Empir Econ
DOI 10.1007/s00181-015-1044-6

Dynamic labor supply adjustment with bias correction

Elizabeth Schroeder[1]

Received: 19 May 2014 / Accepted: 13 November 2015

Abstract I estimate a dynamic fixed effects hours equation for prime-age men with bias correction. Studies using household data typically find a weak response in hours of work to changes in the wage. This paper finds that rather than indicating a small elasticity of intertemporal substitution, the weak dependence of hours on wages is the result of delayed adjustment. The coefficient on the lagged dependent variable is found to be between 0.31 and 0.33, which suggests that it takes 1.5 years for an individual in the sample to adjust hours of work to a change in the wage or other preference variables, an important consideration in policy evaluation. Failure to correct for incidental parameter bias leads to underestimating this effect by more than 15 %. Time-varying endogeneity of the wage is handled using a control function approach.

Keywords Labor supply · Dynamic adjustment · Bias correction · Control function

1 Introduction

The estimation and correct interpretation of labor supply elasticities are crucial to the evaluation of public policies regarding taxes, social security, and other social programs. For example, an important component of many macro-economic models is the intertemporal substitution elasticity, which measures the response of hours worked to changes in the wage, holding marginal utility of wealth constant. This elasticity is found to be negative or close to zero in many studies using micro-data, despite the theoretical implication of utility maximization that it should be positive. In addition, several studies in the macro-literature conclude that the intertemporal substitution elasticity should be relatively high.

✉ Elizabeth Schroeder
liz.schroeder@oregonstate.edu

[1] Department of Economics, Oregon State University, 303 Ballard Hall, Corvallis, OR 97331, USA

Published online: 19 January 2016

The typical assumptions underlying the identification of this parameter are quite strong. One particularly questionable assumption, which is nonetheless regularly employed, is that individuals are free to choose any number of hours of work in each period at the offered wage. Under this assumption, the intertemporal elasticity of substitution can be estimated in panel datasets as the wage coefficient in a log-linear hours equation with fixed effects.[1] In reality, however, contracts with employers, search costs, and other frictions in the labor market introduce dependence of current individual labor supply on past hours of work. Workers may face hours constraints that make it impossible to fully reoptimize each period in response to changing wages or preference variables. If individuals instead adjust over time, moving closer to their desired labor supply period by period, then the interpretation of the wage elasticity as the intertemporal elasticity of substitution no longer holds. Alternatively, realized hours and wages could be the outcome of bargaining between employers and employees. In this case, both hours and wages can become state-dependent, and the wage elasticity in the standard hours equation once again no longer represents the intertemporal elasticity of substitution. The failure of empirical work to date to robustly estimate the intertemporal elasticity of substitution may reflect the necessity of including dynamics in the hours equation, and thus, a rejection of the equilibrium model of labor supply that assumes away constraints or contracts. If labor supply decisions do depend on past labor supply, the speed of adjustment becomes an important parameter for policy evaluation. Quantifying the amount of time that it takes for workers to fully adjust their behavior to a tax or other reform is necessary to interpret the effect of the policy change. Initial estimates may underestimate the impact of the reform if adjustment is slow. Including lagged hours in the standard linear hours equation makes it possible to estimate the number of periods that must pass after a change in the wage before an individual's resulting change in labor supply is complete.

In estimating the speed of adjustment, it is crucial to distinguish between the state dependence of hours and individual heterogeneity. Some of the persistence in hours could be generated by time-invariant individual effects and therefore unrelated to contracts or other restrictions on hours. To address this issue, I estimate the adjustment speed of labor supply for prime-age males using a dynamic labor supply equation, in which hours worked depend on hours worked in the previous period, as well as the wage and a set of exogenous variables. Adjustment speed is given by the coefficient on lagged hours. The reduced-form wage equation is also dynamic, allowing wages to depend on lagged values of the wage. Estimation uses a bias-corrected dynamic panel data estimator to allow for fixed effects. Using the control function approach of Fernandez-Val and Vella (2011), I control for both time-invariant and time-varying endogeneity of the wage. Different interpretations of the cause of state dependence give rise to different sets of conditioning variables, but the results on the speed of adjustment are robust across specifications. In the next section, I describe various potential sources of state dependence in hours of work discussed in the labor supply literature, as well as the assumptions necessary in each case to generate a linear labor supply equation with a lagged dependent variable.

[1] See Blundell and MaCurdy (1999) for an overview.

2 Literature

Life cycle labor supply theory has typically viewed the hours decision as the outcome of a utility maximization problem in which hours of work are freely chosen. Beginning with Heckman and Macurdy (1980, 1982) and MaCurdy (1981, 1983), the labor supply decision has commonly been modeled as a function of current state variables, including wages and household characteristics. Blundell and MaCurdy (1999) present a summary of this classical literature. Assuming a utility function that is separable between consumption and labor, as well as positive hours of work (as is standard in papers focusing on prime-age males), the first-order condition for hours produces a log-linear labor supply equation. When fixed effects are included, the wage coefficient is an estimate of the Frisch elasticity, defined as the effect of a change in wages on hours, holding marginal utility of wealth constant. In this model, the Frisch elasticity is the intertemporal elasticity of substitution.

The log-linear labor supply equation has remained popular, despite evidence that persistence in hours worked remains even after controlling for fixed effects. Holtz-Eakin et al. (1988) estimate a vector autoregression with individual effects to analyze hours and wage dynamics and find that the first lag of hours has a significant effect on current hours of work; the coefficient is in the range of 0.145–0.170. The VAR framework does not take a stand on mechanisms, but recent evidence suggests that state dependence may be due to the presence of frictions. Ham and Reilly (2002) model two leading potential sources of such frictions. The first is an hours restrictions model, in which workers face an upper bound on the number of hours they are able to work. The second is an implicit contracts model, in which wages and hours are the outcome of bargaining between employers and employees. While Ham and Reilly reject the hours restrictions model in favor of implicit contracts, I consider both alternatives below in turn, as each can generate a dynamic hours equation. The differing interpretations of what is driving the dynamics lead to different sets of exogenous conditioning variables in the hours equation. I find that the estimated speed of adjustment is quite similar under the two specifications.

2.1 Hours restrictions

The literature on hours restrictions suggests that treating labor supply as an unconstrained choice can lead to biased estimates of labor supply parameters, including the intertemporal substitution elasticity. Ham (1986), Blundell et al. (1987), and Biddle (1988) find evidence of involuntary unemployment and underemployment, concluding that workers are constrained away from their labor supply curves due to limitations on hours set by employers.

There is also evidence that workers adjust labor supply toward their optimal number of hours over time. In samples of women, Euwals et al. (1998) find evidence that workers adjust hours in the direction of desired hours of work, and Altonji and Paxon (1992) find evidence that workers can adjust hours more easily when changing employers, suggesting that frictions relating to search and matching delay responses to labor supply determinants. In this spirit, Baltagi et al. (2005) model hours constraints as a cost to adjusting labor supply. Workers have a desired number of hours, but within a time period, they can only move part of the way between their previous hours of work and their desired hours. Thus, a partial adjustment mechanism, representing an hours restriction, generates a dynamic hours equation. Using Arellano and Bond's difference GMM estimator, Baltagi et al. find that the coefficient on lagged hours is between 0.41 and 0.45 for a sample of physicians in Norway.

Other work provides evidence of these types of frictions without focusing on dynamic labor supply. Motivated by large differences between micro- and macro-estimates of the Frisch elasticity (documented in Chetty et al. 2013, 2011b), Chetty et al. (2011a) model both hours constraints and adjustment costs, allowing these two factors to be determined endogenously in an equilibrium search model. Using matched employer–employee data in Denmark, they conclude that hours constraints and adjustment costs are likely to attenuate observed elasticities. Their model is static, however, and does not focus on the dynamics of labor supply adjustment. Similarly, Chetty (2012), rather than directly estimating a model with frictions, derives bounds on structural preference parameters in a model with optimization frictions. He finds that the bounds accounting for frictions do reconcile micro- and macro-estimates of the intensive-margin Frisch elasticity.

2.2 Implicit contracts

A competing view of the dynamics of hours and wages comes from the literature on contracts between firms and workers. In the implicit contracts model of Beaudry and DiNardo (1991, 1995), contracts induce state dependence in both wages and hours. Firms and workers share risk by entering into contracts that specify wages and hours for all future contingencies. As the direct relationship between wages and productivity is broken, the resulting log-linear hours equation includes a worker's marginal productivity of labor, parameterized by a function of industry-specific productivity effects in each time period, as well as the individual's experience and tenure on the job. Estimation exploits the state dependence in wages.

This model would correspond to a set of dynamic hours and wage equations if the history dependence of hours and wages could be summarized by their lagged values. Inclusion of the variables capturing marginal productivity allows the dynamic hours equation estimated below to be interpreted in an implicit contracts framework. An interesting note is that the coefficient on the log wage now represents a pure income effect and is predicted to be negative, which is a departure from the standard model discussed above, in which this coefficient represents the intertemporal substitution elasticity and must be positive.

2.3 Alternative sources of dynamics

Additional possible sources of dynamics in the hours equation include nonseparable preferences, such as habit formation (Shaw 2013), or human capital formation. Neither of these types of model can lead to a linear hours equation with a lagged dependent variable, however, without making the unrealistic assumption that individuals are completely myopic in choosing their level of labor supply. Kniesner and Li (2002) estimate a nonlinear dynamic adjustment equation for labor supply in which hours depend on an unspecified function of lagged hours and wages. Their estimates imply the average man takes about 10 months to fully adjust his labor supply. Allowing for interaction between lagged hours and the wage term not only permits examination of heterogeneous responses to wage changes, but also corresponds to models of habit formation. This approach rules out the presence of individual effects, however. While I impose linearity, I will be able to control for this important source of endogeneity of the wage, as well as distinguish between true state dependence and persistence due to individual effects.

3 Empirical Model and Estimation

I estimate the following system of dynamic equations.

$$\begin{aligned} \ln \text{wage}_{it} &= \gamma_0 + \gamma_1 \ln \text{wage}_{i(t-1)} + x'_{it}\pi + \alpha_{1i} + \varepsilon_{1it} \\ \ln \text{hours}_{it} &= \beta_0 + \beta_1 \ln \text{hours}_{i(t-1)} + \beta_2 \ln \text{wage}_{it} + x'_{it}\varphi + \alpha_{2i} + \varepsilon_{2it} \end{aligned}$$

Logged hours and wages depend on their own lagged values, individual characteristics, and both time-varying and time-invariant unobserved characteristics. The variables in X are described in detail below and include the controls for marginal productivity of labor in the implicit contracts specification. For ease of the exposition, let $x_{1it} = \left[\ln \text{wage}_{i(t-1)}, x_{it}\right]$ and $x_{2it} = \left[\ln \text{hours}_{i(t-1)}, \ln \text{wage}_{it}, x_{it}\right]$.

$$\begin{aligned} \ln \text{wage}_{it} &= x'_{1it}\theta_1 + \alpha_{1i} + \varepsilon_{1it} \\ \ln \text{hours}_{it} &= x'_{2it}\theta_2 + \alpha_{2i} + \varepsilon_{2it} \end{aligned}$$

Here, α_{1i} and α_{2i} are treated as fixed effects, potentially correlated with the variables in the x_{it}. The time-varying error terms are assumed to satisfy the following sequential moment conditions, which imply that the explanatory variables are predetermined relative to the disturbances, allowing for lags of the dependent variables.

$$\begin{aligned} E[\varepsilon_{1it}|x_i(t), \alpha_{1i}] &= 0 \\ E[\varepsilon_{2it}|x_i(t), \lambda_i(t), \alpha_{2i}] &= 0 \end{aligned}$$

for $i = 1, \ldots, N$; $t = 1, \ldots, T$, and where $x_i(t) = \left[x_{1i}(t)', x_{2i}(t)'\right]'$ and $r_i(t) = [r_{i1}, \ldots, r_{it}]'$ for $r \in \{x_1, x_2, \lambda\}$. Here, λ_{it} is the control function, defined in detail below. No restrictions are placed on the joint distribution of the fixed effects conditional on $x_i(t)$. The Fernandez-Val and Vella estimator also requires a stationarity assumption, which rules out time dummies and deterministic time trends. For comparison, results are presented below both with and without time dummies, where appropriate.

Endogeneity of the wage in the hours equation operates through two channels: correlation between α_{1i} and α_{2i} and correlation between ε_{1it} and ε_{2it}. Correlation between the fixed effects comes from two sources. The first is unobserved worker quality, including ability, motivation, and taste for work. This quality affects the wage an individual receives and may impact the number of hours of work an employer is willing to demand. It can also be expected to affect hours through differences in disutility from time spent working. In addition, in the formulation of linear hours equations like the one here, the fixed effect contains the lifetime marginal utility of wealth term. Any individual characteristics that affect wages in every time period (i.e., any components of α_{1i}) will affect lifetime earnings and thus the marginal utility of wealth. In general, characteristics that increase the wage will, by doing so, increase lifetime wealth, decreasing marginal utility of wealth. Endogeneity caused by correlation in these sources of unobserved heterogeneity can be removed by estimating both equations by fixed effects.

Estimation of the hours equation must also take into account correlation in the time-varying errors in the two equations, which will not be eliminated through fixed effects transformations. Correlation between ε_{1it} and ε_{2it} could result from several factors. Any time-varying shocks to the household that affect ability to work would impact both the wage and the number of hours worked. A shock such as an injury or illness could reduce both the wage and the amount of labor supplied, inducing a positive correlation in the error terms. In the implicit contracts framework, the hours worked and the wage rate also reflect an agreement between employees and employers about what to do in the state of the world realized in each time period, inducing further correlation.

On top of such shocks, a key source of correlation in the time-varying errors is measurement error, an issue that is frequently discussed in the labor supply literature. I use annual hours worked as the labor supply variable, as is typical in studies using the PSID. The wage variable is constructed from the survey data as total labor earnings divided by annual hours worked. Any measurement error in hours and wages will be correlated due to the fact that both variables are constructed using the same measure of hours. Following Altonji (1986), who finds evidence that measurement error can substantially bias labor supply estimates, I assume that the measurement error terms v_{1it} and v_{2it} are additive in the log hours and log wage equations, respectively, and uncorrelated with the true values, $\ln \text{hours}_{it}^{**}$ and $\ln \text{wage}_{it}^{**}$.

$$\begin{aligned}
\ln \text{hours}_{it} &= \ln \text{hours}_{it}^{**} + v_{2it} \\
\ln \text{wage}_{it} &= \ln \text{wage}_{it}^{**} + v_{1it}
\end{aligned}$$

The measurement errors are typically modeled as white noise (Hamilton 1994, p. 47), an assumption maintained here, and the measurement error in hours appears in the measurement error term for the wage due to that variable's construction. If present, this type of measurement error will induce a negative correlation between the time-varying error terms, ε_{1it} and ε_{2it}.

The lagged wage allows for state dependence in wages due to implicit contracts, or delayed response to productivity changes. The lagged wage also provides an exclusion restriction for identification of the wage effect in the hours equation. The assumption is that, conditional on time t wages, time $t-1$ wages should not affect the number of hours an individual works in time t. This source of variation was suggested by Borjas (1980) as a natural instrument for the current wage to control for time-varying heterogeneity and has been widely used. Measurement error in the lagged wage will be uncorrelated with measurement error in the current wage, given the error structure assumed here. As discussed in French (2003), expectation errors in time t will be uncorrelated with time $t-1$ information if expectations are rational, so lagged information provides a valid instrument. Any unexpected shocks to preferences will therefore be uncorrelated with past wages. In addition, the inclusion of the lagged hours term controls for any persistent effect of lagged wages on hours choices.

It is well known that estimation of a dynamic panel data model using fixed effects produces inconsistent estimates for fixed T. One possible solution to this problem is to use a GMM estimator, as in Baltagi, Bratberg, and Holmas. This approach involves decisions about which and how many instruments to use to control for the endogeneity of the lagged dependent variable, however, which may involve trade-offs. An alternative approach, adopted here, is to use least-squares dummy variable (LSDV) estimation and compute the asymptotic bias directly as a function of the number of time periods, T.

Fixed effects estimation controls for one source of endogeneity of the wage, the time-invariant heterogeneity captured by α_{1i} and α_{2i}. A control function included in the hours equation eliminates the remaining time-varying endogeneity. Fernandez-Val and Vella (2011) provide a bias-corrected estimator, derived using large-T asymptotic approximations, that accounts for this additional source of bias. Their estimator also has the advantage of allowing for predetermined regressors, including lagged dependent variables.

Below the estimation problem and bias correction are described, following the notation and exposition of Fernandez-Val and Vella as closely as possible, first for the reduced-form wage equation and then the primary hours equation.

Wage equation Letting $z = \{x, \ln \text{wage}\}$, the population parameters are identified by

$$\left(\theta_{10}, \{\alpha_{1i0}\}_{i=1}^{n}\right) = \arg \max_{\theta, \{\alpha_{1i}\}_{i=1}^{n}} E\left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} g_1\left(z_{it}; \theta_1, \alpha_{1i}\right)\right]$$

where the objective function is the least-squares criterion.

$$g_1\left(z_{it}; \theta_1, \alpha_{1i}\right) = -\left(w_{it} - x'_{1it}\theta_1 - \alpha_{1i}\right)^2 / 2$$

The score functions are denoted as follows,

$$u_{1it}\left(\theta_1, \alpha_1\right) = \partial g_1\left(z_{it}; \theta_1, \alpha_1\right) / \partial \theta_1$$
$$v_{1it}\left(\theta_1, \alpha_1\right) = \partial g_1\left(z_{it}; \theta_1, \alpha_1\right) / \partial \alpha_1$$

and the arguments are omitted when these functions are evaluated at the true parameter values. Partial derivatives are denoted by additional subscripts, e.g., $u_{1it\theta}\left(\theta_1, \alpha_1\right) = \partial u_{1it}\left(z_{it}; \theta_1, \alpha_1\right) / \partial \theta'_1$. The estimating equation for $\widehat{\theta_1}$ is therefore

$$0=\sum_{i=1}^{N}\sum_{t=1}^{T}u_{1it}\left(\widehat{\theta}_1,\widehat{\alpha}_1\left(\widehat{\theta}_1\right)\right)$$

where $\widehat{\alpha}_1\left(\widehat{\theta}_1\right)$ is the solution to

$$0=\sum_{i=1}^{N}\sum_{t=1}^{T}v_{1it}\left(\theta_1,\widehat{\alpha}_1\left(\theta_1\right)\right)$$

and

$$\begin{aligned} u_{1it} &= x_{1it}v_{1it} \\ v_{1it} &= \left(\ln \text{wage}_{it}-x_{1it}'\theta_1-\alpha_{1i}\right) \end{aligned}$$

The solution for $\widehat{\theta}_1$ can be obtained using a matrix that purges the fixed effects: $Q=I_{NT}-\frac{1}{T}\left(I_{NT}\otimes J_T\right)$, where I_{NT} is an identity matrix and J_T is a $T\times T$-matrix filled with ones.

$$\widehat{\theta}_1=\left(X_1'QX_1\right)^{-1}X_1'Q\ln wage$$

and the variance is

$$\text{var}\left(\widehat{\theta}_1\right)=\sigma_{\varepsilon_1}^2\left(X_1'QX_1\right)^{-1}$$

After the wage equation is estimated by LSDV, the coefficients are corrected for bias. Fernandez-Val and Vella express the bias of the estimating equation using three terms.

$$b_{1i}=\overline{E}_T\left[u_{1it\alpha}\psi_{1is}\right]+E_T\left[u_{1it\alpha}\right]\beta_{1i}+E_T\left[u_{1it\alpha\alpha}\right]\sigma_{1i}^2/2$$

where E_T denotes the probability limit over the time dimension and the sample analog $\widehat{E}_T$ is the sample average over time. $\overline{E}_T$ is a spectral expectation, defined in Fernandez-Val and Vella, with bandwidth set to m=1 (see Hahn and Kuersteiner (2011) for details on optimal bandwidth selection).

The expression for b_{1i} contains components of a higher-order expansion for $\widehat{\alpha}_{1i}$ at the true parameter value: $\widehat{\alpha}_{1i}\left(\widehat{\theta}_{10}\right)=\alpha_{10}+\psi_{1i}/\sqrt{T}+\beta_{1i}/T+o_p(1/T)$, and $\sigma_{1i}^2=\overline{E}_T\left[\psi_{1it}\psi_{1is}\right]$. The first term in b_{1i} is present because the fixed effects are estimated from the same observations as the parameters θ_1. Since u_{1it} is linear in α_{1i}, this term would be zero if the x_{it} were strictly exogenous. The second and third terms are due to nonlinearities in α_{1i}. As the estimating equation in this application is linear in α_{1i}, the second and third terms are zero, and b_{1i} reduces to:

$$b_{1i}=\overline{E}_T\left[u_{1it\alpha}\psi_{1is}\right]$$

The asymptotic bias is given by

$$B_1=-J_1^{-1}E_n\left[b_{1i}\right]$$

where $J_1 = E_n[J_{1i}]$ is the probability limit of the Jacobian of the estimating equation for θ_1.

$$J_{1i} = E_T\left[u_{1it\theta}\right] - E_T\left[u_{1it\alpha}\right] E_T\left[v_{1it\theta}\right] / E_T\left[v_{1it\alpha}\right]$$

The final bias-corrected estimator is $\widehat{\theta}_1^{bc}$.

$$\widehat{\theta}_1^{bc} = \widehat{\theta}_1 - \widehat{B}_1/T$$

Hours equation The control function, λ_{it}, is the residual from the estimated wage equation.

$$\lambda_{it} = \ln \text{wage}_{it} - x_{1it}'\widehat{\theta}_1^{bc} - \widehat{\alpha}_{1i}^{bc}$$

In the second step of estimation, the control function is included in the hours equation. The remaining error term has been purged of correlation with the wage variable, and the labor supply parameters can be consistently estimated. In other words, conditioning on $\lambda_{i,t}$ restores the sequential moment conditions required of the ε_{2it} above. As lagged wages can be expected to have no effect on current hours choices, once the current wage is controlled for, no further exclusion restrictions are required in the X variables for identification of the coefficients in the hours equation. The final equation is:

$$\ln \text{hours}_{it} = x_{2it}'\beta + \rho\lambda_{it} + \alpha_{2i} + \varepsilon_{2it}$$

This hours equation is estimated via the LSDV procedure described above, and the coefficients corrected for bias following Fernandez-Val and Vella. Let $\theta_2 = [\beta, \rho]$. As above, the bias is

$$\widehat{\theta}_2^{bc} = \widehat{\theta}_2 - \widehat{B}_2/T$$

where again J_2 and b_2 are the probability limits of the Jacobian and asymptotic bias of the estimating equation for θ_2.

The estimating equations for the second stage are $u_{2it} = \left[\left(u_{2it}^{\beta}\right)', u_{2it}^{\rho}\right]'$, where $u_{2it}^{\beta} = x_{2it}v_{2it}$ is the score function for β, and $u_{2it}^{\rho} = \lambda_{it}v_{2it}$ is the score function for ρ, with $v_{2it} = (\ln \text{hours}_{it} - x_{2it}'\beta - \rho\lambda_{i,t} - \alpha_{2i})$.

The bias of the estimating equation, derived by Fernandez-Val and Vella, is:

$$\begin{aligned} b_{2i} = {} & \overline{E}_T\left[u_{2it\alpha}\psi_{2is}\right] + E_T\left[u_{2it\alpha}\right]\beta_{2i} + E_T\left[u_{2it\alpha\alpha}\right]\sigma_{2i}^2/2 \\ & + E_T\left[u_{2it\lambda\alpha}\lambda_{it\alpha}\right]\sigma_{12i} + \overline{E}_T\left[u_{2it\lambda}\lambda_{it\alpha}\psi_{1is}\right] \\ & + E_T\left[u_{2it\lambda}\left(\lambda_{it\alpha}\beta_{1i} + \lambda_{it\alpha\alpha}\sigma_{1i}^2/2\right)\right] + E_T\left[u_{2it\lambda\lambda}\lambda_{it\alpha}^2\right]\sigma_{1i}^2/2 \end{aligned}$$

The first three terms are the same as in the first stage bias correction; as above, the terms due to nonlinearity in α_{2i} drop out in the present application due to linearity. The additional terms are due to fixed effects estimation of the control function and nonlinearity or dynamics in the second stage. The fourth term arises because both stages use the same observations to estimate the fixed effects, and σ_{12i} is the asymptotic covariance between the estimators of α_{1i} and α_{2i}. The fifth and sixth terms capture bias coming from the fixed effects estimation of λ_{it} due to dynamic feedback or nonlinearities—since the control function in the present application is linear in α_{1i}, the sixth term drops out as well. The final term is due to nonlinearity of the second-stage estimating equations in the control function. The score function for β is linear in λ_{it}, but the score function for ρ is not; thus, this final term only adds to the bias of the coefficient on the control function. The bias thus reduces to

$$
\begin{aligned}
b_{2i}^{\beta} &= \overline{E}_T \left[(u_{2it\alpha} - E_T (u_{2it\alpha})) (\psi_{2is} - \rho \psi_{1is}) \right] \\
b_{2i}^{\rho} &= \overline{E}_T \left[u_{2it\alpha} \psi_{2is} \right] + E_T \left[u_{2it\lambda\alpha} \lambda_{it\alpha} \right] \sigma_{12i} + \overline{E}_T \left[u_{2it\lambda} \lambda_{it\alpha} \psi_{1is} \right] \\
&\quad + E_T \left[u_{2it\lambda\lambda} \lambda_{it\alpha}^2 \right] \sigma_{1i}^2 / 2
\end{aligned}
$$

Standard errors for the bias-corrected estimates are computed via a pairs- (or nonparametric-) bootstrap design, which resamples with replacement in the cross-sectional dimension. When an individual is drawn, his entire vector of dependent variable and lags over time is included, along with controls. Gonçalves and Kaffo (2015) show that this method of bootstrapping is consistent when inference is based on bias-corrected estimates for linear dynamic panel models with fixed effects. These standard errors are robust to conditional heteroskedasticity.

The data are from the Michigan Panel Study of Income Dynamics (PSID) from the years 1984 through 1996. The sample was chosen to most closely match the samples used in the standard papers on life cycle labor supply, beginning with MaCurdy (1981, 1983). The sample includes men, ages 25–55, who were employed during each period in the sample. The result is 699 individuals observed 13 times, with a resulting $T = 12$ time periods used in estimation to allow for the lags. As discussed above, the hours variable used is annual hours of work, and the wage variable is average hourly earnings.

The results below are presented for two specifications, which correspond to different sources of state dependence in hours. In the specification labeled "hours restrictions," the set of exogenous variables includes the standard variables from the life cycle labor supply literature for fixed effects equations. These are years of experience, experience-squared, marital status and self-reported health status. As there is almost no variation in the education variable over time in the sample, education cannot be included along with the fixed effects. In addition, the hours equation includes number of children present in the household and number of children under age six. In the specification labeled "implicit contracts," an additional set of control variables is added to the hours and wage equations. These variables parameterize the marginal productivity of labor, following Beaudry and DiNardo. The additional variables include tenure at the worker's present job, tenure squared, and a set of interactions of dummy variables for industry and time effects, which control for the impact of industry-specific productivity shocks. All control variables are standardized by their standard deviations.

4 Results

Table 1 shows the results of step 1, estimation of the reduced-form wage equation, for the hours restrictions specification. Even after controlling for individual heterogeneity, lagged wages are an important determinant of current wages. The estimated elasticity

Table 1 Hours restrictions specification. Dependent variable: log wage

	OLS	LSDV	AB	LSDV-BiasCorr
Lag log wage	0.87***	0.35***	0.29***	0.41***
	(0.01)	(0.01)	(0.03)	(0.02)
Exper	−0.04	0.29***	0.41***	0.25***
	(0.03)	(0.03)	(0.08)	(0.04)
Exper2	0.03	−0.22***	−0.30***	−0.19***
	(0.03)	(0.03)	(0.08)	(0.04)
Health	−0.039***	−0.002	0.00	−0.004
	(0.006)	(0.007)	(0.01)	(0.007)
Married	0.01	0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)

Standard errors, in parentheses, are computed via 250 bootstrap iterations. The first three columns report OLS, least-squares dummy variables, and Arellano–Bond estimates. Estimates in the last column are bias-corrected

is 0.41 between current and past wages. The quadratic terms in experience are also significant. Failure to correct for bias results in underestimating the impact of lagged wages by more than 15 %.

Table 2 presents the results of the dynamic hours equation estimation under the hours restrictions framework. The first column shows the OLS estimates, and the second the results of LSDV estimations that does not account for the time-varying endogeneity of the wage. The experience terms appear to be significant determinants of labor supply. Marital status is also significant, indicating that married men work slightly longer hours. The coefficient on the log wage is around −0.55 and strongly significant.

The last two columns of Table 2 show the estimates after the control function is included. Controlling for time-varying endogeneity has a large impact on the coefficient on the log wage, which goes from −0.55 and highly significant in the first column, to 0.13 and no longer statistically significant at standard levels in the third column. The increase in this coefficient is a result of the negative coefficient on the control function, which is an indication that the error terms in the two equations are negatively correlated. This result is consistent with the presence of measurement error in the data affecting hours and average earnings in opposite directions, as discussed above. A t-test on the control function coefficient is a test of the exogeneity of the wage, once fixed effects have been controlled for. The null hypothesis of exogeneity is strongly rejected, as the control function is highly significant in the last two columns.

The coefficient on lagged hours is positive and significant in each case. Failure to account for endogeneity and dynamic panel bias results in severe underestimation of the effect of lagged hours. Controlling for the time-varying endogeneity of the wage raises the coefficient on lagged hours from 0.23 to 0.27. Bias correction also makes a large difference, increasing the control function-adjusted estimate from 0.27 to 0.33.

Tables 3 and 4 present the results of estimating the implicit contracts specification of the dynamic hours model, in which an additional set of regressors is added to both

Table 2 Hours restrictions specification. Dependent variable: log hours of work

	OLS	LSDV	AB	LSDV-CF	LSDV-CF BiasCorr
Lag log hours	0.61***	0.23***	0.27***	0.27***	0.33***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)
Log wage	−0.12***	−0.55***	−0.31***	−0.11***	0.13
	(0.01)	(0.02)	(0.09)	(0.04)	(0.18)
Exper	−0.04	0.24***	0.19	0.02	0.09
	(0.03)	(0.05)	(0.14)	(0.06)	(0.13)
Exper^2	0.02	−0.16***	−0.19	0.00	−0.10
	(0.03)	(0.05)	(0.14)	(0.06)	(0.13)
Health	−0.04***	−0.001	0.010	−0.000	−0.011
	(0.01)	(0.011)	(0.014)	(0.01)	(0.016)
Kids	−0.002	0.02	−0.02	0.02	0.02
	(0.007)	(0.02)	(0.03)	(0.02)	(0.02)
Young kids	−0.01**	−0.01	0.03	−0.01	−0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Married	0.04***	0.05***	0.05**	0.04***	0.04**
	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)
Control fct				−0.52***	−0.75***
				(0.05)	(0.20)

Standard errors, in parentheses, are computed via 250 bootstrap iterations. The first three columns report OLS, least-squares dummy variables, and Arellano–Bond estimates. The specifications in the final two columns include a control function, and estimates in the last column are bias-corrected

equations. The signs and significance levels of the coefficients in the wage equation are quite similar, despite the inclusion of a large set of industry and time interactions. In addition, the quadratic terms in tenure are significant, indicating a positive effect of tenure on wages that diminishes over time.

The coefficients from the hours equation also approximately follow the signs and significance levels of the previous specification, with the tenure terms not statistically significant. The notable point of departure between the two sets of estimates is the coefficient on the log wage. Under the implicit contracts specification, inclusion of the control function to eliminate the time-varying endogeneity of the wage again makes the wage coefficient less negative. The final bias-corrected estimate, however, remains negative in the implicit contracts case, with a t-statistic of -1.14. The coefficient on the control function is -0.47 and strongly significant, confirming the result that time-varying endogeneity is present in the hours equation and reinforcing the measurement error interpretation of the source of this endogeneity. Several of the cross-industry–time effects are significant at the 5 % level as well. The coefficient on the lag of log hours increases from 0.27 to 0.31 after bias correction. As the results in Fernandez-Val and Vella have not been extended to include time dummies, the implicit contracts model is estimated again excluding the time effects. The results are very robust, with the coefficient on lagged log hours remaining at 0.31, as shown in the last column of Table 4.

Table 3 Implicit contracts specification. Dependent variable: log wage

	OLS	LSDV	AB	LSDV-BiasCorr
Lag log wage	0.86***	0.34***	0.27***	0.40***
	(0.01)	(0.01)	(0.03)	(0.02)
Exper	−0.04	0.32***	0.42***	0.28***
	(0.03)	(0.03)	(0.08)	(0.04)
Exper^2	0.03	−0.19***	−0.27***	−0.16***
	(0.03)	(0.03)	(0.09)	(0.04)
Health	−0.04***	−0.002	0.00	−0.003
	(0.01)	(0.007)	(0.01)	(−0.008)
Married	0.01	0.008	−0.00	0.007
	(0.01)	(0.008)	(0.01)	(0.009)
Tenure	0.01	0.14***	0.12***	0.13***
	(0.02)	(0.02)	(0.04)	(0.02)
Tenure^2	0.01	−0.11***	−0.11***	−0.11***
	(0.01)	(0.02)	(0.03)	(0.02)

Controls include time and industry effects and their interactions. Standard errors, in parentheses, are computed via 250 bootstrap iterations. The first three columns report OLS, least-squares dummy variables, and Arellano–Bond estimates. Estimates in the last column are bias-corrected

In all tables, the results from estimating the equations by Arellano–Bond difference GMM are also shown for comparison. These estimates are computed using the first-differences, one-step version of the estimator with robust standard errors. In the hours equation, the differenced wage term is instrumented using lags of two periods and beyond, while the differenced lagged dependent variables are instrumented using lags of one period and beyond. The results for the hours equations (Tables 2, 4) show that the Arellano–Bond coefficients on the lagged hour term are in between the LSDV estimates and the bias-corrected estimates. Using Arellano–Bond is roughly equivalent to including the control function in the LSDV estimation without bias correction. This pattern does not hold in the wage equations (Tables 1, 3), where the Arellano–Bond estimates are below the LSDV estimates, moving in the opposite direction from the bias-corrected estimates. These estimates are sensitive to the choice of how many lags to include as instruments, however, and can be made higher or lower by up to 10 % by restricting the instrument set.

5 Discussion

The results on the adjustment speed of labor supply are quite similar across the hours restrictions and implicit contracts specifications above. Regardless of which interpretation of the state dependence of labor supply is chosen, the estimated coefficient on the lagged hours term is between 0.31 and 0.33. The robustness of this parameter estimate to the inclusion of different sets of control variables is evident despite the fact that many of the variables added in the implicit contracts specification are significant.

Table 4 Implicit contracts specification. Dependent variable: log hours of work

	OLS	LSDV	AB	LSDV-CF	LSDV-CF-BC	LSDV-CF-BC
Lag log hrs	0.61***	0.23***	0.27***	0.27***	0.31***	0.31***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)
Log wage	−0.12***	−0.56***	−0.35***	−0.11***	−0.16	−0.01
	(0.01)	(0.02)	(0.10)	(0.04)	(0.14)	(0.24)
Exper	−0.04	0.27***	0.10	0.03	0.21	0.22
	(0.03)	(0.05)	(0.14)	(0.06)	(0.17)	(0.19)
Exper^2	0.01	−0.13**	−0.04	0.004	−0.19	−0.21
	(0.03)	(0.06)	(0.14)	(0.057)	(0.18)	(0.21)
Health	−0.04***	−0.000	0.010	0.000	−0.001	0.004
	(0.01)	(−0.011)	(0.014)	(0.011)	(0.02)	(0.017)
Kids	0.001	0.03	−0.01	0.02	0.01	0.03
	(0.007)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Young kids	−0.01**	−0.01	0.02	−0.01	−0.02	−0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)

Table 4 continued

	OLS	LSDV	AB	LSDV-CF	LSDV-CF-BC	LSDV-CF-BC
Married	0.04***	0.05***	0.05**	0.04***	0.05***	0.04*
	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)
Tenure	−0.16***	0.08**	0.03	−0.02	−0.1	−0.14
	(0.02)	(0.03)	(0.07)	(0.04)	(0.07)	(0.13)
Tenure^2	0.14***	−0.08***	−0.03	0.001	0.15*	0.18
	(0.02)	(0.03)	(0.06)	(0.034)	(0.09)	(0.14)
Control fct				−0.52***	−0.47***	−0.61***
				(0.05)	(0.15)	(0.24)
Time effects	✓	✓	✓	✓	✓	

Controls include time and industry effects and their interactions. Standard errors, in parentheses, are computed via 250 bootstrap iterations. The first three columns report OLS, least-squares dummy variables, and Arellano–Bond estimates. The specifications in the final three columns include a control function, and estimates in the last two columns are bias-corrected

An adjustment cost of one is a full-adjustment model, in which the agent can work his desired number of hours in each period. The coefficient on lagged hours of 0.33 implies an adjustment cost of 0.67. In the hours restrictions framework, this result has the interpretation that, from one year to the next, an individual in the sample is only able to change his hours by 67 % of the difference between the hours he worked in the last period and his desired hours this period. In either specification, the estimated coefficient is an indication that full adjustment of labor supply to a change in the wage or other preference variable takes about one and a half years for a prime-age man. Policy makers analyzing the effect of a reform must therefore wait a year and a half for the full impact of the change in labor supply decisions to be realized.

This estimated adjustment time is longer than Kniesner and Li's estimate of ten months. This is a surprising result, since their specification left out individual effects, which would tend to make labor supply seem even more highly correlated over time. The discrepancy could be a result of their allowing for nonlinearities in wages and lagged hours, or their use of sub-annual data.

An important difference between estimates of the standard linear life cycle labor supply equation and the results presented here is the sign of the coefficient on the wage term. In a marginal utility of wealth-constant hours equation that does not account for dynamics, the wage coefficient is an estimate of the Frisch elasticity, or the intertemporal elasticity of substitution. This elasticity must be positive if leisure is a normal good, as it represents the amount labor supply is increased in periods in which the price of leisure is high. In the hours restrictions specification above, the estimate of the wage coefficient is positive, but not significantly different from zero. It may be imprecisely measured because the adjustment frictions decrease the impact of the wage. It may also represent a conflation of income and substitution effects, since the Frisch interpretation no longer holds after time inseparabilities are introduced.

The wage coefficient in the implicit contracts specification is negative, however. A negative wage coefficient is a key prediction of the implicit contracts model of Beaudry and DiNardo, and they interpret a negative coefficient in their estimation as evidence in favor of implicit contracts. Since contracts break the relationship between productivity and wages, the impact of a wage change in hours is a pure income effect. The replication of this key finding here, using a different system of equations to capture the state dependence induced by implicit contracts, is further evidence in favor of the implicit contracts model. The lack of significance of the log wage term, however, is broadly in keeping with much of the literature on labor supply, in which it has been difficult to show any significant impact of current wages on current labor supply.

The result of this distinct interpretation of the wage coefficient in the dynamic labor supply equation is that the intertemporal substitution elasticity is not estimated here. In estimating the adjustment speed parameter, we lose the direct link between the wage coefficient and the standard life cycle labor supply elasticities. The coefficient can only be interpreted as the predicted percent change in hours with respect to a percent change in the wage in period t. Ham and Reilly (2002) estimate the intertemporal substitution elasticity in an implicit contracts model. They derive first-order conditions in terms of the "shadow wage," which is equal to the marginal product of labor, but unobservable. Modeling the shadow wage using labor market variables that are correlated with the demand for labor, they estimate the intertemporal substitution elasticity to be in the range of 0.9–1.0. These estimates are three times higher than typical estimates using micro-data, suggesting that the implicit contracts model may help to bridge the gap between micro- and macro-estimates of the intertemporal substitution elasticity.

6 Conclusion

I contribute to the literature on life cycle labor supply by estimating a dynamic hours equation for prime-age men with bias correction. The coefficient on the lagged dependent variable in this equation provides an estimate of the adjustment speed of labor supply, an important parameter in policy evaluation. The estimated elasticity of hours with respect to lagged hours is between 0.31 and 0.33. Failure to correct for dynamic panel bias leads to underestimating this effect by more than 15 %.

In addition, endogeneity of the wage operates through two channels, fixed effects and time-varying heterogeneity. After controlling for both types of endogeneity, I find the elasticity of hours with respect to wages is positive in a model of hours constraints, but negative in a model of implicit contracts, in keeping with the predictions of both models. In neither model, however, is the wage coefficient significantly different from zero. These results are consistent with the view that state dependence in the hours equation diminishes the impact of current wages on current hours of work.

Acknowledgments I thank Frank Vella for invaluable advice and comments on this paper. I am also grateful to an anonymous referee for very helpful comments.

References

Altonji JG (1986) Intertemporal substitution in labor supply: evidence from micro data. J Polit Econ 94(3 Part 2):S176–S215

Altonji J, Paxon CH (1992) Labor supply, hours constraints, and job mobility. J Hum Resour 27(2):256–278

Baltagi BH, Bratberg E, Holmas TH (2005) A panel data study of physicians' labor supply: the case of Norway. Health Econ 14(10):1035–1045

Beaudry P, DiNardo J (1991) The effect of implicit contracts on the movement of wages over the business cycle: evidence from micro data. J Polit Econ 99(4):665–688

Beaudry P, DiNardo J (1995) Is the behavior of hours worked consistent with implicit contract theory? Q J Econ 110(3):743–768

Biddle JE (1988) Intertemporal substitution and hours restrictions. Rev Econ Stat 70(2):37–351

Blundell R, MaCurdy T (1999) Labor supply: a review of alternative approaches. Handb labor econ 3:1559–1695

Blundell R, Ham J, Meghir C (1987) Unemployment and female labor supply. Econ J 97(388a):44–64

Borjas G (1980) The relationship between wages and weekly hours of work: the role of division bias. J Hum Resour 15(3):409–423

Chetty R (2012) Bounds on elasticities with optimization frictions: a synthesis of micro and macro evidence on labor supply. Econometrica 80(3):969–1018

Chetty R, Friedman JN, Olsen T, Pistaferri L (2011a) Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: evidence from Danish tax records. Q J Econ 126(2):749–804

Chetty R, Guren A, Manoli D, Weber A (2011b) Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins. Am Econ Rev 101(3):471–475

Chetty R, Guren A, Manoli D, Weber A (2013) Does indivisible labor explain the difference between micro and macro elasticities? A meta-analysis of extensive margin elasticities. In: Acemoglu D, Parker J, Woodford M (eds) NBER Macroeconomics Annual 2012, University of Chicago Press, Chicago, pp 1–56

Euwals R, Melenberg B, van Soest A (1998) Testing the predictive value of subjective labor supply data. J Appl Econom 13(5):567–585 Special Issue: Application of Semiparametric Methods for Micro-Data
Fernandez-Val I, Vella F (2011) Bias corrections for two-step fixed effects panel data estimators. J Econom 163(2):144–162
Gonçalves S, Kaffo M (2015) Bootstrap inference for linear dynamic panel data models with individual fixed effects. J Econom 186(2):407–426
Hahn J, Kuersteiner G (2011) Bias reduction for dynamic nonlinear panel models with fixed effects. Econom Theory 27(06):1152–1191
Ham JC (1986) Testing whether unemployment represents intertemporal labor supply behavior. Rev Econ Stud 53(4):559–578 Econometrics Special Issue
Ham JC, Reilly KT (2002) Testing intertemporal substitution, implicit contracts, and hours restriction models of the labor market using micro data. Am Econ Rev 94(2):905–927
Hamilton JD (1994) Time series analysis. Princeton University Press, Princeton
Heckman J, Macurdy T (1980) A life cycle model of female labor supply. Rev Econ Stud 47(1):47–74 Econometrics Issue
Heckman J, Macurdy T (1982) Corrigendum on a life cycle model of female labor supply. Rev Econ Stud 49(1982):659–660
Holtz-Eakin D, Newey W, Rosen HS (1988) Estimating vector autoregressions with panel data. Econometrica 56(6):1371–1395
Kniesner T, Li Q (2002) Nonlinearity in dynamic adjustment: semiparametric estimation of panel labor supply. Empir Econ 27(1):131–148
MaCurdy T (1981) An empirical model of labor supply in a life cycle setting. J Polit Econ 89:1059–1085
MaCurdy T (1983) A simple scheme for estimating an intertemporal model of labor supply and consumption in the presence of taxes and uncertainty. Int Econ Rev 24(2):265–289
Shaw KL (1989) Life-cycle labor supply with human capital accumulation. Int Econ Rev 30(2):431–456