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SOME ESTIMATES FOR INCOME ELASTICITIES OF LEISURE ACTIVITIES IN THE UNITED STATES

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Abstract

The empirical classification of leisure activities into luxuries, necessities, or inferior activities is useful for predicting the impact of economic development or life-cycle variations in wages on the organization of people's leisure. We take a step in that direction. We present theoretical underpinnings to the investigation of leisure-income responses and conduct an empirical examination of four broad activities using a recently collected cross-section of observations on time use in the US. Findings suggest that consumers endowed with more income opt to improve the quality of their leisure activities but not to increase (or increase only slightly) the time spent on them. A positive, direct effect of education on active leisure stemming mainly from men's behavior is also found.

Keywords: Engel aggregation; empirical time-demand functions; income elasticities of time use; American Time Use Survey.

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1. INTRODUCTION

Ever since the seminal works of Mincer (1963) and Becker (1965), the notion that the consumption of market goods requires time has spread among economists to reach, nowadays, the status of a common research tool. Coinciding with the diffusion of that idea, leisure per adult in the US has increased dramatically (Aguiar and Hurst, 2007), and demand analysis, which was fundamentally concerned with the demand for market commodities, has become increasingly interested in the analysis of the demand for leisure (e.g., see Owen, 1971, Gronau, 1976, Wales and Woodland, 1977, Kooreman and Kapteyn, 1987, Biddle and Hamermesh, 1990, and Mullahy and Robert, 2010).

In spite of this growing interest, certain aspects of the demand for leisure are still not well understood. In my opinion, prominent among those aspects is the empirical classification of leisure activities into luxuries, necessities, or inferior activities. Such classification would be useful for predicting the consequences to the organization of people's leisure of, for example, economic development or life-cycle variations in wages. However, it has proved elusive. Kooreman and Kapteyn (1987) estimate the effect of unearned income on the demand for seven types of non-market activities, finding negligible income effects in a sample of 242 households extracted from Juster et al.'s (1978) 1975-1976 Time Use Study (TUS). Similarly, Biddle and Hamermesh (1990) report no evidence of income effects in the demands for sleep and non-market waking time in a sample of 706 individuals extracted from that same survey. Dardis et al. (1994) consider a different though related question: the determinants of households' expenditure on leisure in the US. Using 1988-1989 Consumer Expenditure Survey data on active leisure, passive leisure, and social entertainment, they obtain expenditure elasticities for non-salary income in the range of 0.40 to 0.72, which indicate that the goods consumed in the course of each of those three activities are necessities. Yet, unless goods and time are consumed in fixed proportions, the analysis of consumer expenditure is of limited usefulness for empirically assessing the reaction of activity times to changes in income.

The purpose of this paper is to put in place a re-examination of how the consumer's allocation of time to leisure activities reacts to variations in income. To this aim, we start in Section 2 by briefly discussing two theoretical underpinnings. First, we develop a straightforward implication for the allocation of time of the linear time-budget constraint that is analogous to the Engel aggregation requirement for commodity demand functions. Second, we discuss some issues involved in the specification and estimation of a time-demand regression function. The rest of the paper is oriented towards estimating the income responses of time devoted to the three leisure aggregates considered by Dardis et al. (1994) and of time spent sleeping. The selection of these four activities owes to the sake of facilitating the comparison and interpretation of our results. Moreover, some of our methods of analysis follow those in the now-classic study of sleep by Biddle and Hamermesh (1990). The data and their organization are described in Section 3. For this study, we take advantage of a recently available US time-use survey that is also larger than the 1975-1976 TUS. The estimation, conducted on cross-section observations, assumes that all consumers face the same goods prices, but, as in Mincer (1963), holds constant the opportunity cost of time to avoid creating misinterpretations of income effects. Section 4 presents the results for the entire sample of consumers as well as separately for men and women. The main findings are summarized in Section 5.

2. PRELIMINARIES

2.1 An Engel aggregation condition for the allocation of time

Suppose a consumer purchases goods and combine them with time to maximize satisfaction. The allocation of time must obey the constraint

$$\sum_{m=1}^{M} T_m + T_w = T\,, \tag{1}$$

where T_m is time allocated to activity m, T_w working time, and T time available. For simplicity, assume that demand functions exist and write the "leisure" demand functions and the derived labor supply function as

$$T_m = T_m\left(p_m, w, S', a\right), \quad m = 1,\ldots,M\,, \tag{2}$$

$$T_w = T - \sum_{m=1}^{M} T_m\left(p_m, w, S', a\right) = T_w\left(p_1,\ldots,p_M, w, S', a\right), \tag{3}$$

where p_m is a vector with the unit prices of the market goods consumed in the course of activity m, w the wage rate, $S' = wT + V$, where V is nonlabor income, represents full income, i.e. the maximum money income achievable by the consumer, and a is a vector of characteristics of the consumer.

The requirement that the functions (2) and (3) satisfy the adding-up constraint (1) implies that changes in S' (or, equivalently, in V) will cause rearrangements in the consumer's allocation of time that will leave T unchanged. Written in differential form, this aggregation property results in

$$\sum_{m=1}^{M} \frac{\partial T_m\left(p_m, w, S', a\right)}{\partial S'} + \frac{\partial T_w\left(p_1,\ldots,p_M, w, S', a\right)}{\partial S'} = 0\,. \tag{4}$$

Defining

$$e_{mS'} = \frac{\partial T_m\left(p_m, w^*, S', a\right)}{\partial S'} \frac{S'}{T_m\left(p_m, w^*, S', a\right)}, \tag{5}$$

$$e_{wS'} = \frac{\partial T_w\left(p_1,\ldots,p_M, w, S', a\right)}{\partial S'} \frac{S'}{T_w\left(p_1,\ldots,p_M, w, S', a\right)}, \tag{6}$$

b_m as the share of full income spent indirectly (i.e. through the foregoing of money income) on activity m, and b_w as the share of labor earnings in full income, expression (4) leads to the following elasticity formula:

$$\sum_{m=1}^{M} b_m e_{mS'} + b_w e_{wS'} = 0 . \qquad (7)$$

The adding-up restriction (7) expresses that the sum of income elasticities weighted by b's is zero, whereby either all the e's are zero or there must be at least one positive and one negative elasticity. As the response of labor supply to income is generally negative (e.g., see the survey article by Blundell and MaCurdy, 1999), we would expect at least one $e_{mS'}$ to be positive. If $e_{mS'} > 1$, activity m would be considered a luxury. Since b_m will increase with S' if and only if $e_{mS'}$ is greater than unity, a luxury is therefore an activity that takes up a larger share of S' as S' increases. When an activity takes up a lower share of S' as S' increases it is considered a necessity. In other words, a necessity is an activity for which $0 < e_{mS'} < 1$. Inferior activities are those which take up a lower quantity of time as S' increases. In that case, $e_{mS'} < 0$.

2.2 Specification and estimation of a time-demand regression function

We shall work with time-use observations in levels form. The reason for this is that activity-specific elasticities (e_m) cannot be derived generally from relative time share equations.[1] Since total leisure time, which is in the share's denominator, does also react to changes in exogenous variables, the relative time share elasticity will equal the activity-specific elasticity

[1] Mullahy and Robert (2010) have generalized Papke and Wooldridge's (1996) specification and quasi-likelihood estimator for a dependent variable bounded between 0 and 1 to the context of a system of time-demand equations where the total time analyzed is normalized to 1.

minus the elasticity of total leisure time, so that it is not possible to identify e_m without knowing the latter.

The two most common approaches for modeling the regression function of time-use observations are the linear and the Tobit models. Consider again a consumer rationally allocating her time among a set of leisure activities over, say, a week or month. Following Stewart (2013), let $\overline{T}_m^*$, defined as

$$\overline{T}_m^* = x\beta_m + \varepsilon_m, \tag{8}$$

be the utility-maximizing average daily time to be spent on activity m before imposing non-negativity constraints on the allocation of time. In (8), x and β_m are conformable vectors of explanatory variables and unknown parameters, whereas ε_m is a $N\left(0, \sigma_m^2\right)$ disturbance.[2] Whenever $\overline{T}_m^* > 0$ the consumer is a doer of activity m, and a non-doer otherwise. For a doer, the time eventually spent on m in a certain day may depart from $\overline{T}_m^*$ due to unanticipated circumstances or to the existence of fixed costs associated with m (e.g., see Stewart, 2013). As these factors are generally unobserved by the econometrician, we model the observed amount of time spent on m on the study day as

$$T_m = \begin{cases} \max\left(0, \overline{T}_m^* + v_m\right) & \text{if } \overline{T}_m^* > 0, \\ 0 & \text{if } \overline{T}_m^* \leq 0, \end{cases} \tag{9}$$

where v_m is a $N\left(0, \sigma_{v_m}^2\right)$ disturbance. As in Stapleton and Young (1984), the unobserved factors influencing the consumer's allocation of time on the study day are modeled as a random measurement error affecting the uncensored observations. However, we depart from Stapleton and Young in two interrelated aspects proper to time-use observations. For one

[2] The normality assumption is for exposition purposes only. It will not be used in deriving our empirical results.

thing, if $\overline{T}_m^* + v_m < 0$ the consumer will not spend time on m on the study day ($T_m = 0$). This implies that the zeros observed in a sample of time-use observations pertain to two types of agents: non-doers (true zeros) and doers who, on the study day, spent no time on m (called reference-period-mismatch zeros by Stewart, 2013). Secondly, it is not possible to separate observations for which $T_m = 0$ even though $\overline{T}_m^* > 0$ from those for which $T_m = 0$ because $\overline{T}_m^* \leq 0$.

When $\sigma_{v_m}^2 \neq 0$, Stapleton and Young (1984) showed that the maximum likelihood estimator of all the parameters of the model is generally inconsistent. To correct for this, they proposed a series of estimators based either on the expectation function of T_m or on the expectation function of T_m conditional on $\overline{T}_m^* > 0$. Unfortunately, neither of these estimators can be used here as they rely on the possibility of classifying observations with $T_m = 0$ as censored or uncensored.[3]

It is well-known that ordinary least squares (OLS) estimates of β_m are biased and inconsistent in the context of the standard (i.e., $\sigma_{v_m}^2 = 0$) Tobit model. But when the dependent variable is a corner solution response, β_m is of less interest than marginal effects. McDonald and Moffitt (1980) showed that, for the standard Tobit model, the marginal effect of a continuous regressor x_j on the observed T_m is given by

$$\frac{\partial E\left(T_m | x\right)}{\partial x_j} = \Phi\left(x\beta_m / \sigma_m\right)\beta_{mj}, \tag{10}$$

[3] The modeling frameworks offered by two-part models and the Exponential Type II Tobit model discussed in Wooldridge (2010) are also discarded because these models' first-stage regression represents the consumer's decision about spending time on m on the study day, which is quite different from the consumer's decision about doing activity m.

where $\Phi(\cdot)$ denotes the cdf of the standard normal distribution. In that same context, Stoker (1986) found that if x is multivariate normally distributed the linear regression of T_m on x consistently estimates $E_x\left(\Phi\left(x\beta_m/\sigma_m\right)\right)\beta_{mj}$. A similar conclusion was reached by Greene (1981), whose Monte Carlo study further suggests that that result is surprisingly robust in the presence of uniformly distributed and binary variables, but is consistently distorted by the presence of skewed variables such as chi-squared. Recently, Stewart (2013) has simulated the behavior of the OLS estimator with time-diary data. In line with Greene (1981) and Stoker (1986), he finds that in the presence of both doers and non-doers, the OLS coefficients are downward biased, but after dividing them by one minus the fraction of non-doers (i.e., $1-(1-\Phi)$), the resulting estimates are close to the true parameter values.[4] The reason behind this apparent robustness of OLS may be that the presence of v_m is inconsequential when the estimating model is linear in parameters.

In summary, the existing literature suggests that the combination of a linear specification with a simple OLS estimator may be a reasonable compromise for specifying and estimating a time-demand equation in the presence of observations with $T_m = 0$. When the proportion of zeros in the sample is small, OLS will estimate β_{mj} (which, in that context, coincides with the marginal effect of x_j), and when zeros are more prevalent it will approximate the marginal effect in (10) (particularly if regressors adopt the shapes recommended by Greene, 1981, and Stoker, 1986). A potential complication arises when some explanatory variable can be correlated with ε. In that case, we would need to rely on the method of instrumental variables (IV). Although the behavior of the IV estimator with

[4] The regressors in Stewart's data-generating process are a dummy and two uniformly distributed variables.

time-diary data is still to be studied, intuition suggests that it could follow that of the OLS estimator. This is perhaps most easily seen in the context of the Two-Stage Least Squares (TSLS) estimator, whose second-stage regression is indeed an OLS regression (in which the troublesome regressor has been replaced by OLS fitted values).

3. DATA AND METHODS

The data for this study come from the American Time Use Survey (ATUS), a large-scale, continuous survey on time use in the US begun in 2003. The ATUS sample is drawn from a subset of households that have completed their participation in the Current Population Survey (CPS). In each selected household, one individual aged 15 or older is interviewed over the phone, who is asked to report on her activities over the previous 24-hours, anchored by 4:00 AM. This time interval is the study or diary day. The ATUS also asks for basic labor market information (including labor force status, usual weekly hours of work, and weekly earnings), but an important range of socio-demographic measures (such as household income and the respondent's education and disability status) are carried over from the final CPS interview, which takes place two to four months before the ATUS interview. For a more complete description of the ATUS see Hamermesh et al. (2005).

The ATUS data for this analysis were collected evenly during 2011. Particular of that year in the US is that the price of goods consumed in conjunction with leisure time remained virtually constant.[5] Although this fact does not preclude the existence of spatial price differences, it does make more plausible the maintained assumption that interviewed households faced similar prices of recreation goods. In 2011 the ATUS response rate averaged 54.6 percent. As a rule, this rate is lowered by 1 to 3 additional percentage points during processing and editing, as diaries containing fewer than five activities, or for which

[5] The average inflation rate of the Recreation component of the Consumer Price Index was 0.0 percent in 2011.

refusals or “don‘t remember” responses account for 3 or more hours of the study day, are removed from the sample. The final sample size of the 2011 ATUS contains 12,479 individuals. Of these, I discarded 3446 because they were below 23 or above 64 years old; 660 because they were self-employed and the 2011 ATUS did not collect earnings information for that group; 1098 because annualized reported earnings exceeded reported annual family income;[6] 423 because some of our measures of w and V was below the 1st percentile or above the 99th percentile of the corresponding sampling distribution; and 56 because the individual’s metropolitan status was not identified. This left a usable sample of 6796 persons, of whom 3972 are women.

The selection and grouping of leisure activities for analysis is fundamentally arbitrary. For the sake of facilitating the interpretation of our results, we shall focus on the allocation of time to three types of leisure aggregates plus time spent sleeping. The three leisure aggregates are active leisure, passive leisure, and social entertainment, as in Dardis et al. (1994) and also similar to leisure activities (5), (7), and (6), respectively, of Kooreman and Kapteyn (1987). Active leisure includes a wide range of leisure activities needing some physical effort. Specifically, it comprises all the ATUS codes under the major category “Sports, Exercise, and Recreation” plus sports and exercise as part of job. Passive leisure involves leisure activities which do not demand active participation on the part of the individual. Included here are all the ATUS codes under the 2nd-tier category “Relaxing and leisure”. Social entertainment comprises attendance at spectator activities, going to theaters and museums, hosting social events, and religious activities. Sleep has been previously included in broad definitions of leisure (e.g., Aguiar and Hurst, 2007). Time spent sleeping is here made up of all activity

[6] Besides inconsistent responses, this criterion excludes individuals who changed job between the CPS and the ATUS interviews and whose updated annualized earnings were greater than annual family income at the CPS interview.

examples listed in the 3rd-tier category "Sleeping". All uses of time will be measured in minutes of the diary day.

Our principal explanatory variable is the natural logarithm of the respondent's nonlabor income ($\ln V$). V is constructed as total annual family income minus 52 times the respondent's usual weekly earnings.[7] The use of V as a measure of income instead of the more difficult to operationalize S' makes the coefficient associated to the wage rate to be representing both a price-of-time effect and a total income effect. The income elasticity e_{mV} has the same shape as $e_{mS'}$ but is smaller, since V, and not S', appears in the numerator of the right-most term of expression (5). The baseline set of control variables, taken from Biddle and Hamermesh (1990), Dardis et al. (1994), and Mullahy and Robert (2010), includes characteristics of the respondent (sex, age (in years) and age squared, race/ethnicity, having a physical/mental disability, the natural logarithm of the respondent's usual weekly earnings divided by her usual weekly hours of work ($\ln w$)), of the household (presence of a spouse/partner, presence of one or more children under 3), and of the diary day (day of week, being a holiday, and season of the year).

Table 1 presents the sample characteristics. Women devote more time than men to social entertainment (an average of 72 vs. 58 minutes per day) and sleep (525 vs. 514), whereas the opposite is true for active leisure (14 vs. 23) and passive leisure activities (199 vs. 243). All these differences are statistically significant at 0.05 level. The percentage of sample members who did not sleep during the study day is 0.1. Among leisure aggregates, the

[7] All income measures are expressed before payments. The answer to the question on family income is provided in 16 intervals. I take the midpoint of the selected interval when the respondent's annualized earnings are either 0 or below the lower limit of the selected interval. When annualized earnings fall into the selected interval, I take the midpoint between annualized earnings and the interval's upper limit.

proportion of zeros is greater, in some cases much more so: 10.4 in the case of passive leisure, 54.9 for social entertainment, and 82.0 for active leisure (figures pertain to the full sample of men and women). Particularly in the case of social entertainment and active leisure, the size of these figures suggests that persons who did not do the activity on the study day might coexist in the sample with persons who never do the activity in question. In part for this reason, and pursuant to the results in Greene (1981) and Stoker (1986) pointed out in Subsection 2.2, we have included V and w in log form to reduce these variables' degree of skewness.

Since the wage rate is observed only if the person works, the use of average hourly earnings to valuing the opportunity cost of time introduces a potential sample selection problem if we use data only on workers to estimate time-demand functions. To overcome this problem, I predict $\ln w$ for non-workers (2378 of the 6796 sample members) from wage regressions run on workers only. In addition to all the explanatory variables listed above, these wage regressions contain an inverse Mills ratio term (which appears as statistically insignificant) and the following set of regressors, taken from Biddle and Hamermesh (1990) and from the empirical immigration literature (e.g., see Borjas, 1999): The respondent's educational attainment, region of residence, metropolitan status, immigrant status, and number of years since entry into the US.[8]

On the other hand, a potential complication for workers is the endogeneity of $\ln w$ due to errors of measurement or omitted variables. To overcome this problem, I test for the endogeneity of $\ln w$ among workers in each time-demand function, using some of the additional regressors listed in the previous paragraph as instrumental variables. Whenever the exogeneity assumption is rejected $\ln w$ is instrumented, but otherwise we maintain the

[8] I have not considered union membership, occupation, and industry because these variables are available for workers only.

original wage measurements to avoid the efficiency loss associated to instrumenting. As explained in the following two paragraphs, the selection of instruments for $\ln w$ in each time-demand equation combines the use of reduced-form regressions to check the intuition behind an instrument with formal tests of instruments' validity and reliability.

The first column of Table 2 lists reduced-form estimates of the equation for $\ln w$ obtained on the entire sample. Columns 2 through 5 present the corresponding time-demand equations estimates where $\ln w$ has been excluded from the regression. The potential instruments for $\ln w$ appear in the lower area of Table 2. We follow Biddle and Hamermesh (1990) and interpret the inverse association between education and sleep to be entirely due to educational wage differentials. (We would expect the uncompensated wage effect to be negative in all time-demand functions.) However, the positive association between education and active leisure cannot be rationalized in the same terms. Rather, it seems to be representing a positive direct effect of education on preferences for active leisure, whereby education would help people choose healthier lifestyles (Kenkel, 1991). Moreover, and in comparison with the effect on sleep, the negative effect of education on passive leisure seems too large to be entirely due to educational wage differentials. For all these reasons, education will be excluded from the set of instruments for $\ln w$ in the three leisure aggregates equations (and included instead as an additional explanatory variable). Living in the western part of the US is associated with more active leisure and sleep, an effect that, attending to the estimated coefficient on the dummy for the west region in the wage regression, does not seem caused by regional wage differentials. Hence, the West dummy will be excluded from the set of instruments. Similarly, the positive effect on sleep of living in a metropolitan area does not seem the result of an indirect wage effect, as average hourly earnings are higher on average in metropolitan areas. The metropolitan area dummy will be therefore excluded from the set of instruments in the sleep equation. We also have excluded the foreign born dummy from the set of instruments. The strong negative association between this and passive leisure does not seem the result of an indirect wage effect. Moreover, its effect on sleep seems too large to be considered an indirect wage effect only. All these patterns hardly change in the subsamples of men and women, whereby the sets of instruments for $\ln w$ will be kept the same there.

Table 3 lists the set of instrumental variables for $\ln w$ by time-demand function, and presents, as well, the values of test statistics for assessing the endogeneity of $\ln w$ among workers and the validity and reliability of the instruments. To test for endogeneity, the residuals from regressing $\ln w$ on all the exogenous variables were added to each of the time-demand regression equations. Then, the statistical significance of the residual term in each regression was tested using a heteroskedasticity-robust *t*-statistic (Wooldridge, 2010, p. 131). In the full sample and in the subsample of men, the exogeneity of $\ln w$ is rejected at the 5 percent level of significance in the active leisure and sleep equations, but not in the case of social entertainment and passive leisure. In the subsample of women, the exogeneity assumption is never rejected (although for little margin in the case of sleep). Since the number of excluded instruments exceeds the number of endogenous variables, it is possible to test the overidentifying restrictions on the excluded instruments. The test statistic (Sargan, 1958) is calculated as the number of observations times the *R*-squared from regressing the TSLS residuals on all the exogenous variables. The Sargan statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the number of overidentifying restrictions. The *p*-value for this test is above standard significance levels in all cases except the sleep equation run on the subsample of women and the social entertainment equation run on men, where the validity of the instruments is questioned (*p*-values .01 and .05, respectively). Table 3 also provides the value of the robust *F*-statistic for testing the statistical significance of the excluded instruments in the first-stage regression of TSLS. Staiger and Stock (1997) report that the finite sample bias of TSLS is of the order of the inverse of that *F*-statistic. In our case, instruments appear as strong (the lowest value of the F-statistic is 18.8), which helps to moderate the bias of TSLS even if the instruments were not perfectly valid.

4. EMPIRICAL RESULTS

Table 4 presents the estimates of the time-demand regression functions obtained on the full sample of men and women. In columns (1) and (4), pertaining, respectively, to active leisure and sleep, TSLS estimates, which control for the endogeneity of $\ln w$ among workers, are presented. The estimated coefficients in columns (2) and (3), which correspond to passive leisure and social entertainment activities, are OLS estimates. In all the four regressions, $\ln w$ for non-workers has been predicted from a wage regression run on workers only. Heteroskedasticity robust standard errors are shown in parentheses.

The estimated income coefficient in the regressions for the three leisure aggregates is generally small, attaining statistical significance at 0.05 level in the case of passive leisure only. The implied income elasticity of this activity, calculated as the estimated coefficient associated to $\ln V$ divided by the mean time devoted to passive leisure in the sample, is 0.021 (*S.E.* = 0.008), which suggests that passive leisure is a necessity. The implied reaction of passive leisure to variations in income is such that, at average time allocation values, passive leisure would increase by 2.1 percent (some 5 minutes per day) for a doubling of the income. For sleep, the income coefficient is very small and does not attain statistical significance.

Overall, our results tend to agree with those found by Kooreman and Kapteyn (1987) and Biddle and Hamermesh (1990) using the 1975-1976 TUS.[9] They indicate that the effect of income is generally unimportant, perhaps with the exception of passive leisure activities. (Of course, this conclusion is compatible with the existence of very significant income effects

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[9] Findings, in particular, do not seem to be affected by the different design of the diary instrument: The 1975-1976 TUS, while using a one-day diary format, obtained four time diaries at three-month intervals from each respondent.

at a more disaggregated level, such as, for example, the many different sports comprised within the active leisure aggregate.) However, for the same three leisure aggregates Dardis et al. (1994) obtain expenditure elasticities for non-salary income in the range of 0.40 to 0.72, which suggests that recreation goods and leisure time are not consumed in fixed proportion: *Ceteris paribus*, an increase in income leads consumers to increase the goods intensity of active leisure, passive leisure, and social entertainment. In other words, consumers opt to increase the quality (understood as the amount of dollars spent per unit of time) of each of those three leisure aggregates when endowed with more income. This conclusion is in line with Gronau and Hamermesh's (2006) findings on the effect of education and age (two correlates of household income) on the relative goods intensity of leisure in the US and Israel.

Given the small income effects, the value of the coefficient associated to $\ln w$ will be representing essentially a price-of-time effect on the demand for leisure/sleep. There are two reasons why this price effect is expected to be negative, Becker (1965) argues: When the wage rate is relatively high, consumers will economize on recreation, but they will also have an incentive to economize on time and to spend more on goods in producing recreation. The estimated wage effects on active leisure (-22.9), passive leisure (-22.0), and sleep (-44.5) agree with this reasoning. Estimates are precise and attain statistical significance at 0.05 level. At average time allocation values, the implied wage elasticities are, respectively, -1.30 (*S.E.* = 0.47), -0.10 (*S.E.* = 0.02), and -0.09 (*S.E.* = 0.01), which suggest that consumers will reduce their weekly active leisure, passive leisure, and sleep by around 16, 15, and 33 minutes, respectively, when offered a 10 percent increase in the wage rate. Our estimated sleep-wage elasticity is substantially larger than that obtained by Biddle and Hamermesh (-0.04, *S.E.* = 0.02), which may be due to the different set of instruments for $\ln w$ utilized. The estimated wage effect on social entertainment is positive but small, and does not attain statistical significance. Instrumenting for $\ln w$ in the social entertainment equation yields an estimated wage effect in the neighborhood of -10.0 (*S.E.* = 15.9).

Other significant effects are evident in Table 4. As expected, education exerts an independent effect on the demand for active and passive leisure. What is perhaps surprising is the magnitude of the effect: In comparison with a person who did not complete high school, a college graduate spends on average some 23 minutes more per day in active leisure pursuits, and some 64 minutes less in passive leisure activities. A consumer having a physical/mental disability spends on average 105 minutes more per day on passive leisure, and sleeps 32 minutes more. Her active leisure activities, however, are curtailed by some 8 minutes per day, but time spent on social entertainment is essentially unaffected. Living in the west region of the US increases the time spent on active leisure by some 8 minutes per day. In comparison with a native, a foreign born person sleeps 13 minutes more per day and spends some 25 minutes less in passive leisure on average. Residing in a metropolitan area has a substantial positive effect on sleep duration (17.0, *S.E.* = 4.8).

Tables 5 and 6 present the estimation output separately for women and men, respectively. The estimated coefficients listed in Table 5 and in columns (2) and (3) of Table 6 are OLS estimates. Columns (1) and (4) of Table 6 present TSLS estimates, which control for the endogeneity of $\ln w$ among workers. As in the full sample, $\ln w$ for non-workers has been predicted from wage regressions (one for women and other for men) run on workers only. To test for the equality of beta coefficients across sexes, I carry out tests of structural break with unequal variances (e.g., see Greene, 2003). The null hypothesis is that $\beta_m^{x_j;women} = \beta_m^{x_j;men}$, where $\beta_m^{x_j}$ denotes the coefficient associated to x_j in the equation for activity m. Assuming that the samples of men and women are independent, the robust *t*-statistic

$$t = \frac{\hat{\beta}_m^{x_j;women} - \hat{\beta}_m^{x_j;men}}{\sqrt{\widehat{\mathrm{var}}\left(\hat{\beta}_m^{x_j;women}\right) + \widehat{\mathrm{var}}\left(\hat{\beta}_m^{x_j;men}\right)}}, \tag{11}$$

where $\hat{\beta}$ denotes either the OLS or the TSLS estimator and $\widehat{\mathrm{var}(\cdot)}$ is the corresponding robust estimate of variance, has a limiting standard normal distribution under the null.

The estimated coefficients associated to $\ln V$ are generally small, not observing significant differences between men and women. The wage effects on passive leisure and social entertainment are also similar, but some differences are evident in the equations for sleep and, especially, active leisure. The test of structural break does not reject the equality of wage effects across sexes in the equation for sleep (*p*-value 0.10), but it does strongly reject that restriction in the equation for active leisure (*p*-value 0.00). For women, a variation in the wage rate holding other factors fixed leaves the time devoted to active leisure essentially unchanged. For men, a 10 percent increase in the wage rate reduces their weekly active leisure by some 33 minutes on average. The independent effect of education on active and passive leisure discussed above derives essentially from men's behavior. In the case of women, we see no significant differences across educational categories in the time devoted to active leisure pursuits. (Although for little margin, a test of the joint significance of the three education dummies in the active leisure equation for women does not reject the null of no significance, *p*-value 0.07). Similarly, we see that the increase in active leisure associated to living in the West is essentially a male phenomenon: While a male living there spends some 14 minutes more per day on active leisure pursuits than a comparable male living in other regions of the US, the implied effect for a female is an increase of about just 3 minutes.

5. CONCLUSION

There is evidence that the expenditure on goods consumed in the course of active leisure, passive leisure, and social entertainment activities increases (moderately) with income. However, we have found no evidence of income effects on the demand for time spent on active leisure and social entertainment, and a very small positive reaction of passive leisure to changes in income. We conclude, therefore, that the mix of recreation goods and leisure time is not constant across income strata, as consumers endowed with more income opt to improve the quality of their leisure activities but not to increase (or increase only slightly) the time spent on them. As in Biddle and Hamermesh (1990), our estimated income elasticity of sleep is not significantly different from zero.

Our estimated wage effects suggest that, at average time allocation values, consumers will reduce their weekly passive leisure and sleep by around 15 and 33 minutes, respectively, when offered a 10 percent increase in the wage rate. The same wage increase will have no consequences for the demand of time spent on social entertainment, will leave women's time spent on active leisure activities essentially unaffected, but will induce men to reduce their weekly active leisure by some 33 minutes on average. There is also evidence of a positive direct effect of education on preferences for active leisure which derives essentially from men's behavior.

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Table 1. Sample descriptive statistics, the American Time Use Survey 2011

Variable (minutes)	Mean	SD	Min	Max	% = 0
Women (3972 persons)					
Active leisure	13.7	44.6	0	850	83.4
Passive leisure	198.6	180.8	0	1380	11.2
Social entertainment	72.1	117.2	0	1030	51.2
Sleep	524.5	131.8	0	1359	0.1
Men (2824 persons)					
Active leisure	23.1	66.3	0	800	80.1
Passive leisure	243.1	210.4	0	1430	9.4
Social entertainment	57.9	108.8	0	1015	60.0
Sleep	514.2	134.4	0	1317	0.1

Variable	Mean	SD	Min	Max
Age	43.9	11.4	23	64
Annual nonlabor income (1000)	38.8	38.5	0.3	175.0
Average hourly earnings[a]	22.8	13.3	4.6	72.1
Years since migration[b]	19.5	12.8	1	62.5

Variable (%)	Mean	*Variable (%)*	Mean
Spouse/partner present	61.6	Winter	25.5
Children < 3 years old	13.8	Spring	25.0
Black	14.3	Summer	25.7
Hispanic	14.3	Autumn	23.8
Disabled	8.9	Less than high school graduate	8.5
Sunday	25.2	Exactly high school graduate	25.6
Monday	9.5	Some college	28.4
Tuesday	10.1	College graduate	37.5
Wednesday	10.4	Northeast	17.7
Thursday	10.1	Midwest	24.4
Friday	9.9	South	36.2
Saturday	24.8	West	21.7
Holiday	1.6	Metropolitan area	84.8
		Foreign-born	17.0

Notes: Data are of 6796 persons aged 23-64 who are not self-employed. [a]: Workers only. [b]: Foreign-born persons only.

Table 2. Reduced-form regressions

Explanatory variable	$\ln w$ (1)	Active leisure (2)	Passive leisure (3)	Social entertainment (4)	Sleep (5)
	Dependent variable				
$\ln V$	-0.008	0.593	4.927	-0.018	0.973
	(0.017)	(0.628)	(1.846)*	(1.182)	(1.394)
Male	0.166	9.268	43.498	-15.048	-9.308
	(0.022)*	(1.438)*	(4.516)*	(2.725)*	(3.181)*
Age	0.057	-1.246	-5.901	-1.193	-6.084
	(0.007)*	(0.486)*	(1.628)*	(0.979)	(1.142)*
Age^2	-0.001	0.012	0.094	0.012	0.061
	(0.000)*	(0.005)*	(0.018)*	(0.011)	(0.013)*
Spouse/partner present	0.054	0.089	-44.148	8.329	-10.116
	(0.027)*	(1.592)	(5.523)*	(3.183)*	(3.964)*
Children < 3 years old	0.083	-6.987	-20.817	-2.877	-9.434
	(0.025)*	(2.084)*	(5.943)*	(4.253)	(4.582)*
Black	-0.128	-7.045	34.426	17.841	14.924
	(0.027)*	(1.553)*	(8.013)*	(4.753)*	(5.672)*
Hispanic	-0.132	-3.039	-14.194	12.424	11.938
	(0.026)*	(2.241)	(7.184)*	(4.964)*	(5.463)*
Disabled	0.011	-5.913	106.566	-1.809	34.584
	(0.093)	(1.994)*	(10.558)*	(4.903)	(7.293)*
Sunday	0.047	4.397	66.825	55.755	63.685
	(0.028)	(2.290)	(7.732)*	(4.256)*	(5.975)*
Tuesday	0.006	0.680	-3.707	-3.140	-11.581
	(0.032)	(2.405)	(8.896)	(4.219)	(6.693)
Wednesday	0.039	0.787	-2.852	-0.952	-13.615
	(0.032)	(2.738)	(8.617)	(3.881)	(6.528)*
Thursday	-0.007	-3.351	4.522	6.315	-13.811
	(0.032)	(2.196)	(8.946)	(4.462)	(6.593)*
Friday	0.033	-4.096	2.666	16.056	-24.512
	(0.032)	(2.285)	(8.964)	(4.557)*	(7.341)*
Saturday	0.034	4.886	44.587	56.706	27.508
	(0.027)	(2.300)*	(7.804)*	(4.476)*	(6.008)*
Holiday	-0.065	1.120	27.067	31.581	37.954
	(0.059)	(5.202)	(19.885)	(12.618)*	(14.687)*
Winter	0.009	-10.191	22.757	-14.725	7.378
	(0.019)	(1.810)*	(6.042)*	(3.742)*	(4.371)
Spring	-0.015	-6.635	6.331	-4.515	-1.062
	(0.020)	(1.972)*	(6.015)	(3.904)	(4.371)
Autumn	-0.016	-6.049	8.890	-10.735	1.692
	(0.020)	(2.147)*	(6.106)	(3.901)*	(4.408)
Exactly high school grad.	0.217	0.571	-18.424	-13.480	-14.981
	(0.041)*	(2.439)	(10.506)	(6.292)*	(7.247)*
Some college	0.348	1.876	-53.364	-10.298	-32.518
	(0.050)*	(2.454)	(10.397)*	(6.341)	(7.335)*
College grad.	0.701	5.636	-81.013	-6.363	-39.003

	(0.062)*	(2.435)*	(10.265)*	(6.274)	(7.150)*
Midwest	-0.130	2.724	-5.380	-0.242	3.212
	(0.021)*	(1.869)	(6.621)	(4.163)	(4.701)
South	-0.085	1.793	2.673	0.110	4.717
	(0.021)*	(1.651)	(6.348)	(3.928)	(4.507)
West	0.030	7.601	-3.295	-0.775	8.544
	(0.024)	(2.167)*	(6.782)	(4.320)	(4.854)
Metropolitan area	0.189	-4.291	0.563	-3.775	8.282
	(0.020)*	(2.087)*	(6.410)	(3.804)	(4.479)
Foreign born	-0.109	1.799	-17.905	-7.973	20.951
	(0.045)*	(2.799)	(9.974)	(6.784)	(7.653)*
Years since migration	0.004	-0.151	-0.389	0.157	-0.372
	(0.002)*	(0.095)	(0.426)	(0.268)	(0.345)
Inverse Mills ratio	-0.121				
	(0.110)				
Intercept	1.049	46.550	284.537	80.325	658.386
	(0.194)*	(11.595)*	(36.825)*	(22.206)*	(26.389)*
R-squared	0.34	0.03	0.17	0.07	0.10
Number of observations	4418	6796	6796	6796	6796

Notes: The estimation method is OLS in all columns. Heteroskedasticity robust standard errors are in parentheses. * Significant at 5 percent.

Table 3. Instrument sets for $\ln w$ and associated specification tests, by sample and time-demand function

	Full sample (1)	Women (2)	Men (3)
Active leisure			
Excluded instruments (EI):	Region[a], living in metro area, years since migration		
Hausman test for endogeneity of	3.67	1.38	3.93
$\ln w$ (robust t-statistic):	[.00]	[.17]	[.00]
Sargan test of overidentifying	1.17	1.29	2.82
restrictions:	[.76]	[.73]	[.42]
Test of joint significance of EI	37.66	21.36	18.82
(robust F-statistic):	[.00]	[.00]	[.00]
Passive leisure			
Excluded instruments:	Region[a], living in metro area, years since migration		
Hausman test for endogeneity of	1.67	1.46	1.35
$\ln w$ (robust t-statistic):	[.09]	[.14]	[.18]
Sargan test of overidentifying	1.04	.07	.98
restrictions:	[.79]	[.99]	[.81]
Test of joint significance of EI	37.66	21.36	18.82
(robust F-statistic):	[.00]	[.00]	[.00]
Social entertainment			
Excluded instruments:	Region[a], living in metro area, years since migration		
Hausman test for endogeneity of	.66	.64	.61
$\ln w$ (robust t-statistic):	[.51]	[.52]	[.54]
Sargan test of overidentifying	1.12	3.06	7.87
restrictions:	[.77]	[.38]	[.05]
Test of joint significance of EI	37.66	21.36	18.82
(robust F-statistic):	[.00]	[.00]	[.00]
Sleep			
Excluded instruments:	Education, region[a], years since migration		
Hausman test for endogeneity of	2.85	1.90	1.97
$\ln w$ (robust t-statistic):	[.00]	[.06]	[.05]
Sargan test of overidentifying	9.14	14.65	2.80
restrictions:	[.10]	[.01]	[.73]
Test of joint significance of EI	202.1	113.0	92.33
(robust F-statistic):	[.00]	[.00]	[.00]

Notes: Probability values are in brackets. [a]: Except west region.

Table 4. Time-demand functions (full sample)

	Dependent variable			
	Active leisure	Passive leisure	Social entertainment	Sleep
Explanatory variable	(1)	(2)	(3)	(4)
$\ln V$	0.017	4.560	-0.020	-0.236
	(0.672)	(1.838)*	(1.179)	(1.373)
$\ln w$	-22.911	-21.976	2.846	-44.462
	(8.207)*	(4.903)*	(3.443)	(6.296)*
Male	13.501	47.495	-15.607	-0.960
	(2.216)*	(4.624)*	(2.776)*	(3.353)
Age	0.183	-4.584	-1.364	-3.202
	(0.712)	(1.652)*	(1.010)	(1.221)*
Age^2	-0.002	0.081	0.014	0.032
	(0.007)	(0.019)*	(0.011)	(0.014)*
Exactly high school grad.	6.170	-13.151	-14.291	
	(3.165)	(10.609)	(6.348)*	
Some college	10.833	-44.800	-11.607	
	(4.203)*	(10.566)*	(6.470)	
College grad.	23.053	-63.574	-9.062	
	(6.900)*	(10.888)*	(6.856)	
Spouse/partner present	1.823	-42.731	8.216	-6.560
	(1.742)	(5.505)*	(3.177)*	(3.978)
Children < 3 years old	-5.430	-19.298	-3.022	-6.173
	(2.129)*	(5.954)*	(4.249)	(4.602)
Black	-10.356	33.173	17.879	9.030
	(1.879)*	(7.937)*	(4.669)*	(5.780)
Hispanic	-6.221	-15.903	12.622	7.480
	(2.439)*	(7.142)*	(4.940)*	(5.631)
Disabled	-7.777	104.774	-1.443	31.758
	(2.128)*	(10.577)*	(4.918)	(7.339)*
Sunday	5.484	67.900	55.673	65.768
	(2.307)*	(7.705)*	(4.258)*	(5.961)*
Tuesday	0.973	-3.334	-3.168	-11.185
	(2.393)	(8.876)	(4.212)	(6.673)
Wednesday	1.695	-1.811	-1.053	-11.852
	(2.716)	(8.588)	(3.873)	(6.520)
Thursday	-3.443	4.459	6.350	-14.261
	(2.197)	(8.897)	(4.451)	(6.589)*
Friday	-3.265	3.461	15.955	-23.408
	(2.300)	(8.936)	(4.553)*	(7.336)*
Saturday	5.692	45.442	56.601	29.150
	(2.306)*	(7.773)*	(4.468)*	(6.000)*
Holiday	-0.298	24.966	32.244	35.590
	(5.281)	(19.763)	(12.567)*	(14.634)*
Winter	-9.968	22.926	-14.775	7.642
	(1.801)*	(6.044)*	(3.739)*	(4.370)
Spring	-6.960	5.785	-4.469	-1.847
	(1.968)*	(6.005)	(3.901)	(4.362)
Autumn	-6.387	8.456	-10.671	0.979

	(2.153)*	(6.103)	(3.901)*	(4.396)
West	8.267	-0.330	-1.359	9.158
	(2.054)*	(5.181)	(3.298)	(3.794)*
Foreign born	-2.136	-25.478	-5.328	13.220
	(1.849)	(6.300)*	(4.225)	(4.777)*
Metropolitan area				16.965
				(4.768)*
Intercept	66.640	306.102	74.591	687.158
	(13.462)*	(36.476)*	(22.118)*	(25.485)*
R-squared		0.17	0.07	

Notes: The number of observations is 6796 in all columns. The estimation method is TSLS in columns (1) and (4) and OLS in columns (2) and (3). $\ln w$ for non-workers has been predicted from a wage regression run on workers only. Heteroskedasticity robust standard errors are in parentheses. * Significant at 5 percent.

Table 5. Time-demand functions (women)

Explanatory variable	Active leisure (1)	Passive leisure (2)	Social entertainment (3)	Sleep (4)
	Dependent variable			
$\ln V$	0.828	3.526	-0.029	-0.860
	(0.756)	(2.305)	(1.674)	(1.820)
$\ln w$	2.327	-22.626	2.681	-21.196
	(1.691)	(6.119)*	(4.882)	(4.463)*
Age	-0.667	-5.623	-2.302	-5.983
	(0.546)	(2.041)*	(1.381)	(1.481)*
Age^2	0.005	0.093	0.025	0.061
	(0.006)	(0.023)*	(0.015)	(0.017)*
Exactly high school grad.	-2.405	4.148	-22.406	
	(2.612)	(13.484)	(8.663)*	
Some college	0.486	-25.539	-15.443	
	(2.831)	(13.530)	(8.921)	
College grad.	2.631	-43.607	-12.534	
	(3.056)	(13.866)*	(9.586)	
Spouse/partner present	-0.977	-34.824	7.001	-0.713
	(1.729)	(6.869)*	(4.481)	(5.348)
Children < 3 years old	-4.897	-8.311	-11.810	-3.672
	(2.441)*	(7.498)	(5.285)*	(5.768)
Black	-7.599	37.303	10.100	16.817
	(1.497)*	(9.852)*	(5.938)	(7.163)*
Hispanic	-4.486	-19.592	15.879	12.019
	(2.258)*	(8.777)*	(6.366)*	(6.609)
Disabled	-6.660	86.800	3.084	45.883
	(1.371)*	(13.440)*	(6.795)	(9.979)*
Sunday	1.100	46.473	57.686	55.903
	(2.375)	(9.890)*	(6.072)*	(7.987)*
Tuesday	1.557	-2.950	-5.668	-15.264
	(2.468)	(11.428)	(6.000)	(8.712)
Wednesday	-2.329	-11.012	-4.782	-14.436
	(2.239)	(10.791)	(5.445)	(8.473)
Thursday	-3.660	-4.286	2.888	-14.977
	(2.289)	(11.424)	(6.707)	(9.174)
Friday	-2.476	1.463	13.743	-23.660
	(2.437)	(10.855)	(6.287)*	(9.750)*
Saturday	3.293	26.490	56.561	23.577
	(2.432)	(9.947)*	(6.285)*	(8.048)*
Holiday	7.332	-23.385	41.828	41.877
	(6.773)	(21.038)	(17.242)*	(19.047)*
Winter	-11.792	27.061	-22.338	11.603
	(2.100)*	(7.530)*	(4.934)*	(5.749)*
Spring	-10.742	13.242	-8.951	-5.013
	(2.173)*	(7.500)	(5.349)	(5.698)
Autumn	-8.402	6.818	-12.398	10.429
	(2.393)*	(7.487)	(5.397)*	(5.856)
West	3.082	4.281	-7.820	5.944

	(1.949)	(6.445)	(4.308)	(4.833)
Foreign born	-1.256	-20.329	-10.122	12.245
	(2.015)	(7.829)*	(5.509)	(6.279)
Metropolitan area				13.012
				(5.875)*
Intercept	32.703	316.690	108.294	683.575
	(13.479)*	(45.221)*	(30.840)*	(31.596)*
R-squared	0.03	0.15	0.08	0.09

Notes: The number of observations is 3972 in all columns. The estimation method is OLS in all columns. $\ln w$ for non-workers has been predicted from a wage regression run on workers only. Heteroskedasticity robust standard errors are in parentheses. * Significant at 5 percent.

Table 6. Time-demand functions (men)

	Dependent variable			
	Active leisure	Passive leisure	Social entertainment	Sleep
Explanatory variable	(1)	(2)	(3)	(4)
$\ln V$	-0.438	4.374	0.763	0.106
	(1.091)	(3.015)	(1.674)	(2.105)
$\ln w$	-47.032	-23.545	3.822	-39.422
	(15.276)*	(7.901)*	(4.844)	(10.006)*
Age	1.261	-1.991	-0.649	-1.348
	(1.470)	(2.787)	(1.483)	(2.013)
Age^2	-0.012	0.051	0.007	0.012
	(0.015)	(0.031)	(0.016)	(0.022)
Exactly high school grad.	15.447	-37.200	-3.151	
	(5.806)*	(16.762)*	(9.202)	
Some college	20.009	-68.971	-7.506	
	(7.318)*	(16.555)*	(9.222)	
College grad.	41.538	-86.622	-5.926	
	(12.295)*	(17.087)*	(9.638)	
Spouse/partner present	6.410	-51.501	8.300	-15.048
	(3.382)	(9.007)*	(4.629)	(6.078)*
Children < 3 years old	-9.365	-34.838	10.713	-12.510
	(3.897)*	(9.876)*	(7.274)	(7.622)
Black	-15.082	26.827	29.265	6.142
	(4.144)*	(13.232)*	(7.590)*	(9.611)
Hispanic	-7.836	-10.503	8.300	15.103
	(4.904)	(12.095)	(7.817)	(9.595)
Disabled	-5.329	131.108	-8.461	22.512
	(4.448)	(16.810)*	(6.927)	(10.599)*
Sunday	13.237	97.753	51.715	77.869
	(4.583)*	(12.167)*	(5.753)*	(8.930)*
Tuesday	0.636	-6.099	-1.102	-5.301
	(4.692)	(14.125)	(5.723)	(10.547)
Wednesday	9.573	9.552	3.451	-8.378
	(5.843)	(14.290)	(5.531)	(10.227)
Thursday	-0.317	18.656	8.581	-11.854
	(4.137)	(14.057)	(5.531)	(9.395)
Friday	-5.094	6.595	17.460	-24.845
	(4.278)	(15.138)	(6.612)*	(11.105)*
Saturday	9.729	73.054	54.406	35.802
	(4.334)*	(12.346)*	(6.179)*	(9.004)*
Holiday	-11.407	108.452	14.247	26.313
	(7.861)	(34.869)*	(15.781)	(21.893)
Winter	-6.608	17.434	-4.332	2.357
	(3.153)*	(9.976)	(5.714)	(6.786)
Spring	-0.623	-3.843	1.408	3.997
	(3.582)	(9.787)	(5.662)	(6.792)
Autumn	-2.071	12.985	-9.192	-11.376
	(3.865)	(10.145)	(5.597)	(6.647)
West	13.908	-6.703	6.895	9.103

	(1)	(2)	(3)	(4)
	(3.763)*	(8.551)	(5.074)	(6.064)
Foreign born	-3.531	-30.828	1.212	17.018
	(3.483)	(10.639)*	(6.663)	(7.376)*
Metropolitan area				14.011
				(7.565)
Intercept	104.718	318.074	24.091	634.352
	(22.893)*	(60.988)*	(31.630)	(41.858)*
R^2		0.19	0.06	

Notes: The number of observations is 2824 in all columns. The estimation method is TSLS in columns (1) and (4) and OLS in columns (2) and (3). $\ln w$ for non-workers has been predicted from a wage regression run on workers only. Heteroskedasticity robust standard errors are in parentheses. * Significant at 5 percent.