# Dynamic Labor Supply Adjustment with Bias Correction*

Elizabeth Schroeder†

July 15, 2010

**Abstract**

I estimate a dynamic fixed-effects hours equation for prime-age men with bias correction. The coefficient on the lagged dependent variable is found to be between 0.35 and 0.38. These estimates suggest 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 dynamic panel bias leads to underestimating this effect by more than 25 percent. Time-varying endogeneity of the wage is handled using a control-function approach. I find the elasticity of hours with respect to wages is negative and significantly different from zero. This result is consistent with the view that state dependence in the hours equation is generated by implicit contracts between workers and employers.

JEL Classification: J22
Keywords:

---

*

†Department of Economics, Georgetown University, Washington DC 20057 USA. eas3@georgetown.edu

# 1 Introduction

The consistent estimation and correct interpretation of labor supply elasticities are crucial to evaluation public policies regarding taxes, Social Security, and other social programs. For example, one important component of many macroeconomic 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.

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. In reality, however, contracts with employers, search costs, and other frictions in the labor market introduce dependence of an individual's current labor supply on his or her past hours of work. Workers may face hours constraints that make it impossible to fully re-optimize labor supply each period in response to changes in the wage or preference variables. If individuals reoptimize 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. Alternately, 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. Thus 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 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 be therefore unrelated to contracts or other restrictions on hours. To address these issues, 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 (2009), 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 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.

# 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. Blundell and MaCurdy (1999) present a summary along the following lines. An agent solves a lifetime optimization problem subject to a budget constraint.

$$V(a_{it}, t) = \max \left[ U\left(c_{it}, h_{it}, Z_{it}\right) + \beta E_t V\left(a_{i,t+1}, t+1\right)\right]$$

$$\text{s.t. } a_{i,t+1} = \left(1 + r_{t+1}\right)\left(a_{it} + w_{it} h_{it} - c_{it}\right)$$

where Z includes observed and unobserved taste shifting variables, and a is the real value of assets. A typical specification among panel data applications of life-cycle labor supply theory uses a utility function that is separable between consumption and labor. Assuming positive hours of work, as is standard in many papers on prime-age men, the first order condition for hours produces the following equation.

$$\ln h_{it} = \beta_0 + \beta_1 \ln w_{it} + z_{it}'\gamma + \alpha_{i0} + \mu_t + e_{it}$$

Hours of work depend on current wages and preference variables. The fixed effect contains the marginal utility of wealth, which the agent holds constant (in expectation) throughout the lifecycle. Inclusion of this term controls for the impact of variables in all other time periods. Estimating the equation by fixed effects gives 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 above labor supply equation has remained popular, despite evidence that persistence in hours of work remains even after fixed effects have been controlled for. Newey, Holtz-Eakin and Rosen (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 on lagged hours is in the range of 0.145 to 0.170. The VAR framework does not take a stand on whether costly adjustment, nonseparable preferences, or some other mechanism are generating the results. The authors conclude, however, that lagged hours are an important determinant of labor supply, consistent with alternatives to the simple labor supply model.

Ham and Reilly (2002) discuss two leading alternatives to the standard life-cycle model, both of which generate state-dependence in labor supply. 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. Ham and Reilly first find that labor demand shocks affect hours even after conditioning on the wage, which contradicts the standard intertemporal model without restrictions. They go on to examine the alternatives, testing cross-equation parameter restrictions generated by both the hours restrictions and implicit contract models. The hours restriction model is rejected, but the implicit contracts framework is not. Both of these alternative labor supply models can generate the dynamic hours equation I estimate below, however. I will therefore consider them each in turn. 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 estimates of the speed of adjustment are 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 (1982) estimates a sample selection model using prime-age males, and finds that failure to account for selection into full employment significantly biases labor supply parameter estimates. Ham (1986) explores the issue further by testing a model of involuntary unemployment and underemployment. He finds that dummy variables for unemployment and underemployment are significant in the hours equation, and concludes that workers who experience these states are constrained away from their labor supply curves. Blundell, Ham, and Meghir (1987) find similar results in extending the idea of involuntary unemployment to female labor supply. Biddle (1988) makes use of a set of questions in the PSID that ask whether workers would have liked to work more or fewer hours in the previous year. He estimates a labor supply equation for the full set of prime-age males, and then again for the subset who report they were unconstrained in their hours choices. He finds large differences in parameter estimates, and concludes that estimates that include the constrained group do not represent labor supply elasticities. Instead, he suggests, the constrained workers may be off their labor supply curves due to limitations on hours set by employers.

There is also evidence that, despite not being free to choose in each period, workers do adjust labor supply toward their optimal number of hours over time. Euwals, Melenberg and van Soest (1998) use survey data on desired hours of work to test whether the difference between desired hours and actual hours worked helps to predict hours of work in the next period. In this model, workers adjust labor supplied in the direction of their desired hours, but adjustment is slow and may take place over many periods. They find evidence that women adjust hours in the direction of their optimal hours of work, although tests of the predictive power of desired hours for men were inconclusive. Altonji and Paxson (1992) provide additional evidence in favor of hours constraints, finding that workers can adjust hours more easily when changing employers than they can within a given job. For a sample of married women, they estimate that preference variables have a much greater impact on hours when a job change has occurred. If full optimization requires a job change to relax constraints on hours, frictions relating to search and matching are a further reason to expect delayed responses to changes in the determinants of labor supply.

Baltagi, Bratberg and Holmas (2005) model the state dependence of labor supply in the context of hours restrictions. They estimate an hours equation for physicians in Norway. Instead of explicitly modelling a particular constraint on hours, they introduce a cost to adjusting hours that represents doctors' inability to work their desired number of hours in each period. The standard log-linear hours equation resulting from utility maximization is taken as the model for desired hours.

$$\ln hours^*_{i,t} = \beta_0 + \beta_1 \ln wage_{i,t} + x'_{i,t}\varphi + \alpha_i + \varepsilon_{i,t}$$

Upon reaching time t, however, agents are unable to achieve the utility-maximizing labor supply, or desired hours of work. A partial adjustment mechanism is adopted, so that actual hours worked depend on desired hours, as well as hours worked in the previous period. The realized change in hours is a function of the distance between this period's desired hours and last periods actual hours. Theta is the cost of adjustment.

$$\ln h_{i,t} - \ln h_{i,t-1} = \theta(\ln h^*_{i,t} - \ln h_{i,t-1})$$

where $0 < \theta \leq 1$. Substitution into the desired hours equation gives an equation for actual hours worked.

$$\ln hours_{i,t} = \beta_0 + \beta_1 \ln hours_{i,t-1} + \beta_2 \ln wage_{i,t} + x'_{i,t}\varphi + \alpha_i + \varepsilon_{i,t}$$

In this way, an hours restriction interpretation is used to generate a dynamic labor supply equation. The variables in X include individual and household characteristics such as marital status, number of children, education and age. Using Arellano and Bond's difference GMM estimator, Baltagi et. al. find that the coefficient on lagged hours for the group in question is between 0.41 and 0.45.

## 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), contracts induce state dependence in the wage equation. Specifically, a worker who starts out at a high wage in a period of favorable labor market conditions will see a lasting benefit to wages over the lifetime. In each subsequent period, improvements in labor market conditions increase the individual's wage, but corresponding decreases in wages do not take place during bad times. The authors find empirical evidence of this pattern in wages and labor market conditions, and interpret it as evidence in favor of the implicit contract model.

Beaudry and DiNardo (1995) extend the implicit contracts model to look at its implications for labor supply. Firms and workers share risk by entering into contracts with limited enforcement. Uncertainty is summarized in each period by a random variable $\theta_t$, where $\theta^t = \{\theta_0, ...\theta_t\}$ is the time t contingency. A contract agreed on at time $\tau$ specifies wages and hours for all future contingencies: $\{w\left(\theta^{\tau+j}, X_{i,\tau+j}\right), h\left(\theta^{\tau+j}, X_{i,\tau+j}\right)\}$. This is an equilibrium model in the sense that bargaining between firms and workers results in setting the marginal rate of substitution equal to the marginal product of labor.

$$\frac{-U_h\left(w\left(\theta^t, X_{i,t}\right) h\left(\theta^t, X_{i,t}\right), h\left(\theta^t, X_{i,t}\right)\right)}{U_c\left(w\left(\theta^t, X_{i,t}\right) h\left(\theta^t, X_{i,t}\right), h\left(\theta^t, X_{i,t}\right)\right)} = \psi\left(\theta^t, X_{i,t}\right)$$

where a worker's marginal productivity is given by $\psi\left(\theta^t, X_{i,t}\right)$. Beaudry and DiNardo derive a log-linear hours equation from this condition.

$$\ln h\left(\theta^t, X_{i,t}\right) = \Omega_1 \ln w\left(\theta^t, X_{i,t}\right) + \Omega_2 \ln \psi\left(\theta^t, X_{i,t}\right)$$

An interesting feature of this framework is that the direct relationship between wages and productivity is broken. The coefficient on the wage term now represents a pure income effect, as controlling for productivity eliminates the substitution effect of a change in the wage. The coefficient on the log wage 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.

Beaudry and DiNardo estimate this model by exploiting the state dependence in wages. Hours, wages and productivity will all be affected by the labor market conditions in $\theta^t$. The history of an individual's wages, however, will only affect current wages. The authors therefore instrument for the individual's wage with year-of-entry effects, capturing the impact over time of the conditions under which the job was started. The marginal productivity term is parameterized as a function of industry-specific productivity effects in each time period, as well as the individual's experience and tenure on the job.

The model of Beaudry and DiNardo would correspond to a system of dynamic hours and wage equations if the history dependence of hours and wages could be summarized by their lagged values. Assuming that the impact of labor market conditions up to period t-1 on a contract can be summarized by wages and hours in t-1, the hours equation can be rewritten.

$$\ln h_{i,t}\left(h_{i,t-1},\theta_t,X_{i,t}\right)=\Omega_1\ln w_{i,t}\left(w_{t-1},\theta_t,X_{i,t}\right)+\Omega_2\ln\psi\left(\theta^t,X_{i,t}\right)$$

This equation has the advantage of allowing time-of-entry to affect both hours and wages separately. For example, if workers hired in good times are able to work more hours in subsequent periods as a result of their contracts, hours will exhibit history dependence that is not captured by the wage. Estimating the system of equations

$$\ln hours_{i,t}=\beta_0+\beta_1\ln hours_{i,t-1}+\beta_2\ln wage_{i,t}+x_{i,t}'\varphi+z_{it}'\delta+\varepsilon_{i,t}^h$$

$$\ln wage_{i,t}=\gamma_0+\gamma_1\ln wage_{i,t-1}+x_{i,t}'\pi+\varepsilon_{i,t}^w$$

captures the intuition of this model. Here, Z in the hours equation is the set of variables that Beaudry and DiNardo use to parameterize the marginal productivity of labor. Inclusion of these variables allows the same dynamic hours equation derived above in a different context to be interpreted as the implication of an implicit contracts framework.

## 2.3 Alternative sources of dynamics

Additional possible sources for dynamics in the hours equation include nonseparable preferences, such as habit formation (Shaw 1989), 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. When agents take into account the impact of today's hours of work on tomorrow's budget constraint or utility function, nonlinearities in the first order conditions are introduced. 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.

$$\ln h_{it} = \theta\left(\ln h_{i,t-1}, w_{it}\right) + z_{it}'\gamma + u_{it}$$

This equation is estimated using local linear kernel methods to estimate the unknown function $\Theta\left(\right)$. Using SIPP data with time periods of four months, Kniesner and Li find that the average coefficient on lagged ours is 0.57. The implication is that the average man takes about 10 months to fully adjust his labor supply. Allowing for nonlinearity in the lagged hours and wage terms not only permits examination of heterogeneous responses to wage changes, but also corresponds to models of habit formation that imply interactions between lagged hours and wages in the hours equation. 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.

$$\ln hours_{i,t} = \beta_0 + \beta_1 \ln hours_{i,t-1} + \beta_2 \ln wage_{i,t} + x'_{i,t}\varphi + \alpha_i^h + \varepsilon_{i,t}^h$$

$$\ln wage_{i,t} = \gamma_0 + \gamma_1 \ln wage_{i,t-1} + x'_{i,t}\pi + \alpha_i^w + \varepsilon_{i,t}^w$$

The hours and wages depend on their own lagged values, exogenous individual characteristics, and both time varying and time-invariant unobserved characteristics. Here, $\alpha_i^h$ and $\alpha_i^w$ are fixed effects, potentially correlated with the variables in X.

Endogeneity of the wage in the hours equation operates through two channels: correlation between $\alpha_i^h$ and $\alpha_i^w$, and correlation between $\varepsilon_{i,t}^h$ and $\varepsilon_{i,t}^w$. The lagged wage allows for state dependence in the wage 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.

Correlation between the fixed effects comes from two channels. 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 (see Blundell and MaCurdy 1999 for a discussion). Any individual characteristics that affect wages in every time period (i.e., any components of $\alpha_i^w$) 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.

Consistent 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 $\varepsilon_{i,t}^h$ and $\varepsilon_{i,t}^w$ 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 follow other studies using the PSID, which typically use annual hours worked as the labor supply variable. 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, $v_{it}^h$ and $v_{it}^w$, are additive in the log hours and log wage equations, respectively, and uncorrelated with the true values, $\ln h_{it}^{**}$ and $\ln w_{it}^{**}$.

$$\begin{aligned} \ln h_{it} &= \ln h_{it}^{**} + v_{it}^h \\ \ln w_{it} &= \ln w_{it}^{**} + v_{it}^w \end{aligned}$$

If present, this type of measurement error will induce a negative correlation between the time-varying error terms, $\varepsilon_{i,t}^h$ and $\varepsilon_{i,t}^w$.

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 tradeoffs. An alternative approach, adopted here, is to use least-squares dummy variable (LSDV) estimation, and compute the inconsistency directly as a function of the number of time periods, T. The bias-corrected estimates presented below have been calculated using the method of Bun and Carree (2005).

Fixed effect estimation controls for one source of endogeneity of the wage, the time invariant heterogeneity captured by $\alpha_i^h$ and $\alpha_i^w$. Fernandez-Val and Vella (2009) propose a two-step control-function strategy to handle the fixed effects as well as the remaining endogeneity generated by the time-varying error terms.

In the first step, the wage equation is estimated by LSDV and the coefficients are corrected for bias. Defining $\widetilde{x}_{i,t} = x_{i,t} - \overline{x}_i$, the transformed wage equation is:

$$\widetilde{\ln w}_{i,t} = \gamma_0 + \gamma_1 \widetilde{\ln w}_{i,t-1} + \widetilde{x}'_{i,t}\pi + \widetilde{\varepsilon}^w_{i,t}$$

Denoting the bias corrected estimates with "bc," the estimated residuals are

$$\widehat{\widetilde{\varepsilon}}^w_{i,t} = \widetilde{\ln w}_{i,t} - \widehat{\gamma}_0^{bc} - \widehat{\gamma}_1^{bc} \widetilde{\ln w}_{i,t-1} - \widetilde{x}'_{i,t}\widehat{\pi}^{bc}$$

In the second step of estimation, these residuals are included as a control function 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. 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 $\beta_2$. The final estimating equation is:

$$\ln hours_{i,t} = \beta_0 + \beta_1 \ln hours_{i,t-1} + \beta_2 \ln wage_{i,t} + x'_{i,t}\delta + \rho\widehat{\widetilde{\varepsilon}^{w}_{i,t}} + \alpha_i^h + \varepsilon_{i,t}^h$$

This hours equation is estimated via fixed effects and the coefficients corrected for bias.

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 and 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. 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. These are education, self-reported health status, age, age-squared, and an age and education interaction. In addition, the hours equation includes number of children present in the household and marital status. In the specification labeled "implicit contracts," an additional set of control variables is added to the hours equation. These variables, denoted Z in the previous section, 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.

## 4 Results

Table 1 shows the results of step 1, estimation of the reduced form wage equation. Even after controlling for individual heterogeneity, lagged wages are an important determinant of current wages. The estimated elasticity is 0.474 between current and past wages. The nonlinear terms in age and education are also significant. Failure to correct for bias results in underestimating the impact of lagged wages by more than 26 percent.

Table 2 presents the results of the dynamic hours equation estimation under the hours restrictions framework. The first two columns show the results of LSDV estimations that do not account for the time-varying endogeneity of the wage, before and after bias-correction. The nonlinear age and education terms appear to be significant determinants of labor supply, with t-statistics above 2 in absolute value. Marital status is also significant, indicating that married men work slightly longer hours. The coefficient on the log wage is around -0.242 after bias correction and strongly significant.

The next 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 -0.24 and highly significant in column 2, to -0.027 and no longer statistically significant at standard levels in column 4. 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 significant, with a t-statistic of -9.73.

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 .227 to .269. Bias correction makes a larger difference, increasing the control-function adjusted estimate from 0.319 to 0.379.

Table 3 presents the results of estimating the hours equation under the implicit contracts specification, in which an additional set of regressors is added to the hours equation. The signs and significance levels of the original set of variables follows the same pattern as in the implicit hours specification, with the exception of the coefficient on the log wage. Here, including the control function to eliminate the time-varying endogeneity of the wage again makes the wage coefficient less negative. The final bias-corrected estimate is significantly different from zero, however, in the implicit contracts case. In addition, both tenure and tenure squared are significant, indicating a positive effect of tenure on hours that diminishes over time. Several of the cross industry-time effects are significant at the 5% level as well. The coefficient on the control function is -0.231 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. The coefficient on the lag of log hours increases from .300 to .354 after bias correction.

# 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 0.35 and 0.38. 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.

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 0.379 implies an adjustment cost of 0.621. In the hours restrictions framework, this means that, from one year to the next, an individual in the sample is only able to change his hours by 62.1% 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 on 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. This 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 negative, 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 and significant, 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 on 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 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. Ham and Reilly (2006) 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. Modelling 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 to 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 0.35 and 0.38. Failure to correct for dynamic panel bias leads to underestimating this effect by more than 25 percent.

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 negative and significantly different from zero. This result is consistent with the view that state dependence in the hours equation is generated by implicit contracts between workers and employers.

# References

[1] Abowd, John M & Card, David, 1987. "Intertemporal Labor Supply and Long-term Employment Contracts," *American Economic Review*, vol. 77(1), pages 50-68, March.

[2] Altonji, Joseph G. (1986): "Intertemporal Substitution in Labor Supply: Evidence from Micro Data." *Journal of Political Economy*, Vol. 94, No. 3, Part 2, pp. S176 - S215.

[3] Altonji, Joseph G. and Christina H.Paxson. (1992) "Labor Supply, Hours Constraints, and Job Mobility." *The Journal of Human Resources*, Vol. 27, No. 2, pp. 256-278

[4] Baltagi, Badi H., Espen Bratberg, and Tor Helge Holmas. (2005) "A Panel Data Study of Physicians Labor Supply: the Case of Norway." *Health Economics*, vol. 14(10), pages 1035-1045.

[5] Beaudry, Paul & DiNardo, John, 1991. "The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from Micro Data," *Journal of Political Economy*, University of Chicago Press, vol. 99(4), pages 665-88.

[6] Beaudry, Paul & DiNardo, John, 1995. "Is the Behavior of Hours Worked Consistent with Implicit Contract Theory?," *The Quarterly Journal of Economics*, MIT Press, vol. 110(3), pages 743-68.

[7] Biddle, Jeff E. (1988) "Intertemporal Substitution and Hours Restrictions." *Review of Economics and Statistics*, vol 70, no2. pp 347-351.

[8] Bun, Maurice J.G. and Martin A. Carree. (2005). "Bias-Corrected Estimation in Dynamic Panel Data Models." *Journal of Business and Economic Statistics*; vol 23, no 2. pp. 200 - 210.

[9] Blundell, Richard & Ham, John & Meghir, Costas. (1987). "Unemployment and Female Labour Supply," *Economic Journal*, Royal Economic Society, vol. 97(388a), pages 44-64, Supplemen.

[10] Blundell and T. MaCurdy (1999): "Labor Supply: A Review of Alternate Approaches," Handbook of Labor Economics, Volume 3.

[11] Browning, Deaton and Irish (1985): "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle." *Econometrica* Vol. 53, No. 3. pp. 503-544.

[12] Chamberlain, G. (1982): "Multivariate Regression Models for Panel Data." *Journal of Econometrics* 18, 5 - 46.

[13] Euwals, R., Bertrand Melenberg, and Arthur van Soest. (1998) "Testing the Predictive Value of Subjective Labor Supply Data." *Journal of Econometrics*, vol 13, no. 5, Special Issue: Application of Semiparametric Methods for Micro-Data. pp. 567-585.

[14] Fernandez-Val, Ivan and Francis Vella (2009). "Bias Corrections for Two-Step Fixed Effects Panel Data Estimators." IZA working paper 2690.

[15] Ham, John C. (1982). "Estimation of a Labour Supply Model with Censoring Due to Unemployment and Underemployment." *The Review of Economic Studies*, Vol. 49, No. 3, pp. 335-354

[16] — (1986). "Testing Whether Unemployment Represents Intertemporal Labour Supply Behaviour." *The Review of Economic Studies*, Vol. 53, No. 4, Econometrics Special Issue, pp. 559-578

[17] Ham, John C. and Kevin T. Reilly. (2002) "Testing Intertemporal Substitution, Implicit Contracts, and Hours Restriction Models of the Labor Market Using Micro Data." *The American Economic Review*, vol. 94, no 2, pp 905-927.

[18] Heckman, J. and T. MaCurdy (1980): "A Life Cycle Model of Female Labor Supply." *The Review of Economic Studies,* Vol. 47, No.1, Econometrics Issue. pp. 47 - 74.

[19] Holtz-Eakin, Douglas, Whitney Newey, and Harvey S. Rosen (1988). *Econometrica*, vol 56, no6. pp 1371-1395.

[20] Kniesner, Thomas and Qi Li. (2002) "Nonlinearity in Dynamic Adjustment: Semiparametric Estimation of Panel Labor Supply." *Empirical Economics*, Springer, vol. 27(1), pages 131-148.

[21] MaCurdy, T. (1981). "An Empirical Model of Labor Supply in a Life Cycle Setting." *Journal of Political Economy* 89, 1059–1085.

[22] —— (1983): "A Simple Scheme for Estimating an Intertemporal Model of Labor Supply and Consumption in the Presence of Taxes and Uncertainty." *International Economic Review*, Vol. 24, No. 2. pp. 265-289.

Table 1: Dependent variable: log wage.

| | LSDV | LSDV-BiasCorr |
|---|---|---|
| lag log wage | 0.3498 | 0.4740 |
| | (32.9004) | (40.2669) |
| age | 0.0098 | 0.0067 |
| | (1.6590) | (1.1340) |
| age2 | -0.0003 | -0.0002 |
| | (-5.3131) | (-3.9934) |
| age*educ | 0.0015 | 0.0012 |
| | (5.7516) | (4.4734) |
| health | -0.0013 | -0.0019 |
| | (-0.3562) | (-0.5224) |
| n=8388 | | |

T-statistics in parentheses.

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

| | LSDV | LSDV-BiasCorr | LSDV Control Fct* | LSDV Control Fct - BiasCorr* |
|---|---|---|---|---|
| lag log hrs | 0.2272 | 0.3191 | 0.2687 | 0.3792 |
| | (22.3817) | (29.6697) | (25.0717) | (19.3211) |
| log wage | -0.2403 | -0.2415 | -0.0771 | -0.0272 |
| | (-32.7170) | (-33.0474) | (-4.7611) | (-1.3399) |
| health | -0.0002 | 0.0001 | -0.0002 | 0.0002 |
| | (-0.0904) | (0.0343) | (-0.0638) | (0.0712) |
| kids | 0.0041 | 0.0042 | 0.0033 | 0.0030 |
| | (1.5633) | (1.5796) | (1.2395) | (1.0462) |
| young kids | -0.0025 | -0.0029 | -0.0027 | -0.0032 |
| | (-0.5451) | (-0.6333) | (-0.5969) | (-0.6707) |
| age | 0.0024 | 0.0024 | -0.0004 | -0.0012 |
| | (0.5659) | (0.5783) | (-0.0880) | (-0.2460) |
| age sq | -0.00010 | -0.00010 | -0.00001 | 0.00001 |
| | (-2.1520) | (-2.1492) | (-0.2764) | (0.2691) |
| age*educ | 0.00059 | 0.00057 | 0.00018 | 0.00003 |
| | (3.1733) | (3.1080) | (0.9476) | (0.1446) |
| married | 0.0296 | 0.0280 | 0.0274 | 0.0250 |
| | (3.8077) | (3.6227) | (3.5512) | (2.8064) |
| control fct | | | -0.1965 | -0.2580 |
| | | | (-11.2943) | (-9.7329) |

T-statistics in parentheses.

Table 3: Implicit contracts specification. Dependent variable: log hours of work.

| | LSDV | LSDV-BiasCorr | LSDV Control Fct* | LSDV Control Fct - BiasCorr* |
|---|---|---|---|---|
| lag log hrs | 0.1833 | 0.2997 | 0.2130 | 0.3539 |
| | (15.4435) | (23.6157) | (16.7980) | (25.5751) |
| log wage | -0.2691 | -0.2734 | -0.1444 | -0.0719 |
| | (-30.2544) | (-30.9997) | (-6.8175) | (-3.4008) |
| health | -0.0014 | -0.0008 | -0.0015 | -0.0009 |
| | (-0.4721) | (-0.2821) | (-0.4942) | (-0.3140) |
| kids | 0.0047 | 0.0051 | 0.0041 | 0.0042 |
| | (1.3652) | (1.4931) | (1.2022) | (1.2623) |
| young kids | 0.0023 | 0.0020 | 0.0021 | 0.0016 |
| | (0.4218) | (0.3670) | (0.3785) | (-1.3130) |
| age | -0.0139 | -0.0129 | -0.0112 | -0.0084 |
| | (-2.0763) | (-1.9365) | (-1.6734) | (0.3685) |
| age sq | 0.0000 | 0.0000 | 0.00002 | 0.00002 |
| | (-0.0441) | (-0.0865) | (0.2102) | (0.6481) |
| age*educ | 0.0009 | 0.0009 | 0.0005 | 0.0002 |
| | (3.1383) | (2.9376) | (1.7151) | (0.2925) |
| married | 0.0163 | 0.0152 | 0.0156 | 0.0140 |
| | (1.7953) | (1.6836) | (1.7244) | (1.5582) |
| tenure | 0.0046 | 0.0039 | 0.0037 | 0.0025 |
| | (4.6209) | (3.9720) | (3.7279) | (2.5379) |
| tenure sq | -0.0156 | -0.0132 | -0.0129 | -0.0088 |
| | (-3.9663) | (-3.3897) | (-3.2880) | (-2.2876) |
| control fct | | | -0.1426 | -0.2306 |
| | | | (-6.4876) | (-10.468) |

T-statistics in parentheses. Also included as exogenous regressors are a set of interactions of time and industry effects.