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Estimates of a labor supply function using alternative measures of hours of work

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Abstract

Depending on data source, estimates of hours of work give widely different results both as to level and change. In this paper three alternative measures of hours worked are used to estimate a simple labor supply function to investigate if the estimated wage rate and income effects are data dependent as well. The measures used include those from time-use surveys and those from regular surveys. The latter are based on the responses to a question about normal weekly hours of market work. The results suggest that the estimates become much smaller (in absolute value) when measures of normal hours are used compared to data from time-use surveys.

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1. Introduction

Time-use studies have been motivated by their ability to give data for analysis and valuation of household work, but also because they give information about leisure (the ultimate utility yielding activities?), commuting and travel behavior, etc. In addition most time-use surveys have data on hours of work. One could argue that time-use studies, taking various deviations from normal work hours into account, give better data of hours actually worked as contrasted with the number of contracted hours. Time-use data also have the potential to improve the analysis of labor supply by explicitly including competing activities in the home, and making feasible studies of gender differences in market and nonmarket work, and thus also improving our understanding of female labor supply, However, most labor supply studies have used more conventional data sources such as labor force surveys.

Simple comparisons of levels and trends in hours worked demonstrate that different measures and data sources tell different stories (see below). No previous studies have though used a common data set to evaluated how the choice of measure will influence estimates of wage rate elasticities and income elasticities in labor supply functions. This is the topic of this paper. These elasticities are of key importance in economic policy and they have, for instance guided politicians in designing new tax systems.

Section 2 below gives a survey of the few comparisons of time-use estimates and more conventional survey estimates that can be found in the literature and also presents some stylized facts about average weekly hours of work in Sweden obtained from different sources. Then follows in Section 3 a more detailed account for the data used in this study, in section 4 a specification of the economic and econometric models used, and in Section 5 the empirical results. A few concluding remarks ends the paper.

2. Measures of market time.

Conventional measures of market time based on survey questions about normal weekly hours tend to give empirical frequency distributions which have pronounced peaks at full-time hours for men and at half-time and full-time hours for women. The observed high concentration to peak hours is probably exaggerated. There are good reasons to believe that many respondents report their contracted number of hours disregarding or forgetting any nonwork episodes at work and any irregular overtime work. Even if asked explicitly about secondary work it might also be difficult to report hours retrospectively, in particular if the respondent only works intermittently in this job. In general, those who have irregular work hours will find it difficult to respond to questions about normal hours. Time-use diaries are, however, normally collected such that meals, coffee breaks and other work breaks, over-time and time on secondary jobs are carefully recorded. In particular if a time diary is given in a “yesterday interview” and not in a leave behind diary, its sequential nature makes it difficult to falsify. [1] Time-use surveys also have the advantage of giving data on travel to and from work. Sometimes it is desirable to add commuting time to pure market work time.

Figure 1 (borrowed from Klevmarken, 1998) illustrates the differences between data based on questions about current hours per week including overtime and secondary jobs (“survey

[1] For this reason one might also argue that work time from a time-use diary will not only include time in the regular “white” market but also in the “black” market.

data") and time-use data from the same samples of people. Data were obtained from the HUS surveys (Klevmarken & Olovsson 1993, Flood et.al 1997). The time-use data distributions are much smoother and have a larger variance. The explanation is partly that just given but also the noisiness of time-use data due to the fact that only a few days are observed for each respondent. (One might also note that independently of data source the distribution for women have become more alike that of men.)

Carlin & Flood(1997) compared estimates of male labor supply from time-use data with those from conventional survey data using a so called double-hurdle model. Referring to previous studies they noted that the presence of young children normally decreases work hours for women while the effect for males has typically become nonsignificant or weakly positive. Sweden's active policy to bring women into the labor market and involve fathers more actively in the care of children, and independent evidence that this policy to some extent has been successful, suggested that one might expect a negative effect on labor supply also for Swedish males. They found no significant effect of the presence of young children when the estimates were based on the responses to the survey question about normal weekly hours, but they found a negative effect when they used time-use data. The double-hurdle model suggested that the largest share of this effect came from fathers loosing entire days rather than reducing hours of work when working. The explanation to this difference in results is thus that time-use data recorded temporary, unusual and unexpected episodes of absence from work (in this case probably because kids became sick), while this was not the case with data based on responses to the question about normal hours of work. In their study the number of children in different age groups were treated as exogenously given. Using a Hausman test they could not reject this assumption, but there is still a question as to what would happen if children were endogenous to the labor supply decisions. For the other explanatory variables the parameter estimates did not depend much on whether time-use or survey data were used.

Depending on the importance of breaks, nonwork at work, overtime and secondary jobs and irregular jobs there are reasons to expect systematic differences in estimates of average work hours from time-use diaries compared to conventional labor force surveys. Juster and Stafford(1991) report that "conventional respondent reports of labor supply seriously overstate the amount of hours actually supplied to the market" (p. 486). They also claimed that conventional Current Population Survey estimates underestimated the 1965-1981 decline in work hours (compared to time-use estimates). This conclusion was, however, questioned by Leete & Schor(1994) who suggested that the Michigan Study, only measuring weekly hours, did not adequately reflect the substantial rise in weeks worked per year found in the CPS.[2] Leete & Schor(1994) found support for the "time-squeeze" hypothesis. According to their results Americans worked longer hours and enjoyed less leisure at the end of the period.

Table 1 compares a number of different measures of weekly hours worked for Sweden. There are three groups of estimates, survey-type estimates from the HUS surveys, estimates from the official labor force surveys and time-use estimates. They all differ in level as well as to rate of change. The official estimates give an average of about 35 hours per week for all men in work including those who are temporarily absent, and about 26 hours for women. These estimates show a small decrease in hours for men and a small increase for women. Conceptually closest comparison is the HUS data estimates for normal hours including overtime and secondary jobs. For men they show a small increase from 41.8 to 42.5hours, and for females there is an increase from 35 to 37.5 hours. The difference in change between the two types of estimates

[2] They also argued that Juster & Stafford(1991) had "not corrected for the fact that in the 1965 sample all household heads were employed. This is especially important because 1981 was a recession year" (p. 41).

is probably on the boarder line of being significant for males but clearly significant for females. The time-use estimates show a completely different picture. The rows “All” include everybody, not only those in the labor force, and thus give much lower mean estimates. To obtain something which is closer to the “survey estimates” the estimates on the last and third last rows in the table were restricted to those who had responded positive “normal hours”. Excluding breaks these estimates are still much lower than the “survey estimates”, but more importantly they show a very strong increase in hours worked. Independent sources indicate that sickness absence decreased drastically and over-time increased in this period. Unemployment was much higher in 1993 compared to 1984, but judging from the time-use estimates for “All” this did not influence average work hours much! More work is needed to understand why all these estimates differ. One hypothesis is that time-use estimates more closely measure hours actually worked and that they are more sensitive to changes in the market than measures based on traditional survey questions. Given that actual hours are more relevant, for instance in measures of productivity, than normal hours or contracted hours, survey-type measures might be misleading.

3. Data sources

Data used in the analysis to follow below come from the 1993 wave of the Swedish household panel survey HUS that included a time-use survey (Flood et al 1997). The design was such that the regular panel survey was executed during the spring of 1993. Most of the interviews were done in the period February – April. In households with two spouses both were interviewed.[3] Because almost everyone in Sweden is retired at the age of 65 the sample used in this paper was limited to the age bracket 18 – 64.[4]

The time-use survey was administered in separate interviews during the period March 1993 – February 1994. Each respondent was asked to participate in two telephone interviews, that were randomly allocated over this period, such that one was on a week day and the other on a weekend day and one was done during the winter half and the other during the summer half of the year.

Time-use data were collected by the yesterday method, i e each respondent was called up the day after the selected day and asked to recapitulate what he or she did in that day (24 hours). Activities were recorded in free format and in the wording of the respondent and afterwards coded into activities. For each time span the respondent could give two activities, one main activity and one secondary activity. In the analysis of this paper hours of market work includes the sum of time in both the primary and secondary activity “market work”, but excludes breaks and job related trips.

In these time-use interviews the respondents were also asked how many hours they worked in the market in the week preceding the week of the interview.

Data on age, gender, schooling, housing, etc were obtained from the main survey interview. The gross wage rate estimate was also obtained from this interview. It originates from a sequence of questions about hourly, weekly or monthly pay. The respondent could chose to respond by either mode. A large majority was paid by the month. The estimate of the hourly

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[3] The joint dependence of spouses’ market work is ignored in this paper.

[4] Many labor contracts had 65 as an upper age limit and the social security system was designed for retirement at the age of 65.

wage rate was then obtained by dividing by the product of the average number of weeks per month (4.3) and normal weekly hours worked. The measure of normal weekly hours was obtained as the response to a direct question about normal hours.[5]

To estimate the labor supply function measures of the marginal tax rate and virtual income are needed. Unfortunately the income and tax data in the 1993 HUS wave refer to the year 1992. However, in the 1996 wave register data on 1993 incomes were added to the survey data. These data could be used to compute virtual income for those respondents that participated in both waves and gave us permission in 1996 to collect register data. This implies though a major reduction in sample size as demonstrated by the following numbers.

Number of respondents below the age of 65 with information about,

Basic demographics	3522
Time-use from first interview	2268
Time-use from second interview	2669
Annual work hours	2673
Hourly wage rate	3392
Virtual income 1993	1593

Using the virtual income measure thus results in a partial nonresponse of about two thirds of the original sample, and it is not likely that it is random. On the contrary, informal inspection suggests that people who work in the market and in particular full-time workers are overrepresented in the reduced sample. This is unfortunate for any inference to the Swedish population below 65 years of age, but the reduced sample might still be useful in evaluating the relative magnitude of incentive effects due to alternative measures of hours of work.

To reduce partial nonresponse missing virtual incomes were imputed with a hotdeck imputation technique. Using the share of the sample with nonmissing virtual income observations a regression was run for each gender of virtual income on the following variables: Net income in 1992, weeks worked in 1992, hourly wage rate in 1993, if unemployed or not in the labor force at the time of the main interview 1993, tax assessed value of owner occupied house[6], age, age squared, if health problem, number of adults in the household, number of children in the household, years of schooling and annual work hours. The imputation procedure was bootstrapped and the number of observations contributing to the regression varied a little from one bootstrap draw to another but was typically around 400 for each gender. The regression R-square was usually in the range 0.3 – 0.35. For each sample member the prediction from the regression was computed. For observations with missing virtual income a nearest neighbor was found among nonmissing observations based on the least distance between the predictions from the regression. Depending on the bootstrap sample about 200 observations were imputed for each gender. Thus about one third of the observations have imputed virtual income data.

In 1992 the income tax system had two brackets. In the first there was only a municipal tax of approximately 30% and above a certain threshold there was an additional state tax of 20%.

[5] There is also a question about number of hours worked on the latest day of work. To increase the precision of the estimate, the measure used to compute the hourly wage rate was actually a weighted average of the response to the question about normal hours and that about hours in the latest day of work. (In the subsequent analysis of normal hours of work only the response to the question about normal hours was used.)
[6] If the household did not own a house the value of this variable was set to zero.

The municipal tax was decided locally and varied from one municipal to another, but because our data include information about where the respondent lived this was not a problem. To know if the state tax applied to a respondent we need to know the respondent's taxable labor income for 1993. This information was only available for the reduced sample.

Following the definition in Blundell & MaCurdy virtual income was computed as the sum of capital income and the income obtained when the respondent's budget segment is extended to zero hours of work. Only the rules of the income tax system were considered in these computations, while nontaxable transfers were neglected.[7] Capital incomes are taxed by a flat rate 30% tax in Sweden. The base of this tax does not only include interest and dividends but also realized capital gains. In the definition of virtual income one might like to exclude capital gains. Unfortunately there is no information about capital gains for 1993 in the data source. To check for the sensitivity of the results to the definition of virtual income some models were also estimated with capital incomes deleted from virtual income. The disadvantage in using this second definition is of course that interest and dividend incomes are not included. The results below will show that the choice between these two alternatives is important.

In summary, the following measures of hours of work have been used in the analytical part of this study:

1. Time-use estimates of hours of work in a designated day.
2. Hours worked last week from the time-use survey.
3. Annual hours of work=normal weekly hours*4,3*months with market work as main activity.

The time-use estimates were multiplied by 7 and the annual hours divided by 50 to make all data approximately interpretable as hours per week.

4. Economic and econometric models

For the purpose of this paper a simple economic model that has been used in previous work will be needed. Taking the income tax system into account we will use the following simple model,

$$h = \beta_0 + \beta_1[w(1 - mtax)] + \beta_2 y + \varepsilon_h; \qquad (1)$$

where h is hours of work, w the hourly wage rate, mtax the marginal income tax rate, y virtual income and ε a random error. Both mtax and y will in this model depend on hours of work and they are thus endogenous. An alternative specification also used in previous research is to replace the marginal net wage rate with its log, ln(w(1-mtax)). This model variant has also been estimated.

The interpretation of the labor supply function (1) as the outcome of a behavioral model assuming utility maximization is discussed in Blundell & MaCurdy (1999).

Because the tax system operates on an annual basis it is natural to think of h as the annual hours of work. Most measures available however span a much shorter time period. The HUS

[7] A SAS code with the details of these computations is available from the author on request.

time-use data only give information for at most two days per respondent and other survey measures have a week as their reference period. In the HUS time-use survey the two measurement occasions were randomly chosen among all days of the year 1993.[8] In principle one could thus use the sampling weights and for each respondent estimate the annual hours of work, although this estimate would of course become very uncertain. With the sampling design used all work days had the same selection probability and all weekend days also the same selection probability. We would thus get an estimate of the total number of work hours on each type of day by simply multiplying with the number of workdays and the number of weekend days respectively. In the analysis to follow below we have chosen not to multiply with these constants but to use the observed hours per day and model potential workday/weekend differences in labor supply. The reason for this choice is that we would otherwise loose the respondents who only participated in one of the time-use interviews.

Analogously for the measure of hours worked last week, we could blow them up to an annual level but can as well use the original weekly hours and assume that the constant sampling weight is absorbed into the parameters of the labor supply function.

In these two cases one might thus hope that variations in hours across respondents because of the sampling design will capture some of the variation in hours during a year.

For the measure "normal weekly hours worked" there is no similar inference. In this case it is a matter of interpretation of "normal". Did the respondents average over a year, and if they did which year? Or did they interpret "normal" as the contracted hours at the time of the interview? With this measure we will most likely miss the variation in hours worked due to the fact that all respondents did not work all year or switched from part-time to full-time or vice versa during the course of the year 1993. This measure is neither likely to capture absence due to sickness, child care and other irregular decreases and increases in work hours. Part of the variation across the year we try to capture by using survey information about months with market work in 1993.

<u>Econometric specification</u>

Only for respondents who work it is possible to observe a wage. The well-known selectivity problem in the estimation of a labor supply function will in this paper be handled by a Heckit approach.

Taking into account that most respondents contribute five observations, two "hours of work last week" and two time-use estimates of hours of work, and one annual hours observation we will specify the following five equation model,

[8] The Christmas and Easter holidays were excluded.

$$
\begin{aligned}
&h_{11} = \beta_{01} + \beta_{11}[w(1-mtax)] + \beta_{21}y + \beta_{31}\lambda_{11} + \varepsilon_{11};\\
&h_{12} = \beta_{01} + \beta_{11}[w(1-mtax)] + \beta_{21}y + \beta_{31}\lambda_{12} + \varepsilon_{12};\\
&h_{21} = \beta_{02} + \beta_{12}[w(1-mtax)] + \beta_{22}y + \beta_{32}\lambda_{21} + \beta_{42}D + \varepsilon_{21};\\
&h_{22} = \beta_{02} + \beta_{12}[w(1-mtax)] + \beta_{22}y + \beta_{32}\lambda_{22} + \beta_{42}D + \varepsilon_{22}; \qquad \text{(2a-2f)}\\
&h_{3} = \beta_{03} + \beta_{13}[w(1-mtax)] + \beta_{23}y + \beta_{33}\lambda_{11} + \varepsilon_{3}\\
&E(\varepsilon_{ij} \mid X) = 0;\\
&Let\ \varepsilon = \{\varepsilon_{11}, \varepsilon_{12}, \varepsilon_{21}, \varepsilon_{22}, \varepsilon_{3}\}'\ and\ E(\varepsilon\varepsilon' \mid X) = \Omega;
\end{aligned}
$$

where the λ:s are the inverse Mill's ratios estimated separately for week data, time-use data and annual data using the assumption of normal errors and the following explanatory variables: an intercept variable, age, age squared, number of children in the household, if the respondent was single, if someone in the household had health problems, the tax assessed value of the house[9] of the household, years of schooling, if summer[10], and for time-use data also if weekend.

D is a dummy variable that takes the value 1 if the time-use observation applies to a Saturday or a Sunday.

X is a vector of instruments: An intercept variable, age, age squared, if single, number of adults in household, number of children in the household, if someone in the household had health problems, if summer, if weekend (D), floor area in square meters of house/apartment, tax assessed value of house, wage rate, years of schooling, and the λ:s.

The covariance matrix Ω is through the λ:s a function of data, and ideally the model should have been estimated taking this into account. When doing this in a GMM framework, the estimated weight matrix in the efficient GMM step occasionally became nonpositive definite. The problem seemed to be that the number of observations contributing to each equation was rather different. This is a small sample problem and to bypass it the assumption of homoskedasticity was imposed. This implies that the model was estimated by 3SLS. The estimates are still consistent and hopefully they are more efficient than the 2SLS estimates that were used in the first step of the GMM (3SLS) procedure. Both 2SLS and 3SLS estimates are presented below. To take account of the variability introduced in the imputation procedure, the model was estimated by bootstrapping the 3SLS (2SLS) estimates. More specifically the estimation proceeded in the following way. A bootstrap sample was drawn from the original data set. The imputation regression was estimated and missing virtual income observations were imputed. The model was then estimated by 3SLS (2SLS). This sequence was repeated 1000 times. The estimates presented are the means from the bootstrap distribution and the corresponding 95% percentile bootstrap confidence intervals.[11]

[9] If the respondent did not live in a house the value was put to zero.
[10] Not used with annual hours of work
[11] Application of the percentile bootstrap intervals builds on the assumption that the bootstrap distribution is an unbiased estimate of the true distribution of the parameter estimates. An alternative estimation method is to use the multiple imputation approach outlined in Brownstone & Valetta(1996) and large sample formulas.

5. Estimation results

Table 2a exhibits bootstrapped 3SLS estimates of model (2) by gender and data type. For the marginal effect of the net wage rate all three types of data give positive means of the bootstrap distributions. Time-use data give considerably higher estimates than week data and annual data for both gender. The confidence intervals are, however, rather wide. For males only time-use data give an interval that is entirely on the positive side, i e only time-use data reject a negative effect. For females one can reject a negative effect with both time-use and week data, but not with annual data.

The mean estimates of the income effects are negative with one exception, the estimate for females using time-use data. All confidence intervals extend well into the negative side and all but one include zero. The exception is the interval for males using time-use data. In this case it is possible to reject the hypothesis of a positive income effect.

With time-use data it is not possible to reject the hypothesis that there is no selection due to nonwork. In time-use data nonwork is not only a matter of nonparticipation but also of sickness, child care and other reasons to be temporary absent that might not correlate so highly with hours of work if working.

The 2SLS estimates in Table 2b give approximately the same results as the 3SLS estimates.

The corresponding estimates using the log of the net wage rate can be found in Appendix tables A1a and A1b. The results approximately parallel those of Tables 2a and 2b. One exception is that the mean wage rate estimate using annual data now turns negative both for males and females. The confidence intervals are wide though and one cannot reject the hypothesis of a positive effect.

Results for the case when after tax capital income is deleted from virtual income are given in Appendix table 2. The wage rate effects are approximately the same as those in table 2a. Most but not all income effects are now closer to zero.

The bootstrap percentile confidence intervals are in most cases so wide that it is difficult to draw firm conclusions about the differences in estimates across data types. A more formal test would be useful. Tests were set up in the following way. In each bootstrap replication six t-scores were computed. Each t-score was a difference between two estimates, for instance the estimates of the net wage rate effects using time-use and annual data, divided by a large sample estimate of the standard error of the difference. This was done for the estimates of the wage rate and income effects and for the three data comparisons time-use data/annual data, week data/annual data and time-use data/week data. Under the null hypothesis that there is no difference in effects due to data source these t-scores are pivotal statistics and the distributions of these statistics have zero mean. Table 3 displays the means of the bootstrap distributions. With one exception they are not close to zero. Do they differ so much from zero that the differences cannot be a result of the fact that we do not have the true distribution, only an estimate based on 1000 bootstrap replications? With one exception the answer is yes, because the t-scores for the test of zero mean are very high, see Table 3. We thus conclude that with the model and estimation method used time-use data and week data tend to give higher estimates of the net wage rate effect than annual data, while week data give higher estimates than annual data. This applies both to males and females. For males we also find that time-use data give smaller estimates of the (negative) income effect than week and annual data, while week data give (marginally) higher estimates than annual data. For females and time-use data the mean income effect is positive and significantly higher than the negative mean estimates based on week data and annual data. There is no significant difference between the mean estimates using week data and annual data.

6. Conclusions

The results from this study suggest that estimates of the net wage rate effects based on time-use data tend to become higher than estimates based on data that uses information about "normal" weekly hours. Estimates using responses on a question about hours worked last week tend to come in between the estimates from the other two data sources. For males we get similar results for the income effect. With time-use data the income estimates tend to become more negative than with the other two types of data. For females the mean time-use estimate of the income effect is positive and significantly higher than the negative mean estimates for non time-use data. In spite of the tests it is possible that this diverging result is caused by the relatively small time-use data sample and the missing virtual income information.

Our results also show that the confidence intervals are rather wide. This implies that two different samples could just by chance give rather different estimates. This is not only a result of our imputation procedure. A larger sample would improve the precision of the estimates, but the wide intervals also suggest that the model used is too simple. If the same study was to become repeated on more numerous data one should probably use a more realistic model.

Why would time-use data tend to give larger estimates (in absolute value) than the alternative data types? A reasonable hypothesis is that estimates based on normal weekly hours tend to smooth or leave out overtime, days with unusually long or short hours, market work at home, etc. There is thus less variability in week data. This is, however, not enough. There must also be a correlation between the net wage rate (virtual income) and the under/over reporting. If people with high wages work long hours but tend to under report those in regular surveys, and people with low wages work short hours but tend to over report those, then the kind of result we have got could emerge. Future research about measurement errors in surveys would have to tell us if such a correlation can be verified.

Although the estimates are uncertain, the differences in estimates are of a magnitude that is policy relevant. This at least suggests that economists should pay much more attention to measurement issues in applied work. Given that the target is to measure hours actually worked in the market our results also suggest that time-use data should be used more frequently in labor supply studies. Although not exploited in this study time-use data capture the interdependence between market work and other activities, something that might be important even if labor supply is the main focus.

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Table 1. Alternative estimates of weekly work hours by gender 1983/84 and 1992/93

	1983 m	1983 f	1984 m	1984 f	1992 m	1992 f	1993 m	1993 f
"Survey estimates"								
HUS data								
Annual hours/weeks worked	41.8	40.3			41.9	35.0		
	(0.2)	(0.3)			(0.3)	(0.3)		
5*hours latest workday			43.0	38.5			44.5	38.9
			(0.3)	(0.4)			(0.4)	(0.5)
Normal hours incl. secondary jobs*			41.8	35.0			42.5	37.5
			(0.5)	(0.5)			(0.2)	(0.2)
Latest week worked							41.9	33.6
							(0.4)	(0.4)
Labor force Survey. Statistics Sweden								
All in work and temporary absent, 16-64 years old			35.1	25.7			34.6	26.1
All in work 16-64 years old			40.6	31.7			39.9	32.5
Employed 16-64(74) years old			39.7#	31.4#			38.6	32.2
Time-use estimates								
Excluding break time								
All 20-64 years old			25.6	17.6			33.6	24.7
			(0.7)	(0.6)			(0.8)	(0.7)
If normal hours >0			30.5	22.9			36.6	29.1
			(0.8)	(0.7)			(0.9)	(0.9)
Including break time								
All 20-64 years old			29.3	20.1			42.5	31.4
			(0.8)	(0.7)			(1.1)	(1.0)
If normal hours>0			35.0	26.2			46.4	37.0
			(0.9)	(0.8)			(1.2)	(1.1)

*Employed only. The questions used were phrased: "On average, how many hours per week are you currently working at your primary job, including both paid and unpaid overtime", "Do you have another job in addition to your primary job?" and if YES, "How many hours do you spend on your other job(s)?" (Replies given per day, week, month or year).

[#] 16-74 years old

Note 1. The estimates for "Annual hours/weeks worked" were obtained using a sequence of questions about weeks worked in full-time and part-time work last year and about the average number of hours during those full-time and part-time weeks respectively.

Note 2. The hours of work question in the Labor Force surveys were: "The question which follows applies to a certain week, Monday the ….. to Sunday the …, that is week no …. How many hours did you work that week in your main job? How many hours in any secondary job?"

Note 3. Time-use estimates include the sum of work hours in primary and secondary activities, but market work as a secondary activity is very small. Secondary jobs are also included. Breaks include lunch, coffee breaks, personal errands and telephone calls while at work. The sample is limited to respondents who gave two complete time-use interviews (one work day and one weekend day). If the respondent had a job at the time for the workday time-use interview and had not been away for more than 8 weeks, the respondent was classified as in work or temporarily absent.
Source: Klevmarken(1998)

Table 2a Bootstrap 3SLS estimates of labor supply functions by gender and type of data

Variable	Males			Females		
	Weekly hours	Time-use hours	Annual hours	Weekly hours	Time-use hours	Annual hours
Intercept	41.221 *37.45 44.26*	53.538 *41.13 64.42*	44.356 *41.20 48.50*	33.329 *27.93 37.76*	46.668 *34.34 58.81*	37.528 *30.46 43.31*
W(1-mtax)	0.0245 *-0.017 0.086*	0.129 *0.0047 0.291*	0.0018 *-0.074 0.058*	0.074 *0.004 0.153*	0.165 *0.023 0.298*	0.011 *-0.092 0.128*
Virtual inc*	-0.052 *-0.013 0.021*	-0.136 *-0.268 -0.015*	-0.069 *-0.148 0.010*	-0.079 *-0.237 0.076*	0.055 *-0.213 0.335*	-0.070 *-0.229 0.087*
If weekend		-18.118 *-30.35 -4.39*			-13.073 *-27.73 1.21*	
Lambda	-3.229 *-8.07 -1.80*	-5.708 *-19.18 7.40*	-8.774 *-16.32 -2.64*	-5.532 *-10.379 0.125*	-4.444 *-17.941 8.729*	-8.611 *-13.984 -3.239*
Nobs** hours>0 period 1, period 2	 431 462	 279 290	 490	 418 453	 223 259	 490
Total nobs	718	718	718	750	750	750

*1000 SEK. **These numbers vary a little between bootstrap drawings. The numbers given are from a case using the original data.
Note: The table gives the means and 95% confidence intervals of the bootstrap distribution of the slope parameters. Virtual income was defined to include net capital incomes, see text.

Table 2b Bootstrap 2SLS estimates of labor supply functions by gender and type of data)

Variable	Males			Females		
	Weekly hours	Time-use hours	Annual hours	Weekly hours	Time-use hours	Annual hours
Intercept	41.918 *38.12 45.07*	54.318 *41.54 64.79*	45.008 *41.94 49.16*	35.051 *30.15 39.43*	47.554 *36.65 58.33*	39.069 *32.46 44.39*
W(1-mtax)	0.020 *-0.022 0.076*	0.123 *-0.002 0.285*	-0.005 *-0.078 0.049*	0.049 *-0.016 0.122*	0.143 *0.019 0.253*	-0.013 *-0.103 0,095*
Virtual inc*	-0.037 *-0.113 0.034*	-0.125 *-0.263 -0.004*	-0.057 *-0.138 0.020*	-0.048 *-0.226 0.119*	0.050 *-0.201 0.291*	-0.078 *-0.228 0.074*
If weekend		-17.016 *-28.80 -4.26*			-12.765 *-26.99 1.30*	
Lambda	-4.604 *-9.85 0.48*	-6.606 *-19.75 6.92*	-9.773 *-17.36 -3.56*	-7.295 *-12.407 -2.380*	-4.210 *-17.095 9.173*	-8-812 *-13.557 -3.834*
Nobs** hours>0 period 1, period 2	 431 462	 279 290	490	 418 453	 223 259	 490
Total nobs	718	718	718	750	750	750

*1000 SEK. **These numbers vary a little between bootstrap drawings. The numbers given are from a case using the original data.
Note: The table gives the means and 95% confidence intervals of the bootstrap distribution of the slope parameters. Virtual income was defined to include net capital incomes, see text.

Table 3 **Pair wise comparisons of differences in net wage rate and income effects**

Comparison	Males		Females	
	Mean	Test of zero mean	Mean	Test of zero mean
Differences in net wage rate effects				
Time-use/annual data	3.19	59.57	3.97	31.34
Week/annual data	1.22	33.10	2.02	18.48
Time-use/week data	2.65	49.41	2.80	36.02
Differences in virtual income effects				
Time-use/annual data	-1.61	-30.13	2.08	16.89
Week/annual data	0.60	13.30	0.04	0.42
Time-use/week data	-2.11	-40.80	2.13	20.54

Note: These tests apply to the same models, data sets and estimation method as in Table 2a. Mean is the mean of the bootstrap distribution of pair wise differences in estimates standardized by an estimated large sample standard deviation. Test of zero mean is the t-score obtained by dividing the mean by the standard deviation of the bootstrap distribution and multiplying by the square root of the number of bootstrap replications (1000).

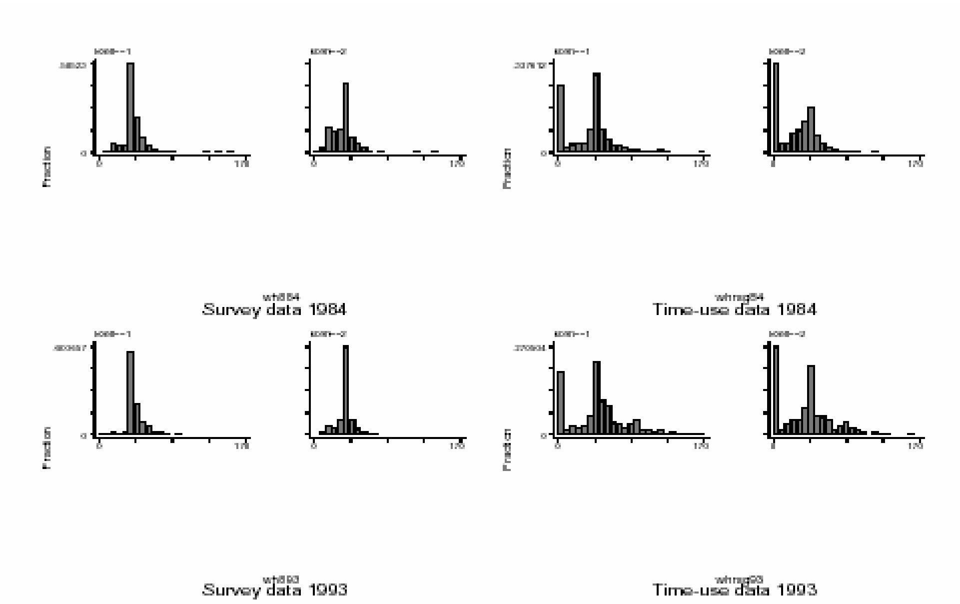

Figure 1 Weekly workhours by gender and data type

Source: Klevmarken(1998)

APPENDIX

Table A1a Bootstrap 3SLS estimates of labor supply functions by gender and type of data

Variable	Males			Females		
	Weekly hours	Time-use hours	Annual hours	Weekly hours	Time-use hours	Annual hours
Intercept	40.060 *34.36 46.12*	49.987 *39.25 60.43*	51.942 *38.48 67.58*	32.284 *26.93 37.19*	46.750 *33.99 59.22*	44.817 *27.88 65.90*
LN(W(1-mtax))	1.031 *-0.985 2.935*	4.357 *1.419 7.223*	-3.004 *-9.154 2.353*	1.724 *0.068 3.561*	3.408 *0.116 6.456*	-2.409 *-9.971 3.641*
Virtual inc*	-0.048 *-0.132 0.030*	-0.120 *-0.255 0.008*	-0.072 *-0.145 -0.002*	-0.072 *-0.234 0.090*	0.034 *-0.235 0.302*	-0.084 *-0.220 0.064*
If weekend		-16.966 *-27.94 -5.04*			*-11.195* *-25.05 3.41*	
Lambda	-3.297 *-8.18 1.87*	-6.535 *-18.71 6.13*	-7.152 *-15.40 -0.04*	-5.545 *-10.192 -0.673*	-5.960 *-19.527 7.350*	-7.656 *-12.830 -2.966*
Nobs** hours>0 period 1, period 2	431 462	279 290	490	418 453	223 259	490
Total nobs	718	718	718	750	750	750

*1000 SEK. **These numbers vary a little between bootstrap drawings. The numbers given are from a case using the original data.
Note: The table gives the means and 95% confidence intervals of the bootstrap distribution of the slope parameters. Virtual income was defined to include net capital incomes, see text.

Table A1b Bootstrap 2SLS estimates of labor supply functions by gender and type of data

Variable	Males			Females		
	Weekly hours	Time-use hours	Annual hours	Weekly hours	Time-use hours	Annual hours
Intercept	*40.705* *35.02 46.58*	*50.503* *40.24 60.71*	*53.981* *38.46 70.87*	33.327 *28.80 37.61*	45.614 *34.35 56.87*	45.821 *29.92 65.79*
LN(W(1-mtax))	*0.945* *-1.160 2.807*	*4.364* *1.420 7.123*	*3.721* *-10.641 2.447*	1.537 *0.071 3.098*	3.576 *0.868 6.230*	-2.675 *-9.987 2.934*
Virtual inc*	*-0.030* *-0.111 0.046*	*-0.107* *-0.253 0.018*	*-0.062* *-0.136 0.008*	-0.045 *-0.223 0.130*	0.038 *-0.215 0.299*	*-0.089* *-0.227 0.055*
If weekend		*-15.916* *-26.93 -3.86*			-11.734 *-25.314 1.145*	
Lambda	*-4.714* *-10.330 0.631*	*-7.624* *-19.567 4.667*	*-7.645* *-16.422 -0.385*	-7.325 *-11.942 -2.461*	-4.953 *-17.688 8.326*	-7.851 *-12.497 -2.959*
Nobs** hours>0 period 1, period 2	431 462	279 290	490	418 453	223 259	490
Total nobs	718	718	718	750	750	750

*1000 SEK. **These numbers vary a little between bootstrap drawings. The numbers given are from a case using the original data.
Note: The table gives the means and 95% confidence intervals of the bootstrap distribution of the slope parameters. Virtual income was defined to include net capital incomes, see text.

Table A2 Bootstrap 3SLS estimates of labor supply functions by gender and type of data. Capital incomes deleted from virtual income

Variable	Males			Females		
	Weekly hours	Time-use hours	Annual hours	Weekly hours	Time-use hours	Annual hours
Intercept	*41.881* *37.04 46.68*	*57.464* *45.56 69.08*	*46.704* *41.36 52.06*	*32.265* *27.25 37.33*	*44.861* *31.94 57.40*	*36.995* *29.65 44.00*
W(1-mtax)	*0.021* *-0.044 0.095*	*0.112* *-0.059 0.298*	*0.009* *-0.075 0.092*	*0.061* *-0.028 0.170*	*0.142* *-0.015 0.295*	*0.015* *-0.106 0.150*
Virtual inc*	*-0.008* *-0.192 0.194*	*-0.045* *-0.360 0.303*	*-0.081* *-0.278 0.128*	*0.024* *-0.232 0.284*	*0.127* *-0.253 0.485*	*-0.029* *-0.313 278*
If weekend		*15.217* *-27.23 -1.72*			*-14.560* *-29.30 -0.06*	
Lambda	*-4.297* *-8.934 0.281*	*-10.267* *-23.406 1.636*	*-11.568* *-18.518 -5.603*	*-5.434* *-10.255 -0.473*	*-3.224* *-15.921 9.446*	*-8.737* *-14.361 -3.556*
Nobs** hours>0 period 1, period 2	 435 473	 268 294	 518	 418 453	 223 259	 490
Total nobs	718	718	718	750	750	750

*1000 SEK. **These numbers vary a little between bootstrap drawings. The numbers given are from a case using the original data.

Note: The table gives the means and 95% confidence intervals of the bootstrap distribution of the slope parameters. Virtual income was defined to include net capital incomes, see text.