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Revisiting the Role of Home Production in Life-Cycle Labor Supply

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Abstract

This paper revisits the argument, posed by Rupert, Rogerson, and Wright (2000), that estimates of the intertemporal elasticity of labor supply that do not account for home production are biased downward. I use the American Time Use Survey, a richer and more comprehensive data source than those used previously, to replicate their analysis, but I also explore how other factors interact with household and market work hours to affect the elasticity of labor supply. An exact replication of their analysis yields an elasticity of about 0.4, somewhat larger than previously estimated. Once I account for demographics and household characteristics, particularly the number of children in the household, the estimate is essentially zero. This is true even when accommodating extensive-margin labor adjustments. Households' biological inability to smooth childbearing over the life cycle and the resulting income effect on market work hours drive this result.

JEL Codes: D13, D91, J22
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1. Introduction

The intertemporal elasticity of labor supply plays a critical role in business cycle theory, yet there still exists a debate on its magnitude over the long run. Early real business cycle models, such as that of Kydland and Prescott (1982), postulate a relatively high elasticity, while micro labor studies of supply decisions over individuals' life cycles (MaCurdy, 1981; Altonji, 1986) find elasticity estimates that are positive but economically small. Rupert, Rogerson, and Wright (1995, 2000) argue that the estimates from these micro studies are biased downward because they neglect the role of household production in the labor supply decision and its behavior over the life cycle. When they include time spent on non-market work in their analysis, they find estimates of the elasticity of labor supply that are considerably larger, though still lower than those posited by macroeconomists.

This paper revisits the role of household production in the labor supply decision over the life cycle. It does so using data from the American Time Use Survey (ATUS). Previous studies generally appealed to either individual panel data (e.g., MaCurdy, 1981; Altonji, 1986) or time-use data (Rupert, Rogerson, and Wright, 2000, henceforth RRW). The panel data do not have information on time spent outside of market work, while the earlier time-use data come from relatively small surveys with limited labor market information. The ATUS, on the other hand, is considerably larger, and since it is drawn from the Current Population Survey (CPS), it contains a wealth of labor market information.

I replicate the RRW analysis using the ATUS data from 2003 through 2007, which involves estimating the elasticity of labor supply using data on male workers aggregated into synthetic age cohorts. I obtain estimates that are slightly higher than those found by Rupert, Rogerson, and Wright. Including household work hours in their study produces labor supply elasticity estimates between 0.22 and 0.34. Including household work hours with the ATUS data produces estimates between 0.33 and 0.40. In every specification, the inclusion of household work hours produces a considerably higher estimate than the regressions in which they are ignored.

The RRW analysis is not ideal, however. For one, RRW focus only on male workers. In addition, RRW do not account for household characteristics, such as the hours or earnings of the spouse and the number of children in the household, in addition to home production. Finally, they do not account for extensive-margin labor adjustments, i.e., whether or not the individual chooses market work at all. All three issues arise in most studies of intertemporal labor supply. Regarding the first issue, the ATUS data allow me to construct finer synthetic cohorts, disaggregated by gender, marital status, and other demographics. I estimate the elasticity separately for each demographic group and also use a fixed effects specification on a panel of cohorts that controls for demographic characteristics. The first approach produces similar estimated elasticities, between 0.22 and 0.35, for most groups. The second approach, however, yields significantly lower estimates. Including household work when using the fixed effects approach produces an estimated elasticity between 0.09 and 0.11.

I also have data that allow me to control for household characteristics. Arguably, at least some substitution between home work and market work over the life cycle is driven by things like the number of children in the household and the employment behavior of one's spouse. Controlling for these characteristics reduces the effect of including household work hours on the estimated elasticity of labor supply further. The estimate from using age cohort data (analogous to the RRW approach) falls to 0.18, and the estimate from using the panel of finer demographic cohorts falls to 0.05, which is about the same estimate obtained if one ignores both household work and household characteristics. From an economic standpoint, it is essentially zero.

Finally, I explore the effect of accounting for extensive labor adjustments on the estimated elasticity of labor supply. Seminal work by Hansen (1985) and Rogerson (1988) suggests that labor is indivisible and that the participation decision, rather than hours adjustment, matters more for macroeconomic fluctuations in labor supply. Fiorito and Zanella (2008) estimate a small elasticity of labor supply at the micro level (analogous to the estimation in this paper and related studies), but estimate a much larger elasticity when they aggregate across all individuals. The difference is accounted for primarily by extensive-margin adjustments. Since the ATUS is cross-sectional, it does not allow an ideal examination of the role of the extensive margin. Therefore, I bound the estimates using two estimation approaches. The approach for the upper bound includes all individuals (including the non-employed) when aggregating the hours measure into synthetic cohorts and imputes the average wage for the cohort for these individuals (equivalent to setting the non-employed wages to "missing.") The approach for the lower bound includes only the non-employed who were employed in their final CPS interview and assigns them their wage from that interview. Expanding the study to these two groups increases the elasticity estimate when household work is included from 0.29 to 0.86 (first approach) or 0.35 (second approach). Both estimates are much higher than the case in which household work hours are omitted. When I add the controls for demographics and household characteristics, and in particular, the number of children in the household, the elasticity estimate falls to almost zero in both cases.

These results suggest, as RRW argue, that accounting for hours worked at home is an important part of estimating the intertemporal elasticity of labor supply over the life cycle. Other factors such as demographics and the work behavior of other household members are at least as important. The number of children in the household is particularly important for explaining the movement of market work hours over the life cycle. Intuitively, it is biologically impossible to smooth childbearing over the life cycle. This gives a hump shape to the number of children in the household over the life cycle that peaks when individuals are in their thirties. Increasing the number of children in the household increases the demand for household consumption. So long as some portion of this consumption cannot be produced at home, this will produce an income effect that increases market hours supplied, giving them a similar hump shape over the life cycle. Based on my estimates, movements in market work hours over the life cycle are dominated by this income effect. Accounting for these children in addition to household work and demographics produces an estimated elasticity of labor supply that is essentially zero.

2. Model

2.A. Labor Supply Theory

I motivate my analysis with a standard model of lifetime labor supply. The model appears in various forms in numerous studies of the intertemporal elasticity of labor supply, including the RRW study.[1] In the model, individuals maximize lifetime utility subject to an intertemporal budget constraint. Like RRW, I assume that consumers receive utility from a composite consumption good, c_{it}, and household goods and services. The consumption good must be purchased in the market at a numeraire price, while household goods and services can either be purchased in the market at a price p_t or produced at home. The amount of household goods required at any point in time, Z_{it}, is determined exogenously and can vary over the life cycle. For now, one can think of changes in Z_{it} over time as changes in household characteristics such as the number of children in the household. At age t, individual i allocates her time between market work, h_{it}^m, which earns a real wage w_{it}, household work, h_{it}^H, and leisure. The individual solves

$$\max_{c_{it}, x_{it}, h_{it}^m, h_{it}^H} \sum_{t=1}^{T} \beta^t \left[u\left(c_{it}, x_{it} + g(h_{it}^H)\right) - v\left(h_{it}^m, h_{it}^H\right)\right],$$

subject to

i.) $$\sum_{t=1}^{T} (1+r)^{-t} \left(c_{it} + p_t x_{it}\right) = A_0 + \sum_{t=1}^{T} (1+r)^{-t} w_{it} h_{it}^m ,$$

ii.) $Z_{it} \leq x_{it} + g(h_{it}^H)$, and

iii.) $H \geq h_{it}^m + h_{it}^H \geq 0$,

where x_{it} is the amount of household goods and services purchased in the market and A_0 is the initial level of assets. Household goods and services are produced at home using the production function $g(h_{it}^H)$, with $g' > 0$, $g'' \leq 0$, and $g(0) = 0$. The total per period time

[1] The seminal examples include Lucas and Rapping (1969), Ghez and Becker (1975), MaCurdy (1981), and Altonji (1986).

endowment is H, the discount rate is β, and the real interest rate is r. As is typical in the literature, I assume that utility is additively separable in hours and consumption.

Given this formulation and assuming an interior solution, the first-order conditions are

(1.1) $$\beta^t U_{1,it} = (1+r)^{-t} \lambda_{it} ,$$

(1.2) $$\beta^t U_{2,it} = (1+r)^{-t} \lambda_{it} p_t + \mu_t ,$$

(1.3) $$\beta^t v_{m,it} = (1+r)^{-t} \lambda_{it} w_{it} \text{, and}$$

(1.4) $$\beta^t \left(g' U_{2,it} - v_{H,it} \right) = \mu_{it} .$$

The Lagrange multiplier on the budget constraint is λ_{it}, which represents the marginal utility of wealth, and the Lagrange multiplier on the provision of household goods and services is μ_{it}. Equation (1.3) usually forms the basis for estimating the intertemporal elasticity of labor supply over the life cycle. For example, if as in RRW, one lets $v(\cdot) = \phi\left(h_{it}^m + h_{it}^H\right)^\gamma$, one can express (1.3) in logs as

(2) $$(\gamma - 1)\ln\left(h_{it}^m + h_{it}^H\right) = \ln \lambda_{it} - \ln \gamma\phi - t \ln \beta(1+r) + \ln w_{it} .$$

The intertemporal elasticity of labor supply in this case would be $1/(\gamma - 1)$, which one could theoretically estimate through (2) using OLS. In the empirical section, I appeal to a more general form of $v(\cdot) = \phi h_{it}^{m\,\gamma_1} h_{it}^{H\,\gamma_2}$, which allows for imperfect substitution between market work and household work. The first-order condition in this case is

(3) $$(\gamma_1 - 1)\ln h_{it}^m = \ln \lambda_{it} - \ln \phi\gamma - t \ln \beta(1+r) + \ln w_{it} - \gamma_2 \ln h_{it}^H .$$

Again, one can recover the labor supply elasticity, now measured as $1/(\gamma_1 - 1)$ and interpreted as an elasticity of *market* labor supply, from (3) using OLS. The key point of the RRW study is that the omission of hours of household work from the estimating equation will introduce a downward bias in the estimated elasticity of labor supply.

2.B. Empirical Considerations

Even if one correctly includes a measure of household work hours in the estimation of (3), other issues make it difficult to obtain consistent estimates of the elasticity using available data sources without some strong assumptions. There have generally been two empirical approaches to estimating the intertemporal elasticity of labor supply. The first, used prominently by MaCurdy (1981), Altonji (1986), and more recently by Imai and Keane (2004) and Chang and Kim (2006), involves appealing to longitudinal household micro-data, such as the Panel Study of Income Dynamics (PSID) or the National Longitudinal Survey of Youth (NLSY). The use of longitudinal data is appealing because it allows a first differencing of the data and hence an estimation of the labor supply elasticity that accounts for unobservable individual characteristics. In addition, these data include plausibly valid proxies for the marginal utility of wealth, such as food expenditures (PSID) or assets (NLSY).

The data have shortcomings, though. For one, earnings and work hours are measured at an annual frequency. As Altonji (1986) and others acknowledge, the ratio of reported annual earnings to annual hours produces a wage measure that suffers from some degree of measurement error. Since this wage measure uses the dependent variable from (3) in its denominator, any measurement error in hours will be negatively correlated with the measurement error in the wage, creating a downward bias in the elasticity estimate. The proxies for the marginal utility of wealth may also be inadequate. Recent work by Aguiar and Hurst (2005) suggests that food expenditures may be a poor proxy for consumption in this setting because individuals tend to substitute time for money in food consumption over the life cycle.[2] The asset measure in the NLSY79 is a suitable measure of wealth, but annual data are available only for individuals up to 36 years of age in the NLSY79, forcing Imai and Keane (2004), who use the data in their study, to use simulated data for later years of the life cycle. This is problematic because one would expect the wealth effects to matter most in these later years. The biggest issue with the longitudinal data from the perspective of this study, though, is their lack of information on time spent on anything besides market work, including hours of household work.

The second empirical approach involves aggregating cross-sectional household data into synthetic age cohorts and estimating the intertemporal elasticity of labor supply using the cohort observations. This was the approach used in early studies by Ghez and Becker (1975) and Smith (1977) and the household production study by Rupert, Rogerson, and Wright (2000). It is also the approach used in this study. The use of age cohorts also has its shortcomings, the inability to follow specific individuals not the least of them, but given that time-use data are not longitudinal, the approach is necessary if one wants to include data on time use outside of market work in the analysis. One issue is whether the marginal utility of wealth, λ_t, interpreted as the marginal utility for a representative agent when using age cohorts, is constant over the life cycle. The RRW study addresses this issue by assuming complete markets for the representative agent, so that the agents can perfectly smooth their consumption over the life cycle, and a balanced growth path for wages. I appeal to these same assumptions in this study.

[2] Specifically, with detailed time-use and expenditure data, Aguiar and Hurst show that individuals tend to spend more time shopping for bargains and preparing food later in their life cycle, reducing their food expenditures but keeping their food consumption essentially constant.

3. Data

I use the time diary data from the American Time Use Survey (ATUS) produced by the Bureau of Labor Statistics (BLS). I pool the data for all individuals in the survey years 2003 through 2007. The pooled panel contains demographic, labor market, and time use information for 72,922 individuals. This is a large increase in the number of observations used in previous studies, in many cases by an order of magnitude.[3] Individuals are sampled from the outgoing rotation groups of the Consumer Population Survey (CPS). Each respondent keeps a detailed time diary for one full day, and respondents' activities are classified into a wide range of categories. Respondents are also re-interviewed about their current labor market situation, with the time-use survey asking many of the same questions as in the standard CPS survey. The survey also collects basic information about the household and includes the responses from the final month in the CPS for *all* household members.[4]

Respondents report their time diaries for a single day, which can prove problematic for identifying employed individuals. Namely, full-time workers who report on a weekend will likely report zero work hours and would incorrectly be identified as non-employed if one were to use the time-use work hours to determine employment status. Luckily, respondents also report their "usual" weekly hours at their current jobs. I use this information to identify employed individuals. This results in a sample of 16,787 males and 18,834 females between the ages of 22 and 62 that have positive "usual" hours and positive reported wages.

[3] For example, MaCurdy uses 5,130 person-year observations and Altonji uses between 3,269 and 10,036 person-year observations from the PSID, while RRW use either 799 or 1,165 individual observations pooled from three different time-use surveys.

[4] The final CPS interviews occur 2 to 5 months prior to the ATUS interview. I note potential measurement issues with this timing below.

Given the potential for day-of-week bias in the responses for time use, I aggregate respondents into synthetic weeks prior to my creation of the synthetic cohorts. The aggregation groups respondents into those reporting on a weekday, Saturday, or Sunday, with holidays treated as Sundays. It then calculates the (sample-weighted) mean of the time devoted to each activity by day-of-week group and age cohort and aggregates these means to a weekly total. Even though I identify employed individuals through the usual work hours measure, I use the work hours derived from this synthetic week aggregation in the regression analysis so that they are consistent with the measured time spent in other activities.

The work hours measure includes all time spent working on the job (including multiple jobs), including time in work-related activities (e.g., business-related outings), and down time at work (e.g., lunch breaks). It does not include time spent commuting or searching for work. I also replicate my analyses using various other definitions of work hours, including just the "core" time spent working at all jobs, a total work time measure that includes commuting and job search, and the total usual work hours measure. All measures produce very similar results. I measure household work hours as the total time spent in housework, child and adult care, pet care, vehicle care, shopping for goods, and purchasing services. They are aggregated into synthetic weeks and then synthetic age cohorts in the same manner as work hours.

Real wages are measured as total weekly earnings (deflated by the CPI) divided by total usual work hours. Earnings are reported as part of the re-interview information. The measure is a considerable improvement over those used in previous studies. First, the information is up to date and of high enough frequency to be a reliable measure of the current price paid for market work. The longitudinal data used in the earlier studies (MaCurdy, 1981; Altonji, 1986) relied on annual earnings and hours data, where the propensity for measurement error was high. Second, the wages reported correspond to the individuals reporting the time-use data. The RRW study used wages from an outside source—they matched CPS wage data to the time-use data at the age-cohort level—which is likely also fraught with measurement error.

Table 1 reports the average wage and time spent by individuals aged 22 to 62 in various activities. It reports the estimates for all workers (male and female) and married male workers.[5] Male workers have higher wages and considerably more hours of market work than female workers, 42.0 to 34.9, but women have more hours in household work, 26.4 to 17.2. The difference in household work is higher for housework, child care, and purchasing goods and services. Combined, women perform about two hours more total work and engage in 5.2 hours less leisure and socializing than male workers.

Figure 1 shows the behavior of wages, market work, and household work for workers over the life cycle. I show the trends of each using a fourth-order polynomial. Again, the differences between male and female workers are clear. Aside from the obvious differences in levels, there are also differences in the life-cycle patterns. The market work hours of male workers increase during their twenties and thirties, while the hours of female workers are mostly flat until their late fifties. Female workers have greater changes in their household work hours over the life cycle, though. Male workers also have a wage profile that rises throughout their life cycle, while the wages of female workers flattens out in their late thirties.

[5] For a more detailed analysis of individual time-use patterns over time, see Aguiar and Hurst (2007). I draw my distinctions for types of market and household work in part from their study.

4. Evidence on the Labor Supply Elasticity

4.A. Replication of Previous Findings

The main purpose of this paper is to compare my estimates of the intertemporal elasticity of labor supply over the life cycle to earlier estimates when home production is included. The natural starting point is to replicate the earlier research with the ATUS data. I focus on the results from the RRW study, since theirs is the only other analysis that looks at the role of home production. RRW pool their time-use data and aggregate them into age cohorts. They then estimate the regression in equation (2) for male workers aged 22 to 62 using the synthetic age cohorts as their observations. They use several alternative specifications for the $v(h)$ function, which include $v(h) = \phi h_{it}^{\gamma}$, $v(h) = -\phi(112 - h_{it})^{\gamma}$, $v(h) = -\phi(168 - s_{it} - h_{it})^{\gamma}$, and $v(h) = \phi \exp\{\gamma h_{it}\}$, where $h_{it} = h_{it}^{m} + h_{it}^{H}$, H = 112 is a measure of total hours that deducts 56 hours per week for sleep, and s_{it} is a measure of reported actual time spent sleeping and on personal care. They estimate their regressions weighting by cohort size and weighting by the variance of work hours.

Table 2 reports the results of replicating the RRW analysis using the ATUS data alongside the original estimated labor supply elasticities from their study. I report only results weighted by cohort size, since the variance-weighted results are nearly identical.[6] In their study, RRW find that ignoring household work produces an estimated labor supply elasticity between 0.09 and 0.13, while accounting for it produces substantially

[6] As RRW do, I also replicate the results for 22-45 year olds. The results are qualitatively similar to those reported in Table 2. In addition, I replicate the results using the reported usual work hours, “core” work hours, and all work time, including commuting and job search. The usual hours measure produces slightly higher estimates. The other measures of work hours produce nearly identical estimates to those reported.

higher elasticities, on the order of 0.22 to 0.34. Using the ATUS data, I find somewhat higher elasticities when ignoring home production for all but the specification that accounts for variations in sleep and personal care. The other three elasticity estimates range from 0.11 to 0.21. When I include household production in the regressions, all four specifications produce higher elasticity estimates than the case when household work is excluded and produce higher elasticity estimates than those found by RRW. The elasticity estimates when household work is included range from 0.33 to 0.40. In addition, the estimates imply larger biases from the exclusion of household work than those found by RRW. Including household work in their study increases the point estimate of the elasticity between 10 and 24 basis points, while including household work with the ATUS data increases the point estimate between 18 and 31 basis points.

If anything, the replication of the RRW study using a more robust source of time-use data reinforces their finding that accounting for household production is important for consistently estimating the intertemporal elasticity of labor supply. This direct replication of their specifications produces estimates that are near the upper bound of those found in previous studies (e.g., Ghez and Becker, 1975; MaCurdy, 1981; and Altonji, 1986), which find estimates ranging between -0.06 and 0.45.

4.B. Accounting for Demographics and Household Characteristics

The data used in earlier studies often did not allow a thorough analysis of the labor supply elasticity by demographics. Analyzing the behavior of women proved particularly difficult. For one thing, the data sets used produced very small sample sizes of both male and female workers. In addition, the time periods over which most of these studies occur (the 1960s and 1970s) are when women's labor force participation was substantially lower than it is now. The estimating equations similar in (2) and (3) implicitly require that individuals have positive work hours. Thus, much of the earlier work (Ghez and Becker, 1975, and Smith, 1977, are notable exceptions) focuses on either male workers or married male workers.

Luckily, the ATUS allows me to study the role of the effect of various demographic characteristics on estimates of the labor supply elasticity. I do so in two ways. In the first approach, I split the data by various demographic dimensions and estimate equation (3) using synthetic age cohorts for each demographic group. In my second approach, I use synthetic cohorts disaggregated by age and various demographic characteristics and estimate the labor supply elasticity using a fixed effects regression that controls for these characteristics.

The results of the first method are in Table 3. I estimate elasticities separately by gender, race, and education. I also include married men and white males, since previous research also used these subgroups. The results for male workers are very similar to the ATUS results in Table 2. Including household work hours on the right-hand side of the regression (rather than as part of the dependent variable) reduces the elasticity estimate only slightly, from 0.39 to 0.34.[7] White men have a similar response to the inclusion of household work. Married men also have a similar response (about a 15 basis-point increase in the point estimate), but much lower elasticity estimates overall. Even when household work is included, I find an elasticity of labor supply for married men of 0.10, which is statistically insignificant.

[7] One might be concerned that putting the household work hours variable on the right-hand side of the regression introduces an endogeneity issue. To check this, I replicate the analyses presented here and in the remainder of the paper with household work hours as part of the left-hand side variable, as in RRW and equation (2). Doing so changes the results only very slightly. I report these results in Appendix Tables 1-3.

As one might expect, the intertemporal elasticity of women's labor supply is more sensitive to the inclusion of household work hours, rising by 23 basis points, versus the 11 basis-point increase men experience. Overall, however, women have a lower estimated elasticity, 0.23 compared to 0.33 for men. Estimating the elasticity for all workers combined produces an increase of about 19 basis points in the labor supply elasticity, to 0.34.

Turning to the results by race, white workers have estimated elasticities similar to those for all workers. The results for Hispanic workers are similar as well, though the point estimate is slightly lower, 0.22, when home production is included. The results for black workers show considerably lower elasticities and a smaller effect of including household work. The estimated elasticity rises only 5 basis points, to 0.12.

Finally, save for the results for the college educated, splitting the data by education produces similar estimates for all groups. Accounting for household work increases the estimated elasticity by 12 to 19 basis points across the four education groupings (high school or less, some college, college, and post-graduate) and for all but the college educated produces an estimated elasticity between 0.26 and 0.30. For those with a college degree, it is 0.14.

For my second method, I use two sets of synthetic cohorts. Ideally, I would create one highly disaggregated synthetic cohort panel divided by the various demographic characteristics, but the need to aggregate the time-use data into a synthetic week within each cohort cell limits my ability to do so without creating very sparse cohort cells. I create cohorts for age-gender-partner-education groups and age-gender-partner present-race groups. For the first, I use three education groups: high school or less, some college, and college or more, and for the second, I use three race groups: Hispanic, black (non-Hispanic), and all others (which is predominantly white.) “Partner present” refers to whether respondent has a spouse or partner present in the household. I use this broader measure, rather than marital status, since the presence of a cohabitant matters more for household and market work decisions than marital status.[8] Because of small cell sizes in some categories among the very young (e.g., married individuals with college degrees), I restrict the sample to those aged 25 to 62. The panel regressions are similar to the previous regressions except that they now use $38 \times 2 \times 2 \times 3 = 456$ observations and use fixed effects to control for gender, marital status, and either education or race. As before, I use the estimating equation in (3).

The results are in Table 4. The first two columns list the OLS results for all workers grouped by age cohort using only 25 to 62 year olds. It provides a baseline for evaluating the panel data results. Comparing these results to those for all workers aged 22-62 in Table 3 shows that removing the first three years leads to somewhat lower elasticity estimates (about 6 basis points in both specifications), but otherwise produces similar results. The inclusion of household work in the OLS specification produces an estimated labor supply elasticity of 0.29. The next two columns present the results for the panel of synthetic cohorts that include education with and without household production hours, respectively. The use of finer cohort detail reduces the estimated elasticity dramatically. The estimate that includes household work is 0.11 and represents only a 7 basis-point increase over the case where household work is not included. Using cohorts

[8] Though unreported, results from using marital status rather than “partner present” are nearly identical to those reported here.

that include race rather than education produces nearly the same results, with an estimated elasticity of 0.09 when household work is included.

Household composition could also affect the elasticity of labor supply. Indeed, the model in this paper assumes an exogenous requirement of household goods and services, which the individual must either produce at home or purchase in the market. The number of children in the household can potentially drive exogenous variations in such a requirement over time.[9] In addition, while my model is for a single individual, one can easily envision a model of couples who choose their market and household work hours to jointly maximize utility.[10]

The ATUS includes information on the number of children in the household younger than 18, denoted as $child_{it}$. It also includes a wide array of demographic information on the spouses or cohabitating partners through their most recent CPS interview. I use these data to create a measure of the spouse's/partner's real hourly wage, w_{it}^{s}, in the same way that I create the respondent's real wage, and use their reported total usual hours worked as a measure of their market work hours, $h_{it}^{m,s}$.[11] Unfortunately, since only one respondent per household completes the time diary, I do not have household work hours for the spouse/partner.

[9] While many children are the result of planning by couples, there often remain uncertainties about the timing and success of an actual birth, not to mention the potential for having more than one child per birth. More important, households are generally biologically constrained to have children in the early stage of the life cycle. Thus, for a life-cycle study such as this one, it is plausible to assume that the number of children in the household is exogenous to our estimating equation.

[10] Chang and Kim (2006) derive such a model, though it does not include home production.

[11] The CPS data precede the ATUS interview data by 2-5 months. Thus, there exists the potential for measurement error that arises from potential changes in wages, hours, or labor force status during that time. CPS gross worker flow estimates that about 6 percent of workers leave their jobs each month (including those who immediately find new work; see Fallick and Fleischmann, 2004), so the issue is non-trivial. Unfortunately, I have no suitable alternative measure of partners' employment behavior.

Table 5 presents the results that include the number of children in the household and the wage and work hours of the partner. The first two columns in Table 5 correspond in specification to the first two columns of Table 4, which use only synthetic age cohorts. Including the household information raises the intertemporal elasticity of labor supply slightly, by 5 basis points, when I exclude household work. Comparing the second columns of Tables 4 and 5 shows that adding the household information to the specification where household work is included decreases the estimated labor supply elasticity by about 11 basis points, to 0.18, which is only marginally significant. Though I do not report the results, it turns out that the inclusion of the number of children, more than the partner's hours or wage, accounts for the decline in the estimated elasticity. The next two columns of Table 5 replicate the age-gender-partner present-education cohort specifications from the third and fourth columns of Table 4 with the household information.[12] In this case, including household work hours yields only a marginal increase (3 basis points) in the estimated elasticity of labor supply. In fact, when both household work hours and the household characteristics are included, the estimated elasticity is no different from what one estimates using the fixed effects specification that includes only the real wage (0.041 versus 0.046). Statistically, the point estimate is insignificant, and economically, it is essentially zero. Notably, the coefficient on the number of children in the household is positive and significant in both specifications. The partner's hours and wages are insignificant in both.

The results suggest that the inclusion of household work hours clearly addresses a downward bias in estimates of the intertemporal elasticity of labor supply. At the same

[12] Though unreported, the results by race are very similar.

time, however, it is also clear that demographics and household characteristics, particularly the number of children in the household, matter as well.

4.C. Accounting for Extensive Labor Adjustment

My last exercise explores the effect of extensive-margin labor adjustments on the estimated elasticity of labor supply. Hansen (1985) and Rogerson (1988) suggest that labor is indivisible and that the participation decision, rather than hours adjustment, matters more for macroeconomic fluctuations in labor supply. Work by Rogerson and Wallenius (2010), Chang and Kim (2006), and Fiorito and Zanella (2008) consider estimates of both a micro-level and a macro labor supply elasticity, where the latter is an aggregation of the individual-level responses. All three studies argue that one can have small micro-level elasticities and large macro elasticities because of changes in the extensive margin of labor adjustment (i.e., whether or not someone works at all). The findings in all three studies confirm this. For example, Fiorito and Zanella estimate a micro-level elasticity of 0.1 and a macro level elasticity close to 1.0, with much of the difference attributable to changes on the extensive margin.

The ATUS is cross-sectional, so it does not allow an ideal examination of the role of the extensive margin. I can, however, appeal to some features of the data to obtain upper and lower bounds of the effect of accounting for the extensive margin on the labor supply elasticity. I do so with two approaches. The first approach provides the upper bound estimate. It includes all individuals, both employed and non-employed, age 25 to 62. This increases the sample of individuals used in the analysis from 34,090 to 50,208. The market work hours of the additional individuals are obviously zero, and their household work hours are what they report in the ATUS. When aggregating individuals into synthetic cohorts, I treat the wages of the non-employed as missing, which implicitly imputes the average wage for the cohort as the wage for these individuals.

The second approach yields the lower bound estimate. It includes only the non-employed who were employed during their last CPS interview. Recall that individuals conduct their final CPS interview 2 to 5 months prior to their ATUS interview. These individuals account for nearly 15 percent of the non-employed, and including them in the creation of the synthetic cohorts increases the sample size to 36,428. As with the first approach, these individuals have zero market work hours, and I use their household work hours reported in the ATUS when including them in the creation of the synthetic cohorts. Since the CPS provides information on their last employment spell, I can use the wage from their last CPS interview as their contribution to the average wage in the creation of the synthetic cohorts. The intuition is that the prior wage provides an upper bound on the wage at which the individual would be willing to work any hours and, therefore, provides a lower bound on the response of market hours to a change in the wage (since the observed response will be with respect to a change from the last reported wage).

Figure 2 illustrates the differing behavior of hours, wages, and children in the household over the life cycle for three samples: the original sample of employed workers, the sample of all employed and non-employed individuals, and the sample of the employed plus the non-employed with a reported CPS wage. By construction, the first two samples have the same wage profile over the life cycle (observable in the upper left panel of Figure 2), and it turns out that the third sample has a wage profile that is nearly identical. The upper right panel shows how the number of children in the household varies over the life cycle. As one might expect, there is a strong hump-shaped pattern to the number of children in the household over the life cycle that peaks in the late thirties. Including all non-employed shifts the relationship up slightly in the early part of the life cycle, but the pattern still peaks around the same age. The lower left panel of Figure 2 shows that market work hours differ across the three samples. By construction, the samples that include the non-employed have lower work hours. The sample that includes the non-employed with a CPS wage has work hours that are about 2-3 hours lower, on average, but their behavior over the life cycle is very similar to the sample of the employed only. The sample of all individuals has much lower work hours over the life cycle. In addition, this sample exhibits a much sharper decline in work hours after age 50 than the other two samples. The lower right panel of the figure shows that differences across the samples in household work hours are much smaller. The sample including the non-employed with a CPS wage has household work hours that are only marginally higher than those for the employed-only sample. The sample of all individuals has between 2 and 5 hours more household work hours than the other two samples over the life cycle. It also exhibits a more pronounced rise in the thirties, fall in the fifties, and rise in the sixties than the other samples.

Table 6 presents the results of replicating four key regressions of the previous section with the two new samples. For comparison, the first column of the table lists the results from the previous tables for the employed-only sample. The second column lists the results for the sample of the employed plus the non-employed with a reported CPS wage and the third column reports the results for all individuals. Specification A includes the results of regressing the log of market work hours on the log real wage alone, and corresponds to the first column of Table 4. As one would expect, including non-employed individuals increases the estimated labor supply elasticity. The sample with reported CPS wages has an estimate of 0.16 (compared to a baseline of 0.09), and the sample of all individuals has an estimate of 0.50, more than five times the employed-only estimate. Specification B adds the log of household work hours to the regression (equivalent to the second column in Table 4). Again, the elasticity estimate increases with the number of non-employed individuals added to the sample. Including the non-employed with a CPS wage increases the estimate from 0.29 to 0.35, and including all non-employed nearly triples the estimate to 0.86.

Including controls for the number of children in the household, the partner's wage, and the partner's hours, however, reverses this trend. Specification C (corresponding to the second column of Table 5) shows no change in the elasticity estimate, which is 0.18 when the non-employed with a CPS wage are included, and a large decline, to -0.06, when all non-employed are included. The results are not much different when I use age-gender-partner present-education cohorts and a fixed effects specification. Specification D (corresponding to the sixth column in Table 5) shows that when household work hours, household characteristics, and demographics are all accounted for, the elasticity estimates across the three samples are not statistically different from each other, and in all cases are not statistically different from zero, ranging between 0.03 and 0.06.

5. Children and Hours over the Life Cycle

Surprisingly, even after accounting for household work hours, the inclusion of household characteristics implies an intertemporal elasticity of labor supply of zero essentially. Taken literally, the estimates suggest that the main reason work hours vary over the life cycle is changes in conditions within the household, and in particular, changes in the number of children in the household. The finding is consistent with a version of the model depicted earlier in which the number of children in the household determines the amount of household goods and services that can be either purchased or home-produced, Z_t, and the goods that can be purchased only in the market, c_t. Such an assumption is consistent with recent work by Browning and Ejrnæs (2009), who show that nearly all of the well-documented hump shape in consumption can be explained by changes in family composition, namely, the age and number of children in the household, over the life cycle. It is also consistent with earlier work by Browning, Deaton, and Irish (1985). For example, consider the case in which the number of children in the household, n_t, positively affects the required amount of household goods and services, $Z(n_t)$, and market goods, $c(n_t)$, and consider, in the sense of Becker (1965), the "full income" version of a one-period budget constraint for the model specified in (1). In doing so, assume that all time spent outside of market or household work is on leisure, $l_t = H - h_t^m - h_t^H$. The full-income budget constraint is then

$$wH - pZ(n_t) = c(n_t) + wl_t + wh_t^H - pg(h_t^H). \qquad (4)$$

Under this specification, the number of children in the household will have two effects. The first effect is to decrease full income (through the left-hand side of (4)), which will force the household to consume less of both the market good and leisure. The second effect is its direct increase in the consumption of the market good. Since full income is lower, this will force substitution away from leisure and home production. Leisure unambiguously falls. Whether or not hours spent on home production decrease will depend on the marginal return, i.e., whether $pg' \leq w$. If the substitution effect dominates the household supply of home production for a given level of $Z(n_t)$, then market work hours will unambiguously rise with an increase in the number of children in the household.

Adding more children makes the household "poorer" in the full-income sense. The decline in full income together with the increase in required purchased goods induces the household to supply more market work. Since it is biologically impossible to smooth the consumption required of child-rearing over the life cycle, consumption, and thus market work hours, will tend to parallel the hump-shaped pattern of the number of children in the household over the life cycle. The results presented here suggest that once one accounts for children as a driver of life-cycle movements in hours, changes in the life-cycle wage has no additional effect on hours. Controlling for children produces an intertemporal labor supply elasticity that is essentially zero over the life cycle.

6. Conclusions

This paper revisits the role of home production in the estimation of the intertemporal elasticity of labor supply over the life cycle. Rupert, Rogerson, and Wright (2000) argue that ignoring home production when estimating this elasticity will lead to a downward bias because changes in the wage over the life cycle may occur concurrently with changes in household work. Using a new, more robust data source on individual time use, I replicate the analysis of Rupert, Rogerson, and Wright and find somewhat higher estimates of labor supply elasticity than they do. I then replicate the analysis for various demographic groups, and while the point estimates vary widely, the main finding is that a higher estimated elasticity persists when household work hours are included.

I also explore the role of demographics using more disaggregated synthetic cohorts, which lets me control for several demographic characteristics simultaneously through a fixed effects specification. The estimated labor supply elasticity declines substantially. When I include the number of children in the household and the work hours and wage of an individual's partner, the estimate is essentially zero. Finally, I explore how accounting for changes in employment along the extensive margin affects the results. Including hours of household work but not household characteristics produces estimates between 0.35 and 0.86. Once household characteristics are accounted for, however, I again obtain elasticity estimates that are essentially zero.

I argue that this is because much of the life-cycle relationship between wages and household work are due to changes in household characteristics over the life cycle, namely, the number of children in the household. If the presences of children forces households to increase consumption, for which there is strong evidence that this is the case (Browning et al., 1985; Browning and Ejrnæs, 2009), then households will increase their market work hours to pay for this consumption. This will occur through a substitution toward higher consumption and away from leisure and through an income effect whereby the higher consumption requirement makes households "poorer" in the full-income sense, causing them to reduce leisure further. To the extent that the number of children in the household is hump-shaped over the life cycle, market work hours will also be hump-shaped. My results suggest that once one controls for this relationship, work hours are essentially unresponsive to changes in the wage over the life cycle.

I take from these findings the rather strong implication that, because of the strong role of household composition on life-cycle labor and consumption behavior, using variations in hours and earnings over the life cycle to infer an intertemporal elasticity of labor supply that is relevant for business cycle analysis is generally a bad idea. My findings suggest that this is true even if one controls for extensive-margin labor adjustments. Future research should explore approaches that exploit individual-level variations in hours and wages at business cycle frequencies, conditioning on life-cycle effects, to estimate an intertemporal elasticity of labor supply that is relevant for evaluating macroeconomic theory, such as real business cycle models. Exploiting the longitudinal nature of the Current Population Survey, which surveys households for four consecutive months and thus allows one to observe changes at a quarterly frequency, could be fruitful in this regard.

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Table 1. Wages and Time-Use Patterns

	All Individuals	All Workers	All Male Workers	All Female Workers	Married Male Workers
Real hourly wage (2003 $)	15.20	18.90	20.89	16.85	21.85
Usual work hours	37.76	41.73	44.89	38.29	45.82
Total reported work & work-related time	30.26	38.61	42.03	34.94	43.16
Commuting	2.52	3.26	3.75	2.73	3.93
Job search	0.23	0.06	0.06	0.06	0.04
Total household work	25.28	21.62	17.23	26.41	18.69
Housework (incl. pet and vehicle care)	13.21	11.18	9.02	13.50	9.16
Child and adult care	6.49	5.20	3.98	6.60	5.21
Shopping & purchasing services	5.59	5.24	4.24	6.31	4.32
Leisure & socializing	40.57	37.37	39.86	34.62	38.20
Personal care & sleep	65.78	64.31	62.52	66.23	61.28
N	52,454	35,621	16,787	18,834	10,920

Notes: Estimates are for the listed individuals aged 22-62 in the 2003-2007 surveys of the ATUS. Wages are in 2003 dollars. Time use is hours per week. The real wage and usual work hours use a value of zero for non-employed workers when computing their mean.

Table 2. Estimated Intertemporal Elasticities of Labor Supply

Specification	Without Household Work RRW	Without Household Work ATUS	Including Household Work RRW	Including Household Work ATUS
$y = \ln h$	0.117	0.209	0.274	0.394
	(0.119)	(0.059)	(0.072)	(0.046)
$y = \ln(112 - h)$	0.092	0.113	0.280	0.401
	(0.054)	(0.034)	(0.071)	(0.048)
$y = \ln(168 - s - h)$	0.099	0.024	0.338	0.330
	(0.054)	(0.036)	(0.084)	(0.051)
$y = h$	0.126	0.195	0.222	0.374
	(0.085)	(0.057)	(0.051)	(0.044)

Note: The table reports the regression coefficients from regressing the listed dependent variable on $\ln w_{it}$ and age. Regressions without household work use $h_t = h_{it}^m$, while those with household work use $h_t = h_{it}^m + h_{it}^H$. The columns labeled "RRW" report the results from Rupert, Rogerson, and Wright (2000), and the columns labeled "ATUS" report results when using age cohorts created from pooled ATUS data for 2003-07 for working males aged 22-62. All regressions are weighted by the size of the age cohorts. Standard errors are in parentheses.

Table 3. Estimates of the Intertemporal Elasticity of Labor Supply, Various Worker Groups

	Men		**Women**		**All Workers**		**Married Men**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
t	-0.0013	-0.0024	0.0004	-0.0011	-0.0010	-0.0024	0.0009	-0.0025
	(0.0011)	(0.0013)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0013)	(0.0018)
$\ln w_t$	0.209	0.324	-0.001	0.227	0.148	0.342	-0.084	0.079
	(0.059)	(0.096)	(0.050)	(0.063)	(0.040)	(0.068)	(0.080)	(0.098)
$\ln h_t^H$	---	-0.134	---	-0.318	---	-0.243	---	-0.256
		(0.090)		(0.067)		(0.072)		(0.099)
$\overline{R}^2$	0.36	0.38	-0.04	0.33	0.29	0.44	-0.02	0.11
	White Men		**All White**		**All Black**		**All Hispanic**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
t	-0.0012	-0.0027	-0.0012	-0.0026	0.0012	-0.0006	0.0015	0.0018
	(0.0010)	(0.0013)	(0.0006)	(0.0006)	(0.0017)	(0.0016)	(0.0018)	(0.0015)
$\ln w_t$	0.212	0.350	0.158	0.346	0.072	0.124	0.098	0.220
	(0.054)	(0.093)	(0.036)	(0.059)	(0.105)	(0.097)	(0.120)	(0.101)
$\ln h_t^H$	---	-0.151	---	-0.231	---	-0.331	---	-0.382
		(0.084)		(0.061)		(0.107)		(0.085)
$\overline{R}^2$	0.42	0.46	0.34	0.51	0.00	0.18	0.06	0.38
	High School or Less		**Some College**		**College Degree**		**Postgraduate**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
t	-0.0007	-0.0013	-0.0003	-0.0013	0.0001	-0.0006	0.0011	-0.0004
	(0.0013)	(0.0012)	(0.0016)	(0.0018)	(0.0009)	(0.0009)	(0.0020)	(0.0024)
$\ln w_t$	0.093	0.258	0.177	0.302	-0.041	0.142	0.170	0.263
	(0.127)	(0.122)	(0.096)	(0.137)	(0.050)	(0.077)	(0.127)	(0.150)
$\ln h_t^H$	---	-0.400	---	-0.134	---	-0.151	---	-0.132
		(0.118)		(0.105)		(0.052)		(0.115)
$\overline{R}^2$	-0.04	0.19	0.15	0.16	-0.03	0.14	0.07	0.08

Note: The table reports the regression coefficients from regressing $\ln h_{it}^m$ on the listed dependent variables as specified in equation (3) in the text. All regressions use age cohorts created from pooled ATUS data for 2003-07 for the listed groups of workers aged 22-62. All regressions are weighted by the size of the age cohorts. Standard errors are in parentheses.

Table 4. Synthetic Cohort Panel Regression Estimates

	Age		Age × Gender × Partner Present × Education		Age × Gender × Partner Present × Race	
	(1)	(2)	(3)	(4)	(5)	(6)
t	-0.0006 (0.0007)	-0.0022 (0.0007)	0.0004 (0.0006)	-0.0003 (0.0005)	0.0005 (0.0006)	-0.0002 (0.0005)
$\ln w_t$	0.085 (0.060)	0.286 (0.074)	0.041 (0.037)	0.107 (0.035)	0.034 (0.035)	0.094 (0.034)
$\ln h_t^H$	---	-0.263 (0.071)	---	-0.219 (0.026)	---	-0.235 (0.028)
Fixed Effects?	No	No	Yes	Yes	Yes	Yes
R^2	0.06	0.33	0.48	0.55	0.44	0.52
N	38	38	456	456	456	456

Note: The table reports the regression coefficients from regressing $\ln h_{it}^m$ on the listed dependent variables as specified in equation (3) in the text. All regressions use the noted disaggregation of cohorts created from pooled ATUS data for 2003-07 for the listed groups of workers aged 25-62. Fixed effects regressions use dummy variables for either gender, presence of partner, and education group, or gender, presence of partner, and race, as appropriate. All regressions are weighted by the size of the age cohorts. Standard errors are in parentheses.

Table 5. Synthetic Cohort Panel Regression Estimates, Controlling for Household Characteristics

	Age		Age × Gender × Partner Present × Education	
	(1)	(2)	(3)	(4)
t	-0.0026 (0.0019)	-0.0012 (0.0016)	0.0013 (0.0007)	0.0018 (0.0007)
$\ln w_t$	0.124 (0.119)	0.177 (0.102)	0.017 (0.039)	0.046 (0.036)
$\ln h_t^H$	---	-0.308 (0.084)	---	-0.259 (0.027)
$\ln child_{it}$	-0.021 (0.019)	0.010 (0.018)	0.011 (0.005)	0.026 (0.005)
$\ln w_t^s$	0.058 (0.067)	0.060 (0.057)	-0.064 (0.034)	-0.042 (0.031)
$\ln h_t^{m,s}$	-0.034 (0.113)	-0.016 (0.096)	-0.021 (0.050)	-0.022 (0.046)
Fixed Effects?	No	No	Yes	Yes
R^2	0.11	0.38	0.50	0.59
N	38	38	456	456

Note: The table reports the regression coefficients from regressing $\ln h_{it}^m$ on the listed dependent variables as specified in equation (3) in the text. All regressions use the noted disaggregation of cohorts created from pooled ATUS data for 2003-07 for the listed groups of workers aged 25-62. Fixed effects regressions use dummy variables for either gender, presence of partner, and education group. All regressions are weighted by the size of the age cohorts. Standard errors are in parentheses.

Table 6. Regression Estimates with Proxies for the Extensive Margin

Specification		Employed Only	Including Non-employed w/ CPS Wage	Including All Non-employed
A. OLS, Age cohorts, not including HH work (N = 38)	$\ln w_t$	0.085 (0.060)	0.161 (0.070)	0.501 (0.156)
	$\ln h_t^H$	---	---	---
	R^2	0.06	0.13	0.42
B. OLS, Age cohorts (N = 38)	$\ln w_t$	0.286 (0.074)	0.348 (0.077)	0.855 (0.139)
	$\ln h_t^H$	-0.263 (0.071)	-0.298 (0.078)	-0.728 (0.145)
	R^2	0.33	0.40	0.67
C. OLS, Age cohorts, controlling for HH characteristics (N = 38)	$\ln w_t$	0.177 (0.102)	0.178 (0.109)	-0.062 (0.111)
	$\ln h_t^H$	-0.308 (0.084)	-0.377 (0.093)	-0.807 (0.073)
	R^2	0.38	0.49	0.93
D. Fixed effects, Age-Gender-Partner Present-Education cohorts, controlling for HH characteristics (N = 456)	$\ln w_t$	0.046 (0.036)	0.031 (0.038)	0.063 (0.056)
	$\ln h_t^H$	-0.259 (0.027)	-0.301 (0.030)	-0.693 (0.045)
	R^2	0.59	0.60	0.75
No. of observations used in cohort creation		34,090	36,428	50,208

Note: The table reports regression coefficients from regressing $\ln h_{it}^m$ on the listed dependent variables and various controls, as specified by equation (3) in the text. Regressions use synthetic cohorts disaggregated at the level noted in the first column. Cohorts are created from pooled ATUS data for 2003-07 for individuals aged 25-62. Household characteristics include the logs of number of children in the household, the partner's hourly wage, and the partner's usual work hours. Fixed effects regressions use dummy variables for gender, presence of partner, and education group. The first column of results is for all individuals who report positive usual work hours and a positive wage. The second column is for all individuals in the previous column plus non-employed individuals who earned a positive, reported wage during their last CPS interview. The third column is for all individuals (ignoring any prior CPS wage for the non-employed). All regressions are weighted by the size of the age cohorts. Standard errors are in parentheses.

Appendix Table 1. Robustness Checks for Demographic Groups

Dependent Variable: $\ln(h_t^m + h_t^H)$					
Group	$\ln w_t$	$\bar{R}^2$	**Group**	$\ln w_t$	$\bar{R}^2$
Men	0.394 (0.046)	0.73	Women	0.295 (0.033)	0.68
All Workers	0.374 (0.028)	0.85	Married Men	0.135 (0.054)	0.26
White Men	0.412 (0.041)	0.78	All White	0.387 (0.027)	0.86
All Black	0.107 (0.063)	0.02	All Hispanic	0.183 (0.065)	0.40
High School or Less	0.198 (0.072)	0.14	Some College	0.443 (0.072)	0.60
College Degree	0.352 (0.041)	0.71	Postgraduate	0.340 (0.091)	0.23

Note: Results are a replication of Table 3, col. (2) for each group listed using household work hours as part of the dependent variable. See text for details.

Appendix Table 2. Robustness Checks for All Workers

Dependent Variable: $\ln(h_t^m + h_t^H)$				
	(1)	(2)	(3)	(4)
$\ln w_t$	0.325 (0.040)	0.134 (0.073)	0.107 (0.035)	0.046 (0.036)
Household Controls?	No	Yes	No	Yes
Fixed Effects?	No	No	Yes	Yes
R^2	0.65	0.73	0.55	0.59
N	38	38	456	456

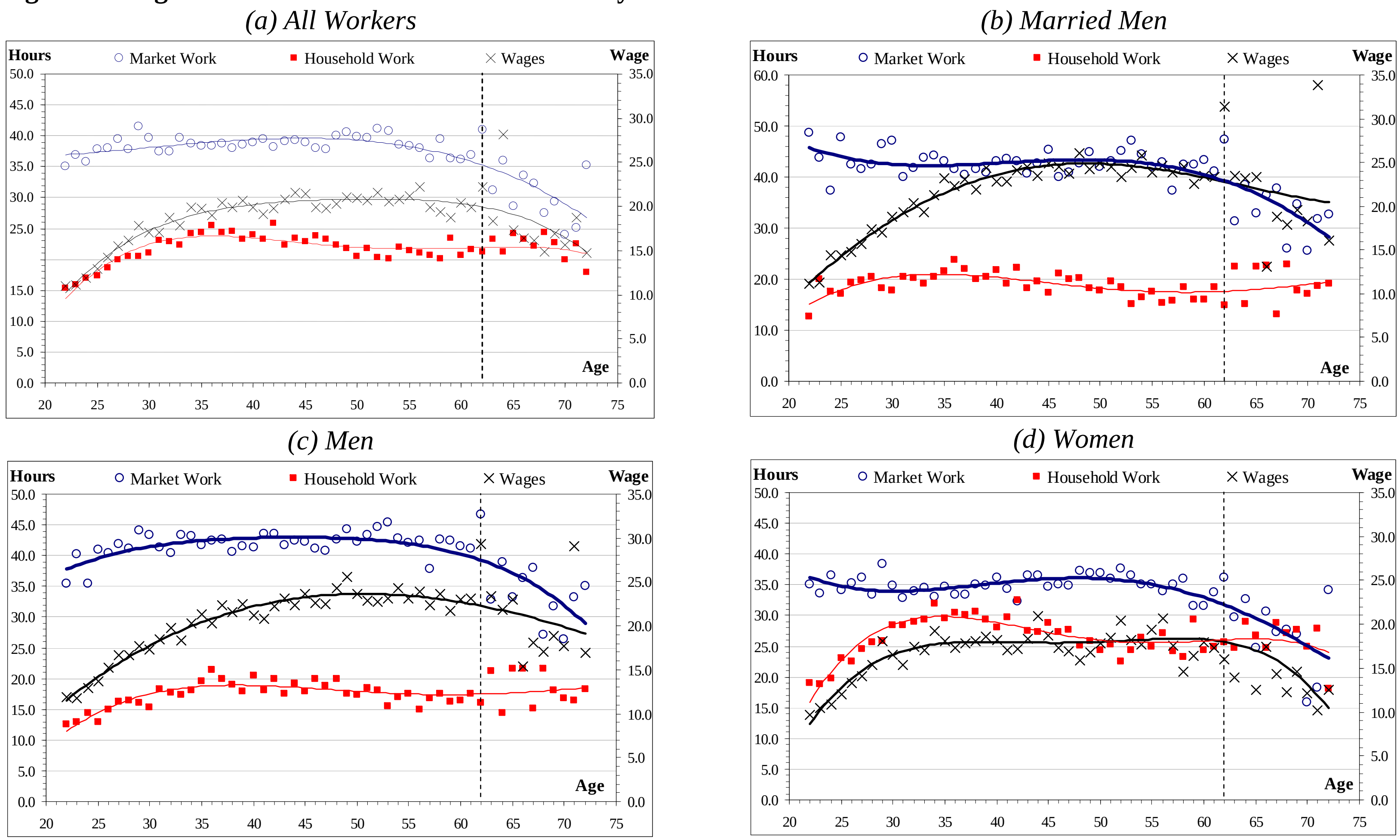
Note: Results are a replication of (in order) Table4, col. (2), Table 5, col. (2), Table 4, col. (4), and Table 5, col. (4). (i.e., using education class groups only) using household work hours as part of the dependent variable.

Appendix Table 3. Robustness Checks for All Workers and the Non-Employed

Dependent Variable: $\ln(h_t^m + h_t^H)$						
	Including Non-employed w/ CPS Wage			**Including All Non-employed**		
	(1)	(2)	(3)	(4)	(5)	(6)
ln w_t	0.338 (0.044)	0.104 (0.073)	0.031 (0.038)	0.483 (0.061)	-0.018 (0.059)	0.063 (0.056)
Household Controls?	No	Yes	Yes	No	Yes	Yes
Fixed Effects?	No	No	Yes	No	No	Yes
R^2	0.62	0.74	0.60	0.75	0.95	0.75
N	38	38	456	38	38	456

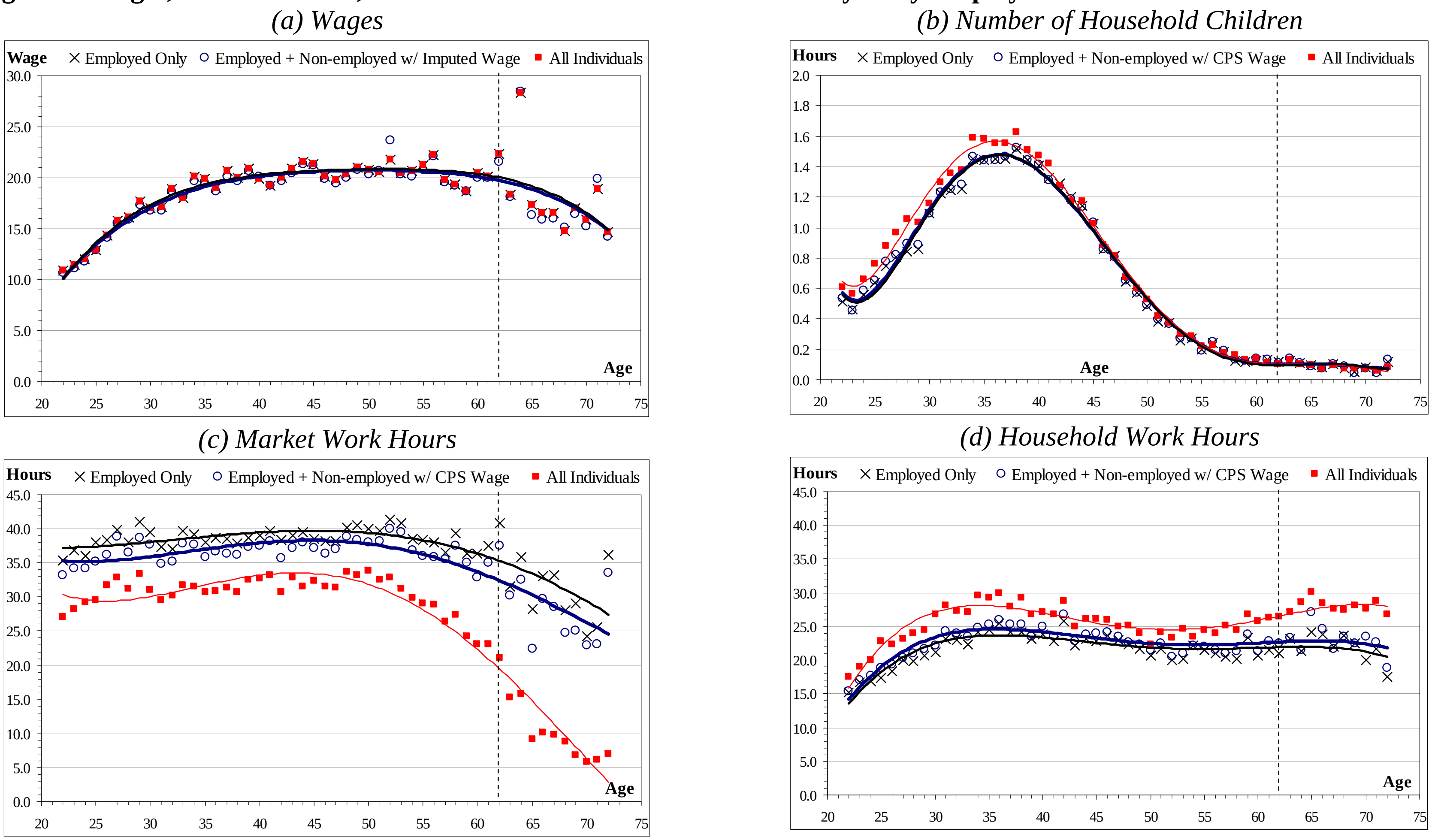
Note: replication of Table 6, rows (2) and (3) for 2nd and 3rd columns.

Figure 1. Wages and Hours Worked Over the Life Cycle



Notes: Each panel illustrates the real wage, total hours spent working and total hours spent on household work for 22 to 72 year olds reporting positive wages and work hours in ATUS data pooled over 2003 to 2007. Trends for each are estimated using a fourth-order polynomial.

Figure 2. Wages, Hours Worked, and Household Children over the Life Cycle by Employment Status



Notes: Each panel illustrates either the average real wage, hours worked, or the number of children in the household for 22 to 72 year olds by three employment states: employed and reporting a positive wage, employed or non-employed with a positive wage reported in the last CPS interview, and all individuals (with no wage reported for the non-employed.) Estimates are from ATUS data pooled over 2003 to 2007. Trends for each are estimated using a fourth-order polynomial.