132 (.95)	.0458 (3.38)	.0463 (3.05)	-.0105 (-.70)
2	.0133 (.96)	.0463 (3.40)	.0479 (3.14)	-.0089 (-.59)
3	-.0168 (-1.10)	.0243 (1.62)	.0280 (1.66)	-.0422 (-2.55)
4	-.0307 (-1.97)	.0140 (.92)	.0096 (.56)	-.0614 (-3.68)
5	-.0383 (-2.37)	.0099 (.63)	.0163 (.09)	-.0743 (-4.30)
6	-.0201 (-1.18)	.0307 (1.86)	.0127 (.67)	-.0721 (-3.98)

Note: Step 1 regresses hours on wages. Step 2 adds nonwage income. Step 3 adds time remaining in the labor force, years of experience, number of children, and whether job information refers to current or last (if not currently working) job. Step 4 adds health and marital status. Step 5 adds education. Step 6 adds 11 one-digit industry dummies.

$$(9) \quad \sigma_v^2 / \sigma^2 (\ln H_u) = .180$$

Thus about 18 percent of the variance in  $\ln$  usual hours can be explained by errors of measurement. Note that even this relatively small error leads to a bias that turns a positive and weak wage elasticity (.016) to a negative and strong elasticity (-.038) of usual weekly hours with respect to the wage rate. We can carry out similar calculations in terms of hours worked last week. After making the appropriate calculations, we find that the proportion of  $\ln H_w$  that can be explained by errors is 23.8 percent. Again, it is important to note that this error turns the wage elasticity from positive (.01) to negative (-.074).

Table 2 also shows a remarkable similarity between the wage elasticities estimated by using equation (6) or (7). This similarity is not coincidental and, in fact, is not affected by what variables are held constant in the equation. Table 3 presents the wage coefficient on both usual hours and last week's hours using both wage constructs: usual wage rate ( $E/H_u$ ) and last week's wage rate ( $E/H_w$ ). The wage coefficients are shown for six steps of the estimation of the hours-of-work equation, each step adding additional variables into the regression. In step 1, the regression is a simple bivariate relationship between log hours and log wage rates. Due to the division bias,

running usual (or last week's) hours on the usual (or last week's) wage rate leads to negative or zero coefficients. The use of a cross-divided wage rate yields positive and significant wage elasticities.

In step 2, other nonwage income of the family is introduced. As can be seen, the wage coefficient is not significantly affected by the introduction of this variable.<sup>21</sup> Step 3 introduces years of experience, expected number of years remaining in the labor force, the number of children living in the household, and a dummy variable indicating whether or not the individual was working at the time of the interview.<sup>22</sup> The introduction of these variables, particularly experience, reduces the wage coefficient in all four specifications. Step 4 introduces two variables highly correlated with earnings: health and marital status. As can be seen, the introduction of these variables and of education in step 5 takes away from the permanent effect of wage rates, leaving the wage-rate variable as a proxy for measurement errors that bias the coefficient toward zero or minus one depending on whether or not there is a spurious correlation between the wage rate and hours of work. Note that the wage coefficients estimated in step 5 are the ones discussed in Tables 1 and 2. Finally, the last step introduces a set of one-digit industry dummies. The introduction of industry leads to either more positive or less negative wage elasticities. This can be interpreted as evidence that, looking across industries, high-wage industries apparently have shorter working weeks. The complete step 6 regressions are presented in Appendix Table A-1.

More convincing evidence on the importance of measurement errors in imparting a negative bias on estimated wage elasticities is shown in Table 4, where the instrument for the usual wage rate is a *lagged* usual wage rate. Despite the high correlation between the 1969 usual wage rate and the 1971 usual wage rate ( $r = .83$ ), the labor-supply wage elasticities are zero or positive with the lagged wage and usually negative with the latter measure. Table 4 also shows the elasticities obtained by using the 1967 usual wage rate as the independent variable. As can be seen, the elasticities are, if anything, increased by further lagging. It is comforting to know that the use of a lagged wage rate does not change the results discussed earlier either qualitatively or quantitatively.

Therefore we have seen that the definition of the wage rate relative to the definition of hours of work is an important determinant of not only the

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- 21 The coefficient of other nonwage income is always negative but never significant. The coefficient hovers around  $-.001$  with income measured in thousands of dollars and using  $\ln(H_u)$  as the dependent variable.
  - 22 Some individuals are not currently working (as of the date of the interview) and the data refer to the last job held, which was completed after 1969. In this small sample of individuals, hours worked last week were set equal to usual hours worked weekly in the last job.

TABLE 4  
WAGE ELASTICITIES USING LAGGED WAGE RATES  
STRAIGHT-TIME SAMPLE

Step	Dependent = $\ln(H_{u71})$		Dependent = $\ln(H_{w71})$	
	$\ln(W_{69})$	$\ln(W_{67})$	$\ln(W_{69})$	$\ln(W_{67})$
1	.0360 (3.13)	.0534 (3.97)	.0437 (3.36)	.0538 (4.05)
2	.0358 (3.10)	.0545 (4.04)	.0455 (3.49)	.0559 (4.21)
3	.0257 (1.99)	.0435 (2.92)	.0374 (2.57)	.0442 (3.01)
4	.0190 (1.45)	.0372 (2.46)	.0281 (1.90)	.0360 (2.43)
5	.0144 (1.07)	.0317 (2.04)	.0235 (1.54)	.0278 (1.82)
6	.0301 (1.30)	.0547 (1.14)	.0335 (2.13)	.0434 (2.70)

Note: See note to Table 3 for a description of the variables held constant in each step.

TABLE 5  
WAGE ELASTICITIES, POOLED SAMPLE, N = 1908

Step	Dependent = $\ln(H_u)$		Dependent = $\ln(H_w)$	
	$\ln(E/H_u)$	$\ln(E/H_w)$	$\ln(E/H_u)$	$\ln(E/H_w)$
1	-.0085 (-.69)	.0235 (1.97)	.0201 (1.46)	-.0413 (-3.08)
2	-.0085 (-.70)	.0237 (1.97)	.0213 (1.55)	-.0402 (-2.99)
3	-.0344 (-2.58)	.0053 (.40)	.0039 (.26)	-.0702 (-4.81)
4	-.0488 (-3.59)	-.0055 (-.41)	-.0159 (-1.05)	-.0900 (-6.14)
5	-.0536 (-3.82)	-.0073 (-.53)	-.0172 (-1.10)	-.0968 (-6.38)
6	-.0389 (-2.63)	.0099 (.69)	-.0122 (-.73)	-.0997 (-6.29)

Note: See note to Table 3 for a description of the variables held constant in each step.

magnitude, but often the *sign* of the estimated wage elasticity. The empirical results in the sample of straight-time workers suggest that errors of measurement in weekly hours of work lead to seriously biased estimates of the wage elasticity. Moreover, the inclusion of overtime workers in the sample does little to change the basic result. The introduction of overtime workers into the analysis complicates the estimation procedure significantly (see Burtless and Hausman [2]). Most previous research has ignored the distinction between average and marginal wages and simply related the labor-supply measure to average wages in the relevant period. This procedure is carried out in Table 5, which presents the estimated wage elasticity obtained by relating *total* weekly hours to the average wage rate. The estimation is conducted on the total sample, including men who worked overtime. As in Table 3, we analyze two separate measures of labor supply—hours worked usually and hours worked last week—and two separate wage constructs— $E/H_u$  and  $E/H_w$ . Again wage elasticities estimated with six different specifications of the labor-supply function are presented. The basic conclusion is unchanged: cross-division leads to less negative or more positive wage coefficients. If no cross-division is attempted, the wage elasticities are often negative and significant; if cross-division is carried out, the wage elasticities are either positive or statistically insignificant from zero.<sup>23</sup>

#### IV. SUMMARY

This paper presents new empirical evidence on the relationship between weekly hours of work and the wage rate. It was seen that, due to the definition of the wage rate (earnings divided by weekly hours of work), a spurious negative correlation between weekly hours of work and the wage rate was created if weekly hours were measured with error. Moreover, it was seen that this spurious correlation arising from division bias is partly responsible for many of the negative signs or zero wage elasticities estimated in this paper.

Several methods were proposed to avoid the division bias. Once the corrective steps were taken, it was found that the strong negative wage elasticities vanished. The unbiased estimates of the wage elasticities were either zero or positive depending on the specification of the labor-supply function. As a by-product of the correction procedure, it was estimated that

23 Interesting results can be seen by comparing Tables 4 and 5. In every case, wage elasticities in the straight-time sample are more positive than in the pooled sample which includes overtime workers. The underlying reason for this finding, which deserves further study, is that the straight-time wage rate is larger for the men who do *not* work overtime.

approximately 15 to 25 percent of the variance in weekly hours is due to errors in measurement.

The analysis in this paper can be extended in several important directions. First, in order to estimate more precisely the degree of bias, the empirical work should be replicated in other bodies of data. This should help establish the robustness of the estimates presented in this paper. Second, the analysis has been conducted with a specific measure of labor supply. Clearly, other measures of hours of work should be studied and the strength of division bias established. Finally, the methods of correction for division bias proposed in this paper highlight the importance of accounting for nonlinearities in the budget constraint, a problem usually ignored in the literature. Hopefully, these and other studies would lead to better empirical estimates of the labor-supply functions facing groups of individuals in the population.

GEORGE J. BORJAS  
*University of California, Santa Barbara*

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TABLE A-1  
LABOR-SUPPLY EQUATIONS, STRAIGHT-TIME SAMPLE

Variable	Dependent = $\ln(H_u)$		Dependent = $\ln(H_w)$	
	Coeff.	t	Coeff.	t
Constant	3.7460		3.5871	
$\ln(E/H_u)$	-.0201	(-1.2)	.0127	(.7)
$\ln(E/H_w)$	—	—	—	—
INCOME	-.0006	(-.3)	-.0033	(-1.4)
REM	-.0002	(-.1)	.0024	(1.4)
EXPER	-.0039	(-1.9)	-.0016	(-.7)
CHILD	.0014	(.2)	-.0009	(-.1)
LAST	-.0889	(-3.1)	-.0580	(-2.8)
MSP	.0616	(2.6)	.0803	(3.1)
HLTH	-.0455	(-2.8)	-.0593	(-3.3)
EDUC	.0057	(1.8)	.0559	(1.6)
IND1	.1572	(3.5)	.0344	(.7)
IND2	.0730	(.9)	.0728	(.8)
IND3	.0403	(1.3)	.0843	(.2)
IND4	.0469	(2.0)	.0272	(1.0)
IND5	.0147	(.5)	-.0010	(-.03)
IND6	.1020	(3.6)	.0916	(2.9)
IND7	-.0159	(-.4)	-.0225	(-.5)
IND8	.0008	(.01)	-.0436	(-.7)
			3.6960	
			-.0721	(-4.0)
			-.0028	(-1.2)
			.0013	(.7)
			-.0023	(-1.0)
			.0025	(.03)
			-.0703	(-2.2)
			.0927	(3.6)
			-.0715	(-4.0)
			.0104	(3.0)
			-.0166	(-.03)
			.0690	(.8)
			.0185	(.5)
			.0251	(1.0)
			-.0016	(-.05)
			.0731	(2.3)
			-.0222	(-.5)
			-.0475	(-.7)

<i>IND9</i>	.0883	(1.3)	.1106	(1.7)	.0889	(1.2)	.0519	(.7)
<i>IND10</i>	.0501	(.6)	.0598	(.7)	.0484	(.5)	.0326	(.3)
<i>IND11</i>	.0258	(.8)	.0409	(1.3)	-.0006	(-.02)	-.0252	(-.8)
<i>R</i> <sup>2</sup>	.058		.060		.041		.063	

Note: Key to variables: *INCOME* = other nonwage income in \$1000, excludes work-conditioned transfer payments such as welfare, etc.; *REM* = years remaining until retirement; *EXPER* = Age - Education - 6; *CHILD* = number of children in household; *LAST* = 1 if job information refers to last job held after 1969; *MSP* = 1 if married, spouse present; *HLTH* = 1 if health limits work; *EDUC* = years of education; *IND1* = 1 if employed in agriculture; *IND2* = 1 if mining; *IND3* = 1 if construction; *IND4* = 1 if manufacturing; *IND5* = 1 if transportation; *IND6* = 1 if wholesale and retail trade; *IND7* = 1 if finance; *IND8* = 1 if business and repair service; *IND9* = 1 if personal service; *IND10* = 1 if entertainment; *IND11* = 1 if professional service. Omitted industry is public administration.