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ON ESTIMATING THE LABOR SUPPLY
EFFECTS OF A NEGATIVE INCOME TAX

by

Irwin Garfinkel

DISCUSSION PAPERS

THE UNIVERSITY OF WISCONSIN, MADISON, WISCONSIN

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Introduction

Several studies have used labor supply schedules derived from cross-sectional data to estimate the potential labor supply effects of enacting a negative income tax. The range of estimates in these studies is enormous.[1] That competent economists can derive such divergent results suggests that the issue is extremely complex. Consequently in this paper I will focus on the methodological problems of deriving labor supply schedules which can be used to simulate labor supply effects of negative income tax programs.

For two reasons, this study is incomplete. First, some of the procedures used in the study are less than ideal.[2] Second, I concentrate on deriving the labor supply schedule of married prime-age, able-bodied males. Since other demographic groups may reduce their labor supply in response to an NIT, this study cannot provide an estimate of total labor supply effects. There are, however, at least two good reasons for focusing on this one particular demographic group.[3]

Married prime-age, able-bodied males are of particular interest because they contribute such a large percentage of existing labor supply. More important, what distinguishes current negative income tax proposals, including Nixon's FAP proposal, from existing welfare programs is that coverage would be extended to the able-bodied working poor. Opposition to NIT proposals stems primarily from the fear that transfers to the working poor will result in very large labor supply reductions. While this paper is less than a comprehensive labor supply study, therefore, it can provide evidence to support or reject the controversial hypothesis of substantial labor supply reductions of the able-bodied, prime-age, male-working poor.

In the first section I discuss the model and data used in this study. Normally, in an empirical study the author then presents his rationale for choosing to operationalize his model with particular dependent and independent variables in preference to others. Because the issues are so complex and intertwined, however, in this paper I reverse the procedure in order to facilitate the exposition. In the second section I present what I consider to be the best estimate of the married prime-age, able-bodied, male-labor supply function. These estimates serve as a benchmark for the discussion which follows in sections III, IV, V and VI respectively, which deal with the problems of (1) constructing the appropriate sample, (2) measuring labor supply, (3) measuring wages, and (4) measuring non-employment income. The seventh section contains a brief summary of the major findings and a few concluding remarks.

I. Model, Simulation and Data

A. Model and Simulation

An individual's budget constraint can be defined in terms of his wage rate (WR) and his income from nonemployment sources (NEY).[4] Since detailed discussions of the economic theory of the work-leisure choice are available elsewhere [2, 6, 7, and 9], I will not discuss the theory in detail. Suffice it to say that the basic model for all the studies including this one is:

$$L = L(WR, NEY, \overline{X}, U) \tag{1}$$

where L = labor supply, WR = wage rate, NEY = nonemployment income, $\overline{X}$ = a vector of other variables presumed to effect measured labor supply, and U = an error term. The WR and NEY regression coefficients are a measure of the effect of a unit change of WR or NEY on L. They can be used to estimate the impact that introduction of an NIT would have on work effort.

The most straightforward manner of estimating this impact is to evaluate the function (1) at pre- and post-subsidy levels of WR and NEY for each individual. Consider an individual with WR = $2.00 and NEY = 0. Suppose we were considering the NIT with a guarantee = $3000 and a tax rate = 50 percent. Suppose further that the existing marginal tax rate was equal to zero.[5] Introduction of the NIT would increase the individual's NEY to $3000 and decrease his net wage rate to $1.00. To estimate the reduction in work effort that enactment of this program would have, L should be evaluated first at WR = $2.00 and NEY = 0, and then at WR = $1.00 and NEY = $3000. The difference is a measure of the impact of the NIT on work effort.

Although the above is rather elementary, there are two reasons for mentioning it. First, it is possible to give approximate estimates of labor supply reductions without resorting to elaborate simulations.[6]

More important, confidence in the simulation results can be no stronger than confidence in the assumption that all the relevant variables are included in $\overline{X}$. But clearly, $\overline{X}$ cannot include all the relevant variables. The nonpecuniary desirability of a job is likely to influence the amount of time an individual will work at it. If desirability varies positively with the wage rate--a fairly reasonable assumption--and if desirability is not controlled for, the use of the WR coefficient to estimate work supply reductions will result in an overestimate. For while introduction of an NIT with a 50 percent tax rate will reduce the effective wage rate of \$2.00 per hour jobs to \$1.00 an hour, it will not reduce the nonpecuniary desirability of \$2.00 an hour jobs to the level of \$1.00 an hour jobs.

Similarly, consider the variable of personal ambition. A greater than average amount of ambition may lead an individual to work harder than average, have a higher than average wage rate, and a higher than average amount of nonemployment income. In the absence of a variable to reflect differences in ambition, the WR coefficient will reflect not only the effect of wage rates on labor supply but the positive effect of ambition on both wage rates and labor supply. Consequently, the WR coefficient will be positively biased. The NEY coefficient, on the other hand, will reflect the positive effect of ambition on NEY and labor supply as well as the negative effect of NEY on labor supply. Consequently, the NEY coefficient will be positively biased. In this case the use of the WR and NEY coefficients from (1) will overestimate the effect on work effort of reducing WR and underestimate the effects of increasing NEY.[7]

What all of this suggests is that estimates of the effect of an NIT on labor supply derived from even carefully done cross-section labor supply schedule studies should be approached with a healthy dose of skepticism.

B. Source of Data

The Survey of Economic Opportunity conducted only for the years 1966 and 1967 was designed to supplement the Current Population Survey. Data were collected from 30,000 households in two categories: (1) a national self-weighting sample of 18,000 households and (2) a supplementary sample of 12,000 households from areas with a large percentage of nonwhite poor. I use only the 1967 national self-weighting sample. There are two major advantages of the SEO vis-á-vis the CPS. First, the former has data on personal health, and assets and liabilities. Without information on assets for which no returns are reported, the income coefficient may be biased since most of NEY derives from assets which have reported returns. Second, there is a better hourly wage variable in the SEO. In the CPS the hourly wage rate must be derived as follows:

$WR = \frac{E_{LY}}{WW_{LY}H_{LW}}$, where WR = wage rate, E_{LY} = last year's earnings, WW_{LY} = last year's weeks worked, and H_{LW} = hours worked last week. Hours worked last week may not be representative of average hours worked during the weeks of the preceding year. Moreover, the weeks worked variable is available only in intervals. In contrast, the SEO hourly wage rate is defined as last week's earnings divided by last week's hours worked.

II. Best Estimate

A. Presentation of Basic Results

The sample from which the regression results discussed below are derived consists of married males age 25-61 who (1) had no temporary or permanent health problems which limited the kind or amount of work they could do, (2) were not enrolled in school, (3) worked 1 or more weeks in the previous year and 1 or more hours during the survey week, (4) were not self-employed, (5) were not in the Armed Forces during the survey week, or the previous year, (6) were not unemployment insurance, workmens compensation, veterans disability or compensation, or public assistance beneficiaries, or pensioners, and (7) had no missing information. I refer to this as the basic sample. The rationale for limiting the sample in this fashion is discussed in detail in Section III.

The two dependent variables used are: (1) WW_2, the sum of weeks worked and weeks looking for work in the previous year,[8] and, (2) FT_2, a dummy variable which assumes the value of one if the individual normally worked full time, or would have worked full time if not for slack work and zero if he normally worked part time for any reason other than slack work. The wage rate variable (WR) is defined by earnings last week divided by hours worked last week. The non-employment income variable (NEY) is the sum of interest, dividends, rent, social security payments, and a miscellaneous category called other non-employment income. The rationale for choosing these measures as well as a detailed discussion of alternative measures of labor supply, wage rates and non-employment income is presented in Sections IV, V, and VI.

Other independent variables include education, age, race, location, earnings of other family members[9] and net equity in a farm or business, net equity in the family's own home, net equity in automobiles, net value of other assets of the family, cash in checking and banking accounts, and consumer debt. The rationale for inclusion of the set of asset variables is discussed in the section on non-employment income.

The set of WR and NEY dummy coefficients as well as linear WR and NEY coefficients (with t-values in parenthesis) for the WW_2 and FT_2 equations are reproduced below in Table I.[10]

The coefficients of each dummy should be interpreted relative to the omitted dummy. For example, in the WW_2 equation, the -.58 coefficient for the \$.75-1.25 wage rate bracket indicates that this group worked about 6/10 of a week less than the group which earned \$1.75-2.25 an hour. Similarly, in the FT_2 equation the .013 coefficient for the \$2.75-3.25 rate bracket indicates that the probability of a worker in this group working full time is 1.3 percent greater than the probability that a worker in the group which earned \$1.75-2.25 an hour would work full time.

The most striking result is the almost non-existent relationship between NEY and labor supply. In the WW_2 equation the signs of the dummy coefficients are positive, and the relative magnitude of the coefficients does not suggest a possible negative relationship. The sign of the linear coefficient is also incorrect. While there is evidence of a negative relation in the FT_2 regression, the relative magnitude of the coefficients, as well as their t-values suggests the relationship is weak. In the FT_2 regression the linear NEY coefficient while equal to $-.6 \cdot 10^{-6}$ with a t-value of only .5, is not significantly different from zero.

TABLE I: WAGE RATE AND NON-EMPLOYMENT INCOME COEFFICIENTS FOR WW_2 AND FT_2 EQUATIONS

WW_2				FT_2			
WR	Coefficient (t-value)	NEY	Coefficient (t-value)	WR	Coefficient (t-value)	NEY	Coefficient (t-value)
$ < .75	-.87 (1.6)	$ < 100	.23 (1.5)	$ < .75	.014 (0.7)	$ < 100	-.004 (0.8)
7.5-1.25	-.58 (2.4)	100- 200	1	.75-1.25	.009 (1.1)	100- 200	
1.25-1.75	-.10 (0.6)	200- 500	.28 (1.5)	1.25-1.75	-.003 (0.4)	200- 500	-.009 (1.3)
1.75-2.25		500-1000	.05 (0.3)	1.75-2.25		500-1000	-.019 (2.6)
2.25-2.75	-.08 (0.6)	1000-1500	.11 (0.4)	2.25-2.75	.011 (2.3)	1000-1500	-.012 (1.2)
2.75-3.25	.08 (0.6)	1500-2500	.37 (1.3)	2.75-3.25	.013 (2.8)	1500-2500	.000 (0.0)
3.25-3.75	.03 (0.2)	2500-3500	.02 (0.1)	3.25-3.75	.017 (3.4)	2500-3500	-.001 (0.1)
3.75-4.25	-.16 (1.0)	3500-5000	.38 (0.6)	3.75-4.25	.019 (3.4)	3500-5000	-.002 (0.1)
4.25-5.25	-.08 (0.6)	5000-7500	.17 (0.3)	4.25-5.25	.020 (3.6)	5000-7500	-.088 (3.7)
> 5.25	-.01 (0.1)	> 7500	.55 (0.9)	> 5.25	.017 (3.1)	> 7500	.000 (0.0)
		($) Linear	$.48 \cdot 10^{-5}$ (.15)			($) Linear	$-.61 \cdot 10^{-6}$ (.53)

The relationship of wage rates to labor supply is stronger. While only the \$.75-1.25 dummy coefficient is significantly different from zero in the WW_2 equation, our concern lies primarily with this lower tail of the wage distribution. (An NIT is less likely to effect those in the higher wage brackets.) Most of the dummy coefficients in the FT_2 regression are significantly different from zero. But the relationship is weaker at the lower end of the wage distribution.

Assume that existing marginal tax rates are equal to zero. Then, depending upon whether the WW_2 function is evaluated at an initial wage rate of \$3.00 or \$2.00 an hour, the coefficients imply that an NIT with a 50 percent reduction rate would lead to a reduction in weeks of labor supplied of from .4 to 1.2 percent. If one assumes that the average number of hours worked per week by part time workers is 20 while the average full time number of hours is 40, the FT_2 coefficients, evaluated at initial wage rates of \$2.00 and \$3.00 respectively, imply a change in hours supplied during the week of -.5 to +.8 percent.[11]

Summing the two dimensions of labor supply implies a reduction in total labor supply of from near zero to 2 percent. Given that (1) the wage rate coefficient reflects non-pecuniary as well as pecuniary differences between jobs, and that (2) only one coefficient in the step WR equation was significantly different from zero, one might optimistically conclude that the introduction of an NIT with a \$3000 guarantee and a 50 percent reduction rate would result in almost no reduction in labor supply. An intermediate estimate would be about 1 percent.

B. Qualifications

1. Adjustments for Taxes and Wage Increases

Labor supply at time t is a function of the net wage at time t. In the WW_2 and FT_2 regressions above, however, labor supply at time t (last year) is treated as a function of gross wage rates at time t + 1 (last week). The coefficients in these regressions, therefore, are negatively biased.

Assume that all taxes are proportional and that Δ WR is also proportional to WR: Then, for all individuals, their net wage rate at time t is k times their gross wage rate at time t + 1, where $0 < k < 1$. The wage rate coefficient will be too small by a factor of $\frac{1}{k}$. If taxes are progressive, (regressive) the bias in the wage rate coefficient will be larger (smaller) than $\frac{1}{k}$; or, if the wage rates of high wage individuals increase by a smaller (larger) percentage of their own wage than that of lower wage individuals, the bias will be larger (smaller) than $\frac{1}{k}$.[12]

Ideally, one would adjust each individual's gross wage rate at time t + 1 to reflect his net wage rate at time t. Unfortunately, it is impossible to make such adjustments for wage changes, and complicated and time consuming to make such adjustments for taxes. Consequently, I will assume that the negative bias in the wage coefficients is canceled by the positive bias in the estimates of labor supply reduction created by assuming that an NIT with a 50 percent reduction rate reduces the effective wage by 50 percent, i.e., that the existing marginal tax rate is equal to zero.[13] Since the wage coefficients which required adjusting are so small, they are not likely to be very sensitive to this assumption.

Similarly, the income coefficient should be adjusted to reflect the difference between gross and net income due to taxes. At this point, however, there is nothing to adjust.

2. Estimate of Bias Created by Exclusion of Non-Labor Force Participants

There are two reasons for excluding non-labor force participants (NLFP) from the sample. First, the number of married prime-aged, able-bodied males in the basic sample who did not work at all during the year is so small--7--that it is difficult to have confidence in results generated by including these observations. More important than the small number, however, is their composition. Five of these 7 non-labor force participants are age 55 or over and the remaining ones are 49 and 43 years old. If non-labor force participants are included, therefore, further disaggregation by age would be necessary to avoid this kind of bias created by the weighting problem discussed in Section III_A below. Second, with one exception, individuals who did not work at all the previous year also did not work during the survey week. Consequently, their hourly wage rates are not available. Thus, in order to derive a WR coefficient, it is necessary to impute a potential wage rate to the NLFPs. While several wage equations have been developed in other studies for precisely this purpose, the use of an imputed wage normally leads to a positive bias in the WR coefficient.

Clearly, however, to exclude NLFPs is to negatively bias the estimate of labor supply reductions. Consequently, on the basis of one of the wage equations noted above,[14] I assigned each NLFP a potential wage rate. The WR and NEY dummy and linear NEY coefficients for the WW_2 regression quation from the basic sample plus the 7 NLFPs are reported below in Table II.[15]

TABLE II: WAGE RATE AND NON-EMPLOYMENT INCOME COEFFICIENTS FOR WW_2

EQUATION: BASIC SAMPLE PLUS 7 NLFPs

WR	Coefficient	(t-value)	NEY	Coefficient	(t-value)
$ < .75	-.541	(.72)	< 100	.223	(1.07)
.75-1.25	-.156	(.46)	100- 200		
1.25-1.75	.088	(.38)	200- 500	.289	(1.12)
1.75-2.25			500-1000	.086	(.30)
2.25-2.75	.230	(1.24)	1000-1500	-.686	(1.91)
2.75-3.25	.409	(2.25)	1500-2500	-.768	(2.04)
3.25-3.75	.422	(2.21)	2500-3500	-.014	(.02)
3.75-4.25	.230	(1.05)	3500-5000	.412	(.49)
4.25-5.25	.306	(1.46)	5000-7500	-4.174	(4.75)
> 5.25	.451	(2.05)	> 7500	.436	(.52)
			Linear	$-.99 \cdot 10^{-4}$	(2.23)

The addition of the 7 NLFPs to the basic sample changes the sign of the linear NEY coefficient and increases the t-value dramatically so that the coefficient is significantly different from zero at the 5 percent level. Five of the NEY dummy variables also now have the correct sign. Depending upon whether the linear coefficient or the appropriate dummy coefficient is used, the addition of the NLFP to the sample implies an additional unadjusted guarantee or income effect of from near zero to about .6 percent. While the addition of the NLFPs to the sample substantially changes some of the WR dummy coefficients, the effect on the estimates of labor supply reduction is small. In fact, the estimates are actually slightly smaller. Given the small numbers, however, this may be due to the peculiarity of the sample.[16]

Taking account of both income (adjusted) and wage rate effects, the addition of the NLFPs to the basic sample increases the maximum total estimated beneficiary labor supply reduction from 2 to almost 3 percent.[17] But, as indicated above, these estimates are more open to question than the ones presented in Section A. Clearly, more work needs to be done on the treatment of non-labor force participants.[18] At this point, the safest inference warranted by the data is that a negative income tax with a $3000 guarantee and a 50 percent reduction rate would lead to a beneficiary labor supply reduction of from near zero to about 3 percent.

C. Summary

In this section I have presented what I consider to be the best estimate of beneficiary labor supply reductions which would be induced by an

NIT with a \$3000 guarantee and a 50 percent tax rate. As yet I have deliberately not dealt with the rationale for my choice of dependent and independent variables. (As we shall see in the next several sections, however, the estimates are highly sensitive to these choices.) Thus, the task was simplified enormously. Even so, a relatively large amount of uncertainty, particularly about labor force participation effects, remained. To reiterate the point made at the end of the introduction, this suggests that all estimates of labor supply functions should be approached with caution.

III. Sample Selection

In this section I will argue that incorrect specification of the sample population will lead to biases in the income and wage coefficients. First, estimating one aggregate labor supply function for all demographic groups will lead to a positive bias in the WR coefficients and a negative bias in the NEY coefficients. Second, including public assistance, unemployment compensation, veteran's and workmen's compensation beneficiaries, and pensioners in the sample will have a similar effect on the income coefficient. Finally, excluding individuals who live in a family with income above some cutoff limit, will also negatively bias the income coefficient.

A. Bias in an Aggregate Regression

Wage and income coefficients vary substantially among sub-groups of the population.[19] These differences can be handled by estimating (1) an aggregate labor supply function from a regression model which uses dummy variables to distinguish among sub-groups or, (2) separate supply functions for each, or at least several, of the sub-groups. For two reasons the second method is preferable to the first.

First, while the income and wage coefficients in the aggregate regression are weighted averages of the sub-groups' coefficients, they are inappropriately weighted. Consider the following three age groups of adult males: the young (14-24), prime-age (25-61) and the old (62+). The income and wage coefficients of a regression based on a sample of all adult males in which age is an independent variable, will be a weighted average of the WR and NEY coefficients of the different age groups. But the weights will be a function of the percentage of males in an age group relative to all males in the sample, rather than a percentage of labor supply contributed by an age group relative to the total male labor supply.

The young and the old account for a much larger percentage of total males than they do of total male labor supply or output. For example, although males over 61 years of age constitute 15 percent of all males in the 1967 self weighting SEO sample, they contribute only 7.7 percent of labor supply and account for only 6 percent of male earnings. Comparable figures for young and prime-age males are given in Table X on p. 62.

Since the income coefficient for prime-age males is smaller than that of the other two groups,[20] and since prime-age males make up only 60 percent of the sample but contribute 77 percent of male labor supply and 86 percent of the male output, estimates of labor supply or GNP reduction based upon the aggregate coefficient will be positively biased.

The same argument applies to the disabled, secondary-workers, and unmarried men. A priori, there are good reasons to believe that these groups, which also work less than normal, are more sensitive to economic incentives.[21] Work is likely to be more of a chore for the disabled[22] and hence less work, or more leisure, is likely to be a more highly prized good, while individuals in the latter two categories have less responsibility than prime-age married males.

Second, public evaluation of labor supply reductions will probably depend on whose labor supply is being reduced. Few individuals are likely to care if the elderly worked less because of a negative income tax.

Retirement for the aged is considered honorable--even encouraged--in our society. Nor are many individuals likely to mind if the young curtailed their work effort as a result of an NIT in order to enhance their education. What haunts the imagination of those who fear enactment of a NIT is that it will result in wholesale work reductions by prime-age, able-bodied males.

B. Spurious Correlations between NEY and Labor Supply

Negative correlations between NEY and some measure of labor supply may be observed for one of three reasons: (1) NEY leads to reduced work effort, (2) involuntary limitations on work effort lead to NEY, or (3) some third factor simultaneously causes higher than average NEY and lower than average work effort. Only the first should be considered for purposes of estimating a labor supply schedule. Correlations between public assistance, unemployment compensation, veterans pensions, workmens compensation, and retirement pensions on the one hand, and labor supply on the other hand, are likely to be observed for either the second or third reason.

Consider public assistance. A priori, it is impossible to specify whether public assistance beneficiaries work less in order to receive aid or receive aid because they cannot work or earn enough. In the latter case, public assistance payments should not be included in NEY since causation runs the wrong way. But consider for a moment the implications of the former hypothesis. If beneficiaries work less in order to qualify for public assistance, non-beneficiaries could supposedly do the same thing. That is, beneficiaries and non-beneficiaries with the same potential wage rate face identical budget constraints.[23] To attribute their differences in work effort to differences in NEY is erroneous. The differences in this case must be a result of different tastes. This is illustrated in Figure I on the following page.

Hours worked is measured from left to right on the horizontal axis and total income is measured along the vertical axis. Assume both individuals have a market wage rate of OW. Further assume that if they earn less than G dollars (work less than H hours) they are eligible for a public assistance subsidy equal to $G less whatever they earn. Hence, the budget line is OGJW. (Although not all public assistance programs have implicit 100 percent tax rates as depicted in Figure I, most did in 1967. The analysis would not be altered by assuming a less than 100 percent tax rate.) I_1 represents an indifference curve of man I. It is tangent to the JW segment of the budget line at E_1. Man I, therefore, works F hours and receives no public assistance. I_2 represents the indifference curve of man II. Man II clearly has a much stronger aversion to work (vis-á-vis income) than does man I. He achieves a corner solution at E_2, works 0 hours and receives OG dollars in public assistance. Clearly, to the extent that work reductions are a voluntary response to the availability of transfers, the transfer is a proxy for taste differences.

Consequently, whether the (promised) receipt of public assistance leads to reduced work effort or vice versa, public assistance payments should not be included in NEY.

Moreover, because of the implicit marginal tax rates in the PA programs, it is difficult and in some cases impossible to specify the potentially effective wage rate that confronts PA beneficiaries.[24] Consequently, including PA

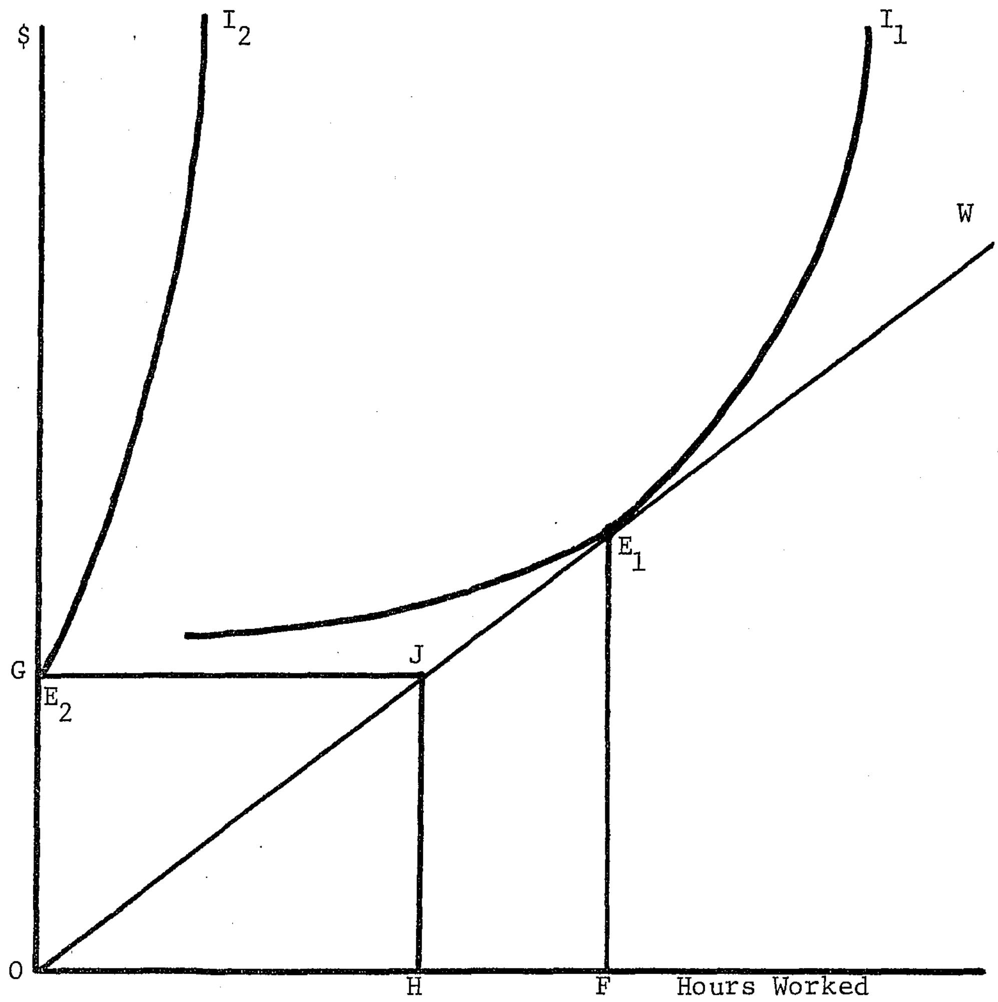


Figure 1

beneficiaries not only leads to negative biases in the NEY coefficient, but may distort the WR coefficient as well. Given these problems, the simplest and most straightforward procedure is to exclude PA beneficiaries from the sample.

The same arguments apply to unemployment compensation (UC) beneficiaries. If one assumes that the receipt of UC depends upon involuntary cessation or reduction of work, clearly UC should not be included in the measure of NEY. This appears to be a reasonable assumption for at least the initial qualification for benefits. Even if one assumes that once unemployed, the availability of benefits induces less effort to become re-employed, the budget constraint of the short term unemployed person is identical to that of a longer term unemployed who has an identical wage and lives in the same state. The difference in length of unemployment, therefore, must in this case be attributed to differences in tastes.

Unemployment compensation programs also have implicit marginal tax rates which make it difficult to specify the potentially effective wage rate of UC beneficiaries.[25] Again, the best approach would appear to be to exclude unemployment compensation beneficiaries from the sample.

Workmens Compensation (WC) and Veterans Disability and Compensation (VD) pose a somewhat different kind of a problem. A WC or VD beneficiary in year X may have incurred the injury for which he is receiving compensation in year X, or some prior year. If he was injured in year X, it is safe to assume that his injury might have led to some reduction in work effort. In this case the correlation between NEY and work effort is spurious. If the individual was injured in a prior year there are two possibilities: Either the injury affected or it did not affect the amount of work the individual can do. In the former case, the correlation between NEY and work effort will again be spurious. In the latter case there is less reason to assume that any measured correlation would be spurious. However, I have excluded the latter group as well, along with other individuals who have disabilities that limit the kind of work they can do.

An additional reason for excluding individuals in families which received VD payments is that in the SEO, veterans compensation and disability payments are lumped together with veterans pensions. The latter is an income-tested, transfer program. Hence, the same rationale for excluding UC and PA beneficiaries also applies to at least some of the VD beneficiaries.

Retirement pensions also pose a problem of holding tastes constant. Many individuals in the civil service, the military, and the private sector become eligible for retirement pensions well before the age of 65. To claim the pension, however, they must actually retire from their current job. If all individuals who were eligible did claim the benefits there would be no problem. But this is not the case. As of 1960, for example, 7.2 percent of civil service employees were composed of eligible retirees below the age of 65 who were not claiming their benefits.[26] One difference between claimants and non-claimants who have identical alternative employment opportunities may be in their tastes for leisure vis-á-vis income.[27] In other words, the pensions of claimants may represent, at least in part, a proxy for taste. The ideal procedure would be to devise a method to correctly describe the opportunity loci of both claimants and non-claimants eligible for retirement. But it would be very difficult to identify the non-claimant eligibles, and even if this could be done easily, the introduction of alternative budget constraints would complicate the estimation problem. Moreover, eligibility for pensions may in part reflect taste differences. Some occupations like the military and the civil services offer relatively generous pensions at an early age. Individuals who want to retire early are more likely to be attracted by such occupations. Consequently, the combination of including pensioners in the sample and counting pensions in NEY undoubtedly leads to a negative bias in the NEY coefficient.[28]

Empirically, it turns out that the NEY coefficient is very sensitive to the inclusion or exclusion of pensioners. Recall that the WW_2 and FT_2 NEY coefficients reported in Section II for the basic sample were frequently of the wrong sign and in all but two cases insigificantly different from zero. When pensioners are added to the basic sample, the WW_2 and FT_2 linear NEY coefficients are respectively $-.12 \cdot 10^{-3}$ (3.8) and $-.31 \cdot 10^{-5}$ (2.7).[29] More informative are the dummy coefficients reproduced in Table III below.[30]

There is no strong relationship between NEY and WW_2 for NEY less than \$3500. The three highest NEY cells dominate the relationship. (The relationship of NEY to FT_2 is not changed as dramatically as that of NEY to WW_2 in the step equations.) Quite clearly in the WW_2 regression, a few extreme cases--namely, pensioners--are dominating the regression results. Only 39 individuals among the non-pensioners have NEY in the third highest, second highest, and highest NEY cells. While sixteen pensioners have NEY greater than \$3500, all but 5 worked full time. Thus 5 pensioners dominate a sample of 4035. This appears to be a case of the tail wagging the dog.

TABLE III: INCOME COEFFICIENTS FOR WW_2 AND FT_2 EQUATIONS FROM BASIC SAMPLE PLUS PENSIONERS

$NEY	$\underline{WW}_2$		$\underline{FT}_2$	
< 100	.25	(1.6)	-.004	(.68)
100- 200				
200- 500	.27	(1.4)	-.009	(1.21)
500-1000	.06	(.3)	-.019	(2.48)
1000-1500	.11	.4	-.021	(2.16)
1500-2500	.34	(1.3)	-.001	(.07)
2500-3500	.03	(.1)	-.003	(.21)
3500-5000	-1.43	(2.7)	-.001	(.06)
5000-7500	-1.57	(2.8)	-.164	(8.32)
> 7500	-1.41	(2.3)	-.001	(.04)

If there were no a priori grounds for excluding pensioners, perhaps the effect of these few extreme cases would be of less concern. Moreover, the NEY coefficients remain quite small even when pensioners are added to the basic sample. But, there are a prior grounds for believing that the inclusion of pensioners negatively biases the NEY coefficient. And, as I will show below, inclusion of these handful of pensioners who should not be included, leads to very large biases when the sample is inappropriately defined in other ways.

If unemployment compensation, public assistance, workmens compensation and veterans disability beneficiaries in addition to pensioners are added to the basic sample and PA, UC, WC, and VD benefits are counted as part of NEY, the NEY coefficient actually decreases very slightly from that in the basic sample so long as WW_2 is the dependent variable. However, if only actual weeks working (WW_1) rather than weeks working plus looking (WW_2) is the dependent variable, the linear NEY coefficient is 1 1/2 times as large when PA, UC, WC, and VD benefits are included in NEY as when they are excluded. The linear coefficients are reproduced in Table IV.[31]

TABLE IV: INCOME COEFFICIENTS FOR WW_2 AND WW_1 EQUATIONS FROM BASIC SAMPLE PLUS PENSIONERS, UC, PA, VD, AND WC BENEFICIARIES

	NEY	NEY + PA, VC, VD, and WC Benefits
WW_2	$-.11\cdot10^{-3}$ (3.3)	$-.96\cdot10^{-4}$ (3.2)
WW_1	$-.15\cdot10^{-3}$ (2.8)	$-.24\cdot10^{-3}$ (4.6)

The WW_2 coefficient is less sensitive to changes in the NEY measure in this case because UC and probably the PA beneficiaries in this sample as well (since I have excluded the disabled) were undoubtedly looking for work in most or all of the weeks in which they did not work. That is, the use of WW_2 as the dependent variable eliminates the spurious correlation between UC or PA and measured labor supply when the receipt of UC or PA is due to involuntary unemployment. The WW_1 variable, on the other hand, does not possess this virtue.

The NEY coefficient which includes the transfers in the WW_1 regression is a measure of the negative bias in the NEY coefficient that results from using cross section data such as the census where (1) there is no way of distinguishing among types of non-employment income and (2) no attempt is made to control for unemployment.[32]

In succeeding sections I will again exclude PA, UC, WC, and VD beneficiaries from the sample. In many cases, however, I will present results for samples which include as well as exclude pensioners. There are two reasons for presenting results for the former sample: (1) to facilitate comparability with other studies and (2) to enable the reader to see that in almost all the cases the alternative procedures discussed make no difference if pensioners are excluded, but make a huge difference when pensioners are included. The latter point is clearly demonstrated in the following subsection.

C. Income Cutoffs and the NEY Coefficient

The income and wage elasticities of low income workers may be higher than those of high income workers. In a study designed to estimate labor supply reductions that would be induced by a negative income tax, however, only the former are of primary concern. One procedure which has been used for dealing with this problem is to exclude individuals in families whose incomes exceed some arbitrary figure.[33] The effect of this procedure, however, is to negatively bias the NEY coefficient. Other things being equal (WR, NEY and earnings of other family members) total income is a function of hours worked. Consequently, to exclude those with incomes above some arbitrary figure is to exclude individuals who are hard workers even though they may have NEY.

This point is illustrated with the aid of Figure II. Individuals I, II, and III have hourly wage rates of OW, but I and II have NEY of OG = $4,000. Assume their tastes are such that equilibriums for the three individuals are as denoted by E_1, E_2, and E_3 in the diagram. The correlation between NEY and labor supply is weak. However, if individuals with total incomes greater than $10,000 per year are eliminated from the sample, i.e., individual II, the relationship between NEY and labor supply will become very negative and very strong.

There is no need to eliminate anyone from the sample to get wage coefficients that are not contaminated by upper income preferences. The simplest procedure is use a set of dummy variables for different wage rates rather than linear or quadratic wage rate variables and then focus on the lower end of the wage rate distribution.

An alternative procedure for getting NEY coefficients which are uncontaminated by the preferences of upper income individuals is to exclude individuals whose wage rate exceeds some arbitrary figure. So long as wage rates are completely exogenous, this procedure will not lead to a biased NEY coefficient. But, there is every reason to believe that the observed wage rate is probably endogenous for many pensioners,

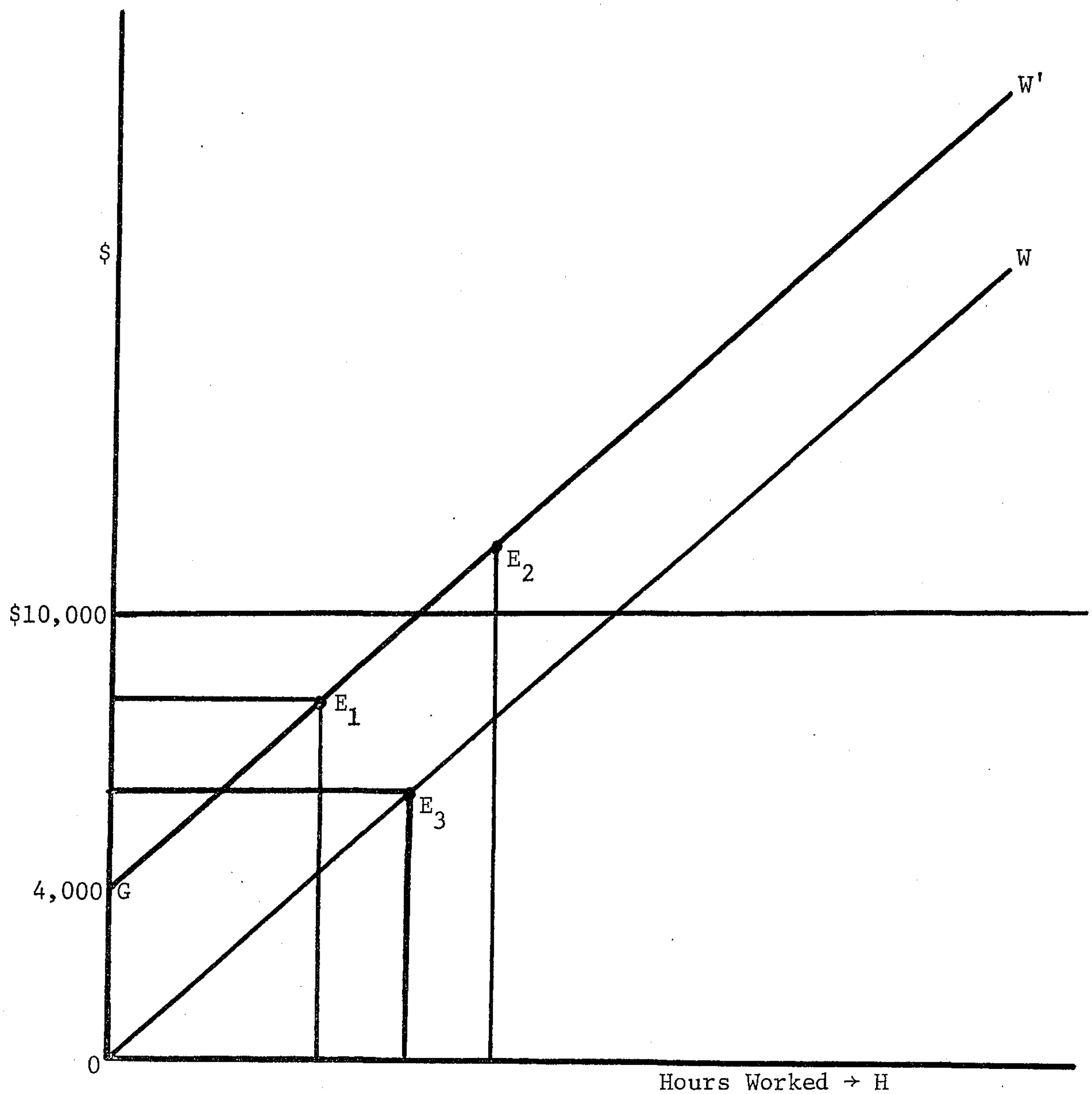


Figure 2

particularly those who want to work part time. The number of well paying, part time jobs that pensioners or others in their late 40's or 50's can qualify for is very small. In other words one of the costs of working part time is likely to be a smaller hourly wage rate than the individual could obtain in a full time job. Particularly when pensioners are included in the sample, excluding individuals by their wage rate might also lead to a negative bias in the NEY coefficient.

The NEY linear coefficients for WW_2 regressions are presented in Table V below for the following six samples: (1) the basic sample, (2) the basic sample less anyone in a family whose income exceeded \$10,000, (3) the basic sample less anyone whose wage rate exceeded \$3.75 per hour,[34] and (4), (5), and (6) which are identical to (1), (2), and (3) except pensioners are included.[35]

TABLE V: INCOME COEFFICIENTS OF WW_2 EQUATIONS WITH WAGE RATE AND CUTOFFS AND WITHOUT CUTOFF--WITH AND WITHOUT PENSIONERS

	Without Pensioners	With Pensioners
No Cutoff	$.5 \cdot 10^{-5}$ (.1)	$-.12 \cdot 10^{-3}$ (3.8)
Y Cutoff	$.77 \cdot 10^{-4}$ (.4)	$-.86 \cdot 10^{-3}$ (5.9)
Wage Cutoff	$.34 \cdot 10^{-4}$ (.5)	$-.37 \cdot 10^{-3}$ (6.5)

The coefficients in the second column indicate that when pensioners are included in the sample, the NEY coefficient is extremely sensitive to both income and wage rate cutoffs. With an income cutoff of \$10,000, the income coefficient increases by a factor of 7! The wage rate cutoff of

$3.75 an hour increased the coefficient somewhat less dramatically. But even an increase of 3 times is quite substantial.

The income and wage exclusions, as predicted, eliminate many individuals with substantial NEY who nevertheless worked full time. Once these individuals are excluded the few pensioners with very large NEY dominate the largest NEY cells.

In marked constrast, note that while the magnitude changes, the signs of all the coefficients in the first column--the one without pensioners--are wrong. The t-values indicate that none of them are significantly different from zero. Once pensioners are excluded from the sample, the NEY coefficient is, for all practical purposes, totally insensitive to income or wage rate cutoffs.

D. Other Exclusions

In addition to the groups discussed above, all individuals who were self-employed, or in the Armed Forces in the week previous to the survey or during the previous year, or for whom information was missing were also excluded from the sample. The self-employed were excluded for two reasons. First, there are no data on either weekly earnings or hours worked for them. Thus the hourly wage rate variable is unavailable. Second, part of the yearly earnings of the self-employed should be counted as non-employment income since at least a part is likely to reflect a return to assets. But the proportion which should be so allocated can only be decided on an arbitrary basis. Given these two difficulties, the simplest procedure at this stage was to eliminate this group from the sample.

Wage rates are also unavailable for individuals who were in the Armed Forces the week previous to the survey. Labor supply is incorrectly measured for individuals who were in the Armed Forces during the year previous to the survey since only information on weeks worked as a civilian is provided. Finally, an extremely large number of individuals were eliminated from the sample because information, particularly on their assets and liabilities, was missing. Unfortunately, due to time limitations, I have not attempted to test the sensitivity of the results to these exclusions.

E. Summary

Non-employment income and, to a lesser extent, wage rate coefficients are very sensitive to the use of alternative sample populations. A sample which lumps all demographic groups together will lead to negatively biased NEY and positively biased WR coefficients. Since certain kinds of NEY such as PA, VC, VD, and WC benefits, and pensions are spuriously correlated with some measures of labor supply, the inclusion of PA, UC, VD, WC, and pensions beneficiaries in the sample will lead to a negative bias in the NEY coefficient. Finally, the exclusion of individuals with income (and to a lesser extent wage rates) above some arbitrary limit will have a similar effect. The most important empirical findings relate to the combination of including pensioners and using income or wage rate cutoffs. The inclusion of pensioners alone has only a relatively minor effect on the NEY coefficients. The use of an income or wage rate cutoff alone has no effect on the NEY coefficients. But the combination of including pensioners and using an income or wage rate cutoff has a dramatic effect on the NEY coefficient.

Alternatively, the separate components of labor supply may be summed. This is, the WR and NEY elasticities of either WW_1 or WW_2 and the HW equations may be summed or the elasticities of either the WW_1 or WW_2 and FT_1 or FT_2 equations may be summed. Again, providing that the zero values for weeks worked are included, we will have a total measure of labor supply. Unfortunately, there are serious problems involved with using most of these comprehensive measures.

There are two reasons why the use of either HW or TH_1 or TH_2 will result in biased wage rate coefficients. First, errors of measurement in the hours variables will lead to a negative correlation between the error term and the dependent variable when hours worked appears in the dependent variables. This problem, discussed in detail below, creates a very strong negative bias in the WR coefficient. Second, an inverse correlation between unemployment and wage rates will create a positive bias in the WR coefficient unless there is some control for unemployment. As I argue in parts B and C this suggests that the WW_2 and FT_2 variables are preferable to the WW_1, FT_1, and HW variables.

A. Measurement Errors and Bias in the WR Coefficients

The observed or measured wage rate variable is derived by dividing earnings last week by hours worked last week.[36] But hours worked last week also appears in the numerator of the dependent variable when the latter is either total hours worked ($TH_2 = WW_2 \cdot HW$) or hours worked last week (HW). Consequently, if HW is too high (low) the wage rate will be too low (high) and the dependent variable too high (low). Thus, the negative bias.

If weekly earnings (E) rather than the hourly wage rate is used as the wage variable, the correlation between the error term and a dependent variable which includes hours worked will be positive. Weekly earnings is the product of the hourly wage and hours worked. That is to say, hours worked last week now implicitly appears in the numerator of both the independent and dependent variable. If the individual worked an unusually high (low) number of hours last week, his earnings will be unusually high (low), and, of course, his measured labor supply will be unusually high (low). Thus, a positive bias will result.

Since measurement error gives rise to a negative bias when the hourly wage rate is used and a positive bias when the weekly earnings is used as the independent variable, it is possible to establish outer bounds to the variance in the wage coefficient that can arise from measurement errors. The coefficients (with t-values in parenthesis) reported in Table VI provide estimates of this range.[37]

The extremely large t-values for both the negative wage rate and the positive earnings coefficient in the TH_2 and HW equations indicate that measurement error is rather serious. While the wage rate coefficient implies that a 50 percent reduction in the wage rate would lead to a 6.2 percent <u>increase</u> in hours worked during the week and a similar increase in hours worked during the year, the earnings coefficients imply that a similar decrease in the wage rate would lead to a 6.3 percent <u>decrease</u> in hours worked during the week and a 6.8 percent <u>decrease</u> in total hours worked during the year.

TABLE VI: WAGE RATE AND WEEKLY EARNINGS COEFFICIENTS FROM TOTAL HOURS (TH_2), HOURS WORKED, AND WEEKS WORKED (WW_2) REGRESSIONS AND IMPLIED REDUCTIONS IN LABOR SUPPLY

	TH_2[a]	HW[b]	WW_2[c]	FT_2
WR	-130.0 (18.1)	-2.61 (19.0)	.04 (1.3)	$.34\cdot10^{-2}$ (3.1)
WR^2	2.0 (9.0)	.04 (9.4)	$-.8\cdot10^{-3}$ (.8)	$-.70\cdot10^{-4}$ (2.1)
Percent Reduction in L.S.[d]	+6.2	+6.2	-4/10 of 1 percent	-2/10 of 1 percent
E	3.11 (11.9)	.059 (11.65)	.0032 (2.8)	$.17\cdot10^{-3}$ (4.4)
E^2	$-.26\cdot10^{-2}$ (7.2)	$-.5\cdot10^{-4}$ (7.06)	$-.3\cdot10^{-5}$ (1.86)	$-.16\cdot10^{-6}$ (3.0)
Percent Reduction in L.S.[e]	-6.8	-6.3	-1/10 of 1 percent	-3/10 of 1 percent

[a]Evaluated at 2000 hours

[b]Evaluated at 40 hours

[c]Evaluated at 50 weeks

[d]Evaluated at initial wage of $2.00 per hour

[e]Evaluated at initial earnings of $80 a week.

Both the negative bias in the wage rate and the positive bias in the earnings equations are avoided if WW_2 and FT_2 rather than TH_2 or HW are used as the dependent variables. The most striking findings presented in Table VI is that the coefficients of the wage and earnings variables for the WW_2 (FT_2) equations imply a remarkably similar estimate of a 1 to 4 tenths (2-3 tenths) of one percent reduction in weeks worked (hours worked) for a 50 percent reduction in the wage rate.

B. Unemployment and a Bias in the Wage Rate Coefficient

In cross section analysis one expects that, at least at the lower end of the wage distribution, the lower the wage rate, the more likely the individuals is to be unemployed. Consequently, without some control for unemployment the WR coefficient will pick up demand as well as supply effects. While there is very little difference between the quadratic WR coefficients in the WW_1 and WW_2 equations, there is an enormous difference in the low wage WR dummy coefficients when WW_1 or FT_1 rather than WW_2 of FT_2 is the dependent variable. This is illustrated in Table VII.[38] Thus, an additional reason for not using either the HW or the TH_1 or TH_2 variables is that it is impossible to control for demand factors when hours worked last week is, or appears in, the dependent variable. The WW_2 and FT_2 variables are the only ones which aviod both the negative bias created by the correlation of the error term and the dependent variables, and the positive bias created by the correlation between unemployment and wage rates.[39]

C. FT_2 vis-á-vis HW as a Measure of Labor Supply Within Weeks

The full time-part time variable is a very crude measure of hours worked during the week. First, it measures only whether the individual works full or

TABLE VII: WAGE DUMMY COEFFICIENTS FROM WW_1, WW_2 FT_1 AND FT_2 EQUATIONS

	WW_1	WW_2	FT_1	FT_2
$ < .75	-2.800 (3.29)	-.863 (1.57)	-.106 (4.43)	.014 (0.72)
.75-1.25	-1.584 (4.17)	-.600 (2.45)	-.038 (3.57)	.009 (1.07)
1.25-1.75	-.484 (1.87)	-.110 (0.66)	-.005 (0.69)	-.003 (0.44)
1.75-2.25				
2.25-2.75	.171 (0.83)	-.079 (0.59)	.013 (2.27)	.011 (2.31)
2.75-3.25	.341 (1.69)	.073 (0.56)	.013 (2.21)	.013 (2.76)
3.25-3.75	.321 (1.52)	.015 (0.11)	.019 (3.11)	.017 (3.50)
3.75-4.25	.114 (0.47)	-.158 (1.01)	.020 (2.96)	.019 (3.39)
4.25-5.25	.166 (0.71)	-.088 (0.58)	.018 (2.71)	.020 (3.63)
> 5.25	.133 (0.54)	-.030 (0.19)	.017 (2.48)	.017 (3.06)

part time for most of the year. Second and perhaps more serious, it does not measure the sensitivity of overtime labor supply to economic factors. Neither of these shortcomings is present in the HW variable. However, for reasons discussed in subsections A and B above, it is impossible to get an unbiased wage rate coefficient when HW is the dependent variable. Moreover, in the basic sample the relationship of NEY to FT_2, although weak, is stronger than that of NEY to HW.[40]

D. Summary

Wage coefficients are very sensitive to alternative measures of labor supply. Only the WW_2 and FT_2 measures avoid the negative biases in the wage coefficients which result from pure errors of measurement and the positive biases in the wage coefficients which result from the inverse correlation of unemployment and wage rates. Consequently, they appear to be the best measures of labor supply that one can construct from the SEO data.

V. An Alternative Wage Rate Measure

A few economists have suggested that the problems in using the observed wage rate are serious enough to warrant the use of an imputed wage rate. In this section, I argue that the use of an imputed or instrumental wage rate variable leads to a positive bias in the wage rate coefficient. The bias may be quite large. The reduction in weeks worked (WW_2) implied by the imputed wage rate coefficients is greater than that implied by the observed wage rate or earnings coefficients by a factor of 1.7 times.[41] In the first part of this section I discuss the alleged advantages of the imputed wage rate. In the second part I attempt to account for the source of the large positive bias in the imputed wage rate.

A. The Alleged Advantages of An Instrumental Wage Variable

In order to estimate from individual data the effect of wage rates on labor force participation, there is, as noted above, no alternative to imputing a wage rate for non-workers. There are three other possible arguments for using an instrumental wage rate variable even in cases where the WR is available.

First, as noted above in Section IV, if the dependent variable is, or includes, hours worked last week, there will be a spurious negative correlation between wage rates and the dependent variable if reported hours worked are either abnormally large or small.

The use of an instrumental variable is, in this circumstance, a legitimate technique for avoiding this bias. But there are other procedures which in this particular case appear to be superior. As I noted in the fourth section, it is not only possible to avoid this problem entirely by using WW_2 and FT_2 as dependent variables, but it is also possible to place an upper and lower bound on the biases created by measurement error when the HW dependent variable is used. The instrumental wage coefficient, however, exceeds that upper bound! It implies a larger percentage reduction in hours worked during the week than the positively biased earnings coefficient.[42]

Second, a spurious negative correlation between wage rates and labor supply arises out of the "fact" that some individuals are given higher than normal wages to compensate them for lower than normal availability of work in their occupation.[43] Construction workers come immediately to mind.

I experimented with two methods to reduce the negative bias in the wage coefficient which arises out of high wage rates compensating for low availability of work. The first is to eliminate from the sample workers in industries, such as construction, where one has grounds for believing that compensation wage rates exist. Unless there is some reason to believe that workers in such industries differ in some other important way from the remaining workers in the sample, this procedure should reduce and perhaps eliminate the bias. The second procedure is to eliminate from the sample all individuals who have higher than average wage rates and lower than average weeks worked. This procedure undoubtedly over-corrects for compensation wages; i.e., it leads to a positive bias in the wage coefficient. Even if no individuals received higher than normal wage rates to compensate for lower than normal availability of work, some individuals in a random sample will have a combination of higher than average wage rates and lower than average weeks worked. To exclude these individuals is to destroy the randomness of the sample and to bias the wage coefficient upwards.[44] Consequently, excluding individuals with a combination of high wage rate and low weeks worked as a method of correcting for the negative bias, probably over-corrects the bias. The wage coefficient derived from this procedure, therefore, can be taken as a maximum estimate.

While these procedures double the extremely small quadratic WR estimates of labor supply reduction, they hardly effect the much larger wage dummy coefficients in the low wage range at all.[45] The reason is quite simple. Individuals with low wage rates are not receiving high wage rates to compensate for low availability of work.

Third, if there are pure errors of measurement in the wage rate variable, they would bias the WR coefficient towards zero. (Note that abnormalties in hours worked need not imply errors in measurement in the wage rate variable.) The use of an instrumental variable in this case would avoid the bias which arises out of pure measurement error, but only at the cost of introducing another potentially more serious bias.

B. A Positive Bias in the Instrumental Wage Variable

The use of an instrumental variable is appropriate when there are a set of variables which account for a substantial amount of variance in the independent variable of interest but have no direct effect on the dependent variable. The problem is that the variables which are the most important determinants of wage rates also have direct positive effects on measure labor supply.

In the two studies which used an instrumental wage variable the wage equations were as follows:

(1) WR = WR (Age, Education; Race, Sex, Current Location.)

(2) WR = WR (Age, Education; Race, Sex, Current Location; Dummy for foreign location at age sixteen, Dummy for Union Membership, Health.)

Most of the independent variables in both equations probably have a direct as well as an indirect effect through wages on measured labor supply. Health, for example, undoubtedly effects the supply of labor independent of the individuals' wage rate. Age may be a good proxy for tastes and may also reflect demand factors. The demand for labor varies by race. Being black leads to both lower wages and lower availability of work. It should not be necessary to discuss the effects of sex in detail.

But it is worth discussing the education variable in detail. Education not only increases an individual's productivity but it also changes his tastes and affects the kinds of jobs which an individual can get. It does not seem unreasonable to assume that those with more education are most likely to have been socialized into a greater desire to work and that the more education an individual has the more pleasant his job is likely to be. Even more important, the number of years of education that an individual has completed may be the best proxy that we have for his ambition. That is, it is reasonable to assume that, on the average, individuals who drop out of school earlier than average will not only be less bright than average but less ambitious as well.

All of the variables discussed above, with the possible exception of age, have positive direct effects on both the wage rate and labor supply.

Consequently, if they are excluded from the labor supply equation, the instrumental wage variable will be biased upwards. On the other hand, if all the variables are included in the labor supply regression, there will be no independent variation in wage rates. Unfortunately, the attempt to use an instrumental wage variable inevitably leads to this "damned if you do and damned if you don't" bind. This is a very good reason for not using the instrumental wage variable if a viable alternative exists.

As used in other studies, the instrumental wage rate variable has amounted to little more than an education variable scaled in wage units.[46] This suggests that the positive bias in the instrumental wage rate coefficients reported in these studies may be quite strong.

C. Summary

While there are several potential sources of negative bias in using an observed wage rate variable, all of these biases with the exception of that arising from pure errors of measurement in the wage rate, may be avoided by the use of procedures which do not entail the use of an instrumental wage variable. Furthermore, while the use of the instrumental wage variable also avoids all of these sources of negative bias, it does so only at the cost of creating a positive bias in the wage rate coefficient. The choice between the reported or instrumental wage rate variable depends upon one's judgment about the seriousness of the bias created by pure errors of measurement vis-á-vis the bias created by including the effects of other variables, particularly education, on labor supply in the instrumental wage rate estimates.

VI. Alternative Measures of NEY

Obtaining unbiased NEY coefficients is as difficult as, or even more difficult than, obtaining unbiased wage coefficients. As I pointed out in Section III, including certain transfers in the measure of NEY will lead to a negative bias in the NEY coefficient. On the other hand, including in NEY an imputed return to assets for which there is no reported return will lead to a positive bias in the NEY coefficient.

A. Reported NEY

Reported NEY in the SEO includes (1) Social Security (old age survivors and disability insurance) or Railroad Retirement, (2) pensions from retirement programs for government employees or military personnel, (3) pensions from private employers, (4) veterans disability or compensation, (5) public assistance, relief or welfare from state or local governments, (6) unemployment insurance, (7) workmens compensation, illness, or accident benefits, (8) other regular income such as payments from annuities, royalities, private welfare or relief, contributions from persons not living in the household, and alimony or Armed Forces allotments, (9) interest, (10) dividends, and (11) rent.

I have already discussed in Section III the problems which arise from spurious correlations between transfers, or items 1-7, and labor supply. Because their inclusion would bias the NEY coefficients, I have excluded individuals in families with income from items 1-7 from the sample.[47]

B. Assets

The following information on the family's asset position is available in the SEO: (1) market value and mortgage or other debt of farms, businesses or professional practices, (2) market value and debt of real estate, (3) market value and debt of own home, (4) money in checking, savings accounts or any place else, (5) stocks, bonds, and personal loans and mortgages, (6) market value and debt of motor vehicles, (7) other assets (excluding personal belongings and furniture), and (8) consumer debt.

A conceptually appropriate measure of NEY will include imputed returns to assets as well as reported returns from assets. A house no less than a bond produces a stream of goods and services unrelated to current work effort. If assets with no reported return vary directly (inversely) with measured or reported non-employment, failure to impute a return to assets will lead to a negative (positive) bias in the NEY coefficient. But while it is clear that some return should be imputed to assets, doing so creates several problems.

First, it is not clear what interest rate to use for imputing returns to these assets. The interest rate is important because, given observations on labor supply and net worth, the NEY coefficient will vary inversely with the interest rate.

To get an idea of how important the interest rate is, assume for the moment that all NEY consists of income imputed to assets. Then changes in the interest rate are equivalent to changes in the scale of NEY. A 25 percent decrease in the interest rate from 8 to 6 percent would reduce all the NEY observations to three-quarters of their previous value and thereby increase the NEY coefficient by four-thirds. While not all of NEY consists of income imputed to assets, the sensitivity of this element to the interest rate is great enough to suggest that the overall NEY coefficient may also be sensitive to the interest rate.

Since the rate of return and the liquidity of assets varies, this problem is even more complicated. The appropriate interest rate of each kind of asset must be ascertained.

A second much more serious problem is that certain kinds of assets may be spuriously correlated with labor supply. For example, a positive spurious correlation between normal consumer debt and work effort--which implies a negative correlation between NEY and work effort--may be expected for two reasons: (1) the supply of debt available will depend in part on how "steady" a worker the individual is and (2) the individual's demand for debt will probably also vary directly with hiw own perceived ability to repay, which in turn is likely to vary directly with the steadiness of his work. On the other hand, debt might also vary inversely with work effort because it is incurred during times of unemployment or because bad health resulted in both work reductions and medical debt. Inclusion of debt in the NEY variable would result in a negatively biased NEY coefficient in the former case and a positively biased coefficient in the latter case.

More important, a positive spurious correlation between the individual's equity in his home and his work effort may be expected for three related reasons. First, the supply of mortgage loans will depend in part on how steady a worker the individual is. Second, home ownerships normally entails a commitment to steady work to repay a large mortgage debt. Finally, both home ownership and full time work are, in part, reflections of individual characteristics such as steadiness and ambition. (These same arguments apply with somewhat less force to interest, dividends, and rent, those reported components of NEY, which are, after all, just returns to assets. See the discussion on ambition in the introduction.)

The spurious positive correlation between home ownership and labor supply may dominate the theoretical negative relationship between NEY and labor supply if an imputed return to the individual's equity in his home is added to reported NEY. Home equity accounts for about one-half of all assets for which no return is reported. And, even if only a 5 percent return is imputed to home equity, this one source of imputed NEY will be slightly larger than total reported NEY.

Given the biases in the NEY coefficient that are likely to arise from spurious correlations if imputed returns to assets are counted as NEY, an alternative procedure is desirable. The simplest alternative is to include separate independent variables in all regressions for each of the assets which have no reported return in the SEO in addition to a reported NEY variable. This approach not only provides a solution to the spurious correlation problem but also solves or skirts the problem of choosing the appropriate interest rate to impute to each asset. So long as the asset variables are included in the equation the NEY coefficient will be unbiased.[48]

When pensioners are excluded from the sample, whether assets are ignored entirely, included as separate independent variables, or included in discounted form in the NEY variable itself, the NEY coefficients in regressions where WW_2 is the dependent variable remain slightly positive but not significantly different from zero.[49] When pensioners are included in the sample, however, the strong negative relationship between reported NEY and labor supply is weakened considerably when imputed income from assets is added to reported NEY. While the NEY coefficient without imputed income is equal to $-.12 \cdot 10^{-3}$ with a t-value of 3.8 the NEY coefficient with income imputed to assets (at an interest rate of 8 percent) is $-.22 \cdot 10^{-4}$ with a t-value of only 1.4.[50]

This result reinforces the above hypothesis of the existence of a positive spurious correlation between some kinds of assets and labor supply. More direct and strong evidence is gleaned by examining the various asset coefficients themselves. The coefficients (and t-values in parenthesis) for equity in own home (HOMES), equity in a business or farm, (BUSFRM), money in savings, banking or checking accounts (BNKACC), equity in automobile (AUTOS), net value of other assets (OTHAST), and consumer debt (DBT) are given in Table VIII below.[51] Note that only the BSFRM, the OTHAST and the DBT variables have the correct sign. But neither these nor the BNKACC nor the AUTOS variables are significantly different from zero. The only variable which is significantly different from zero is the HOMES variable, but the coefficient is positive.[52]

Thus, including in NEY, income which has been imputed to assets will bias the NEY coefficient towards zero because of the positive spurious correlation between home equity and labor supply--so long as pensioners are included in the sample. But when pensioners, as well as non-labor force participants, are excluded from the sample, the NEY coefficient is already so close to zero or slightly positive without the inclusion of imputed income in the NEY, that the addition of the imputed income has little effect.

TABLE VIII: COEFFICIENTS AND T-VALUES OF ASSET VARIABLES IN WW_2 REGRESSION

	Coefficient	(t-value)
BUSFARM	$-.53 \cdot 10^{-6}$	(.12)
HOMES	$.14 \cdot 10^{-4}$	(2.8)
BNKACC	$.16 \cdot 10^{-6}$	(.03)
AUTOS	$.23 \cdot 10^{-5}$	(.39)
OTHAST	$-.49 \cdot 10^{-4}$	(1.2)
DBT	$.18 \cdot 10^{-4}$	(.70)

C. Summary

Although a conceptually appropriate measure of NEY would include income imputed to assets for which no return is reported, the existence of a strong spurious positive correlation between the most important such asset--home equity--and labor supply, will lead to positively biased NEY coefficients when the NEY value includes income imputed to assets. Because there is no relationship between NEY and labor supply for married prime-age, able-bodied males--once pensioners and non-labor force participants are excluded from the sample--this bias is not severe for this group. However, the bias might be important for other demographic groups where the relationship between NEY and labor supply is stronger. In this case, the procedure of using separate asset variables would appear to be superior to imputing returns to assets.

VII. Conclusion

My best estimate of the labor supply reduction of married prime-aged, able-bodied male beneficiaries that would be induced by an NIT with a guarantee of $3000 and a tax rate of 50 percent is from near zero to 3 percent. Even the maximum estimate of a 3 percent reduction is much lower than most estimates derived from other cross section studies.

The sources of difference are identified in Sections III through VI. First, in this study only married prime-aged, able-bodied males are included in the sample. Second, the spurious negative correlation between some measures of labor supply and the reported amount of public assistance, unemployment compensation, workmens compensation, veterans benefits, and pensions is avoided by eliminating from the sample persons who received these transfers. Third, individuals whose income exceeded some arbitrary amount are not eliminated from the sample. (The combination of including pensioners and excluding those with incomes above an arbitrary amount produces very large negative NEY coefficients.) Similarly, the use of the WW_2 and FT_2 variables avoids the positive bias which results from the correlation between unemployment and wage rates. Finally, an observed wage rate variable is not subject to the inherent positive bias on an imputed wage rate variable.

On the other hand, my WR and NEY coefficients imply larger reductions in labor supply than those in other studies for two reasons. First, the use of separate asset variables eliminates the positive bias in the NEY coefficient which results from imputing returns to assets which are spuriously positively correlated with labor supply. Second, the use of the WW_2 and FT_2 variables also avoids the negative bias in the WR coefficient which results from the negative correlations between reported labor supply and wage rates when hours worked are abnormal.

As I noted in the introduction, my best estimate, like all other estimates derived from cross section studies must be viewed with caution because, given the data it is not possible to control for either non-pecuniary differences in jobs or for ambition. Consequently, studies such as this one are best utilized in conjunction with studies derived from longitudinal and experimental data.

FOOTNOTES

[1]Hall's [6] labor supply functions are almost perfectly inelastic with respect to wage rates and income for prime-age, able-bodied males. While the Kalachek-Raine's functions imply that a negative income tax with a 50 percent tax rate and a $2000 guarantee would lead to a reduction in the labor supply of prime-age males of 65 percent.

[2]Probably the most serious shortcoming is my treatment of non-labor force participants. See the discussion in Section II.

[3]For reasons discussed in Section III, it is necessary to derive separate labor supply schedules for major demographic groups. Given the limitations of time, I believe that to examine in detail the difficulties of obtaining the labor supply schedule of one important demographic group is preferable to attempting to make estimates for all groups.

In a forthcoming monograph on the Labor Supply Effects of a Negative Income Tax, Stan Masters and I will derive labor supply schedules for all demographic groups.

[4]Alternatively his budget constraint may be defined in terms of WR and the sum of NEY + WR · 2000 hours. The last term, called full income by Hall in [6], defines that income given WR and NEY which the individual would have if he worked full time.

In some cases, the budget constraint cannot be defined in terms of single WR's and NEY's. For example, the earnings limitation provisions of the Social Security Act which apply to those between the age of 65 and 72 place a zero percent marginal tax rate on earnings up to $1680, a 50 percent marginal tax rate on earnings between $1681 and $2880, a 100 percent marginal tax rate on earnings between $2881 and the individuals annual benefit payment, and a zero marginal tax rate on earnings in excess of the annual benefit. But the average tax rate, which is relevant for all or nothing work decisions, is of course greater than zero throughout all but the first range.

[5]Since the existing marginal tax rate of most potential NIT beneficiaries exceeds zero, the estimated wage rate effect will be too high. See Section II-B-1.

[6]In at least one study [5] which simulated the effect of an NIT on work effort, the estimated work reduction is more than twice that which results from simply evaluating the function at the difference pair values of WR and NEY. Any method which does not produce results similar to

evaluating the function at different values of WR and NEY is suspect. It appears that their error results from evaluating the pure substitution elasticity at the original rather than at the midpoint between the original and post NIT wage rate.

[7]IN [5] the authors do devise a measure of this variable. Unfortunately I have been unable to replicate their results. This may be due to my use of different samples. Or perhaps misinterpretation of the author's specifications for the variable or programming errors have led to the discrepancy.

In any case, since the asset preference variables used in [5] is a function only of the wage rate and age, an alternative method of controlling for this variable is to aggregate individual observations by age and wage groups. I used the following 6 age groups; 25-30, 30-35, 35-40, 45-50, 50-55, and 55-61 plus the following 10 wage groups; < .75, .75-1.25, 1.25-1.75, 1.75-2.25, 2.25-2.75, 2.75-3.25, 3.25-3.75, 3.75-4.25, 4.25-5.25, and > 5.25 to give me a total of 60 observations. In both the WW_2 and TH_2 regressions, the NEY coefficient remains positive and insignificantly different from zero. See regression numbers 42 and 43.

[8]Weeks worked are given in intervals of 1-13, 14-26, 27-39, 40-47, 48-49 and 50-52, while weeks looking for work are given in intervals of 1-4, 5-14, 15-26, 27-39 and 40 or more. In both cases the individuals were assigned the midpoints of their intervals.

[9]Earnings of other family members (OTHERN) is not a completely exogenous variable. The wage rate of all other family members would be a more desirable variable to use, but it is unavailable for the other family members who did not work during the survey week.

The OTHERN coefficient provides an alternative estimate to the NEY coefficient of the income effect. It will be negatively biased due to the cross-substitution effect. (The higher the wage rate of another family member, the more this family member's labor should be substituted for that of the primary worker.) On the other hand, earnings of other family members undoubtedly reflects the family preferences for income vis-á-vis leisure. This taste effect will lead to a positive bias in the coefficient. The net bias cannot be determined a priori. In the WW_2 equations the OTHERN coefficients are invariably positive and sometimes significantly so, indicating that the taste bias dominates. When either FT_2 or hours worked during the week (HW) or total hours (TH_2), the product of WW_2 and HW is used as the dependent variable, however, the coefficients are negative. See regression numbers 1, 4, 20, and 21. What accounts for the difference is not clear.

[10]See regression equation numbers 1, 2, 3, and 4 for the complete regression equations.

[11] If the average part time work week is smaller (larger) the percentage reduction in hours worked would be larger (smaller). Both the WW_2 and FT_2 functions are evaluated at the mean values of the dependent variable.

[12] Skill differentials have narrowed over time during the 20th century and have narrowed more rapidly during the upswing of the business cycle. See [12]. Consequently, if anything, the proportionality assumption is a conservative one in that it leads to an overadjustment of the WR coefficient.

Wages increased by 4.6 percent between 1966 and 1967. See [3]. Average total (federal, state, and local) tax rates for individuals with under \$2000, \$2000-4000, \$4000-6000, \$6000-8000, \$8000-10,000 \$10,000-15,000 and \$15,000 and over were respectively 44, 27, 27, 26, 27, 27, and 38 percent in 1965. See [11]. Thus, with the exception of the very lowest bracket which is so high because of the effect of property taxes on the aged, the proportionality assumption is reasonable throughout the low income range for average tax rates. Effective marginal tax rates may vary more positively with income. On the other hand, some state and local taxes such as the property tax are not directly related to earnings and, consequently, perhaps they should be omitted.

[13] Assume the current marginal tax rate (proportional) is 20 percent and that wage rates changed proportionally by 5 percent. The coefficients should be adjusted by a factor of 4/3. In this case, however, a 50 percent reduction rate reduces existing effective wages by only 3/8 rather than by 1/2. While the biases need not exactly offset one another as in the example above, the figures chosen are not unrealistic.

[14] I used the wage equation developed in [7]. Since the equation is based on a sample taken a year prior to the sample in my study, the imputed wages will be too low. Moreover, their sample is confined to individuals whose wage rate did not exceed \$5.00 per hour. Thus individuals with low education but very high wage rates are excluded from the sample. This will also lead to a negative bias in the imputed wage.

[15] See regressions 5 and 6.

[16] Since the 7 NLFPs are such extreme observations in terms of WW_2 the WR dummy coefficients are fairly sensitive to the potential WR assigned to the NLFPs.

[17] The income coefficient was adjusted by a factor of $k = .25$.

[18] An alternative procedure is to use aggregate data based on SMSAs. However, the NEY coefficient will be positively biased for two reasons. First, because of selective migration, SMSAs in Florida and California,

for example, are likely to have higher than average NEYs and lower than average LFPRs. Second, just as spurious negative correlations between certain kinds of NEY and labor supply give rise to biases on the individual level, they can also cause biases on the aggregate level. This problem is likely to be most serious for disability insurance and assistance payments, veterans compensation, and pensions. The WR coefficient will also be biased to the extent that unemployment is inadequately controlled for.

[19] See [1], [5], and [6].

[20] The income coefficient is no larger for the young if those in school are excluded as in [6] but is larger if those in school are not excluded. See [5]. See [1] and [6] for the substantial difference between the aged and non-aged.

[21] Overtime labor supply of primary workers, however, may also be more sensitive to economic incentives.

[22] Along with those who had a permanent health problem which limited the amount or kind of work they could do, I also excluded those who had a temporary health problem which limited the amount of work they did in the previous year on the grounds that their reported weeks worked is not an accurate measure of their voluntary labor supply.

[23] The statement in the text should be qualified slightly. Guarantees and implicit marginal tax rates vary from state to state. In addition, eligibility depends upon other variables besides income. But for each P.A. beneficiary in the sample, it remains true that numerous non-beneficiaries living the same state, with the same family size, potential wage rate, etc., have the same budget constraint.

[24] Prior to the 1967 Social Security Amendments most, but not all, P.A. beneficiaries were subject to implicit 100 percent marginal tax rates over a large and, in many cases, the whole of the relevant range of earnings. Since tax rates vary from state to state, without data on state residence of beneficiaries it is impossible to specify the potentially effective wage of beneficiaries. Such data are not available in the SEO or CPS samples.

[25] Once unemployed, an individual becomes eligible in most states for either full or partial benefit payments. Partial benefits are paid to individuals who secure part time work. The potentially effective wage rate of the fully employed individual would be equal to the hourly wage in a prospective job less the hourly value of his UC benefits. Although the latter varies both among and within states, it might be possible to impute it from

the total dollar value of UC received by the individual. In the case of partial benefits, it is more difficult. The effective wage rate for increases in work effort will depend upon the rate at which partial benefits are reduced. Since the tax rate also varies both among and within states, and since there is no way of imputing it from data on the individual beneficiary which does not include state residence, it would be impossible to assign effective wage rates to these individuals.

[26]See [9] p. 87. It would be preferable to have data on what percentage of those eligible for pensions claim them. Unfortunately, I could not find such data.

[27]Another difference may be in skill transference to the private market. That is, some individuals in the military or civil service might find a higher demand for their skills in the private market than other individuals.

[28]In addition, retirement pensions pose another problem, which while not unique to pensions is most acute for pensions. Non-employment income in the SEO is attributed to the interview unit as a whole, not to any particular individual. Since the interview unit is limited to blood relatives, in most cases it makes sense to think of the interview unit as pooling all of its resources. But, in the case where a retired parent, or parents, lives with offspring but has an independent source of income such as a pension, this may not be an accurate assumption. If the pension is not available to the son, we mis-specify his budget constraint by including the pension in his NEY. This leads to a positive bias in the NEY coefficient.

Undoubtedly, whether or not the pension is available to the son in these circumstances varies from family to family.

[29]See regression numbers 7 and 8.

[30]See regression numbers 9 and 10. If non-labor participants (including pensioners) are added to the sample which includes pensioners and excludes those with incomes above \$10,000, the resulting WW_2, NEY coefficient implies that in response to a guarantee of \$3000, beneficiaries would reduce their weeks worked by 19 percent.

[31]See regression numbers 11, 12, 13, and 14.

[32]See for example [4].

[33] See [4], [5], and [7]. The cutoff in [5], $15,000 may not be as serious as that in [4], $7,000 or the one in [7], $8,200 for a family of four. Because the one in [5] is so much higher, many fewer individuals are excluded.

[34] The mean wage rate in the basic sample is $3.56 an hour.

[35] See regression numbers 2, 15, 16, 7, 17, 18 in the Appendix.

[36] In the SEO, the individual is asked for his earnings and hours worked during the previous week. If he raises any questions, he is told to give his normal weekly earnings but actual hours worked. Due to overtime, therefore, the hourly wage rate may be incorrectly measured in some cases. Since the wage rate and earnings coefficients imply almost identical reductions in labor supply in the WW_2 equations, however, this problem would not appear to be very serious.

[37] See regression numbers 19, 20, 21, 22, 23, 24, 44 and 45. The sample for these regressions includes pensioners.

[38] See regression numbers 2, 25, 3, and 26.

[39] It is possible that a week or day looking for work should be weighted less heavily than an actual week or day worked. Ultimately, this is a matter of judgment.

[40] See regression numbers 4 and 27.

When pensioners are excluded from the sample the NEY coefficient in the HW equation, like the coefficient in the WW_2 equation, is positive but insignificant. However, even when pensioners are included in the sample, there is a positive relationship between non-employment income and hours worked during the survey week. [See regression #20.] This is true as long as those who worked zero hours during the survey week are excluded from the sample. The same thing is true of the TH_2 variable, which includes HW. [See regression #21.] It is not clear why the inclusion of pensioners fails to change the sign of the NEY coefficient in the HW as well as the WW_2 equations.

The most plausible hypothesis is that a few pensioners or other individuals with very high NEY worked an abnormally high numbers of hours during the survey week. This hypothesis is reinforced by the fact that when a family income cutoff of $10,000 is used and pensioners are included in the sample, the NEY coefficients become negative and highly significant: -.0016 (2.9) in the HW and -.106 (3.7) in the TH_2 equation. [See regression numbers 38 and 39.] Another puzzling result is that when weekly earnings are substituted for the hourly wage rate in the HW and TH_2 equations, the sign of the NEY coefficient switches from positive to negative. The t-values, however, are still quite small: below one for the HW and slightly larger for the TH_2 equation. (See regression numbers 40 and 41.)

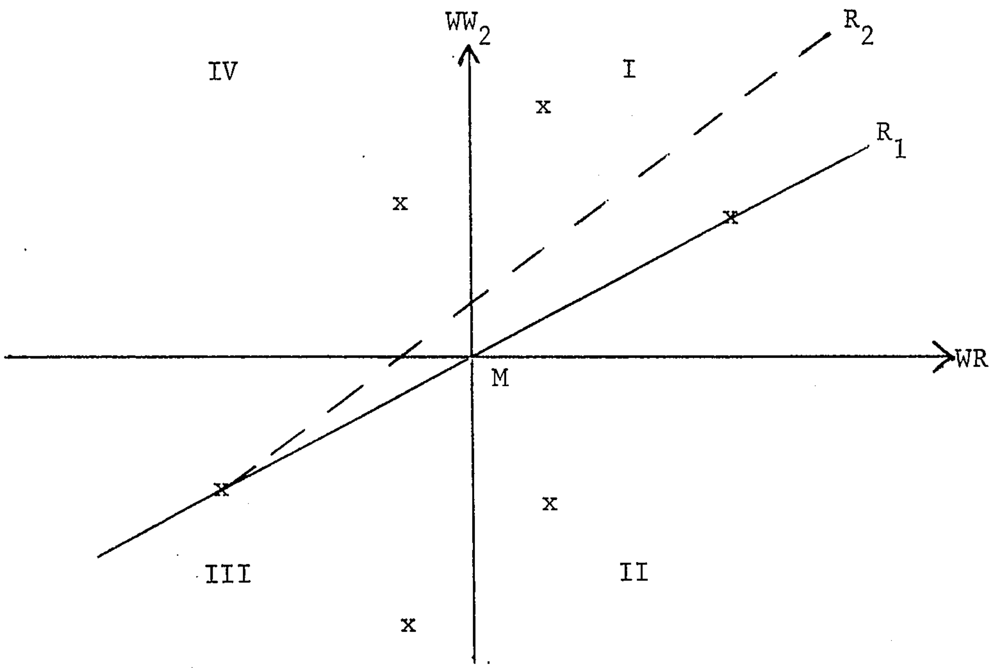
[41] See regression numbers 28 and 1.

The PW coefficients for prime-age males in [6] are so small only because of the negative correlation between PW and the measure of labor supply used in the study: $L = E_{LY}/PW$, where L = labor supply, E_{LY} = earnings last years and PW = the imputed wage rate. Measurement error in PW leads to a negative bias in the PW coefficient (See Section IV_A.)

[42] See regression numbers 29 and 23.

[43] See [6] and [7].

[44] Let R_1 be the wage rate regression line fitted by least squares and M be the mean value of wages and weeks worked. The horizontal and vertical lines divide the $WW_2 \cdot WR$ space into four quadrants. The second quadrant corresponds to the high wage- low weeks work case.



To simplify, suppose there are only six observations. Now remove the observation in the second quadrant. The new least squares regression line will be the dotted R_2 line.

[45] The \$.75-1.25 dummy actually decreases slightly when individuals in the construction-agriculture-forestry and fisheries industries are excluded from the sample, while when individuals with high wages and low weeks worked are excluded, this low wage dummy increases slightly. Mean weeks worked and mean wages were calculated for sixteen age-education groups. The age groups are 25-30, 30-40, and 50+. The education groups are < 6 years of education, 6-8 year, 9-11, and 12 and over. Compare coefficients in regression numbers 30, 31, 32, and 33 to those in 7 and 19. All three samples include pensioners.

[46] In [7] only education was omitted from the labor supply equations, while in [6] only education and the less important variables, current location, residence at age 16, and union membership were eliminated from the labor supply equation. That is to say, the instrumental wage rate variable boils down to little more than scaling years of education in wage units.

[47] Other NEY, the 8th item, presents a few problems. If certain groups are not excluded from the sample, inclusion of this component of NEY may lead to a positive bias in the coefficient. Consider Armed Forces allotment payments. These are payments to wives of husbands in the Armed Forces. Since the measure of weeks worked includes only weeks in the civilian labor force, there will be a very strong inverse correlation between family allotment payments and measured work effort for males who were in the Armed Forces in the year previous to the survy. If these individuals are excluded, the problem, of course, will not arise. Similarly, private transfers and gifts are likely to include many which were stimulated by the donors' belief that the beneficiary could not work enough to support himself. Educational scholarships and fellowships will also bear a strong negative correlation to work effort, which for reasons discussed above should not be included in a measure of work effort responsiveness to NEY. The last two problems are avoided and the first is mitigated to a great extent when the disabled and those attending school are eliminated from the sample. If members of the Armed Forces, the disabled, and those in school are excluded from the sample, the NEY coefficient is insensitive to the inclusion or exclusion of the other income component of NEY.

[48] Call the conceptually correct measure of NEY, i.e., the one which includes income imputed to assets for which no return has been reported, total NEY. Total NEY (NEY_T) can be decomposed into the elements NEY_1, NEY_2 through NEY_n. Assume the effects of the components on labor supply are identical. Then in a regression in which NEY_1, NEY_2 through NEY_n are independent variables, the coefficients of the variables should be identical. Moreover, they should be equal to the NEY_T coefficient obtained from a regression where NEY_T, rather than the components, was used as an independent variable. Our situation is complicated, of course, because the components are measured in different units. Therefore, the coefficients will not be identical because they will be measuring the same effect on a different scale. But the complication is less serious than it would appear to be. For it is reasonable to assume that the reported NEY component is measured in the correct scale. Consequently, there is no need to impute an interest rate to various assets. The asset value itself can be used as an independent variable. The interest rate will then be determined empirically. That is, given the asset coefficient a_i and the measured NEY coefficient b, the interest rate for the ith asset is the one which satisfies the equality $r_i = \frac{a_i}{b}$.

Since the interest rates implied by most of the asset coefficients appear to be absurd--they are negative in some cases--this can be interpreted as evidence of a spurious correlation. Hence, the approach of using several asset variables not only avoids the problem of discovering the appropriate interest rate but provides a solution to the spurious correlation problem as well.

[49] See regression numbers 2, 34, and 35.

[50] See regression numbers 7, and 36.

[51] See regression number 37. The sample includes pensioners.

[52] If weekly earnings rather than the hourly wage rate is used as an independent variable, the sign of the HOMES coefficient switches from positive to negative in the HW and TH equations. See regression numbers 40 and 41. Moreover, the negative coefficients no less than the positive ones are more than twice the size of their standard errors. But the substitution of weekly earnings for the hourly wage rate has absolutely no effect on the HOMES coefficient in the WW_2 regressions. See regression number 22.

Stanley Masters has suggested a possible explanation for these findings in terms of the permanent income hypotheses. For any given earnings level, the higher the wage rate, the higher permanent income is and, of course, the lower must be hours worked. If home ownership is correlated with permanent income, the use of the earnings rather than the hourly wage rate variable could change the sign of the HOMES coefficient from positive to negative.

APPENDIX

TABLE IX: SEO SAMPLE COMPOSITION BY DEMOGRAPHIC CHARACTERISTICS

		# in Sample	% in Sample	% Labor Supply WW_2	% Earnings
Everyone	Women	19,382	53.10	35.87	20.66
	Men	17,117	46.90	64.13	79.34
Men	< 25	4,408	25.75	15.56	7.41
	25-61	10,143	59.26	76.73	86.43
	61 +	2,566	14.99	7.71	6.16
Prime-Age Men	Married and Healthy	7,403	72.99	76.87	81.72
	Disabled or Sick	1,393	13.73	11.40	9.60
	Single	1,347	13.28	11.73	8.68
Married and Healthy Prime-Age Males	In School or Institution	62	.84	.35	.36
	In Armed Forces	25	.34	.09	.20
	Missing Information	1,811	24.46	18.88	27.60
	Self-Employed	562	7.59	5.85	7.94
	Didn't Work Last Week	337	4.55	3.43	3.59
	PA Beneficiaries	58	.78	.57	.50
	UC Beneficiaries	242	3.27	2.53	2.62
	Retirement Pensioners	82	1.11	.77	1.00
	WC and VP Beneficiaries	255	3.44	2.69	3.31
	NLF Participants	7	.10	.00	.00

	Basic Sample.	3,962

TABLE X: LIST OF SAMPLES

Sample Number		Number of Observations
I:	Basic Sample	3962
II:	Basic Sample Plus Pensioners	4035
III:	Basic Sample Plus Pensioners, UC, PA, WC, and VD Beneficiaries	4585
IV:	I Minus Individuals in Families with Income > $10,000	2342
V:	II Minus Individuals in Families with Income > $10,000	2372
VI:	I Minus Individuals with WR > $3.50	2702
VII:	II Minus Individuals with WR > $3.50	2751
VIII:	I Plus non-Labor Force Participants	3969
IX:	II Minus Individuals with Higher Than Average WR and Lower Than Average Weeks Worked	3958
X:	II Minus Individuals in Construction	3616
XI:	Basic Sample Aggregated by Wage and Age Groups	60

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A GUIDE TO THE REGRESSION EQUATIONS

The first 10 rows, NEY_1 through NEY_{10} normally contain the NEY dummy coefficients (less than \$100 through \$7500 or more). In equations where only a linear NEY variable was used, the linear coefficient is reproduced in the first row of the NEY variables. When NEY is defined to include income imputed to assets, the linear coefficient is reproduced in the second row of the NEY variables. When NEY is defined to include PA, UC, WC, and VD benefits, the linear NEY coefficient is reproduced in the third row of the NEY variables.

The second 10 rows normally contain the WR dummy coefficients (less than 75¢ per hour through more than \$5.25 per hour). In equations where only a linear WR was used the WR coefficient is reproduced in the first row of the WR variables, while quadratic WR coefficients are reproduced in the first and second rows. Quadratic imputed WR coefficients are reproduced in the ninth and tenth rows of the WR variables. Quadratic earnings coefficients are reproduced in the fifth and sixth rows of the WR variables.

The next 7 rows, Age_1 through Age_7, normally contain the following age dummies: 25-30, 31-35, 36-40, 41-45, 46-50, 51-55, and 56-61. The coefficients should be interpreted as indicating the amount worked relative to the reference age group 36-40. In equations 42 and 43 where a linear age variable was used, the coefficient is reproduced in the first row of the age variables.

OTHERN is an abbreviation for earnings of the other family members during the previous year. BUSFARM, HOMES, BANKACC, AUTOS, OTHASST, and OTHDBT are the set of asset variables defined in the text. NONWHI is a dummy race variable.

EDUCATION is measured by years of school completed. KIDS measures the number of children per family. The location variables are dummies which should be interpreted as indicating the amount worked relative to the omitted locational areas, central city SMSA and North Central States, UFSMSA indicates the individual lived in the urban fringe of an SMSA, UXSMSA in a non-SMSA urban area, and RXSMSA in a non-SMSA rural area.

	Equation #1		Equation #2		Equation #3		Equation #4	
Sample Number	I		I		I		I	
Dep. Variable	WW_2		WW_2		FT_2		FT_2	
NEY_1	.229	(1.49)	$.475 \cdot 10^{-5}$	(.15)	$-.434 \cdot 10^{-2}$	(.79)	$-.609 \cdot 10^{-6}$	(.53)
2								
3	.279	(1.48)			$-.864 \cdot 10^{-2}$	(1.28)		
4	.052	(.25)			-.019	(2.61)		
5	.109	(.41)			-.012	(1.22)		
6	.370	(1.34)			$.391 \cdot 10^{-3}$	(.04)		
7	.022	(.05)			$-.109 \cdot 10^{-2}$	(.07)		
8	.384	(.62)			$-.240 \cdot 10^{-2}$	(.11)		
9	.168	(.25)			-.088	(3.67)		
10	.546	(.90)			$.311 \cdot 10^{-3}$	(.01)		
WR_1	-.867	(1.57)	-.863	(1.57)	.014	(.72)	.014	(.72)
2	-.583	(2.37)	-.600	(2.45)	$.943 \cdot 10^{-2}$	(1.07)	$.897 \cdot 10^{-2}$	(1.02)
3	-.104	(.62)	-.110	(.66)	$-.261 \cdot 10^{-2}$	(.44)	$-.268 \cdot 10^{-2}$	(.45)
4								
5	-.075	(.56)	-.079	(.59)	.011	(2.31)	.011	(2.35)
6	.080	(.62)	.073	(.56)	.013	(2.76)	.013	(2.70)
7	.028	(.21)	.015	(.11)	.017	(3.50)	.017	(3.49)
8	-.161	(1.03)	-.158	(1.01)	.019	(3.39)	.019	(3.42)
9	-.084	(.56)	-.088	(.58)	.020	(3.63)	.019	(3.60)
10	-.013	(.08)	-.030	(.19)	.017	(3.06)	.017	(2.95)
Age_1	-.119	(1.01)	-.112	(.95)	$-.258 \cdot 10^{-2}$	(.61)	$-.175 \cdot 10^{-2}$	(.42)
2	-.192	(1.58)	-.187	(1.54)	$.665 \cdot 10^{-3}$	(.15)	$.147 \cdot 10^{-2}$	(.34)
3								
4	-.038	(.30)	-.034	(.28)	$.583 \cdot 10^{-2}$	(1.30)	$.607 \cdot 10^{-2}$	(1.35)
5	-.215	(1.59)	-.213	(1.59)	$.462 \cdot 10^{-2}$	(.96)	$.510 \cdot 10^{-2}$	(1.06)
6	-.222	(1.46)	-.211	(1.39)	$.436 \cdot 10^{-2}$	(.80)	$.503 \cdot 10^{-2}$	(.92)
7	.091	(.58)	.086	(.55)	$.755 \cdot 10^{-2}$	(1.34)	$.705 \cdot 10^{-2}$	(1.26)
OTHERN	$.142 \cdot 10^{-4}$	(.93)	$.145 \cdot 10^{-4}$	(.95)	$-.118 \cdot 10^{-5}$	(2.16)	$-.123 \cdot 10^{-5}$	(2.25)
BUSFARM	$-.261 \cdot 10^{-5}$	(.63)	$-.274 \cdot 10^{-5}$	(.66)	$.143 \cdot 10^{-7}$	(.10)	$.458 \cdot 10^{-8}$	(.03)
HOMES	$.114 \cdot 10^{-4}$	(2.33)	$.108 \cdot 10^{-4}$	(2.23)	$.186 \cdot 10^{-6}$	(1.06)	$.132 \cdot 10^{-6}$	(.76)
BNKACC	$-.293 \cdot 10^{-5}$	(.62)	$-.311 \cdot 10^{-5}$	(.66)	$.174 \cdot 10^{-6}$	(1.03)	$.144 \cdot 10^{-6}$	(.86)
AUTOS	$.285 \cdot 10^{-5}$	(.51)	$.230 \cdot 10^{-5}$	(.41)	$.440 \cdot 10^{-7}$	(.22)	$.543 \cdot 10^{-7}$	(.27)
OTHAST	$-.475 \cdot 10^{-4}$	(1.17)	$-.466 \cdot 10^{-4}$	(1.15)	$-.269 \cdot 10^{-5}$	(1.86)	$-.254 \cdot 10^{-5}$	(1.76)
OTHDBT	$.874 \cdot 10^{-5}$	(.36)	$.118 \cdot 10^{-4}$	(.50)	$-.274 \cdot 10^{-6}$	(.32)	$-.172 \cdot 10^{-6}$	(.20)
NONWHI	-.097	(.77)	-.090	(.72)	$-.177 \cdot 10^{-2}$	(.39)	$-.199 \cdot 10^{-2}$	(.44)
EDUCATION	.020	(1.69)	.020	(1.66)	$-.252 \cdot 10^{-2}$	(5.94)	$-.259 \cdot 10^{-2}$	(6.11)
KIDS	.085	(3.27)	.086	(3.35)	$.236 \cdot 10^{-2}$	(2.56)	$.244 \cdot 10^{-2}$	(2.65)
UFSMSA	.024	(.28)	.031	(.37)	$-.202 \cdot 10^{-2}$	(.66)	$-.152 \cdot 10^{-2}$	(.50)
UXSMSA	-.032	(.28)	-.029	(.25)	$-.386 \cdot 10^{-2}$	(.93)	$-.450 \cdot 10^{-2}$	(1.08)
RXSMSA	-.077	(.69)	-.068	(.61)	$-.252 \cdot 10^{-2}$	(.63)	$-.216 \cdot 10^{-2}$	(.54)
NOREST	.114	(1.21)	.112	(1.19)	$.239 \cdot 10^{-2}$	(.71)	$.213 \cdot 10^{-2}$	(.63)
SOUTH	.172	(1.83)	.178	(1.90)	$.126 \cdot 10^{-2}$	(.37)	$.130 \cdot 10^{-2}$	(.39)
WEST	.021	(.20)	.024	(.23)	$-.205 \cdot 10^{-4}$	(.01)	$.198 \cdot 10^{-3}$	(.05)
Constant	50.17		50.38		1.01		1.01	
R^2	.01		.01		.03		.01	
F	1.47		1.7		2.83		2.85	

	Equation #5		Equation #6		Equation #7		Equation #8	
Sample Number	VIII		VIII		II		II	
Dep. Variable	WW_2		WW_2		WW_2		FT_2	
NEY_1	.223	(1.07)	$-.985 \cdot 10^{-4}$	(2.23)	$-.118 \cdot 10^{-3}$	(3.77)	$-.306 \cdot 10^{-5}$	(2.72)
2								
3	.289	(1.12)						
4	.086	(.30)						
5	-.686	(1.91)						
6	-.768	(2.04)						
7	-.014	(.02)						
8	.412	(.49)						
9	-4.174	(4.75)						
10	.436	(.52)						
WR_1	-.541	(.72)	-.537	(.71)	-.849	(1.46)	.013	(.64)
2	-.156	(.46)	-.188	(.55)	-.787	(3.09)	$.913 \cdot 10^{-2}$	(1.01)
3	.088	(.38)	.094	(.41)	-.172	(.98)	-.010	(1.64)
4								
5	.230	(1.24)	.225	(1.21)	-.053	(.38)	.011	(2.23)
6	.409	(2.25)	.410	(2.25)	.114	(.84)	.013	(2.64)
7	.422	(2.21)	.415	(2.17)	.033	(.23)	.017	(3.40)
8	.230	(1.05)	.260	(1.19)	-.085	(.52)	.020	(3.38)
9	.306	(1.46)	.308	(1.47)	-.022	(.14)	.020	(3.53)
10	.451	(2.05)	.414	(1.89)	.116	(.70)	.016	(2.68)
Age_1	-.171	(1.06)	-.121	(.75)	-.087	(.70)	$-.163 \cdot 10^{-2}$	(.37)
2	-.261	(1.57)	-.219	(1.32)	-.176	(1.38)	$-.438 \cdot 10^{-3}$	(.10)
3								
4	-.106	(.62)	-.085	(.50)	-.036	(.28)	$.659 \cdot 10^{-2}$	(1.41)
5	-.315	(1.71)	-.268	(1.46)	-.225	(1.61)	$.420 \cdot 10^{-2}$	(.84)
6	-.248	(1.19)	-.238	(1.14)	-.315	(1.98)	$.443 \cdot 10^{-2}$	(.78)
7	-.279	(1.30)	-.310	(1.44)	-.042	(.26)	$.888 \cdot 10^{-2}$	(1.53)
OTHERN	$.309 \cdot 10^{-4}$	(1.48)	$.327 \cdot 10^{-4}$	(1.57)	$.262 \cdot 10^{-4}$	(1.65)	$-.116 \cdot 10^{-5}$	(2.06)
BUSFARM	$.235 \cdot 10^{-6}$	(.04)	$.574 \cdot 10^{-6}$	(.10)	$-.527 \cdot 10^{-6}$	(.12)	$.383 \cdot 10^{-7}$	(.25)
HOMES	$.945 \cdot 10^{-5}$	(1.41)	$.698 \cdot 10^{-5}$	(1.05)	$.143 \cdot 10^{-4}$	(2.82)	$.185 \cdot 10^{-6}$	(1.03)
BNKACC	$-.590 \cdot 10^{-5}$	(.91)	$-.751 \cdot 10^{-5}$	(1.17)			$.204 \cdot 10^{-6}$	(1.16)
AUTOS	$.488 \cdot 10^{-5}$	(.64)	$.357 \cdot 10^{-5}$	(.47)	$.227 \cdot 10^{-5}$	(.39)	$.651 \cdot 10^{-7}$	(.31)
OTHAST	$-.437 \cdot 10^{-4}$	(.79)	$-.334 \cdot 10^{-4}$	(.60)	$-.494 \cdot 10^{-4}$	(1.16)	$-.230 \cdot 10^{-5}$	(1.52)
OTHDBT	$.227 \cdot 10^{-4}$	(.68)	$.377 \cdot 10^{-4}$	(1.15)	$.175 \cdot 10^{-4}$	(.70)	$.328 \cdot 10^{-6}$	(.37)
NONWHI	.097	(.56)	.081	(.47)	-.105	(.80)	$-.325 \cdot 10^{-3}$	(.07)
EDUCATION	.041	(2.55)	.035	(2.17)	$.238 \cdot 10^{-2}$	(.19)	$-.259 \cdot 10^{-2}$	(5.89)
KIDS	.104	(2.96)	.107	(3.03)	.089	(3.29)	$.294 \cdot 10^{-2}$	(3.06)
UFSMSA	.070	(.60)	.095	(.82)	$.987 \cdot 10^{-3}$	(.01)	$-.191 \cdot 10^{-2}$	(.60)
UXSMSA	.164	(1.03)	.148	(.93)	-.036	(.30)	$-.287 \cdot 10^{-2}$	(.66)
RXSMSA	-.066	(.43)	-.058	(.38)	-.119	(1.02)	$-.671 \cdot 10^{-3}$	(.16)
NOREST	.103	(.81)	.082	(.64)	.109	(1.11)	$.339 \cdot 10^{-2}$	(.97)
SOUTH	.106	(.82)	.109	(.85)	.109	(1.11)	$.130 \cdot 10^{-2}$	(.37)
WEST	$-.348 \cdot 10^{-2}$	(.02)	$-.606 \cdot 10^{-2}$	(.04)	.039	(.36)	$.155 \cdot 10^{-2}$	(.40)
Constant	49.57		49.79		50.56		1.01	
R^2	.01		.01		.01		.02	
F	2.37		1.77		2.36		3.26	

	Equation #9		Equation #10		Equation #11		Equation #12	
Sample Number	II		II		III		III	
Dep. Variable	WW_2		FT_2		WW_2		WW_2	
NEY_1	.252	(1.56)	$-.387 \cdot 10^{-2}$	(.68)			$-.107 \cdot 10^{-3}$	(3.32)
2								
3	.274	(1.38)	$-.851 \cdot 10^{-2}$	(1.21)	$-.956 \cdot 10^{-4}$	(3.19)		
4	.055	(.25)	-.019	(2.48)				
5	.108	(.40)	-.021	(2.16)				
6	.336	(1.28)	$-.670 \cdot 10^{-3}$	(.07)				
7	.032	(.08)	$-.305 \cdot 10^{-2}$	(.21)				
8	-1.431	(2.68)	$-.107 \cdot 10^{-2}$	(.06)				
9	-1.565	(2.80)	-.164	(8.32)				
10	-1.414	(2.34)	$-.815 \cdot 10^{-3}$	(.04)				
WR_1	-.854	(1.47)	.014	(.66)	-.725	(1.27)	-.723	(1.27)
2	-.781	(3.07)	$.934 \cdot 10^{-2}$	(1.04)	-.603	(2.49)	-.585	(2.41)
3	-.168	(.96)	$-.951 \cdot 10^{-2}$	(1.54)	-.312	(1.80)	-.294	(1.69)
4								
5	-.055	(.39)	.011	(2.26)	-.014	(.11)	-.025	(.18)
6	.123	(.90)	.013	(2.76)	.135	(1.00)	.123	(.92)
7	.042	(.30)	.018	(3.48)	.098	(.70)	.068	(.49)
8	-.099	(.60)	.019	(3.31)	-.044	(.28)	-.073	(.46)
9	-.022	(.14)	.020	(3.63)	.067	(.43)	.019	(.12)
10	.131	(.79)	.018	(2.99)	.214	(1.33)	.150	(.92)
Age_1	-.085	(.69)	$-.284 \cdot 10^{-2}$	(.65)	-.035	(.29)	$-.324 \cdot 10^{-2}$	(.03)
2	-.179	(1.40)	$-.154 \cdot 10^{-2}$	(.34)	-.170	(1.35)	-.147	(1.17)
3								
4	-.039	(.30)	$.608 \cdot 10^{-2}$	(1.32)	-.011	(.08)	-.033	(.26)
5	-.212	(1.51)	$.406 \cdot 10^{-2}$	(.82)	-.115	(.84)	-.149	(1.09)
6	-.316	(1.98)	$.327 \cdot 10^{-2}$	(.58)	-.157	(1.02)	-.206	(1.33)
7	-.017	(.11)	$.967 \cdot 10^{-2}$	(1.67)	$.370 \cdot 10^{-2}$	(.02)	-.054	(.34)
OTHERN	$.231 \cdot 10^{-4}$	(1.46)	$-.114 \cdot 10^{-5}$	(2.04)	$.326 \cdot 10^{-4}$	(2.10)	$.303 \cdot 10^{-4}$	(1.94
BUSFARM	$-.695 \cdot 10^{-6}$	(.16)	$.242 \cdot 10^{-7}$	(.16)			$.270 \cdot 10^{-6}$	(.06
HOMES	$.151 \cdot 10^{-4}$	(2.94)	$.208 \cdot 10^{-6}$	(1.15)			$.125 \cdot 10^{-4}$	(2.48)
BNKACC	$.630 \cdot 10^{-6}$	(.13)	$.229 \cdot 10^{-6}$	(1.31)			$-.928 \cdot 10^{-6}$	(.18)
AUTOS	$.289 \cdot 10^{-5}$	(.49)	$.639 \cdot 10^{-7}$	(.31)			$.269 \cdot 10^{-5}$	(.44)
OTHAST	$-.507 \cdot 10^{-4}$	(1.91)	$-.268 \cdot 10^{-5}$	(1.78)			$-.423 \cdot 10^{-4}$	(.97)
OTHDBT	$.197 \cdot 10^{-4}$	(.78)	$-.165 \cdot 10^{-6}$	(.19)			$.144 \cdot 10^{-4}$	(.60)
NONWHI	-.107	(.82)	$.232 \cdot 10^{-4}$	(.01)	-.144	(1.13)	-.128	(1.00)
EDUCATION	$.396 \cdot 10^{-2}$	(.32)	$-.246 \cdot 10^{-2}$	(5.62)	$.179 \cdot 10^{-2}$	(.15)	$-.981 \cdot 10^{-4}$	(.01)
KIDS	.087	(3.23)	$.280 \cdot 10^{-2}$	(2.93)	.081	(3.09)	.080	(3.04)
UFSMSA	$-.827 \cdot 10^{-2}$	(.09)	$-.208 \cdot 10^{-2}$	(.66)	.027	(.31)	.012	(.14)
UXSMSA	-.033	(.27)	$-.159 \cdot 10^{-2}$	(.37)	.108	(.91)	.098	(.83)
RXSMSA	-.128	(1.10)	$-.951 \cdot 10^{-3}$	(.23)	-.017	(.15)	-.028	(.24)
NOREST	.106	(1.08)	$.349 \cdot 10^{-2}$	(1.01)	.082	(.86)	.080	(.83)
SOUTH	.112	(1.14)	$.117 \cdot 10^{-2}$	(.34)	.057	(.59)	.066	(.68)
WEST	.038	(.35)	$.145 \cdot 10^{-2}$	(.37)	.052	(.49)	.053	(.50)
Constant	50.30		1.01		50.53		50.51	
R^2	.02		.04		.01		.01	
F	2.27		4.48		2.03		1.85	

	Equation #13		Equation #14		Equation #15		Equation #16	
Sample Number	III		III		IV		VI	
Dep. Variable	WW_1		WW_1		WW_2		WW_2	
NEY_1			$-.155 \cdot 10^{-3}$	(2.80)	$.769 \cdot 10^{-4}$	(.41)	$.339 \cdot 10^{-4}$	(.55)
2								
3	$-.237 \cdot 10^{-3}$	(4.60)						
4								
5								
6								
7								
8								
9								
10								
WR_1	-1.993	(2.04)	-1.990	(2.03)	-.763	(1.12)	-.796	(1.41)
2	-1.690	(4.07)	-1.670	(4.01)	-.628	(2.07)	-.584	(2.31)
3	-.674	(2.26)	-.629	(2.11)	-.122	(.59)	-.103	(.60)
4								
5	.085	(.36)	.048	(.20)	-.104	(.58)	-.097	(.70)
6	.377	(1.64)	.338	(1.47)	.034	(.19)	.048	(.35)
7	.376	(1.57)	.287	(1.19)	-.019	(.09)	-.021	(.15)
8	.028	(.10)	-.072	(.27)	-.442	(1.79)	.000	(.00)
9	.348	(1.32)	.200	(.75)	-.090	(.35)	.000	(.00)
10	.275	(1.00)	.043	(.15)	-.285	(.69)	.000	(.00)
Age_1	-.266	(1.28)	-.150	(.72)	-.167	(.96)	-.142	(.97)
2	-.207	(.96)	-.120	(.56)	-.274	(1.48)	-.117	(.76)
3								
4	.062	(.29)	-.012	(.06)	-.078	(.39)	.013	(.08)
5	.146	(.63)	.030	(.13)	-.250	(1.15)	-.225	(1.31)
6	-.094	(.36)	-.277	(1.04)	-.139	(.55)	-.352	(1.85)
7	.395	(1.45)	.175	(.63)	.241	(.94)	.044	(.23)
OTHERN	$.386 \cdot 10^{-4}$	(1.45)	$.304 \cdot 10^{-4}$	(1.14)	$.387 \cdot 10^{-4}$	(.87)	$.303 \cdot 10^{-4}$	(1.56)
BUSFARM			$.590 \cdot 10^{-6}$	(.08)	$-.295 \cdot 10^{-4}$	(2.19)	$-.123 \cdot 10^{-4}$	(1.53)
HOMES			$.331 \cdot 10^{-4}$	(3.83)	$.128 \cdot 10^{-4}$	(1.43)	$.130 \cdot 10^{-4}$	(1.99)
BNKACC			$.459 \cdot 10^{-5}$	(.53)	$-.225 \cdot 10^{-4}$	(.79)	$-.426 \cdot 10^{-5}$	(.61)
AUTOS			$.712 \cdot 10^{-5}$	(.68)	$.605 \cdot 10^{-4}$	(1.07)	$.250 \cdot 10^{-5}$	(.22)
OTHAST			$.120 \cdot 10^{-5}$	(.02)	$-.166 \cdot 10^{-3}$	(.86)	$-.822 \cdot 10^{-4}$	(1.59)
OTHDBT			$-.476 \cdot 10^{-5}$	(.12)	$.510 \cdot 10^{-4}$	(.84)	$.223 \cdot 10^{-4}$	(.51)
NONWHI	-.615	(2.81)	-.559	(2.55)	-.126	(.74)	-.120	(.87)
EDUCATION	.124	(5.98)	.113	(5.41)	.031	(1.68)	.013	(.91)
KIDS	.092	(2.04)	.091	(2.01)	.122	(3.19)	.078	(2.48)
UFSMSA	.087	(.58)	.037	(.25)	.087	(.64)	$.176 \cdot 10^{-2}$	(.02)
UXSMSA	.253	(1.24)	.220	(1.08)	-.014	(.08)	-.053	(.39)
RXSMSA	-.031	(.16)	-.068	(.35)	-.028	(.18)	-.116	(.89)
NOREST	-.064	(.39)	-.079	(.48)	.154	(1.03)	.155	(1.31)
SOUTH	.127	(.77)	.151	(.91)	.264	(1.84)	.179	(1.57)
WEST	-.607	(3.29)	-.616	(3.34)	.079	(.46)	.131	(.93)
Constant	48.48		48.49		50.08		50.45	
R^2	.03		.03		.01		.01	
F	6.70		5.41		1.39		1.47	

	Equation #17		Equation #18		Equation #19		Equation #20	
Sample Number	V		VII		II		II	
Dep. Variable	WW_2		WW_2		WW_2		HW	
NEY_1	$-.862 \cdot 10^{-3}$	(5.89)	$-.374 \cdot 10^{-3}$	(6.46)	$-.122 \cdot 10^{-3}$	(3.86)	$.185 \cdot 10^{-3}$	(1.36)
2								
3								
4								
5								
6								
7								
8								
9								
10								
WR_1	-.850	(1.22)	-.821	(1.35)	.041	(1.29)	-2.608	(18.97)
2	-.558	(1.81)	-.727	(2.72)	$-.802 \cdot 10^{-3}$	(.82)	.040	(9.44)
3	-.224	(1.05)	-.165	(.90)				
4								
5	-.122	(.67)	-.073	(.50)				
6	$.522 \cdot 10^{-2}$	(.03)	.112	(.78)				
7	-.093	(.45)	.035	(.23)				
8	-.478	(1.89)	.000	(.00)				
9	-.108	(.41)	.000	(.00)				
10	-.294	(.69)	.000	(.00)				
Age_1	-.202	(1.13)	-.115	(.74)	-.097	(.79)	-1.124	(2.12)
2	-.291	(1.54)	-.109	(.66)	-.177	(1.39)	-.101	(.19)
3								
4	-.074	(.36)	.021	(.12)	-.039	(.30)	-.319	(.57)
5	-.259	(1.17)	-.208	(1.15)	-.236	(1.68)	-.469	(.78)
6	-.385	(1.49)	-.475	(2.35)	-.323	(2.03)	$.568 \cdot 10^{-2}$	(.01)
7	.195	(.75)	-.088	(.43)	-.054	(.33)	-.232	(.33)
OTHERN	$.447 \cdot 10^{-4}$	(.99)	$.552 \cdot 10^{-4}$	(2.69)	$.294 \cdot 10^{-4}$	(1.86)	$-.281 \cdot 10^{-3}$	(4.13)
BUSFARM	$-.209 \cdot 10^{-4}$	(1.57)	$-.568 \cdot 10^{-5}$	(.67)	$-.401 \cdot 10^{-6}$	(.09)	$.678 \cdot 10^{-4}$	(3.62)
HOMES	$.141 \cdot 10^{-4}$	(1.54)	$.171 \cdot 10^{-4}$	(2.46)	$.141 \cdot 10^{-4}$	(2.78)	$.884 \cdot 10^{-4}$	(4.04)
BNKACC	$.227 \cdot 10^{-4}$	(.85)	$.380 \cdot 10^{-5}$	(.51)	$.144 \cdot 10^{-6}$	(.03)	$.541 \cdot 10^{-4}$	(2.56)
AUTOS	$.482 \cdot 10^{-4}$	(.83)	$.263 \cdot 10^{-5}$	(.21)	$.229 \cdot 10^{-5}$	(.39)	$.608 \cdot 10^{-4}$	(2.40)
OTHAST	$-.147 \cdot 10^{-3}$	(.74)	$-.957 \cdot 10^{-4}$	(1.73)	$-.529 \cdot 10^{-4}$	(1.24)	$.210 \cdot 10^{-3}$	(1.15)
OTHDBT	$.247 \cdot 10^{-4}$	(.40)	$.582 \cdot 10^{-5}$	(.13)	$.182 \cdot 10^{-4}$	(.73)	$.279 \cdot 10^{-3}$	(2.60)
NONWHI	-.200	(1.15)	-.157	(1.07)	-.160	(1.23)	-2.904	(5.19)
EDUCATION	.020	(1.06)	$-.930 \cdot 10^{-2}$	(.59)	$.498 \cdot 10^{-2}$	(.40)	.672	(12.67)
KIDS	.122	(3.14)	.085	(2.56)	.087	(3.22)	.225	(1.94)
UFSMSA	$-.457 \cdot 10^{-3}$	(.00)	-.057	(.49)	$-.817 \cdot 10^{-2}$	(.09)	.563	(1.48)
UXSMSA	-.022	(.12)	-.061	(.42)	-.041	(.34)	.402	(.77)
RXSMSA	-.073	(.44)	-.189	(1.37)	-.157	(1.36)	-.769	(1.55)
NOREST	.129	(.84)	.129	(1.03)	.111	(1.13)	-1.986	(4.71)
SOUTH	.186	(1.27)	.060	(.49)	.070	(.72)	-1.168	(2.80)
WEST	.064	(.37)	.121	(.81)	.024	(.22)	-.826	(1.74)
Constant	50.40		50.73		50.41		45.85	
R^2	.02		.02		.01		.13	
F	2.37		3.11		2.32		24.58	

	Equation #21		Equation #22		Equation #23		Equation #24	
Sample Number	II		II		II		II	
Dep. Variable	TH_2		WW_2		HW		TH_2	
NEY_1	$.427 \cdot 10^{-2}$	(.60)	$-.120 \cdot 10^{-3}$	(3.76)	$.505 \cdot 10^{-4}$	(.36)	$-.254 \cdot 10^{-2}$	(.35)
2								
3								
4								
5								
6								
7								
8								
9								
10								
WR_1	-129.90	(18.15)						
2	1.965	(8.96)						
3								
4								
5			$.318 \cdot 10^{-2}$	(2.79)	.059	(11.65)	3.113	(11.85)
6			$-.295 \cdot 10^{-5}$	(1.86)	$-.498 \cdot 10^{-4}$	(7.06)	$-.262 \cdot 10^{-2}$	(7.16)
7								
8								
9								
10								
Age_1	-60.438	(2.19)	-.069	(.56)	.606	(1.10)	28.147	(.99)
2	-10.002	(.35)	-.171	(1.34)	.409	(.72)	16.087	(.55)
3								
4	-18.647	(.64)	-.032	(.24)	-.341	(.59)	-19.536	(.65)
5	-33.624	(1.07)	-.235	(1.68)	-.630	(1.01)	-41.692	(1.30)
6	-12.050	(.34)	-.316	(1.99)	.091	(.13)	-7.574	(.21)
7	-16.466	(.45)	-.042	(.26)	.155	(.21)	3.538	(.09)
OTHERN	-.013	(3.69)	$.329 \cdot 10^{-4}$	(2.08)	$-.397 \cdot 10^{-4}$	(.56)	$-.727 \cdot 10^{-3}$	(.20)
BUSFARM	$.351 \cdot 10^{-2}$	(3.59)	$-.980 \cdot 10^{-6}$	(.23)	$.603 \cdot 10^{-4}$	(3.11)	$.310 \cdot 10^{-2}$	(3.09)
HOMES	$.509 \cdot 10^{-2}$	(4.47)	$.123 \cdot 10^{-4}$	(2.41)	$-.778 \cdot 10^{-4}$	(3.42)	$-.340 \cdot 10^{-2}$	(2.89)
BNKACC	$.275 \cdot 10^{-2}$	(2.50)	$-.504 \cdot 10^{-6}$	(.10)	$.545 \cdot 10^{-5}$	(.25)	$.261 \cdot 10^{-3}$	(.23)
AUTOS	$.318 \cdot 10^{-2}$	(2.41)	$.145 \cdot 10^{-5}$	(.25)	$-.448 \cdot 10^{-5}$	(.17)	$-.163 \cdot 10^{-3}$	(.12)
OTHAST	$.833 \cdot 10^{-2}$	(.87)	$-.556 \cdot 10^{-4}$	(1.30)	$-.107 \cdot 10^{-4}$	(.06)	$-.295 \cdot 10^{-2}$	(.30)
OTHDBT	.015	(2.67)	$.171 \cdot 10^{-4}$	(.69)	$.980 \cdot 10^{-4}$	(.88)	$.568 \cdot 10^{-2}$	(.99)
NONWHI	-150.61	(5.17)	-.121	(.92)	-.880	(1.51)	-46.798	(1.55)
EDUCATION	33.609	(12.18)	$-.585 \cdot 10^{-2}$	(.46)	-.092	(1.64)	-5.484	(1.88)
KIDS	15.210	(2.52)	.086	(3.20)	.242	(2.02)	16.036	(2.58)
UFSMSA	28.460	(1.44)	-.017	(.19)	$.194 \cdot 10^{-2}$	(.01)	-.263	(.01)
UXSMSA	16.908	(.62)	-.025	(.20)	2.266	(4.21)	111.79	(4.01)
RXSMSA	-45.571	(1.76)	-.127	(1.10)	1.605	(3.12)	75.626	(2.84)
NOREST	-94.437	(4.30)	.126	(1.29)	-1.677	(3.84)	-78.173	(3.45)
SOUTH	-54.925	(2.53)	.094	(.97)	-.317	(.73)	-10.964	(.49)
WEST	-38.993	(1.58)	.024	(.22)	-1.270	(2.59)	-61.390	(2.42)
Constant	2317.4		50.25		38.24		1927.4	
R^2	.12		.01		.07		.07	
F	22.84		2.63		12.61		12.71	

	Equation #25		Equation #26		Equation #27		Equation #28	
Sample Number	I		I		I		I	
Dep. Variable	FT_1		WW_1		HW		WW_2	
NEY_1	$-.607 \cdot 10^{-6}$	(.43)	.076	(.32)	$.201 \cdot 10^{-3}$	(1.37)	.202	(1.32)
2								
3			.153	(.52)			.281	(1.49)
4			-.094	(.29)			.067	(.32)
5			-.296	(.72)			.147	(.56)
6			-.072	(.17)			.383	(1.39)
7			-.578	(.83)			.016	(.04)
8			.143	(.15)			.359	(.58)
9			-.109	(1.01)			.328	(.49)
10			-.668	(.71)			.522	(.86)
WR_1	-.106	(4.43)	-2.800	(3.29)	8.712	(3.50)		
2	-.038	(3.57)	-1.584	(4.17)	8.604	(7.75)		
3	$-.505 \cdot 10^{-2}$	(.69)	-.484	(1.87)	2.521	(3.34)		
4								
5	.013	(2.27)	.171	(.83)	-2.040	(3.36)		
6	.013	(2.21)	.341	(1.69)	-4.401	(7.48)		
7	.019	(3.11)	.321	(1.52)	-5.221	(8.45)		
8	.020	(2.96)	.114	(.47)	-6.042	(8.54)		
9	.018	(2.71)	.166	(.71)	-8.667	(12.74)	2.222	(3.01)
10	.017	(2.48)	.133	(.54)	-11.368	(15.88)	-.437	(2.88)
Age_1	$-.963 \cdot 10^{-3}$	(.19)	-.094	(.51)	-1.243	(2.34)		
2	$.142 \cdot 10^{-2}$	(.27)	-.078	(.42)	-.052	(.10)		
3								
4	$.311 \cdot 10^{-2}$	(.57)	.080	(.41)	-.504	(.89)		
5	$.201 \cdot 10^{-2}$	(.34)	.064	(.31)	-.430	(.71)		
6	$.415 \cdot 10^{-2}$	(.63)	-.046	(.20)	-.224	(.33)		
7	$.609 \cdot 10^{-2}$	(.89)	.433	(1.78)	-.715	(1.01)		
OTHERN	$-.104 \cdot 10^{-5}$	(1.57)	$.104 \cdot 10^{-4}$	(.44)	$-.256 \cdot 10^{-3}$	(3.72)	$.105 \cdot 10^{-4}$	(.69)
BUSFARM	$.530 \cdot 10^{-7}$	(.29)	$.393 \cdot 10^{-7}$	(.01)	$.735 \cdot 10^{-4}$	(3.90)	$-.283 \cdot 10^{-5}$	(.68)
HOMES	$.162 \cdot 10^{-6}$	(.76)	$.218 \cdot 10^{-4}$	(2.87)	$.775 \cdot 10^{-4}$	(3.53)	$.132 \cdot 10^{-4}$	(2.89)
BNKACC	$.162 \cdot 10^{-6}$	(.79)	$-.227 \cdot 10^{-6}$	(.03)	$.466 \cdot 10^{-4}$	(2.20)	$-.154 \cdot 10^{-5}$	(.33)
AUTOS	$.828 \cdot 10^{-7}$	(.34)	$.488 \cdot 10^{-5}$	(.56)	$.588 \cdot 10^{-4}$	(2.33)	$.312 \cdot 10^{-5}$	(.56)
OTHAST	$-.247 \cdot 10^{-5}$	(1.39)	$-.255 \cdot 10^{-4}$	(.41)	$.131 \cdot 10^{-3}$	(.71)	$-.458 \cdot 10^{-4}$	(1.16)
OTHDBT	$-.189 \cdot 10^{-6}$	(.18)	$.231 \cdot 10^{-5}$	(.06)	$.196 \cdot 10^{-3}$	(1.82)	$.881 \cdot 10^{-5}$	(.36)
NONWHI	$-.654 \cdot 10^{-2}$	(1.19)	-.558	(2.87)	-3.819	(6.73)		
EDUCATION	$-.221 \cdot 10^{-2}$	(4.28)	.080	(4.34)	.701	(13.09)		
KIDS	$.238 \cdot 10^{-2}$	(2.12)	.144	(3.60)	.197	(1.69)	.077	(3.27)
UFSMSA	$-.285 \cdot 10^{-2}$	(.77)	.056	(.43)	.487	(1.27)	.044	(.52)
UXSMSA	$-.708 \cdot 10^{-2}$	(1.39)	.219	(1.22)	.035	(.07)	$.293 \cdot 10^{-2}$	(.03)
RXSMSA	$.119 \cdot 10^{-2}$	(.25)	-.043	(.25)	-1.402	(2.78)	-.065	(.59)
NOREST	$.117 \cdot 10^{-2}$	(.29)	$.500 \cdot 10^{-2}$	(.03)	-2.177	(5.14)		
SOUTH	$-.338 \cdot 10^{-2}$	(.83)	.178	(1.22)	-1.945	(4.58)		
WEST	$-.105 \cdot 10^{-2}$	(.23)	-.127	(.78)	-.800	(1.67)		
Constant	1.00		48.87		42.04		47.59	
R^2	.02		.04		.14		.00	
F	3.24		3.82		20.85		1.78	

	Equation #29		Equation #30		Equation #31		Equation #32	
Sample Number	I		IX		IX		X	
Dep. Variable	HW		WW_2		WW_2		WW_2	
NEY_1	-.504	(.68)	$-.123 \cdot 10^{-3}$	(4.50)	$-.129 \cdot 10^{-3}$	(4.72)	$-.116 \cdot 10^{-3}$	(4.21)
2								
3	-.710	(.78)						
4	-.408	(.41)						
5	.569	(.45)						
6	1.642	(1.23)						
7	-2.136	(.98)						
8	1.382	(.46)						
9	1.926	(.60)						
10	.988	(.34)						
WR_1			-.866	(1.74)	.109	(3.94)	-.878	(1.33)
2			-.841	(3.86)	$-.231 \cdot 10^{-2}$	(2.74)	-.701	(2.62)
3			-.219	(1.46)			-.030	(.18)
4								
5			-.058	(.48)			-.012	(.09)
6			.151	(1.29)			.133	(1.08)
7			.102	(.83)			.120	(.93)
8			.204	(1.43)			.169	(1.13)
9	6.919	(1.94)	.162	(1.19)			.251	(1.71)
10	-.951	(1.30)	.360	(2.52)			.289	(1.91)
Age_1			-.117	(1.09)	-.134	(1.26)	-.075	(.66)
2			-.133	(1.21)	-.140	(1.27)	-.066	(.57)
3								
4			-.057	(.50)	-.066	(.58)	.057	(.47)
5			-.270	(2.23)	-.277	(2.29)	.020	(.16)
6			-.339	(2.46)	-.352	(2.55)	-.246	(1.72)
7			-.190	(1.34)	-.210	(1.49)	-.081	(.55)
OTHERN	$-.172 \cdot 10^{-3}$	(2.36)	$.248 \cdot 10^{-4}$	(1.81)	$.277 \cdot 10^{-4}$	(2.03)	$.257 \cdot 10^{-4}$	(1.82)
BUSFARM	$.758 \cdot 10^{-4}$	(3.77)	$.251 \cdot 10^{-7}$	(.01)	$.211 \cdot 10^{-6}$	(.06)	$-.245 \cdot 10^{-6}$	(.06)
HOMES	$-.381 \cdot 10^{-5}$	(.17)	$.893 \cdot 10^{-3}$	(2.03)	$.855 \cdot 10^{-5}$	(1.94)	$.901 \cdot 10^{-5}$	(1.92)
BNKACC	$.299 \cdot 10^{-4}$	(1.31)	$.250 \cdot 10^{-6}$	(.06)	$.142 \cdot 10^{-6}$	(.03)	$.228 \cdot 10^{-5}$	(.51)
AUTOS	$.214 \cdot 10^{-4}$	(.79)	$.750 \cdot 10^{-6}$	(.15)	$.702 \cdot 10^{-6}$	(.14)	$.713 \cdot 10^{-6}$	(.12)
OTHAST	$.605 \cdot 10^{-4}$	(.31)	$-.524 \cdot 10^{-4}$	(1.43)	$-.561 \cdot 10^{-4}$	(1.54)	$-.571 \cdot 10^{-4}$	(1.55)
OTHDBT	$.179 \cdot 10^{-3}$	(1.53)	$.168 \cdot 10^{-4}$	(.78)	$.158 \cdot 10^{-4}$	(.74)	$.161 \cdot 10^{-4}$	(.73)
NONWHI			-.135	(1.19)	-.202	(1.79)	-.088	(.72)
EDUCATION			-.028	(2.58)	-.025	(2.31)	-.020	(1.79)
KIDS	.168	(1.48)	.059	(2.51)	.057	(2.44)	.074	(2.97)
UFSMSA	.312	(.77)	-.119	(1.54)	-.129	(1.68)	-.016	(.20)
UXSMSA	2.481	(4.42)	-.124	(1.18)	-.136	(1.30)	-.029	(.26)
RXSMSA	1.501	(2.79)	-.229	(2.27)	-.274	(2.74)	-.113	(1.05)
NOREST			.138	(1.62)	.135	(1.59)	.129	(1.46)
SOUTH			.022	(.27)	-.026	(.31)	.102	(1.14)
WEST			.034	(.36)	.024	(.25)	.075	(.75)
Constant	32.80		51.11		50.84		50.75	
R^2	.02		.02		.02		.01	
F	4.12		3.46		3.66		2.29	

	Equation #33		Equation #34		Equation #35		Equation #36	
Sample Number	X		I		I		II	
Dep. Variable	WW_2		WW_2		WW_2		WW_2	
NEY_1	$-.121 \cdot 10^{-3}$	(4.38)	$.148 \cdot 10^{-4}$	(.48)				
2					$.758 \cdot 10^{-5}$	(.49)	$-.215 \cdot 10^{-4}$	(1.35)
3								
4								
5								
6								
7								
8								
9								
10								
WR_1	.079	(2.73)	-.876	(1.59)	-.880	(1.60)	-.833	(1.43)
2	$-.157 \cdot 10^{-2}$	(1.81)	-.617	(2.52)	-.615	(2.51)	-.830	(3.26)
3			-.127	(.76)	-.126	(.75)	-.196	(1.12)
4								
5			-.072	(.54)	-.073	(.55)	-.040	(.28)
6			.080	(.61)	.079	(.61)	.126	(.93)
7			.038	(.28)	.036	(.26)	.066	(.47)
8			-.139	(.89)	-.140	(.90)	-.059	(.36)
9			-.053	(.35)	-.056	(.37)	.036	(.23)
10			.015	(.10)	$.928 \cdot 10^{-2}$	(.06)	.186	(1.13)
Age_1	-.081	(.72)	-.136	(1.17)	-.134	(1.15)	-.120	(.98)
2	-.067	(.58)	-.203	(1.68)	-.202	(1.67)	-.194	(1.53)
3								
4	.047	(.40)	-.019	(.15)	-.020	(.16)	-.017	(.13)
5	.017	(.13)	-.188	(1.41)	-.190	(1.42)	-.202	(1.44)
6	-.257	(1.79)	-.173	(1.14)	-.194	(1.15)	-.287	(1.81)
7	-.092	(.63)	.134	(.87)	.129	(.83)	.012	(.07)
OTHERN	$.277 \cdot 10^{-4}$	(1.96)	$.156 \cdot 10^{-4}$	(1.03)	$.154 \cdot 10^{-4}$	(1.01)	$.290 \cdot 10^{-4}$	(1.83)
BUSFARM	$.656 \cdot 10^{-7}$	(.02)						
HOMES	$.886 \cdot 10^{-5}$	(1.88)						
BNKACC	$.229 \cdot 10^{-5}$	(.52)						
AUTOS	$.696 \cdot 10^{-6}$	(.12)						
OTHAST	$-.598 \cdot 10^{-4}$	(1.62)						
OTHDBT	$.150 \cdot 10^{-4}$	(.68)						
NONWHI	-.132	(1.09)	-.103	(.83)	-.102	(.81)	-.127	(.96)
EDUCATION	-.019	(1.69)	.021	(1.76)	.021	(1.74)	$.272 \cdot 10^{-2}$	(.22)
KIDS	.075	(3.04)	.087	(3.39)	.088	(3.40)	.089	(3.28)
UFSMSA	-.021	(.26)	.044	(.52)	.042	(.50)	.021	(.24)
UXSMSA	-.038	(.34)	-.024	(.21)	-.025	(.21)	-.027	(.22)
RXSMSA	-.130	(1.21)	-.068	(.61)	-.071	(.64)	-.102	(.88)
NOREST.	.127	(1.44)	.116	(1.24)	.116	(1.24)	.113	(1.15)
SOUTH	.070	(.80)	.174	(1.86)	.175	(1.86)	.096	(.97)
WEST	.079	(.79)	.025	(.23)	.025	(.24)	.028	(.25)
Constant	50.60		50.40		50.40		50.60	
R^2	.01		.01		.01		.01	
F	2.53		1.79		1.79		2.08	

	Equation #37		Equation #38		Equation #39		Equation #40	
Sample Number	II		V		V		II	
Dep. Variable	WW_2		HW		TH_2		TH_2	
NEY_1	$-.118 \cdot 10^{-3}$	(3.73)	$-.157 \cdot 10^{-2}$	(2.92)	$-.106$	(3.73)	$-.840 \cdot 10^{-2}$	(1.14)
2								
3								
4								
5								
6								
7								
8								
9								
10								
WR_1	-.849	(1.46)	10.736	(4.16)	516.34	(3.81)		
2	-.787	(3.09)	9.126	(8.00)	441.49	(7.36)		
3	-.172	(.98)	3.108	(3.96)	148.05	(3.59)		
4								
5	-.053	(.38)	-2.884	(4.30)	-153.22	(4.35)	1.452	(11.72)
6	.114	(.84)	-5.362	(7.93)	-270.81	(7.63)		
7	.033	(.23)	-6.720	(8.84)	-343.01	(8.59)		
8	-.086	(.52)	-8.404	(9.02)	-445.06	(9.10)		
9	-.023	(.14)	-9.997	(10.22)	-511.28	(9.95)		
10	.116	(.70)	-17.838	(11.40)	-910.61	(11.08)		
Age_1	-.087	(.70)	-.540	(.82)	-34.489	(.99)	11.609	(.41)
2	-.175	(1.38)	.304	(.43)	7.610	(.21)	12.338	(.42)
3								
4	-.037	(.28)	.025	(.03)	-4.077	(.10)	-26.708	(.88)
5	-.225	(1.61)	-.527	(.65)	-37.939	(.89)	-42.093	(1.30)
6	-.315	(1.98)	-1.722	(1.81)	-100.70	(2.01)	-16.937	(.46)
7	-.042	(.26)	-1.733	(1.80)	-79.171	(1.56)	-6.413	(.17)
OTHERN	$.262 \cdot 10^{-4}$	(1.65)	$-.677 \cdot 10^{-3}$	(4.06)	-.033	(3.72)	$-.185 \cdot 10^{-2}$	(.50)
BUSFARM	$-.529 \cdot 10^{-6}$	(.12)	$.205 \cdot 10^{-4}$	(.42)	$.426 \cdot 10^{-3}$	(.17)	$.332 \cdot 10^{-2}$	(3.28)
HOMES	$.143 \cdot 10^{-4}$	(2.82)	$.572 \cdot 10^{-4}$	(1.70)	$.338 \cdot 10^{-2}$	(1.91)	$-.300 \cdot 10^{-2}$	(2.54)
BNKACC	$.162 \cdot 10^{-6}$	(.03)	$.234 \cdot 10^{-3}$	(2.36)	.012	(2.39)	$.340 \cdot 10^{-3}$	(.30)
AUTOS	$.227 \cdot 10^{-5}$	(.39)	$.811 \cdot 10^{-3}$	(3.80)	.043	(3.86)	$.270 \cdot 10^{-4}$	(.02)
OTHAST	$-.494 \cdot 10^{-4}$	(1.16)	$.145 \cdot 10^{-2}$	(1.99)	.063	(1.64)	$-.136 \cdot 10^{-2}$	(.14)
OTHDBT	$.175 \cdot 10^{-4}$	(.70)	$.897 \cdot 10^{-3}$	(3.92)	.046	(3.87)	$.423 \cdot 10^{-2}$	(.73)
NONWHI	-.105	(.80)	-3.690	(5.75)	-191.72	(5.69)	-71.785	(2.38)
EDUCATION	$.236 \cdot 10^{-2}$	(.19)	.614	(8.87)	31.264	(8.60)	-.261	(.09)
KIDS	.089	(3.29)	.151	(1.05)	12.729	(1.69)	15.821	(2.53)
UFSMSA	$.101 \cdot 10^{-2}$	(.01)	-.152	(.29)	-7.108	(.26)	3.714	(.18)
UXSMSA	-.036	(.30)	-.643	(.98)	-33.077	(.96)	101.36	(3.62)
RXSMSA	-.118	(1.02)	-2.071	(3.41)	-108.38	(3.39)	58.468	(2.19)
NOREST	.109	(1.11)	-1.256	(2.22)	-54.125	(1.82)	-82.309	(3.62)
SOUTH	.109	(1.11)	-2.281	(4.24)	-103.91	(3.68)	-27.630	(1.23)
WEST	.039	(.36)	-.441	(.68)	-14.567	(.43)	-57.905	(2.27)
Constant	50.56		42.54		2147.7		2060.8	
R^2	.01		.18		.17		.06	
F	2.29		17.54		16.37		10.97	

	Equation #41		Equation #42		Equation #43		Equation #44	
Sample Number	II		XI		XI		II	
Dep. Variable	HW		WW_2		TH_2		FT_2	
NEY_1	$-.610 \cdot 10^{-4}$	(.43)	$.124 \cdot 10^{-3}$	(3.72)	.269	(24.91)	$-.790 \cdot 10^{-6}$	(.68)
2								
3								
4								
5								
6								
7								
8								
9								
10								
WR_1			.024	(2.31)	-97.772	(28.97)	$.339 \cdot 10^{-2}$	(3.10)
2							$-.698 \cdot 10^{-4}$	(2.09)
3								
4								
5	.027	(11.49)						
6								
7								
8								
9								
10								
Age_1	.291	(.53)	$-.117 \cdot 10^{-2}$	(.81)	4.100	(8.81)	$-.183 \cdot 10^{-2}$	(.44)
2	.338	(.59)					$.167 \cdot 10^{-2}$	(.38)
3								
4	-.477	(.82)					$.553 \cdot 10^{-2}$	(1.23)
5	-.637	(1.02)					$.492 \cdot 10^{-2}$	(1.03)
6	-.087	(.12)					$.419 \cdot 10^{-2}$	(.77)
7	-.034	(.05)					$.604 \cdot 10^{-2}$	(1.08)
OTHERN	$-.611 \cdot 10^{-4}$	(.86)	$.126 \cdot 10^{-3}$	(8.37)	-.076	(15.50)	$-.118 \cdot 10^{-5}$	(2.18)
BUSFARM	$.644 \cdot 10^{-4}$	(3.30)					$.609 \cdot 10^{-8}$	(.04)
HOMES	$-.703 \cdot 10^{-4}$	(3.08)					$.137 \cdot 10^{-6}$	(.79)
BNKACC	$.696 \cdot 10^{-5}$	(.32)					$.135 \cdot 10^{-6}$	(.80)
AUTOS	$-.857 \cdot 10^{-6}$	(.03)					$.510 \cdot 10^{-7}$	(.26)
OTHAST	$.196 \cdot 10^{-4}$	(.10)					$-.260 \cdot 10^{-5}$	(1.79)
OTHDBT	$.704 \cdot 10^{-4}$	(.63)					$-.258 \cdot 10^{-6}$	(.30)
NONWHI	-1.356	(2.33)	-1.868	(17.36)	256.43	(7.36)	$-.346 \cdot 10^{-2}$	(.78)
EDUCATION	$.692 \cdot 10^{-2}$	(.13)	-.048	(4.03)	20.653	(5.40)	$-.261 \cdot 10^{-2}$	(6.18)
KIDS	.238	(1.97)	.188	(14.29)	58.595	(13.75)	$.241 \cdot 10^{-2}$	(2.62)
UFSMSA	.078	(.20)					$-.163 \cdot 10^{-2}$	(.54)
UXSMSA	2.068	(3.83)					$-.577 \cdot 10^{-2}$	(1.39)
RXSMSA	1.279	(2.48)					$-.315 \cdot 10^{-2}$	(.80)
NOREST	-1.756	(4.00)					$.174 \cdot 10^{-2}$	(.52)
SOUTH	-.634	(1.46)					$-.230 \cdot 10^{-3}$	(.07)
WEST	-1.203	(2.44)					$.496 \cdot 10^{-3}$	(.13)
Constant	40.78		50.90		2143.4		1.01	
R^2	.06		.19		.56		.01	
F	10.93		136.179		720.02		3.03	

Equation #45

Sample Number	II
Dep. Variable	FT_2
NEY_1	$-.622 \cdot 10^{-6}$ (.53)
2	
3	
4	
5	
6	
7	
8	
9	
10	
WR_1	
2	
3	
4	
5	$.170 \cdot 10^{-3}$ (4.35)
6	$-.160 \cdot 10^{-6}$ (2.96)
7	
8	
9	
10	
Age_1	$-.734 \cdot 10^{-3}$ (.17)
2	$.188 \cdot 10^{-2}$ (.43)
3	
4	$.594 \cdot 10^{-2}$ (1.33)
5	$.502 \cdot 10^{-2}$ (1.05)
6	$.452 \cdot 10^{-2}$ (.83)
7	$.660 \cdot 10^{-2}$ (1.18)
OTHERN	$-.106 \cdot 10^{-5}$ (1.94)
BUSFARM	$-.257 \cdot 10^{-7}$ (.17)
HOMES	$.861 \cdot 10^{-7}$ (.49)
BNKACC	$.115 \cdot 10^{-6}$ (.68)
AUTOS	$.230 \cdot 10^{-7}$ (.12)
OTHAST	$-.269 \cdot 10^{-5}$ (1.86)
OTHDBT	$-.263 \cdot 10^{-6}$ (.31)
NONWHI	$-.182 \cdot 10^{-2}$ (.41)
EDUCATION	$-.300 \cdot 10^{-2}$ (6.90)
KIDS	$.238 \cdot 10^{-2}$ (2.58)
UFSMSA	$-.194 \cdot 10^{-2}$ (.64)
UXSMSA	$-.536 \cdot 10^{-2}$ (1.30)
RXSMSA	$-.217 \cdot 10^{-2}$ (.55)
NOREST	$.259 \cdot 10^{-2}$ (.77)
SOUTH	$.954 \cdot 10^{-3}$ (.29)
WEST	$.647 \cdot 10^{-3}$ (.17)
Constant	1.00
R^2	.02
F	3.52