RECREATION, HOME PRODUCTION, AND INTERTEMPORAL SUBSTITUTION OF FEMALE LABOR SUPPLY: EVIDENCE ON THE INTENSIVE MARGIN

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The predicted labor supply responses to wage and price variations are important when discussing the economic efficiency of taxes and subsidies, and their extent may also be relevant to the analysis of economic fluctuations. This paper presents new estimates of the wage intertemporal substitution elasticity (ISE) for the intensive margin of female labor supply. It likewise explores this margin's sensitivity to changes in the price of recreation and home consumption goods. Our estimated wage ISE (.9) implies that, at average time allocation values, female labor force participants will increase their annual labor supply by around 14 hours when offered a 1% increase in the wage rate. Approximately 7 hours of this increase will be from less time spent on leisure and the other 7 from less time spent on home production. Annual labor supply is reduced by around 7 hours when the price of home consumption goods rises by 1%, this extra time being almost entirely devoted to home production. An elasticity of substitution between time and goods in home production of approximately 2 is also estimated.

Keywords: female labor supply; intertemporal substitution; home production; system GMM estimation

1 INTRODUCTION

The pioneering study on the intertemporal labor supply decisions of married women by Heckman and MaCurdy (1980, 1982) estimated a wage elasticity that integrated the intensive and extensive margins of labor supply in its response. As the extent to which a labor supply response is spread between marginal variations in market work and variations in the probability of working is of considerable economic and policy interest, posterior research has attempted to estimate the size of each individual margin. Zabel (1997), for example, estimated wage elasticities for the intensive and extensive margins of married women's intertemporal labor supply centered, respectively, at .38 and .42. The corresponding estimates obtained by Altonji (1982a) were .75 and .87. In both studies, the sum of the estimated elasticities is substantially below the 2.23 estimate obtained (based on 1,350 hours of market work) by Heckman and MaCurdy (1982).[1]

The estimation procedure used by Heckman and MaCurdy (1980, 1982) assumed that labor supply falls continuously to zero in response to variations in wages. Yet, if there are fixed costs associated with entry into the labor market, the lowest number of hours that a worker will work may substantially exceed zero (see, e.g., Cogan, 1981). Hence, Zabel (1997) and Altonji (1982a) relaxed the continuity assumption and estimated discontinuous labor supply schedules. Zabel's (1997) estimates were obtained using household Euler equations for labor supply and labor force participation. However, Domeij and Flodén (2006) have recently demonstrated that the Euler equation approach induces a significant downward bias in the

[1] The intertemporal substitution elasticity (ISE) that integrates the intensive and extensive margins of labor supply in its response equals the sum of the two marginal ISEs. The proof is straightforward and follows on from the Law of Iterated Expectations (see Appendix A).

estimated elasticities when liquidity constraints are ignored.[2] Although Altonji (1982a) pursued an alternative approach, in which family expenditure on food was included in the labor supply and participation equations to control for unobserved expectations and wealth, his empirical results for married women were very preliminary. This paper presents new estimates of the wage ISE for the intensive margin of female labor supply. In a similar way to Altonji (1982a), we employ data on family expenditure on restaurants to control for unobservable expectations and wealth. In addition, we test our econometric model against a variety of specification failures. As discussed below, Zabel's (1997) and Altonji's (1982a) estimates for the extensive margin may be further biased. The estimation of the extensive margin is left for future research.

The sensitivity of women's intertemporal labor supply to price changes of goods consumed in recreation and home production activities is also explored. Gronau and Hamermesh (2006) have recently documented that leisure is the daily activity (apart from sleep) on which more time is consumed per dollar spent on the course of the activity. Hence, variations in recreation goods prices might significantly alter the demand for leisure, and require, in turn, a reallocation of time to other pursuits. In González Chapela (2007), for instance, the price of recreation goods was found to influence men's intertemporal allocation of time between market work and leisure. As the extent to which women vary hours of market work in response to wage changes has been found to be greater than that for men,[3] this

[2] The literature has highlighted other sources of downward bias. See Domeij and Flodén (2006) for further discussion.

[3] For male estimates, see e.g. MaCurdy (1981), Altonji (1986), Reilly (1994), Mulligan (1999), and Ham and Reilly (2002). Blundell and MaCurdy (1999) survey the intertemporal labor supply literature.

different response could extend to a model in which recreation goods and leisure were non-separable within the period.

Although a simple dichotomy of market work and leisure may be a useful starting point for analysis, Rupert et al. (2000) have shown that estimates of intertemporal substitution elasticities obtained from life-cycle data on hours and wages may be problematic if work done at home is excluded from the analysis. Hence, in the life-cycle labor supply model presented in Section 2, consumers will not only be allowed to substitute leisure at one date for leisure at other dates in response to wage or price changes, but also to substitute work in the market for work in the home at a given date. Furthermore, they will be able to substitute time for expenditure in response to fluctuations in the price of goods used in home production. The result of the analysis will be a three-activity system—leisure, home production, and market work, that will allow us to identify empirically the labor force participants' willingness to substitute hours intertemporally in response to wage or price changes.

The data and econometric approach employed to estimate this system of structural equations are discussed in Section 3. The main empirical results are presented in Section 4. Our estimated wage ISE for the intensive margin of female labor supply is in the neighborhood of .9 for the population of U.S. women of prime age. (For married women, the corresponding estimate is approximately 1.2.) As predicted in Domeij and Flodén (2006), this estimate is substantially higher than that obtained in Zabel (1997). It is also somewhat higher than Altonji's (1982a) preliminary estimate, a result that seems driven by the different instruments for wages and family expenditure utilized. The estimated wage ISEs for leisure and home production time that we have obtained, -.1 and -.7, respectively, suggest that female labor force participants will reduce both annual time spent on leisure and on home production by some 7 hours when offered a 1% increase in the wage rate. The intensive margin of female intertemporal labor supply appears as unaffected by variations in recreation goods prices, although it does react to changes in the price of home consumption goods: Our estimated market time elasticity with respect to the price of home consumption goods is in the neighborhood of -.7. Thus, annual market time is reduced by some 7 hours (and annual home production time is increased by around 6 hours) when the price of home consumption goods rise by 1%. If home production were excluded from the model's specification, part of this effect would be misleadingly attributed to recreation goods. A more detailed summary of the paper is provided in Section 5.

2 THEORETICAL MODEL

Consider a consumer (i) with preferences at age t represented by the utility function

$$U(c_{it}, x_{it}, s_{it}, l_{it}, h_{it}) = \frac{c_{it}^{1-\eta^{-1}}}{1-\eta^{-1}} + \frac{\psi_{it}}{1-\gamma^{-1}}(x_{it}^{1-\sigma^{-1}} + \alpha_{it} l_{it}^{1-\sigma^{-1}})^{\frac{1-\gamma^{-1}}{1-\sigma^{-1}}} + \frac{\kappa_{it}}{1-\mu^{-1}}(s_{it}^{1-\theta^{-1}} + \chi_{it} h_{it}^{1-\theta^{-1}})^{\frac{1-\mu^{-1}}{1-\theta^{-1}}}, \qquad (1)$$

whose specific functional form allows concrete interpretations to be given to the estimated parameters. In this expression, recreation goods (x) and leisure time (l) are combined to produce recreation such as going to the theatre, whereas home consumption goods (s) and home production time (h) are combined to produce home goods such as food. For tractability purposes, we assume that other consumption goods (c) are not combined with time. The parameters η, γ, and μ denote, respectively, the willingness to substitute c, recreation, and home goods intertemporally, whereas σ and θ represent the ease of substitution at a given date between market goods and time in the production of recreation and home goods, respectively. Variables ψ, α, κ, and χ denote age-specific modifiers of tastes or household production.

Consumer i's intertemporal choice problem consists of maximizing expected lifetime utility subject to an expected wealth constraint. Assuming that the lifetime preference ordering is additively separable over periods of time,[4] solutions for l and h are given by:

$$l_{it} = \psi_{it}^{\gamma} \left(\frac{w_{it}}{\alpha_{it}} \right)^{-\sigma} (p_{it}^{x\,1-\sigma} + \alpha_{it}^{\sigma} w_{it}^{1-\sigma})^{\frac{\sigma-\gamma}{1-\sigma}} c_{it}^{\gamma/\eta} \tag{2}$$

$$h_{it} = \kappa_{it}^{\mu} \left(\frac{w_{it}}{\chi_{it}} \right)^{-\theta} (p_{it}^{s\,1-\theta} + \chi_{it}^{\theta} w_{it}^{1-\theta})^{\frac{\theta-\mu}{1-\theta}} c_{it}^{\mu/\eta} , \tag{3}$$

where p^x represents the price of x, p^s the price of s, and w the offered wage rate (all monetary variables are expressed in units of c). The units of time available in a certain period $(\overline{T})$ are divided into market work (n), l, and h. If the period marginal rate of substitution of l for c (or, what is equivalent in this model, of h for c) is greater than w when $l + h = \overline{T}$, then the consumer will not supply labor in that period. If she does work, w and the period marginal rate of substitution of l (or h) for c are equal, and the supply of labor would be given by $n = \overline{T} - l - h$, l and h being the equilibrium values in (2) and (3).

A log-linear approximation to the condition determining labor force participation results in

$$m_{it}^{*} = \beta_0^p + \beta_1^p \ln w_{it} + \beta_2^p \ln p_{it}^x + \beta_3^p \ln p_{it}^s + \beta_4^p \ln c_{it} + v_{it}^p \tag{4}$$

$$d_{it} \equiv 1(m_{it}^{*} > 0) , \tag{5}$$

where m_{it}^{*} is consumer i's (latent) participation propensity at age t, v_{it}^p is a preference determinant, and the function $1(\cdot)$ equals one if its argument is true and zero otherwise. When participating (i.e. when $d_{it} = 1$), log-linear approximations to (2), (3), and the supply of labor are given by:

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[4] The intertemporal separability assumption is relaxed in the robustness analysis of the empirical results.

$$\ln l_{it} = \beta_0^l + \beta_1^l \ln w_{it} + \beta_2^l \ln p_{it}^x + \beta_3^l \ln p_{it}^s + \beta_4^l \ln c_{it} + v_{it}^l \qquad (6)$$

$$\ln h_{it} = \beta_0^h + \beta_1^h \ln w_{it} + \beta_2^h \ln p_{it}^x + \beta_3^h \ln p_{it}^s + \beta_4^h \ln c_{it} + v_{it}^h \qquad (7)$$

$$\ln n_{it} = \beta_0^n + \beta_1^n \ln w_{it} + \beta_2^n \ln p_{it}^x + \beta_3^n \ln p_{it}^s + \beta_4^n \ln c_{it} + v_{it}^n\,, \qquad (8)$$

where v_{it}^l, v_{it}^h, and v_{it}^n are preference determinants. The participation propensity in (4) as well as the participants' intertemporal time-use functions (6)-(8) follow the approach to modeling intertemporal substitution proposed in Altonji (1982b, 1986) and MaCurdy (1983). Since current decisions on c incorporate information on wealth and on expected prices, wages, and preferences, c is taken as a "sufficient statistic" for unobservable expectations and wealth. Important advantages of this approach are its independence of strong expectational assumptions such as perfect foresight or rational expectations, and that liquidity constraints do not enter the equations (Domeij and Flodén, 2006). An important disadvantage, the fact that goods and time must be separable within the period in order to identify the intertemporal substitution elasticities, is less marked in this study, where separability of goods from time concerns c only.

The parameters associated to $\ln w$, $\ln p^x$, and $\ln p^s$ in expressions (6)-(8) are intertemporal substitution elasticities (ISEs). For those who participate in the labor force, these elasticities give the percentage change in l, h, or n caused by an anticipated 1% change in w, p^x, or p^s. The participation ISEs, which give the percentage change in the probability of labor force participation caused by an anticipated 1% change in w, p^x, or p^s, will be generally proportional to the parameters in (4). For example, if the participation probability followed a probit model, the participation ISEs would be given by

$$\frac{\phi(\cdot)}{\Phi(\cdot)} \frac{\beta_j^p}{\sigma_{v^p}}, \quad j = 1, 2, 3\,, \qquad (9)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the pdf and cdf of the standard normal distribution and σ_{v^p} is the standard deviation of v^p in the population. Even if the participation probability followed a probit model, consistently estimating (9) is not straightforward. Appendix B shows for example that the estimates of (9) pertaining to the wage rate obtained in Zabel (1997) and Altonji (1982a) may be biased due to neglected heterogeneity. Hence, the rest of this paper deals with labor force participants' ISEs.

In the context of the utility function (1), the parameters in (6)-(8) equal to:

$$\beta_1^l = -(\zeta^l \gamma + (1-\zeta^l)\sigma) \tag{10}$$

$$\beta_2^l = (1-\zeta^l)(\sigma - \gamma) \tag{11}$$

$$\beta_3^l = 0 \tag{12}$$

$$\beta_1^h = -(\zeta^h \mu + (1-\zeta^h)\theta) \tag{13}$$

$$\beta_2^h = 0 \tag{14}$$

$$\beta_3^h = (1-\zeta^h)(\theta - \mu) \tag{15}$$

$$\beta_j^n = -\frac{l}{n}\beta_j^l - \frac{h}{n}\beta_j^h, \quad j = 1, 2, 3, 4, \tag{16}$$

where

$$\zeta^l \equiv \frac{\alpha^\sigma w^{1-\sigma}}{p^{x\,1-\sigma} + \alpha^\sigma w^{1-\sigma}} \tag{17}$$

$$\zeta^h \equiv \frac{\chi^\theta w^{1-\theta}}{p^{s\,1-\theta} + \chi^\theta w^{1-\theta}}. \tag{18}$$

Similar to Ghez and Becker's (1975) theoretical results on life cycle demand analysis, the signs of β_1^l and β_1^h are negative, and consequently the sign of β_1^n positive. The intuition behind these results is simple. At ages where the wage rate is relatively high consumers economize on recreation and home goods, which frees up time for market work. They also have an incentive to economize on l and h but to spend more on x and s in producing recreation and home goods. The size of the former substitution (the substitution in consumption) is proportional to γ and μ, the willingness to substitute recreation and home goods intertemporally, whereas the substitution in production is proportional to σ and θ, the ease of substitution between market goods and time in producing recreation and home goods. The signs of β_2^l and β_3^h cannot be determined *a priori* for they depend on the differences $(\sigma-\gamma)$ and $(\theta-\mu)$, respectively. At ages where p^x (respectively, p^s) is relatively high consumers economize on recreation (home goods), but spend more on l (h) and economize on x (s) in producing recreation (home goods). In terms of the demand for l (h), which of these two opposing substitution effects dominates is an empirical matter.[5] The results $\beta_3^l=0$ and $\beta_2^h=0$ are a consequence of the block additivity of within-period preferences and can be tested in the data. If the utility function were strictly concave and x, l, s, and h were normal goods, β_4^l and β_4^h would be positive, and β_4^n negative.

3 DATA AND ESTIMATION METHOD

3.1 Data

The data to estimate (6)-(8) are from two different sources and are aggregated at two different levels: consumer-level data on hours, wages, and consumption expenditure from the Panel

[5] The signs of β_2^l and β_3^h can be alternatively interpreted using, as in Heckman (1974), the "direct" definition of complementarity. Consider for example the demand for l. When $\gamma>\sigma$ x and l are direct complements, in the sense that a reduction in the consumption of x diminishes the marginal utility from consuming l. Thus, at ages where p^x is relatively high the consumer has an incentive to economize on both x and l, and $\beta_2^l<0$. The opposite occurs when $\sigma>\gamma$, i.e. when x and l are direct substitutes, for then the consumer has an incentive to economize on x but to spend more on l at ages where p^x is relatively high.

Study of Income Dynamics (PSID), and metropolitan area-level price indices from the U.S. Bureau of Labor Statistics (BLS). PSID information on hours refers to a typical week, and is then annualized. Market work includes time on the main job, secondary job(s), and overtime, whereas home production time is defined as "time spent cooking, cleaning, and doing other work around the house." Leisure is obtained as the residual category from total annual hours ($\bar{T} = 8760$). Two indicators for the hourly wage are available. The first (denoted hereafter w^{*}) is constructed as total labor earnings divided by hours worked in the market. The second (w^{**}) stems from the question "What is your hourly wage rate for your regular work?", and is only available for those who are paid on an hourly basis. PSID data on consumption expenditure are limited to food used at home and expenditures on restaurants. The question about expenditure on restaurants is: "About how much do you (or anyone else in your family) spend eating out, not counting meals at work or at school?" Amounts generally refer to a typical week or month, and are then annualized.[6]

Since expenditure on food at home can be considered a measure of s, we use expenditure on restaurants as an empirical counterpart to c. For this approach to be workable, however, the expenditure on restaurants data should be sufficiently accurate, plus the limitation of c to expenditure on restaurants should not have an important effect on the results. Regarding the first issue, Browning et al. (2003) note that the information about specific expenditure collected by means of recall questions tends to be valid. The second issue hinges on the degree of separability between expenditure on restaurants and expenditure on

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[6] Questions about expenditure on restaurants, w^{**}, home production time, as well as the residence area refer to the time of the interview (typically March), whereas market time and labor earnings refer to the preceding calendar year. To avoid inconsistencies in timing, market time and labor earnings are forwarded one year.

other goods belonging to c. The maintained assumption in this study is that c is the sum of food expenditure on restaurants raised to an exponent plus expenditure on some other market goods.

Since 1976, the BLS has recorded the price variation of several groups of commodities, such as “Entertainment” and “Food at Home”, for the 27 metropolitan areas (MAs) listed in the Data Appendix. Reading materials, sporting goods and equipment, toys, hobbies, music equipment, photographic supplies and equipment, pet supplies and expense, club memberships, fees for participant sports, admissions, fees for lessons or instructions, and other entertainment services are included under “Entertainment”.[7] “Food at Home” includes cereals and bakery products, meats, poultry, fish, eggs, dairy products, fruits and vegetables, and other food at home. For the 1984-1993 period, “Entertainment” and “Food at Home” represented, respectively, an average of 5 and 9% of consumer expenditure (CE, 2010). We take the log of the price indices for “Entertainment” and “Food at Home” as empirical counterparts to $\ln p^x$ and $\ln p^s$. Figure 1 presents the evolution of both indices for selected MAs (all monetary variables are deflated using the “Food away from Home” component of the CPI). Time-series as well as cross-sectional variation are evident, with the former being more important: the time-series sample standard deviations of p^x and p^s are, respectively, 6.7 and 5.9, whereas the cross-sectional one amounts to 3.1 in both cases. Both types of variation are considered exogenous to an individual consumer.

The MA-level price indices are combined with the data at the consumer level using the geographical identifier available in the PSID. We use waves 9-26 of the PSID for the 1976-

[7] Until 1997, audio and video products came under the “Housing” major group of the Consumer Price Index (CPI).

1993 calendar years.[8] Our sample includes observations of women aged 25-60, residing in MAs with available price indices, and reporting positive expenditure on restaurants.[9] The latter requirement is a consequence of the (notional) demand for restaurant meals being only observed when it is positive, and excludes about 19 percent of the observations that satisfy the other criteria for inclusion in the sample. This leaves us with 3,917 women, contributing a total of 19,286 observations, 14,224 of which were from labor force participants (i.e. women who worked for money at some time in the survey year). As explained in the next subsection, the sample is further restricted for some specifications to women who were paid by the hour for at least one year during the study period, which yields a sample size of 1,868 women, contributing a total of 11,282 observations, 9,724 of which were from participants and 5,486 from hourly-paid participants.

3.2 Estimation Method

Assuming that the preference determinants are a linear function of observed and unobserved characteristics of the person,

$$v_{it}^{g} = \mathbf{x}_{it}^{v\prime}\boldsymbol{\beta}_{v}^{g} + \varepsilon_{it}^{g}, \quad g = l, h, n\,, \tag{19}$$

equations (6)-(8) can be written (more compactly) as

$$\ln g_{it} = \mathbf{x}_{it}^{\circ\prime}\boldsymbol{\beta}_{\circ}^{g} + \varepsilon_{it}^{g}, \quad g = l, h, n\,, \tag{20}$$

with $\mathbf{x}_{it}^{\circ} \equiv (1, \ln w_{it}, \ln p_{it}^{x}, \ln p_{it}^{s}, \ln c_{it}, \mathbf{x}_{it}^{v\prime})'$ and $\boldsymbol{\beta}_{\circ}^{g} \equiv (\beta_{0}^{g}, \beta_{1}^{g}, \beta_{2}^{g}, \beta_{3}^{g}, \beta_{4}^{g}, \boldsymbol{\beta}_{v}^{g\prime})'$. Included in $\mathbf{x}^{v}$ are a quadratic in age, marital status, family size, number of children in different age intervals,

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[8] The 1993 limit is due to contractual arrangements for the use of PSID Sensitive Data Files. These data are not available from the author. Persons interested in obtaining PSID Sensitive Data Files should contact PSIDHelp@isr.umich.edu.

[9] The Data Appendix lists the full set of selection criteria and provides descriptive statistics of the main variables used in this study.

an indicator of work capacity, a race indicator, as well as year and MA dummies. The work capacity indicator is constructed from the answers to "Do you have a physical or nervous condition that limits the type of work, or the amount of work you can do?" Although there are a number of reasons to be suspicious about self-reported work limitations (see for example Bound, 1991), alternative health measurements are not available in most PSID waves. It is assumed that $E(\varepsilon_{it}^{g} \mid \mathbf{x}_i^{\circ}) = 0$, where $\mathbf{x}_i^{\circ} \equiv (\mathbf{x}_{i1}^{\circ}{}', \ldots, \mathbf{x}_{iT_i}^{\circ}{}')$ and T_i is person i's number of periods in the panel.[10]

The evidence clearly shows that survey responses are not perfectly reliable (see for instance Altonji, 1986; Bound, Brown, and Mathiowetz, 2001; French, 2004), and our hours, wages, and expenditure on restaurants measurements may thus contain error:

$$\ln g_{it}^{*} = \ln g_{it} + e_{it}^{g}, \quad g = l, h, n, \tag{21}$$

$$\ln w_{it}^{*} = \ln w_{it} + e_{it}^{w}, \tag{22}$$

$$\ln c_{it}^{*} = \ln c_{it} + e_{it}^{c}. \tag{23}$$

In these expressions, e^{g}, e^{w}, and e^{c} are measurement errors (assumed to be independent of the true values), whereas $\ln g^{*}$, $\ln w^{*}$, and $\ln c^{*}$ denote the natural log of observed hours, average wage rates, and expenditure on restaurants, respectively. Correlation of e^{w} (respectively, e^{c}) with $\ln w^{*}$ ($\ln c^{*}$) would tend to attenuate the estimated β_1^{g} (β_4^{g}). Since n^{*} enters the definition of w^{*} and l^{*}, it is also plausible that e^{n} and e^{w} are negatively correlated and e^{l} and e^{w} positively correlated, further biasing the estimated β_1^{n} and β_1^{l}. Likewise, if

[10] The reason why (20) as well as the reduced-form labor force participation equation (24) do not contain an explicit time-constant, unobserved effect is twofold. Cross-sectional variation in wages and prices aids in identifying the ISEs. Results in Greene (2004) suggest that when T_i is small the pooled probit estimator of (24) is preferred to the fixed effects probit.

consumers with a strong taste for c work more hours in the market and demand less leisure, the estimated β_4^n (respectively, β_4^l) would be positively (negatively) biased if this taste were imperfectly controlled for.

We follow Altonji (1986) and Mroz (1987) and use an estimated individual-specific permanent component of the wage (denoted w_i^{**}), actual years of labor force experience, and experience squared to instrument $\ln w^*$ and $\ln c^*$. More precisely, these three variables are utilized to predict $\ln w^*$ and $\ln c^*$ in the hourly-paid sub-sample, whereas we instrument in the full sample with experience and the square of this only. The w_i^{**} are obtained from a regression of $\ln w_{it}^{**}$ on dummy variables for each woman.[11] Hence, if a woman is never paid by the hour her w_i^{**} is unknown, resulting in a much smaller and possibly less representative sample. However, the inclusion of w_i^{**} in the instrument set will allow us to test overidentifying restrictions. Altonji (1986) argues that since the w_i^{**} estimate a permanent determinant of wages, they should be orthogonal to unsystematic errors of measurement. Mroz (1987) does not reject the validity of experience (measured as the number of years

[11] Variables that fluctuate over time are also included in this dummy-variable regression: year and MA dummies, a work capacity indicator, actual labor force experience and experience squared, the interaction of experience with schooling, and controls for self-selection into the labor force (an inverse Mills ratio term interacted with year dummies). This wage regression is estimated using all observations with good data on the current value of hours worked and on the current values of the variables utilized in the regression.

worked for money since the 18th birthday)[12] and its square as an instrument for $\ln w^*$ after controlling for self-selection into the labor force. Both w_i^{**} and experience are important determinants of lifetime wages and should be related to $\ln w^*$ and $\ln c^*$.

In his preliminary study on the intertemporal labor supply decisions of married women, Altonji (1982a) did not include w_i^{**} in the instrument set for lack of sufficient observations to precisely measure these fixed effects. Instead, he used years of schooling. I was not aware of Altonji's (1982a) analysis when I considered using w_i^{**} to study female labor supply at the beginning of this project. The number of observations on $\ln w_{it}^{**}$ that I have available to estimate w_i^{**} is still rather low: an average of four. Yet, as we will see, the performance of w_i^{**} in the first-stage regressions for $\ln w^*$ and $\ln c^*$ seems satisfactory. Moreover, I will assess the effect of replacing w_i^{**} with years of schooling on the estimated elasticities.

As is well-known, if the group of labor force participants is not (conditionally) representative of the whole population, straightforward methods might result in inconsistent estimation. To control for possible sample selectivity when estimating (20) using data on participants only, let the reduced-form participation propensity be given by

$$m_{it}^* = \mathbf{z}_{it}'\mathbf{q} + v_{it}, \tag{24}$$

where v_{it} is an error term assumed standard normally distributed[13] and independent of $\mathbf{z}_i \equiv (\mathbf{z}_{i1}', \ldots, \mathbf{z}_{iT_i}')$. Besides an intercept, $\mathbf{z}$ includes $\ln p^x$, $\ln p^s$, and the instruments and preference determinants listed above. Assuming that

[12] This information is asked of all heads/wives of PSID families in 1976 and 1985, and of all new heads/wives in all other waves. Experience is then increased in one year when annual market hours are positive.

$$E(\varepsilon_{it}^{g} \big| \mathbf{z}_i, v_{it}) = \beta_{\lambda}^{g} v_{it}, \quad g = l, h, n, \tag{25}$$

the estimating system of time-use equations becomes

$$\ln g_{it} = \mathbf{x}_{it}{}' \boldsymbol{\beta}^{g} + u_{it}^{g}, \quad g = l, h, n, \tag{26}$$

with $\mathbf{x}_{it} \equiv (\mathbf{x}_{it}^{\circ}{}', \lambda(\mathbf{z}_{it}{}'\mathbf{q}))'$, $\boldsymbol{\beta}^{g} \equiv (\boldsymbol{\beta}_{\circ}^{g}{}', \beta_{\lambda}^{g})'$, and $\lambda(\cdot) \equiv \dfrac{\phi(\cdot)}{\Phi(\cdot)}$ (see Heckman, 1979). Substituting (21)-(23) into (26), and defining $\mathbf{y}_{it}^{*} \equiv (\ln l_{it}^{*}, \ln h_{it}^{*}, \ln n_{it}^{*})'$, $\mathbf{X}_{it}^{*} \equiv (I_3 \otimes \mathbf{x}_{it}^{*}{}')$, $\boldsymbol{\beta} \equiv (\boldsymbol{\beta}^{l}{}', \boldsymbol{\beta}^{h}{}', \boldsymbol{\beta}^{n}{}')'$, and $\mathbf{u}_{it}^{*} \equiv (u_{it}^{l*}, u_{it}^{h*}, u_{it}^{n*})'$, where the starred notation emphasizes that imperfect measurements have replaced true values and $\otimes$ is the Kronecker product symbol, we obtain

$$\mathbf{y}_{it}^{*} = \mathbf{X}_{it}^{*} \boldsymbol{\beta} + \mathbf{u}_{it}^{*}. \tag{27}$$

The (pooled) probit estimate of $\mathbf{q}$ is obtained from the model $P(d_{it} = 1 \big| \mathbf{z}_i) = \Phi(\mathbf{z}_{it}'\mathbf{q})$ using all observations, and then $\lambda(\mathbf{z}_{it}'\hat{\mathbf{q}})$ is included in $\mathbf{x}_{it}^{*}$ interacted with year dummies to allow for time-varying selection effects. $\boldsymbol{\beta}$ is estimated by solving

$$\min_{\mathbf{b}} \left[\sum_{i=1}^{N} \sum_{t=1}^{T_i} \mathbf{Z}_{it}' (\mathbf{y}_{it}^{*} - \mathbf{X}_{it}^{*} \mathbf{b}) \right]' \hat{\mathbf{W}} \left[\sum_{i=1}^{N} \sum_{t=1}^{T_i} \mathbf{Z}_{it}' (\mathbf{y}_{it}^{*} - \mathbf{X}_{it}^{*} \mathbf{b}) \right] \tag{28}$$

on the sample of participants, with $\mathbf{Z}_{it} \equiv (I_3 \otimes \mathbf{z}_{it}')$, $\hat{\mathbf{W}} = \hat{\boldsymbol{\Lambda}}^{-1}$, and where our estimator of $\boldsymbol{\Lambda} \equiv Var(\mathbf{Z}_{it}'\mathbf{u}_{it}^{*})$,

$$\hat{\boldsymbol{\Lambda}} \equiv (\sum_{i=1}^{N} T_i)^{-1} \sum_{i=1}^{N} ((\sum_{t=1}^{T_i} \mathbf{Z}_{it}' \hat{\mathbf{u}}_{it}^{*})(\sum_{t=1}^{T_i} \hat{\mathbf{u}}_{it}^{*}{}' \mathbf{Z}_{it})), \tag{29}$$

[13] In their examination of women's labor supply decisions with PSID data, Newey et al. (1990) conclude that parameter estimates are not sensitive to distributional assumptions of the unobservable error terms.

allows for arbitrary heteroskedasticity, permits $E(\mathbf{u}_{it}^{*}\mathbf{u}_{it}^{*\prime}\big|\mathbf{Z}_{it})$ changing across observations, and allows for arbitrary correlation among observations belonging to i.[14]

4 EMPIRICAL RESULTS

Tables 1 and 2 present, respectively, reduced-form probit regressions for the decision to participate in the labor force and OLS regressions for $\ln w^{*}$ and $\ln c^{*}$. Table 1 presents estimated probit coefficients as well as an adjustment factor that allows the marginal effect of continuous variables and an approximation to the marginal effect of discrete variables to be computed. The marginal effect of a probit model is $\frac{\partial \Phi(\mathbf{z}'\mathbf{q})}{\partial z_k} = \phi(\mathbf{z}'\mathbf{q})q_k$, and the adjustment factor (evaluated at mean values of the regressors) is $\phi(\overline{\mathbf{z}}'\mathbf{q})$. Standard errors, shown in parentheses, are clustered at the individual level in Table 1, and are additionally robust to heteroskedasticity and corrected for the presence of generated regressors in Table 2.[15] Probability values are in brackets.

The reduced-form probit regressions yield similar results in both samples. Being married or suffering from a limitation in the type or amount of work that can be done strongly reduce the probability of labor force participation. The presence of children has a negative effect as well, with pre-school children having the strongest effect by far. The price of

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[14] Lee (2004) shows that this system Generalized Method of Moments (SGMM) estimator is generally more efficient than the equation-by-equation GMM estimator, a result that still holds in the presence of common instruments across equations.

[15] When the interaction of λ with year dummies is statistically significant, standard errors are corrected for the presence of estimated parameters in λ. The correct standard errors for the most general model estimated in the paper are derived in Appendix D. The standard errors for the other models are simple special cases.

recreation goods is negatively associated to the probability of participating: at mean values of the regressors, a 1% increase in p^x reduces the probability by .002.[16] Estimates are imprecise, but attain statistical significance in the full sample. Experience is a strong predictor for participating in the labor force, whose likelihood increases with years of experience up until 30 years, and decreases from that moment on. Perhaps not surprisingly, women with a higher w_i^{**} are more likely to participate, with a 1 standard deviation increase in w_i^{**} raising the probability of participating by .032.[17]

In the first-stage regressions for endogenous variables (Table 2), all excluded instruments present expected signs and are statistically significant at .05 level. With two endogenous regressors, however, the statistical significance of the excluded instruments is not sufficient in general to identify $\boldsymbol{\beta}$, for identification requires that the matrix $E\left[\mathbf{z}_{it}\mathbf{x}_{it}^{*\prime}\right]$ has full rank (see, e.g., Wooldridge, 2002, p. 188).[18] We have tested the null of $E\left[\mathbf{z}_{it}\mathbf{x}_{it}^{*\prime}\right]$ not having full rank using the Kleibergen and Paap (2006) rank test, which is robust to arbitrary heteroskedasticity and serial correlation in the errors of the reduced-form regressions. The test statistic, a quadratic form of an orthogonal transformation of the smallest singular value of $E\left[\mathbf{z}_{it}\mathbf{x}_{it}^{*\prime}\right]$, is asymptotically distributed as χ^2 with degrees of freedom equal to the number

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[16] Since the dependent variable is measured in levels and the explanatory variable is in logs, this effect is obtained as the product of the estimated coefficient associated to $\ln p^x$ times the adjustment factor divided by 100.

[17] The w_i^{**}, which are the fixed effects in a regression for $\ln w_{it}^{**}$, are normalized and have a mean of 0. Their sample standard deviation is .4896.

[18] Equivalently, identification requires that the matrix with the reduced-form coefficients associated to the excluded instruments have full rank (Wooldridge, 2002, p. 214).

of overidentifying restrictions plus one. In the hourly paid sample, where the instrument set contains w_i^{**}, experience, and experience squared, the *p*-value of the rank test is .007, whereas in the full sample, where the instrument set contains experience and experience squared only, it amounts to .000. Therefore, both instrument sets appear as adequate to identify $\boldsymbol{\beta}$. The other estimated effects in Table 2 are generally expected,[19] including those for $\ln c^*$. This latter result, and the satisfying explanatory power shown by the first-stage equation for consumption (*R*-squared=.13), provide some reassurance that the expenditure on restaurants data are sufficiently accurate for the problem at hand.

Tables 3 and 4 present the main estimates of the time-use equations (27). In Table 3, OLS coefficients, which do not control for the endogeneity of $\ln w^*$ and $\ln c^*$, are presented. In the first three columns of Table 4, w_i^{**}, labor force experience, and experience squared are used as instruments for $\ln w^*$ and $\ln c^*$. Results presented in the last three columns of Table 4 are obtained instrumenting with experience and the square of this only. Heteroskedasticity robust standard errors clustered at the individual level and corrected for the presence of generated regressors are shown in parentheses, and probability values in brackets.

When $\ln w^*$ and $\ln c^*$ are treated as exogenous, the estimated wage effects on l, h, and n are around .01, -.16, and .14, respectively. Estimates are precise and attain statistical significance at .05 level. For labor force participants, the labor supply ISE with respect to p^x ranges from .07 to .27, whereas that with respect to p^s is in the neighborhood of -.26 to -.29.

[19] The negative association between the number of children and $\ln w^*$ even after controlling for experience is due to our notion of experience not accounting for the human capital foregone in partial market time reductions. If, for example, experience were only augmented when annual market hours were at least 2000, the partial correlations between children and $\ln w^*$ would not be statistically different from zero.

These price effects are estimated with less precision and do not attain statistical significance. The estimated coefficients associated to $\ln c^*$ are small but statistically different from zero in the regressions for h and n.

As the theoretically unexpected positive sign of $\hat{\beta}_1^l$ suggests, the previous estimates may be biased as a consequence of $\ln w^*$ and $\ln c^*$ being endogenous. To test for endogeneity, the residuals from regressing $\ln w^*$ and $\ln c^*$ on all the exogenous variables were added to each of the regressions presented in Table 3. Then, the joint statistical significance of both residual terms in each regression was tested using a robust Wald test (Wooldridge, 2002, p. 121). With the exception of the regression for $\ln h^*$ in the hourly paid sample, where the *p*-value of the test is .11, the evidence at the bottom of Table 3 strongly rejects the exogeneity of $\ln w^*$ and $\ln c^*$.

Instrumenting for $\ln w^*$ and $\ln c^*$ has a pronounced effect on the estimated elasticities. In Table 4, the ISE of l with respect to the wage rate is in the neighborhood of -.06 to -.11, being statistically different from zero at .05 level. (When $\bar{T} = 5000$, this elasticity is in the neighborhood of -.16 to -.22, whereas other results are essentially unchanged.) Home production and market time become more responsive to the wage rate too. The wage ISE of h ranges from -.18 to -.68, whereas that of n ranges from .52 to .86. Both attain statistical significance at .05 level. The effect of the price of recreation goods on the intensive margin of female labor supply ranges from -.00 to .31.[20] Estimates are imprecise and do not attain

[20] Our estimated price effects could be attenuated because, as argued by Geronimus, Bound, and Neidert (1996), an errors-in-variables bias may arise when an aggregate proxy for a microvariable is only imperfectly correlated with it. We think however that the size of this bias could be small, for the kind of commodities included in “Entertainment” and “Food at Home” suggests that the metropolitan area may well approach the consumer’s market.

statistical significance. The ISE of h with respect to p^s ranges from .21 to .59, whereas that of n is in the neighborhood of -.59 to -.71. Both are statistically different from zero at .05 level in the full sample. If p^s were excluded from the specification, wage effects would remain essentially unchanged, but part of the effect of p^s would be misleadingly attributed to the price of recreation goods: The estimated β_2^n would then range from -.36 to .02, and would attain statistical significance around the .05 level in the full sample. Except in the regression for $\ln h^*$, the estimates associated to $\ln c^*$ have theoretically expected signs and attain statistical significance at or around the .05 level.

Since the number of excluded instruments in the hourly paid sample (three per equation) exceeds the number of endogenous variables (two per equation), it is possible to test the overidentifying restrictions on the excluded instruments. The test statistic (Hansen's, 1982, *J*-statistic) is the minimized value of (28), and is asymptotically distributed as χ^2 with degrees of freedom equal to the number of overidentifying restrictions (three in total). The *p*-value for this test, .15, is above standard significance levels, and the validity of the instruments cannot be rejected.[21]

An additional specification check can be carried out by testing the cross-equation restrictions on the coefficients in (16). These restrictions were derived assuming that $\bar{T}$ was exogenous, which seems natural when $\bar{T} = 8760$. Yet, estimation biases can impede their verification in the data. Results of robust Wald tests for the hypothesis in (16) with $j = 1, 2, 3$, and 4 (pertaining, respectively, to coefficients associated to $\ln w^*$, $\ln p^x$, $\ln p^s$, and $\ln c^*$) are

[21] As shown below, the relevance of the instrument set utilized in the hourly paid sample is low. In the context of Two Stage Least Squares (TSLS), Staiger and Stock (1997) find that tests of overidentifying restrictions tend to overreject the null when instruments are weak.

presented in the bottom rows of Table 4. In performing the tests, the ratios l/n and h/n, computed from the samples of participants, were treated as constants. The restrictions on the coefficients associated to $\ln w^{*}$ and $\ln p^{s}$ are questioned in the hourly paid sample, the test *p*-values being .00 and .02, respectively. In the full sample, however, all tests are safely within accepted bounds.

For certain elasticities, the cross-sample variation in estimates observed in Table 4 is so large that might not be due to the different samples. Indeed, estimates obtained on the hourly paid sample seem biased in the direction of OLS, and it is well-known that when the vector of instruments is weakly correlated with the endogenous regressors, standard TSLS and GMM point estimates tend to be biased toward $\text{plim}(\hat{\boldsymbol{\beta}}^{OLS})$ even in very large samples (see, e.g., Bound et al., 1995, Staiger and Stock, 1997, and Stock et al., 2002). Since weak instruments can also distort the significance levels for tests based upon standard TSLS and GMM, we test for weak instruments using the Stock and Yogo (2005) size-based test.[22] Its null hypothesis is that conventional 5%-level Wald tests for $\boldsymbol{\beta}$ based on TSLS statistics have an actual size that exceeds a certain threshold, for example 10%. The test statistic with two endogenous regressors is the Cragg and Donald (1993) statistic, whose value and definition are provided in Table 2. Table 2 presents also the value and definition of the *F*-statistic form of the Kleibergen and Paap (2006) statistic, which can be interpreted as a generalization of the Cragg-Donald statistic to the case with non-*i.i.d.* errors in the reduced-forms for the endogenous regressors.[23] Critical values are taken from Stock and Yogo (2005, Table 5.2).

[22] The alternative Stock and Yogo (2005) bias-based test requires at least four excluded instruments when there are two endogenous regressors.

[23] To put it in *F*-statistic form, the Kleibergen-Paap statistic was divided by the number of excluded instruments and multiplied by a finite-sample adjustment. An alternative

Thus, for example, to assure that the actual size of 5%-level tests for $\boldsymbol{\beta}$ is no greater than 10% (respectively, 15% and 25%), the test statistic must be greater than 13.43 (8.18 and 5.45) with three excluded instruments, and must be greater than 7.03 (4.58 and 3.63) when there are two excluded instruments.

When $\ln w^*$ and $\ln c^*$ are instrumented with w_i^{**}, experience, and experience squared, the value of the Cragg-Donald statistic (11.16) indicates a size distortion between 5 and 10%, though the value of the Kleibergen-Paap *F* statistic (3.28) suggests that the distortion could be much larger. In the full sample, however, where the instrument set contains experience and experience squared only, the null of correct size cannot be rejected: the value of both statistics (25.78 and 7.66, respectively) is above the 10% threshold critical value (7.03). Therefore, the evidence suggests that estimates presented in the first three columns of Table 4 are biased as the instruments are weak. The reason for the low instruments relevance in the hourly paid sample is twofold: reduced predictive capacity of experience in that sample and collinearity between experience and w_i^{**} in predicting $\ln c^*$. To see this, Table 2 presents the value of the *F*-statistic for testing the hypothesis that experience and experience squared do not enter each of the first-stage regressions. This statistic, which evaluates the predictive capacity of experience for $\ln w^*$ and $\ln c^*$, amounts to 42.19 and 11.87, respectively, when calculated on the full sample, and to 29.14 and 5.85 when computed on the hourly paid sample, but excluding w_i^{**} from the instrument set. Including w_i^{**} in the instrument set, the values are 139.3 and 2.86.

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generalization of the Cragg-Donald statistic proposed by Cragg and Donald (1997) was discarded because its value, obtained by numerical optimization, may be unstable. I thank Frank Kleibergen for clarification on this point.

For women and using PSID data, intertemporal labor supply responses to variations in wages have been estimated by Heckman and MaCurdy (1980, 1982), Altonji (1982a), Hotz and Miller (1988), Zabel (1997), and Mulligan (1999). Heckman and MaCurdy (1982) obtained an elasticity of size 2.23 (computed at 1,350 hours of market work) for the population of married women, Hotz and Miller's (1988) estimate for the population of mothers younger than 40 years old was around 1.23, and Mulligan's (1999) estimated elasticity for the population of mothers with a child aged 17 at home ranged from .26 to 1.66. In these three studies, the estimated elasticity integrated the intensive and extensive margins of labor supply in its response. For the population of married women, Zabel (1997) estimated a wage elasticity for the intensive margin of female labor supply ranging from .11 to .72 (and centered at .38), whereas Altonji (1982a) obtained an estimate of size .75. Although referred to the whole population of prime-age women (for married women, our β_1^n estimated on the full sample is 1.18, $S.E. = .33$), our .86 estimate obtained on the full sample is, as predicted in Domeij and Flodén (2006), substantially higher than those obtained in Zabel (1997). It is also somewhat higher than the estimate obtained in Altonji (1982a), who employed a similar approach to modeling intertemporal substitution but used years of schooling (rather than w_i^{**}) as an instrument for wages and family expenditure. To assess the influence of the different instruments, I have re-estimated the first block of regressions presented in Table 4 with w_i^{**} replaced by years of schooling, and have re-estimated the second block of regressions in Table 4 including schooling in the instrument set. When w_i^{**} is replaced by years of schooling, the estimated β_1^n becomes .42 ($S.E. = .20$). Notably, the test for overidentifying restrictions now rejects the instruments validity (*p*-value .00), whereas the values of the Cragg-Donald and Kleibergen-Paap *F* statistics (11.72 and 3.53, respectively) still suggest that instruments are weak. When schooling is included in the instrument set for the second block of regressions presented in Table 4, the estimated β_1^n shrinks to .29 ($S.E.=.14$), and the null of valid instruments is again rejected (*p*-value .00). The evidence thus strongly suggests that including years of schooling in the instrument set for wages and family expenditure imparts a downward bias on the estimated wage ISE for the intensive margin of female labor supply. Since Zabel (1997) used educational category to predict wages, his estimates may also be affected by this bias.

Our estimated wage ISE for market time implies that, at average values for the allocation of time, women participating in the labor force will increase annual labor supply by some 14 hours in periods where the wage rate is anticipated to rise by 1%. The estimated wage ISEs for leisure (-.11) and home production time (-.68) suggest that, of this increase, approximately 7 hours will come from less time spent on leisure and the other 7 from less time devoted to home production. The estimated ISE of home production time with respect to the price of home consumption goods (.59) means that, at average values for the allocation of time, women participating in the labor force will increase annual time devoted to home production by some 6 hours when faced with a 1% grow in the price of home consumption goods. As the corresponding estimated ISEs for leisure (.05) and market time (-.71) suggest, these extra hours devoted to home production will be entirely subtracted from the supply of labor, which will be therefore reduced in a similar amount.

The estimated coefficients can be related back to some structural parameters. For example, rearranging conditions (10) and (11) we have $\gamma=-(\beta_1^l+\beta_2^l)$, and rearranging (13) and (15) we obtain $\mu=-(\beta_1^h+\beta_3^h)$. Results in Table 4 obtained on the full sample yield $\hat{\gamma}=.0917$, $S.E.=.0558$, and $\hat{\mu}=.0870$, $S.E.=.2169$. It is also possible to obtain an estimate of the elasticity of substitution in home production, θ . To this aim, variable ζ^h , which equals the share of the money value of home production time in total expenditure on home goods, is calculated assuming that the cost of time in home production is the market wage and using expenditure on food at home as an empirical counterpart to $p^s s$. Among labor force participants in the full sample, ζ^h amounts to .6853 on average. Then, given for instance the result in (13) and our estimates for β_1^h and μ obtained on the full sample, $\hat{\theta} = 1.96$, which is in line with the 1.8 estimate reported in Aguiar and Hurst (2007).

Significant demographic effects associated to the marital status and to the composition of the family are evident in Table 4. As most of these effects are expected, they are not discussed for brevity. Table 4 likewise presents the value of the Wald statistic for testing the joint statistical significance of λ interacted with year dummies. Under the null of no selection effects, this statistic has a χ^2 distribution with 14 degrees of freedom (the sample period covers 18 years, but there is no information on h for 1982, on food expenditure for 1988 and 1989, and on n for 1993). We find significant evidence of sample selectivity in the equations for n and l, but the evidence against the null is milder in the equation for h.

Our main results appear to be robust to the relaxation of the intertemporal separability assumption and to the exclusion of the poverty subsample from the PSID. When preferences are intertemporally separable, period t demands are not affected by prices from other periods. A simple generalization of intertemporal separability is to include one-period forwarded and lagged prices in demands, Browning (1991) argues. On the other hand, the core PSID sample combines a nationally representative sample of households with some 2,000 low-income families taken from the Survey of Economic Opportunities (SEO). Results calculated on the full sample are presented in Table 5. For each activity, the assumption of intertemporal separability cannot be rejected. Although the exclusion of the poverty subsample rises the imprecision of the estimates, the main findings are preserved.

5 SUMMARY AND CONCLUSIONS

For the population of U.S. women of prime age, this paper has estimated log-linearized structural equations representing labor force participants' intertemporal allocation of time in an uncertain environment. A three-activity system (leisure, home production, and market work) has been jointly estimated combining consumer-level data on hours, wages, and consumption expenditure from the Panel Study of Income Dynamics with metropolitan area-level price indices from the Bureau of Labor Statistics. We have used data on consumer expenditure on restaurants to control for unobservable expectations and wealth, and applied an instrumental variables approach based upon Altonji (1986) and Mroz (1987) to deal with mismeasured explanatory variables. Our empirical model has passed standard tests for instrumental variables regression, an adding-up test for the allocation of time, and a test for the relaxation of the intertemporal separability assumption.

The estimated wage ISE for the intensive margin of female labor supply that we have obtained (.86) is higher than previous estimates, which seems the result of the different approach followed to modeling intertemporal substitution and the different instrument set utilized. Our estimate implies that, at average values for the allocation of time, women participating in the labor force will increase annual labor supply by some 14 hours in periods where the wage rate is anticipated to rise by 1%. The estimated wage ISEs for leisure and home production time that we have obtained, -.11 and -.68 respectively, suggest that approximately 7 hours of this increase will come from less time spent on leisure and the other 7 from less time devoted to home production. The low point estimate for the labor supply ISE with respect to the price of recreation goods (-.00) suggests that the intensive margin of female intertemporal labor supply is not affected by variations in the price of these goods. Yet, this margin does react to changes in the price of home consumption goods. The estimated ISE of home production time with respect to the price of home consumption goods that we have obtained, .59, implies that, at average values for the allocation of time, women participating in the labor force will increase annual time devoted to home production by some 6 hours when faced with a 1% grow in the price of home consumption goods. Moreover, the corresponding ISEs for leisure and market time, .05 and -.71 respectively, suggest that the extra hours devoted to home production will be entirely subtracted from market work, which will be therefore reduced in a similar amount. If home production were excluded from the model's specification, part of this effect would be misleadingly attributed to the price of recreation goods.

A THE TOTAL LABOR SUPPLY ISE

This appendix shows that the total labor supply ISE (i.e. the labor supply ISE integrating the intensive and extensive margins) equals the labor force participants' labor supply ISE plus the labor force participation ISE. In what follows, n represents market time, m^* denotes (latent) labor force participation propensity, and $\mathbf{x}$ is a vector containing the log of the wage rate ($\ln w$), the log of expenditure on restaurants, and possibly other controls.

Let $E(n|\mathbf{x})$ and $P(m^*>0|\mathbf{x})$ denote, respectively, the population regression of n and the population probability of labor force participation. Using the Law of Iterated Expectations and the fact that $E(n|\mathbf{x},m^*<0)=0$, we have

$$E(n|\mathbf{x}) = E_{m^*}(E(n|\mathbf{x},m^*)) = P(m^*>0|\mathbf{x})E(n|\mathbf{x},m^*>0)\,. \qquad \text{(A.1)}$$

Thus, the total labor supply ISE with respect to w is given by the labor force participants' labor supply wage ISE plus the labor force participation wage ISE:

$$\begin{aligned}\frac{1}{E(n|\mathbf{x})}\frac{\partial E(n|\mathbf{x})}{\partial \ln w} &= \frac{1}{E(n|\mathbf{x})}\left[P(m^*>0|\mathbf{x})\frac{\partial E(n|\mathbf{x},m^*>0)}{\partial \ln w} + \frac{\partial P(m^*>0|\mathbf{x})}{\partial \ln w}E(n|\mathbf{x},m^*>0)\right] \\ &= \frac{1}{E(n|\mathbf{x})}\left[\frac{E(n|\mathbf{x})}{E(n|\mathbf{x},m^*>0)}\frac{\partial E(n|\mathbf{x},m^*>0)}{\partial \ln w} + \frac{\partial P(m^*>0|\mathbf{x})}{\partial \ln w}\frac{E(n|\mathbf{x})}{P(m^*>0|\mathbf{x})}\right] \\ &= \frac{1}{E(n|\mathbf{x},m^*>0)}\frac{\partial E(n|\mathbf{x},m^*>0)}{\partial \ln w} + \frac{\partial P(m^*>0|\mathbf{x})}{\partial \ln w}\frac{1}{P(m^*>0|\mathbf{x})}\end{aligned}$$

(A.2)

where the first equality follows from the chain rule.

B LABOR FORCE PARTICIPATION ISEs: WHY ESTIMATES MAY BE BIASED

This appendix shows that the labor force participation wage ISEs obtained in Zabel (1997) and Altonji (1982a) may be biased as a consequence of neglected heterogeneity stemming from mismeasured explanatory variables and reduced-form regression errors.

As showed in Section 2, a log-linear approximation to the condition determining labor force participation is given by

$$m_{it}^{*} = \beta_0^p + \beta_1^p \ln w_{it} + \beta_2^p \ln p_{it}^x + \beta_3^p \ln p_{it}^s + \beta_4^p \ln c_{it} + v_{it}^p \qquad \text{(B.1)}$$

where m_{it}^{*} is consumer i's (latent) participation propensity at age t and v_{it}^p is a preference determinant.[24] If the participation probability followed a probit model, the participation ISEs (evaluated at mean values of the regressors) would be given by

$$\frac{\phi(\overline{\mathbf{x}}'\boldsymbol{\beta}^p / \sigma_{v^p})}{\Phi(\overline{\mathbf{x}}'\boldsymbol{\beta}^p / \sigma_{v^p})}\frac{\beta_j^p}{\sigma_{v^p}}, \quad j = 1,2,3, \qquad \text{(B.2)}$$

where σ_{v^p} is the standard deviation of v^p in the population. To understand our basic idea, it is helpful to assume that measures of the wage rate w are available for all individuals in the population, including non-participants. Yet, since w and c are generally measured with error in survey data, (B.1) becomes

$$m_{it}^{*} = \beta_0^p + \beta_1^p \ln w_{it}^{*} + \beta_2^p \ln p_{it}^x + \beta_3^p \ln p_{it}^s + \beta_4^p \ln c_{it}^{*} + \zeta_{it} + v_{it}^p, \qquad \text{(B.3)}$$

[24] Neither Zabel (1997) nor Altonji (1982a) included $\ln p^x$ and $\ln p^s$ in the labor force participation equation. Zabel (1997) likewise did not include $\ln c$. But this does not affect our main argument.

where the unobserved term ζ_{it} is given by $\zeta_{it} = -\beta_1^p e_{it}^w - \beta_4^p e_{it}^c$, e denoting errors of measurement.

To consistently estimate (B.2) for the wage rate, both Zabel (1997) and Altonji (1982a) implicitly employed the same instrumental variables probit estimator, developed in Lee (1981). Lee (1981) suggested writing (B.3) in reduced form,

$$m_{it}^* = \beta_0^p + \beta_1^p(\boldsymbol{\pi}^{w\prime}\mathbf{z}_{it}) + \beta_2^p \ln p_{it}^x + \beta_3^p \ln p_{it}^s + \beta_4^p(\boldsymbol{\pi}^{c\prime}\mathbf{z}_{it}) + \xi_{it} + v_{it}^p, \qquad \text{(B.4)}$$

where $\boldsymbol{\pi}$ and $\mathbf{z}$ denote, respectively, vectors of reduced-form parameters and regressors, and the unobserved term ξ_{it} is given by $\xi_{it} = \zeta_{it} + \beta_1^p u_{it}^w + \beta_4^p u_{it}^c$, u representing reduced-form errors. Given consistent estimates of $\boldsymbol{\pi}$, the probit participation ISEs obtained from (B.4) are

$$\frac{\phi(\overline{\mathbf{x}}'\,\boldsymbol{\beta}^p / \sigma_{\xi+v^p})}{\Phi(\overline{\mathbf{x}}'\,\boldsymbol{\beta}^p / \sigma_{\xi+v^p})}\frac{\beta_j^p}{\sigma_{\xi+v^p}}, \quad j = 1,2,3 \qquad \text{(B.5)}$$

where $\sigma_{\xi+v^p} = (\text{var}(\xi + v^p))^{1/2}$. (Using the procedure in Wooldridge, 2002, pp. 22-24, expression B.5 could be alternatively written as

$$E_\xi\left[\frac{\phi((\overline{\mathbf{x}}'\boldsymbol{\beta}^p + \xi)/\sigma_{v^p})}{\Phi((\overline{\mathbf{x}}'\boldsymbol{\beta}^p + \xi)/\sigma_{v^p})}\frac{\beta_j^p}{\sigma_{v^p}}\right], \quad j = 1,2,3, \qquad \text{(B.6)}$$

where $E_\xi[\cdot]$ denotes the expectation with respect to ξ.) The elasticities in (B.5) (or, equivalently, B.6) are generally different from those in (B.2). Moreover, if ξ is independent of v^p, $\beta_j^p / \sigma_{\xi+v^p}$ would be closer to zero than β_j^p / σ_{v^p}, but $\phi(\overline{\mathbf{x}}'\,\boldsymbol{\beta}^p / \sigma_{\xi+v^p}) \big/ \Phi(\overline{\mathbf{x}}'\,\boldsymbol{\beta}^p / \sigma_{\xi+v^p})$ would be larger than $\phi(\overline{\mathbf{x}}'\,\boldsymbol{\beta}^p / \sigma_{v^p}) \big/ \Phi(\overline{\mathbf{x}}'\,\boldsymbol{\beta}^p / \sigma_{v^p})$. Therefore, it is not clear the direction of the bias.

C DATA APPENDIX

Our dataset contains the 26,918 women interviewed by the PSID between 1968 and 1993, though variables included cover the 1976-1993 period only. There are a total of 484,524 observations (person-years). Observations must correspond to heads/wives of PSID families (368,199 person-years lost), present in the family at the time of the interview (1,617 person-years lost), and with known age (6 person-years lost). Observations must pertain to person-years living in MAs with available price indices (64,064 person-years lost). Price indices in Miami-Ft. Lauderdale start in 1977 (57 person-years lost). Observations must correspond to women aged 25-60 (13,204 person-years lost) and have valid information on hours, earnings, and expenditure on restaurants (10,611 person-years lost).[25] Observations reporting no labor earnings but positive market hours or vice versa are dropped (71 person-years lost). Observations reporting no market hours but positive hourly wage rates are dropped (186 person-years lost). Hours of housework must not be zero (267 person-years lost). Observations with hours, wages, or expenditure on restaurants below the 1st percentile (but above zero) or above the 99th percentile of the corresponding sampling distribution are dropped (1,449 person-years lost). Observations with missing marital status, number of children, work capacity,[26] labor market experience, or race are deleted (996 person-years lost). Expenditure on restaurants must not be zero (4,511 person-years lost). In the hourly paid subsample, women must be paid by the hour at least one year (8,004 person-years lost). Table C.1 presents descriptive statistics for the main variables used in this study.

The CPI-All Urban Consumers introduced by the BLS in 1987 is a statistical measure of change, over time, of the prices of goods and services in major expenditure groups. The indices of “Entertainment” (whose BLS item code is SA6), “Food at Home” (SA111), and

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[25] Market hours and labor earnings are not available for the calendar year 1993. Expenditure on restaurants are not asked in 1988 and 1989. Hours of housework are not asked in 1982.

[26] Though the wife’s work capacity indicator was not asked between 1977 and 1980, this information is available at the individual level for the years 1977 and 1978. For 1979 (respectively, 1980), the wife’s work capacity is taken from that reported in 1978 (1981).

"Food away from Home" (SE19) are available since 1976 for the following 27 Metropolitan Areas (as denominated by the U.S. Office of Management and Budget in June 1990; BLS area codes are in parentheses): New York-Northern N.J.-Long Island (A101), Philadelphia-Wilmington-Trenton (A102), Boston-Lawrence-Salem (A103), Pittsburgh-Beaver Valley (A104), Buffalo-Niagara Falls (A105), Chicago-Gary-Lake County (A207), Detroit-Ann Arbor (A208), St. Louis-East St. Louis (A209), Cleveland-Akron-Lorain (A210), Minneapolis-St. Paul (A211), Milwaukee (A212), Cincinnati-Hamilton (A213), Kansas City (A214), Washington (A315), Dallas-Fort Worth (A316), Baltimore (A317), Houston-Galveston-Brazoria (A318), Atlanta (A319), Miami-Ft. Lauderdale (A320; price indices available here since 1977), Los Angeles-Anaheim-Riverside (A421), San Francisco-Oakland-San Jose (A422), Seattle-Tacoma (A423), San Diego (A424), Portland-Vancouver (A425), Honolulu (A426), Anchorage (A427), and Denver-Boulder (A433). The price series utilized (downloadable from ftp://ftp.bls.gov/pub/time.series/mu/) are coded MUURAxxxSyyy and MUUSAxxxSyyy, where Axxx stands for an area code and Syyy for an item code; an "R" as the fourth letter indicates the index is available monthly, an "S" semi-annually.

D CORRECTING THE STANDARD ERRORS FOR THE PRESENCE OF GENERATED REGRESSORS

Drawing upon Arellano and Meghir (1992), this appendix derives SGMM standard errors corrected for the presence of estimated parameters in λ. Corrected standard errors for the OLS estimator can be derived similarly.

After having allowed for certain variables being mismeasured, the system of time-use equations has the form

$$\ln g_{it}^{*} = \mathbf{x}_{it}^{\circ *\prime} \boldsymbol{\beta}_{\circ}^{g} + \beta_{\lambda}^{g} \lambda(\mathbf{z}_{it}^{\prime} \mathbf{q}) + u_{it}^{g*}, \quad g = l, h, n, \tag{D.1}$$

$$\lambda(\mathbf{z}_{it}^{\prime} \mathbf{q}) = \phi(\mathbf{z}_{it}^{\prime} \mathbf{q}) \big/ \Phi(\mathbf{z}_{it}^{\prime} \mathbf{q}), \tag{D.2}$$

$\phi(\cdot)$ being the standard normal density function and $\Phi(\cdot)$ the standard normal distribution function. Expression (D.1) can be rewritten as in (D.3),

$$\ln g_{it}^{*} = \mathbf{x}_{it}^{\circ *\prime} \boldsymbol{\beta}_{\circ}^{g} + \beta_{\lambda}^{g} \lambda(\mathbf{z}_{it}^{\prime} \hat{\mathbf{q}}) + \ddot{u}_{it}^{g*}, \quad g = l, h, n, \tag{D.3}$$

in which

$$\ddot{u}_{it}^{g*} = u_{it}^{g*} + \beta_{\lambda}^{g} (\lambda(\mathbf{z}_{it}^{\prime}\mathbf{q}) - \lambda(\mathbf{z}_{it}^{\prime}\hat{\mathbf{q}})) \tag{D.4}$$

and $\hat{\mathbf{q}}$ denotes the probit estimator of $\mathbf{q}$. Since $d\lambda / d(\mathbf{z}_{it}^{\prime}\hat{\mathbf{q}}) = -\lambda\left[\lambda + \mathbf{z}_{it}^{\prime}\hat{\mathbf{q}}\right]$, the error $\ddot{u}_{it}^{g*}$ can be approximated to first order around $\hat{\mathbf{q}} = \mathbf{q}$ by the following expression:

$$\ddot{u}_{it}^{g*} \simeq u_{it}^{g*} - \beta_{\lambda}^{g} (-\lambda\left[\lambda + \mathbf{z}_{it}^{\prime}\mathbf{q}\right]) \mathbf{z}_{it}^{\prime} (\hat{\mathbf{q}} - \mathbf{q}). \tag{D.5}$$

Stacking observations by g, and since the two terms in the right-hand-side of (D.5) are orthogonal, we have

$$\boldsymbol{\Xi} \equiv E\left[\ddot{\mathbf{u}}\ddot{\mathbf{u}}^{\prime}\right] = E\left[\mathbf{u}\mathbf{u}^{\prime}\right] + \begin{bmatrix} A_l QVQ^{\prime} A_l & A_l QVQ^{\prime} A_h & A_l QVQ^{\prime} A_n \\ A_h QVQ^{\prime} A_l & A_h QVQ^{\prime} A_h & A_h QVQ^{\prime} A_n \\ A_n QVQ^{\prime} A_l & A_n QVQ^{\prime} A_h & A_n QVQ^{\prime} A_n \end{bmatrix}, \tag{D.6}$$

where $E\left[\mathbf{u}\mathbf{u}^{\prime}\right]$ has the structure corresponding to (29), $A_g = diag(\beta_{\lambda}^{g}(-\lambda\left[\lambda + \mathbf{z}_{it}^{\prime}\mathbf{q}\right]))$, Q is the matrix with the reduced-form probit regressors, and V denotes the asymptotic covariance matrix for $\hat{\mathbf{q}}$. The estimated asymptotic covariance matrix of the SGMM estimator corrected for the presence of generated regressors is given by expression (D.7),

$$((\mathbf{X}^{\prime}\mathbf{Z})(\mathbf{Z}^{\prime}\hat{\boldsymbol{\Xi}}\mathbf{Z})^{-1}(\mathbf{Z}^{\prime}\mathbf{X}))^{-1}, \tag{D.7}$$

in which all unknown parameters in $\boldsymbol{\Xi}$ have been replaced by consistent estimates, and $\mathbf{X}$ and $\mathbf{Z}$ contain, respectively, all regressors in (D.1) and all exogenous variables stacked by g.

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TABLE 1—REDUCED-FORM PROBIT EQUATIONS FOR PARTICIPATING IN THE LABOR FORCE (ESTIMATED COEFFICIENTS)

Independent variables	(1) Hourly paid sample	(2) Full sample
w_i^{**}	.3902 (.0963)*	
Experience	.1632 (.0109)*	.1957 (.0075)*
Experience^2	-.0027 (.0003)*	-.0032 (.0002)*
$\ln p^x$	-.9088 (.5997)	-.8118 (.3941)*
$\ln p^s$	-.3579 (.6470)	-.0117 (.4521)
Age	-.0445 (.0276)	-.0670 (.0185)*
Age^2	.0000 (.0003)	.0000 (.0002)
Married	-.4714 (.0746)*	-.3548 (.0515)*
Family size	.1175 (.0389)*	.0825 (.0268)*
No. children	-.1484 (.0417)*	-.1255 (.0287)*
No. children [0-5]	-.3874 (.0388)*	-.4303 (.0290)*
Disabled	-.6851 (.0750)*	-.7196 (.0476)*
Black	.0254 (.0673)	-.0525 (.0516)
Intercept	7.842 (2.973)*	5.279 (1.959)*
Log-likelihood	-3,663	-8,020
R-squared	.19	.28
Adjustment factor for marginal effects	.1680	.2875
Observations	11,282	19,286
Participants	9,724	14,224

Notes: All estimations include area and year dummies. Standard errors clustered at the individual level are in parentheses. *R*-squared equals one minus the ratio of the log likelihood of the fitted function to the log likelihood of a function with only an intercept. * Significant at 5%

TABLE 2—FIRST-STAGE REGRESSIONS FOR ENDOGENOUS VARIABLES. OLS ESTIMATES

	Dependent variables			
	(1) Hourly paid sample		(2) Full sample	
Independent variables	$\ln w^*$	$\ln c^*$	$\ln w^*$	$\ln c^*$
w_i^{**}	.8812*	.3301*		
	(.0303)	(.0543)		
Experience	.0784*	.0296*	.0908*	.0407*
	(.0073)	(.0130)	(.0099)	(.0132)
Experience^2	-.0010*	-.0007*	-.0016*	-.0010*
	(.0002)	(.0003)	(.0002)	(.0003)
$\ln p^x$	.0441	.4219	.0310	.2534
	(.1422)	(.2533)	(.1497)	(.2111)
$\ln p^s$	.3261*	-.2588	.6920*	.0597
	(.1660)	(.3136)	(.1773)	(.2526)
Age	-.0140	-.0056	-.0204*	-.0061
	(.0085)	(.0164)	(.0103)	(.0141)
Age^2	.0001	.0001	-.0000	-.0000
	(.0001)	(.0002)	(.0001)	(.0002)
Married	.0224	.3404*	.0479*	.3604*
	(.0194)	(.0429)	(.0237)	(.0326)
Family size	-.0044	.0393*	-.0283*	.0382*
	(.0094)	(.0197)	(.0114)	(.0156)
No. children	-.0140	-.0724*	-.0297*	-.0907*
	(.0102)	(.0217)	(.0125)	(.0178)
No. children [0-5]	-.0412*	-.1083*	-.0632*	-.1189*
	(.0181)	(.0316)	(.0220)	(.0290)
Disabled	-.0181	-.0647	-.1771*	-.1608*
	(.0281)	(.0615)	(.0382)	(.0529)
Black	-.0220	-.2233*	-.0684*	-.2396*
	(.0170)	(.0342)	(.0230)	(.0290)
Intercept	.2425	5.208*	-1.606*	4.407*
	(.6646)	(1.317)	(.7007)	(1.070)
R-squared	.38	.13	.17	.13
Kleibergen-Paap (full) rank test of $E\left[\mathbf{z}_{it}\mathbf{x}_{it}^{*\prime}\right]$	9.90 [.01]		15.40 [.00]	
Cragg-Donald statistic	11.16		25.78	
Kleibergen-Paap F statistic	3.28		7.66	
Test of joint significance of Experience and Experience^2: robust F-statistic	139.33	2.86	42.19	11.87
Observations	9,724		14,224	
Persons	1,868		3,163	

Notes: All estimations include area and year dummies, plus λ interacted with dummies for year. Heteroskedasticity robust standard errors clustered at the individual level and corrected for the presence of generated regressors are in parentheses. Probability values are in brackets. The Cragg-Donald statistic is the minimum eigenvalue of the F-statistic matrix analog for testing the joint significance of the excluded instruments on the first-stage regressions. The Kleibergen-Paap F statistic equals to a quadratic form of an orthogonal transformation of the smallest singular value of the F-statistic matrix analog. The Kleibergen-Paap F statistic reduces to the Cragg-Donald statistic when the reduced-form errors are *i.i.d.* * Significant at 5%.

TABLE 3—MARGINAL RATE OF SUBSTITUTION EQUATIONS FOR THE ALLOCATION OF TIME. OLS ESTIMATES

	Dependent variables					
	(1) Hourly paid sample			(2) Full sample		
Independent variables	$\ln l^*$	$\ln h^*$	$\ln n^*$	$\ln l^*$	$\ln h^*$	$\ln n^*$
$\ln w^*$	.0080*	-.1323*	.1194*	.0102*	-.1788*	.1552*
	(.0040)	(.0184)	(.0220)	(.0029)	(.0139)	(.0164)
$\ln p^x$	.0252	-.0791	.2700	.0219	-.0040	.0653
	(.0389)	(.1942)	(.2518)	(.0325)	(.1572)	(.1975)
$\ln p^s$	-.0334	.2276	-.2913	-.0232	.2570	-.2624
	(.0461)	(.2418)	(.3018)	(.0376)	(.1950)	(.2300)
$\ln c^*$	.0010	-.0265*	.0233*	-.0012	-.0234*	.0333*
	(.0022)	(.0106)	(.0110)	(.0018)	(.0088)	(.0093)
Age	-.0042*	.0241*	-.0141	-.0037*	.0231*	-.0061
	(.0019)	(.0105)	(.0111)	(.0015)	(.0081)	(.0087)
Age^2	.0000	-.0002	.0002	.0000	-.0002	.0001
	(.0000)	(.0001)	(.0001)	(.0000)	(.0001)	(.0001)
Married	-.0145*	.2800*	-.0387	-.0095*	.3137*	-.1017*
	(.0056)	(.0319)	(.0290)	(.0044)	(.0246)	(.0224)
Family size	-.0115*	.0519*	.0177	-.0130*	.0447*	.0373*
	(.0030)	(.0161)	(.0149)	(.0024)	(.0128)	(.0122)
No. children	-.0008	.0816*	-.0376*	.0011	.0996*	-.0787*
	(.0034)	(.0172)	(.0171)	(.0027)	(.0140)	(.0141)
No. children [0-5]	-.0040	.0647*	-.0395	-.0032	.0714*	-.0419*
	(.0039)	(.0183)	(.0248)	(.0031)	(.0145)	(.0192)
Disabled	.0020	-.0001	.0332	.0095	.0252	-.0549
	(.0075)	(.0340)	(.0471)	(.0058)	(.0280)	(.0367)
Black	.0076	-.1142*	.0943*	.0061	-.0765*	.0997*
	(.0056)	(.0284)	(.0306)	(.0045)	(.0232)	(.0244)
Intercept	8.892*	5.514*	7.005*	8.853*	5.053*	7.575*
	(.1849)	(.9779)	(1.214)	(.1532)	(.7873)	(.9767)
R-squared	.06	.24	.14	.05	.25	.14
Hausman test for endogeneity of $\ln w^*$ and $\ln c^*$ (robust Wald statistic)	21.77 [.00]	4.37 [.11]	30.03 [.00]	19.26 [.00]	17.00 [.00]	28.25 [.00]
Observations		9,724			14,224	
Persons		1,868			3,163	

Notes: All estimations include area and year dummies, plus λ interacted with dummies for year. Heteroskedasticity robust standard errors clustered at the individual level and corrected for the presence of generated regressors are in parentheses. Probability values are in brackets. * Significant at 5%.

TABLE 4—MARGINAL RATE OF SUBSTITUTION EQUATIONS FOR THE ALLOCATION OF TIME. SYSTEM GMM ESTIMATES

	Dependent variables					
		(1) Hourly paid sample			(2) Full sample	
Independent variables	$\ln l^*$	$\ln h^*$	$\ln n^*$	$\ln l^*$	$\ln h^*$	$\ln n^*$
$\ln w^*$	-.0587*	-.1825*	.5223*	-.1132*	-.6774*	.8617*
	(.0239)	(.0912)	(.1142)	(.0365)	(.1546)	(.1666)
$\ln p^x$	-.0857	-.0050	.3131	.0215	.1155	-.0038
	(.0719)	(.2088)	(.2877)	(.0433)	(.1789)	(.2218)
$\ln p^s$	-.1812	.2126	-.5869	.0507	.5904*	-.7059*
	(.1395)	(.2534)	(.3498)	(.0527)	(.2356)	(.2736)
$\ln c^*$	.1071	-.0923	-.5058	.1136*	.0311	-.3832
	(.0557)	(.2201)	(.2837)	(.0467)	(.2023)	(.2203)
Age	-.0059*	.0251*	-.0116	-.0021	.0414*	-.0224
	(.0025)	(.0105)	(.0121)	(.0024)	(.0102)	(.0116)
Age^2	.0001*	-.0002	.0001	.0000	-.0004*	.0002
	(.0000)	(.0001)	(.0002)	(.0000)	(.0001)	(.0001)
Married	-.0444*	.3123*	.0876	-.0376*	.3584*	-.0339
	(.0192)	(.0757)	(.0971)	(.0168)	(.0740)	(.0805)
Family size	-.0180*	.0518*	.0521*	-.0243*	.0154	.0922*
	(.0047)	(.0195)	(.0233)	(.0045)	(.0188)	(.0202)
No. children	.0079	.0793*	-.0882*	.0116*	.1035*	-.1159*
	(.0060)	(.0241)	(.0297)	(.0054)	(.0227)	(.0249)
No. children [0-5]	.0103	.0661*	-.1301*	.0172*	.1217*	-.1400*
	(.0082)	(.0314)	(.0419)	(.0072)	(.0305)	(.0349)
Disabled	.0165	.0074	-.0643	.0297*	.0663	-.1470*
	(.0115)	(.0395)	(.0577)	(.0099)	(.0397)	(.0499)
Black	.0287*	-.1324*	-.0083	.0270*	-.0898	.0374
	(.0139)	(.0557)	(.0719)	(.0117)	(.0516)	(.0561)
Intercept	9.695*	5.702*	10.56*	8.039*	3.323*	11.32*
	(.9621)	(1.528)	(2.026)	(.3289)	(1.390)	(1.612)
Hansen J test of overidentifying restrictions (OR)		No. OR: 3 5.39 [.15]			No. OR: 0	
Wald test of joint significance of λ interacted with year dummies	27.26 [.02]	17.50 [.23]	62.19 [.00]	31.28 [.01]	12.75 [.55]	42.31 [.00]
Wald test of the hypothesis						
$\beta_j^n + \frac{l}{n}\beta_j^l + \frac{h}{n}\beta_j^h = 0 : j = 1$		8.56 [.00]			.00 [.98]	
$j = 2$		.01 [.92]			1.24 [.27]	
$j = 3$		5.25 [.02]			.75 [.39]	
$j = 4$		1.07 [.30]			.55 [.46]	
Observations		9,724			14,224	
Persons		1,868			3,163	

Notes: All estimations include area and year dummies, plus λ interacted with dummies for year. Heteroskedasticity robust standard errors clustered at the individual level and corrected for the presence of generated regressors are in parentheses. Probability values are in brackets. * Significant at 5%.

TABLE 5—MARGINAL RATE OF SUBSTITUTION EQUATIONS FOR THE ALLOCATION OF TIME. INTERTEMPORALLY NON-SEPARABLE PREFERENCES AND NON-SEO PORTION OF PSID. SYSTEM GMM ESTIMATES. SELECTED COEFFICIENTS

	Dependent variables					
	(1) Intertemporally non-separable preferences			(2) Non-SEO portion of PSID		
Independent variables	$\ln l_t^*$	$\ln h_t^*$	$\ln n_t^*$	$\ln l_t^*$	$\ln h_t^*$	$\ln n_t^*$
$\ln w_{t+1}^*$	.1074	.8936*	-.5681			
	(.0845)	(.4500)	(.4216)			
$\ln w_t^*$	-.3412	-2.624*	2.087	-.0997	-.9322*	.9737*
	(.2231)	(1.190)	(1.115)	(.0538)	(.2600)	(.2721)
$\ln w_{t-1}^*$	.1132	.8469*	-.6446			
	(.0797)	(.4258)	(.4012)			
$\ln p_{t+1}^x$	.1369	-.2285	-.5138			
	(.0947)	(.5374)	(.4984)			
$\ln p_t^x$	-.2439	.5267	.7418	-.1034	.3017	.3586
	(.1316)	(.7494)	(.7021)	(.0634)	(.3126)	(.3627)
$\ln p_{t-1}^x$	.1681	.1138	-.3599			
	(.1064)	(.5839)	(.5693)			
$\ln p_{t+1}^s$	-.1423	-.4691	.4738			
	(.1333)	(.7441)	(.6915)			
$\ln p_t^s$	.4659	2.057	-2.285	.1156	.4959	-.9473
	(.2714)	(1.451)	(1.365)	(.0860)	(.4328)	(.4936)
$\ln p_{t-1}^s$	-.3399	-1.212	1.415			
	(.1890)	(.9983)	(.9572)			
$\ln c_t^*$	.1220*	.2970	-.6053*	.1234	.2068	-.4132
	(.0577)	(.2938)	(.2805)	(.0703)	(.4083)	(.4088)
Wald test of joint significance of one-period forwarded and lagged variables	6.71 [.35]	4.71 [.58]	7.56 [.27]			
Wald test of the hypothesis						
$\beta_j^n + \frac{l}{n}\beta_j^l + \frac{h}{n}\beta_j^h = 0 : j = 1$		1.36 [.24]			.01 [.94]	
$j = 2$		.21 [.64]			.34 [.56]	
$j = 3$		.86 [.35]			.35 [.55]	
$j = 4$		.01 [.92]			1.56 [.21]	
Observations		9,544			6,504	
Persons		2,231			1,202	

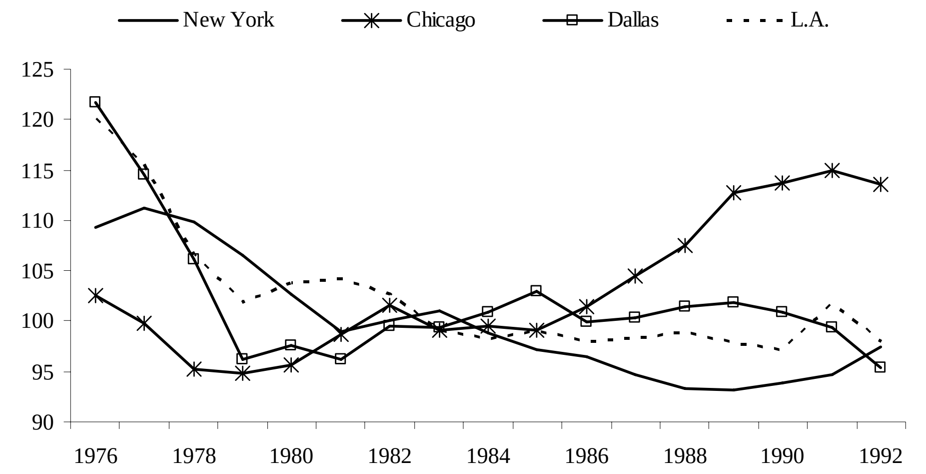
Notes: All estimations include area and year dummies, λ interacted with dummies for year, and the other regressors listed in Table 4. Heteroskedasticity robust standard errors clustered at the individual level and corrected for the presence of generated regressors are in parentheses. Probability values are in brackets. * Significant at 5%.

TABLE C.1—DESCRIPTIVE STATISTICS

	Hourly paid sample			Full sample	
Variable	All	Working	Hourly paid	All	Working
l^*	6,311 (837)	6,193 (754)	6,172 (717)	6,450 (888)	6,226 (751)
h^*	1,093 (742)	994 (650)	943 (594)	1,151 (801)	963 (648)
n^*	1,356 (799)	1,573 (632)	1,645 (566)	1,159 (888)	1,571 (649)
w^*		7.5 (3.9)	7.3 (3.6)		8.2 (4.5)
w^{**}			6.6 (2.6)		
c^*	840 (699)	849 (698)	823 (663)	874 (739)	896 (731)
Age	37.5 (9.3)	37.5 (9.2)	37.5 (9.2)	38.2 (9.9)	37.6 (9.4)
Experience (years)	13.5 (7.8)	14.1 (7.6)	14.1 (7.6)	12.7 (8.1)	14.1 (7.7)
Married (%)	70.3	68.5	65.4	70.8	68.8
Family size	3.4 (1.5)	3.3 (1.5)	3.3 (1.5)	3.4 (1.6)	3.2 (1.5)
Children	1.4 (1.3)	1.3 (1.2)	1.3 (1.2)	1.3 (1.3)	1.2 (1.2)
Children [0-5]	.4 (.7)	.4 (.6)	.4 (.7)	.4 (.7)	.3 (.6)
Disabled (%)	9.5	8.3	7.9	12.1	8.4
Black (%)	38.3	39.0	40.1	35.2	35.4
Person-years	11,282	9,724	5,486	19,286	14,224
Persons		1,868		3,917	3,163

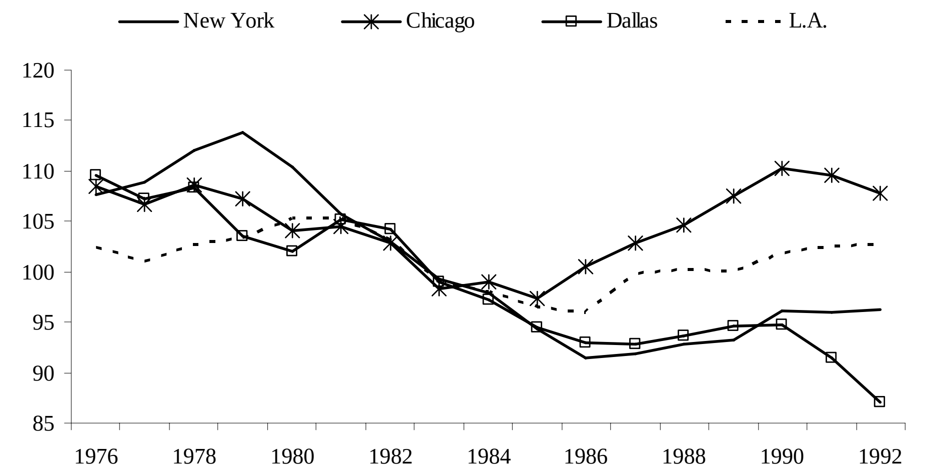
Notes: Figures are sample means or proportions (in %), plus standard deviations (in parentheses). Monetary variables are expressed in 1982-1984 dollars. l^*: Annual hours of leisure, calculated as 8,760-h^*-n^*. h^*: Annual hours of home production, including cooking, cleaning, and doing other work around the house. n^*: Annual hours of market work, including time in the main job, secondary job(s), and overtime. w^*: Average hourly wage. w^{**}: Straight-time hourly wage of hourly-paid workers. c^*: Annual expenditure on restaurants. *Experience*: Accumulated years with positive market time since age 18. *Children (*respectively, *Children [0-5])*: Number of persons in the family unit younger than 18 (6).

FIGURE 1(a)—RELATIVE PRICE OF RECREATION GOODS
SELECTED U.S. METROPOLITAN AREAS (1982-84=100)



Source: U.S. Bureau of Labor Statistics, CPI-All Urban Consumers. The index for the relative price of recreation goods is obtained dividing the CPI category "Entertainment" by "Food away from home". Metropolitan areas are referred to by the name of their central city.

FIGURE 1(b)—RELATIVE PRICE OF HOME CONSUMPTION GOODS
SELECTED U.S. METROPOLITAN AREAS (1982-84=100)



Source: U.S. Bureau of Labor Statistics, CPI-All Urban Consumers. The index for the relative price of home consumption goods is obtained dividing the CPI category "Food at home" by "Food away from home". Metropolitan areas are referred to by the name of their central city.