Essays in Applied Microeconometrics

A Dissertation
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Doctor of Philosophy
in Economics

By

Elizabeth A. Schroeder, M.Sc.

Washington, DC
August 6, 2010

Essays in Applied Microeconometrics

Elizabeth A. Schroeder, M.Sc.

Thesis Advisor: Francis Vella, Ph.D.

Abstract

This dissertation applies recent econometric techniques using control functions to outstanding questions in the labor and development literatures.

The first chapter estimates the Frisch elasticity of labor supply, which represents the intertemporal elasticity of substitution. Previous estimation has focused on hours equations in which individual effects, representing the marginal utility of wealth, enter additively and can be differenced out. Using PSID data, I relax this assumption for a sample of prime-age men. I estimate a semiparametric labor supply equation, using a control function strategy that allows fixed effects to be both non-additive and correlated with the regressors. The average structural function and average partial effects of wages on hours are identified and estimated. The Frisch elasticity is found to be near zero, suggesting that underlying assumptions about separability are not driving the small elasticities found in previous studies.

In the second chapter, 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 0.31 and 0.33. 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 15

percent. Time-varying endogeneity of the wage is handled using a control-function approach.

The third chapter estimates the impact of microcredit borrowing from the Grameen Bank and two similar microfinance institutions in Bangladesh. I find that an increase in the amount borrowed has a positive and significant effect on per-capita household consumption. The estimated elasticity is in the range of 0.193 to 0.212, and these parameters can be interpreted as the impact of borrowing on a randomly selected household in Bangladesh. The model is identified by an assumption on the conditional second moments of the errors. These results contribute to the ongoing debate over whether or not microcredit is helping to reduce poverty.

Table of Contents

Introduction

Recent developments in econometrics have made it possible to relax strong assumptions in a variety of empirical literatures, and to obtain identification in areas of research that have previously proved intractable. This dissertation addresses unresolved issues in labor and development economics through the application of modern control-function techniques.

The first and second chapters are applications of life-cycle labor supply theory. Both chapters address issues that have arisen in the literature on the Frisch elasticity of labor supply. Estimation of this parameter, defined as the elasticity of hours with respect to the wage, holding marginal utility of wealth constant, is complicated by the presence of the unobserved marginal utility of wealth in the individual heterogeneity. The issue is typically handled with linear life-cycle labor supply equations, which are derived from utility functions that are separable in consumption and leisure. The separability assumption implies that the individual effects are additive in the hours equation and can be differenced out. This assumption is widely recognized in the literature as unlikely to be true, and can lead to biased estimates of the Frisch elasticity. The first chapter below uses PSID data on prime-age men to examine the severity of this bias by estimating a semiparametric labor supply equation for married men that allows for a more general form of utility. A control function is used to control for the unobserved individual heterogeneity, allowing individual effects to be both non-additive and correlated with the exogenous variables. The estimation strategy identifies and estimates the average structural effects of wages on hours. I find that the Frisch elasticity is positive and significant, but small, at 0.0076.

The next chapter addresses the puzzle present above and throughout the life-cyle labor supply literature, of why the estimated response of hours to wages is so weak. I find that the weak dependence of hours worked on wages, rather than indicating a small elasticity of intertemporal substitution, is the result of delayed adjustment. Workers are unable to fully re-optimize in each period, and therefore take time to adjust labor supply to changes in the wage. Using PSID data, I estimate a log-linear dynamic labor supply equation. Endogeneity of the wage is handled with a control-function approach, which exploits the fact that lagged wages affect current wages, but not current hours conditional on wages. Estimates are corrected for dynamic panel bias. The estimated elasticity of hours with respect to lagged hours is around 0.3, and failure to bias-correct leads to underestimating this effect by more than 15 percent.

A recurring issue in the literature on microcredit has been the failure to find instrumental variables that can be used to control for the endogeneity of borrowing with respect to outcomes such as household consumption. The final chapter below contributes to this literature by estimating the effects of microcredit loans using an alternative identification strategy that has been introduced in the education literature. In the absence of variables that can be assumed to affect borrowing but not consumption, identification cannot be achieved by making further assumptions on the first moments of the borrowing and consumption error terms. Instead, I impose a restriction on the second moments of the errors, under which the model is identified in the presence of the heteroskedasticity that is evident in the data. Examining the impact of borrowing from the Grameen Bank and two similar microfinance institutions in Bangladesh, I find that an increase in the amount borrowed has a positive and significant effect on per-capita household consumption. The estimated elasticity is in the range of 0.193 to 0.212, and these parameters can be interpreted as the impact of borrowing on a randomly selected household in Bangladesh. These results contribute to the ongoing debate, driven by the rapid expansion of microfinance programs in recent years, over whether or not microcredit is helping to reduce poverty.

Chapter 1: A Semiparametric Life Cycle Labor Supply Model with Non-Additive Fixed Effects

1 Introduction

The intertemporal substitution elasticity is used in many macroeconomic models and is essential to the analysis of tax and benefit policies. This elasticity is often estimated with household data using marginal utility of wealth-constant labor supply functions. The wage elasticity in these equations is known as the Frisch elasticity, and measures the change in hours of labor supplied over time in response to receiving different wages at different periods of the life-cycle. It is interpreted as the response of labor supply to anticipated changes in the wage.

Frisch labor supply equations are typically derived from utility functions that are separable in consumption and leisure, which generate labor supply equations that are additive in marginal utility of wealth. At a minimum, estimation of Frisch, or "lambda-constant", labor supply equations has previously required utility to be quasi-homothetic, in which case marginal utility of can be treated as additive even if preferences are not separable. These assumptions are made so that marginal utility, which is unobserved, can be treated as a fixed effect. The assumption that utility is separable between consumption and leisure is widely recognized in the literature as unlikely to be true. Quasi-homotheticity is also a strong and potentially misleading assumption. If these assumptions are false, estimates of the Frisch elasticity used for policy analysis could be severely biased.

I examine the severity of this bias by estimating a life-cycle labor supply equation for married men that allows for a more general form of utility, and thus does not require additive fixed effects. Specifically, I allow the fixed effect to enter the hours equation in an unspecified, nonlinear, way. The hours equation is estimated using the double-index semiparametric least squares estimator of Ichimura and Lee (1988). A control function is employed to account for the fixed effect, which contains the marginal utility of wealth. This strategy allows the individual effects to be both non-additive and correlated with other variables.

2 Literature

Modern life-cycle labor supply estimation began with Heckman and MaCurdy (1980) and MaCurdy (1981 and 1983). These papers formulate the labor supply decision in a given period as a function of current state variables, including wages and household characteristics. An individual solves the following problem.

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

$$\text{s.t. } a_{i,t+1} = \left(1 + r_{t+1}\right)\left(a_{it} + w_{it}h_{it} - c_{it}\right) \tag{2}$$

The first order conditions, assuming an interior solution for consumption, are:

$$U_c(c_{it}, h_{it}) = \lambda_{it} \tag{3}$$

$$U_h(c_{it}, h_{it}) \geq \lambda_{it} w_{it} \tag{4}$$

where λ_{it} is the marginal utility of wealth, $\frac{\delta V}{\delta a_{it}}$. Demands for quantities of goods and leisure can then be written as functions of current prices and the marginal utility of wealth. These demands are known as Frisch demands. A Frisch labor supply equation takes the following form.

$$h_{it} = f_{it}(w_{it}, \lambda_{it}) \tag{5}$$

Here, $f_{it}()$ may be a function of preference-shifting variables such as household or individual characteristics. Using this equation to estimate labor supply elasticities has two benefits. First, equation (5) does not include consumption, and so can be estimated without consumption data. Second, past and future realizations of wages and any preference variables enter the hours decision only through their effect on current marginal utility of wealth. Marginal utility is unobserved, but the solution to the agent's optimization problem keeps expected marginal utility constant over the life cycle. Assuming rational expectations and perfect capital markets, marginal utility evolves according to the following Euler equation.

$$\lambda_{it} = E[\beta(1 + r_{t+1})\lambda_{i,t+1}] \tag{6}$$

Estimation typically employs a log-approximation of the Euler equation, which breaks λ_{it} into distinct components.

$$\ln \lambda_{it} = \mu_t + \ln \lambda_{i0} + \varepsilon_{it} \tag{7}$$

Individuals determine their marginal utility of wealth at the beginning of the life cycle, setting λ_{i0}. Marginal utility in each subsequent period differs from this initial level by a time effect μ_t, which is a function of the common discount rate and interest rate, and an idiosyncratic forecast error ε_{it}. The Frisch labor supply equation can now be estimated, given proper treatment of λ_{i0}.

In order to handle the unobserved marginal utility of wealth, past studies impose a labor supply function of the following form (Browning 1986).

$$g(h_{it}) = \psi_{it}(w_t) + \phi_i(\lambda_t) \tag{8}$$

The estimate of $\frac{\partial h_{it}}{\partial w_{it}}$ gives an estimate of the Frisch elasticity, the effect of a change in wages holding λ constant. If the function $\phi_i()$ is the natural log, equation (7) can be substituted in for the last term, and the time-invariant individual effect, $\ln \lambda_{i0}$, can be treated as a fixed effect.

The obvious benefit of this framework is that accounting for the fixed effect controls for the influence of all past and future time periods on the current hours choice. The cost, however, is that generating a labor supply equation in which the marginal utility term is additive or log-additive requires restrictions on preferences. A common strategy follows Heckman and MaCurdy (1980) and Macurdy (1981), and is summarized by Blundell and MaCurdy (1999). A log specification is generated by a utility function that is separable in consumption and labor.

$$U_{it} = g(c_{it}, Z_{it}) + \exp(-Z_{it}\rho - v_{it})(h_{it})^{\sigma} \tag{9}$$

Which gives the first order condition:

$$\ln h_{it} = \frac{1}{1-\sigma}\left(\ln w_{it} + \rho Z_{it} + \ln \lambda_{it} - \ln \sigma + v_{it}\right) \tag{10}$$

$$\ln h_{it} = \delta \ln w_{it} + \alpha_{i0} + \mu_t + \beta Z_{it} + e_{it} \tag{11}$$

where $\alpha_{i,t} = \delta(\ln \lambda_{i,t} - \ln \sigma)$ and α_{i0}, the individual effect, comes from substituting in the updating process for $\lambda_{i,t}$.[1] The individual effect contains time zero marginal utility of wealth and is thus theoretically correlated with w_{it} and Z_{it}. Since wages in time t affect wealth, and the preference variables contained in Z affect utility, the wages and preference variables in all time periods can be expected to be correlated with the marginal utility of wealth. The marginal utility term is therefore treated as a fixed effect, and the hours equation is estimated in first differences.

$$\Delta \ln h_{it} = \delta \Delta \ln w_{it} + \beta \Delta Z_{it} + \theta_t + \Delta e_t \tag{12}$$

The estimate of δ is an estimate of the Frisch elasticity.

MaCurdy (1981) estimates an equation of this form and finds the Frisch elasticity to be 0.23, which is reduced to 0.10 when time dummies are included to control for the interest rate effects μ_t. Since then, estimates have tended to fall within or close to this range, include those of Altonji (1986) and Ham (1986), despite different specifications for preferences and different instruments used to control for remaining time-varying endogeneity of the wage.

There is ample evidence, however, rejecting intratemporal separability between consumption and leisure, which is assumed by both MaCurdy and Altonji. Altonji estimates an equation similar to (12), but then tests the separability assumption by adding terms for cross substitution between consumption and hours. He concludes

[1] Here, $\delta = \frac{1}{\sigma - 1}$, $\beta = \delta\rho$, and $e_{it} = \delta v_{it}$.

that the assumption of separability is unlikely to be true. Browning and Meghir (1991) devise a methodology for testing for weak separability. Using a system of conditional demand functions for household commodities in the UK Family Expenditure Survey, they test whether these demands depend on labor supply. The authors find that variation in labor supply variables is important in explaining variation in budget shares. They conclude that separability of demand for goods from both hours of work and labor force participation is rejected, for both males and females. Blundell, Browning and Meghir (1993) use this dataset to extend the idea of conditioning on labor supply to the marginal utility of wealth-constant framework. They specify a set of preferences that allow them to exploit results on two-stage budgeting (Gorman 1959), first estimating within-period preferences, and then aggregating cohorts and estimating intertemporal preferences. They find that labor market variables have significant effects on consumption growth, which is a further rejection of separability.

Blundell, Fry and Meghir (1990) show that relaxing additive separability in a log-hours labor supply equation can only be done by imposing homothetic preferences. An alternative specification is found in Browning, Deaton and Irish (1985). The authors relax additive separability by defining an individual's profit function and deriving the corresponding duel problem to utility maximization. Here, the transformation for g() in equation (5) is linear. The authors show, however, that treatment of λ or $\ln(\lambda)$ as additive in the hours equations implies intra-period quasi-homotheticity. (This point is also discussed in Browning (1986) and Nickell (1988)). Preferences of this type restrict hours of work and expenditures to be linearly related to within-period full income. Browning, Deaton and Irish estimate this model using a pseudo panel created with cohort means. While the elasticity is not parameterized as it is in the MaCurdy-type specification, they find the intertemporal elasticity at the mean of hours to be around 0.4 when allowing nonseparability.

Blundell, Fry and Meghir discuss the limitations of quasi-homothetic preferences. As expenditures increase, preferences become linear Leontief, implying that the rich have zero within-period substitution effects. In addition, the intertemporal elasticity of substitution tends to zero as expenditures rise. The authors conclude that these may be strong restrictions to impose, and a high price to pay for relaxing separability between consumption and leisure.

An alternative approach to estimating the intertemporal elasticity of substitution is to parameterize utility in such a way that preference parameters can be estimated in two stages. First, within-period preferences can be estimated using the first order conditions for consumption and labor. Next, a suitably parameterized intertemporal Euler equation can be estimated to recover intertemporal parameters. This approach requires specification of intertemporal preferences, but has the advantage of removing the restrictions on utility discussed above, as it does not require marginal utility to be additive in the first order condition for hours. It does require data on consumption, however, which can be difficult to obtain at the individual level, since purchases are often made at the household level. The two-stage approach also requires dealing with the endogeneity of consumption in the hours decision.

I relax the restrictions on utility that are needed to estimate an additive fixed effects Frisch labor supply equation, but do not require data on consumption. I estimate a log-hours equation in which the marginal utility term is allowed to enter the equation in an unspecified manner, allowing for nonseparability and nonhomotheticity. I identify and estimate the average structural function, which gives the expected value of the hours function at a given X, averaged over the marginal utility of wealth.

This methodology also has the advantage of allowing the Frisch elasticity to vary at different points in the data. Models that imply a constant Frisch elasticity are typically rejected, and the literature has found significant differences in elasticity among wealth quantiles. For example, using a two-stage approach similar to that discussed above, Ziliak and Kniesner (1999) find that the Frisch elasticity rises with wealth, so that the hours response to a wage change is about 40% higher for the wealthiest quartile of men than for the poorest quartile. The authors conclude that examining only average elasticities obscures the distributional effects of tax policy. I therefore also estimate the distribution of the wage elasticity, both averaged over the individual effect and unconditionally.

3 Estimation and Identification

I relax the assumptions that estimating equation (8) imposes on utility by allowing for an arbitrary relationship between the marginal utility of wealth and the observed variables that determine labor supply. This is achieved by estimating an hours equation that allows the individual effect to enter in an unspecified way. Denote the observed variables $X_{it} = [\ln w_{it}, Z_{it,}\mu_t]$. Let $\eta_{it} = [\lambda_{i0}, \varepsilon_{it}]$. The equation of interest is

$$\ln h_{it} = h^*(X_{it}, \eta_{it}) + e_{it} \tag{13}$$

Here, e_{it} is a zero-mean error term, assumed to be uncorrelated with X and η. The function $h^*()$ is unspecified, and allows for interactions between its two arguments. Life-cycle theory tells us that the marginal utility of wealth is a function of an individual's wages and other characteristics in every period of the life cycle. The unobserved λ_{i0} is therefore correlated with the variables in X_{it}, and correlation between the two arguments of h*() must be taken into account. The objective is to estimate structural effects using equation (13). In order to identify the effects of changes in the X variables on hours, I make the following three assumptions. Maurer, Klein and Vella (2007) apply a similar approach in a semiparametric binary choice model that is estimated by maximum likelihood.

Define X_i as individual i's realization of X for all time periods; $X_i = X_{i,1}$, $X_{i,2}$,..., $X_{i,T}$.

Assumption 1:

$h_{i,t}$ depends on X_i and the error term only through contemporaneous components.

$$h_{i,t} \perp X_i, \eta_i | X_{i,t}, \eta_{i,t}$$

This assumption follows directly from life-cycle theory and is the driving intuition behind the Frisch labor supply equation. Past and future wages and taste-shifters affect labor supply for individual i at time t only by changing the value of marginal utility of wealth. After controlling for the unobserved heterogeneity, λ_{i0}, the variables in X_{it} and the idiosyncratic forecast error ε_{it} have no effect on hours in other time periods.

Assumption 2:

There exists a single index $X_{i,t}\beta$ such that $h_{i,t}$ and $X_{i,t}$ are conditionally independent given $X_{i,t}\beta$ and η_{it}

$$h_{it} \perp X_{it}|X_{it}\beta, \eta_{it}$$

This assumption is a dimensionality reduction, or index restriction, which states that the effect of a change in X_{it} on h_{it} can be summarized through a single index. An index restriction is not required theoretically, but is required for the function to be well identified using a reasonable sample size of data. Note that wages and household characteristics have been included in the same index. Ideally, one might estimate a model with three indices, to allow arbitrary interactions of the wage, the characteristics in Z, and the individual effect. This is not feasible given the assumptions needed for the current estimator, however. Thus I assume that the relationship between the individual effect and the X variables can be summarized by the index restriction.

The remaining barrier to estimating the hours equation is that a conventional orthogonality condition is violated. As described above, theory indicates that X_{it} is correlated with the unobserved marginal utility of wealth effect, λ_{i0}. A control function is therefore employed to restore the desired orthogonality conditions. Once the marginal utility of wealth is controlled for, $X_{i,t}$ is uncorrelated with the remaining error term. The control function assumption is stated as follows.

Assumption 3:

There exists a control function V_i such that η_{it} and $X_{i,t}$ are conditionally independent given V_i

$$\eta_{it} \perp X_{i,t} | V_i$$

This assumption allows for identification of what are known in the semiparametric literature as structural effects. By requiring $X_{i,t}$ and η_{it} to move separately in the data, conditional on the control function, the effects of a change in X while holding λ constant can be identified.

The choice of an appropriate control function is guided by the theory of life-cycle labor supply. Marginal utility of wealth depends on wages, taste-shifters, and any non-wage income that contributes to wealth, in all periods of an individual's life. A linear combination, specifically the average, of these observed variables is employed here to control for the part of the error term that is correlated with X_{it}. Conditioning on this function, X_{it} and λ_{i0} are independent.

Let V_i be a vector of the time means of each X variable for individual i, as well as the mean of household income other than his own wage, for the individual over time. Other household income provides a natural exclusion restriction, entering the control function but not $X_{i,t}$. Income obviously affects wealth, and thus marginal utility, but does not enter the hours equation once marginal utility has been controlled for. In addition, age is left out of the control function, assuming that the men in the sample have the same expected life span and thus the same average age over time. The control function and hours equation to be estimated become:

$$\widetilde{X}_i = \frac{1}{T} \sum_{t=1}^{T} \widetilde{X}_{it}$$

$$V_i = \widetilde{X}_i \gamma \tag{14}$$

$$h_{i,t} = h(X_{i,t}\beta, \widetilde{X}_i\gamma) + e_{i,t} \tag{15}$$

This approach is similar to Chamberlain's (1982) "correlated random effects" model, in which the dependence of the individual effect on the X variables is modeled as a combination of past and future Xs. It is also related to the identification strategy of Altonji and Matzkin (2005), who use additional external variables as controls in a nonlinear panel data model. The approach used here is much more practical to implement, however, because of the index restrictions.

The final estimator is the double-index semiparametric least squares estimator of Ichimura and Lee (1988). Let $\theta = [\beta \;\; \gamma]$. The estimate of the parameters is

$$\widehat{\theta} = \min_{\theta} \sum_{i,t} \tau_{it} \left(h_{it} - \widehat{E}\left[h | X_{it}\beta, \widetilde{X}_i\gamma \right] \right)^2 \tag{16}$$

Here, $\widehat{E}$ is a nonparametric expectation. The indices are orthogonalized, then the joint density is estimated as the product of two normal kernels. Local smoothing is used as a bias-reduction technique, following Klein and Vella (2006). They find that using local smoothing, rather than Ichimura and Lee's suggestion of higher-order kernels, significantly improves the finite sample performance of the double-index estimator. A trimming function, τ_{it}, is employed, placing zero weight on observations that have index values below the fifth or above the 95th percentile of the distributions.

The semiparametric estimation described above allows estimation of the average structural function (ASF) suggested by Blundell and Powell (2000, 2003). The ASF describes how the structural function, $h^*(X_{it}\beta, \eta_{it})$, averaged over the unobserved individual heterogeneity $\eta_{i,t}$, depends on X. This is an important object to estimate in the present application, as the relationship between the structural index, $X_{it}\beta$, and hours of work depends on the marginal utility of wealth. For example, individuals with a lower level of wealth (and thus higher marginal utility), might be less responsive to a change in the index variables if they need to keep working to maintain a minimum level of income. Households with greater wealth may have the ability to be more flexible when preference variables change. In particular, this means that the Frisch elasticity may depend on on an individual's level of marginal utility.

At a fixed realization of X, X_0, the ASF is defined as

$$\mu(X_0) = \int h^*(X_0\beta, \eta_{it}) dF_{\eta_{it}} \tag{17}$$

This gives the average value of the hours function at X_0, with the average taken over the marginal density of the individual heterogeneity. Employing the control function assumption, this expression becomes.

$$\begin{aligned} \mu(X_0) &= \int \int h^*(X_0\beta, \eta_{it}) dF_{\eta_{it}|\overline{X}\gamma} dF_{\overline{X}\gamma} \\ &= \int h(X_0\beta, \overline{X}\gamma) dF_{\overline{X}\gamma} \end{aligned} \tag{18}$$

The estimates of the index parameters, $\widehat{\beta}$ and $\widehat{\gamma}$, and the function $\widehat{h}()$ above, allow computation of the predicted $\widehat{h}$ at any X_{it} and $\widetilde{X}_i$ combination. The average structural function is computed at a given X_0 as

$$\widehat{\mu}(X_0) = \frac{1}{N}\sum_{i=1}^{N}\widehat{h}(X_0\widehat{\beta}, \overline{X_i}\gamma) \tag{19}$$

The average is taken over the marginal distribution of the estimated control function.

The estimation above also allows computation of the average partial effects (APE), which give the change in hours with respect to a change in X, averaged over the marginal distribution of the individual effect. In particular, denote the wage elasticity at a given X_0 as h_w, and the APE as $\delta(X_0)$.

$$\begin{aligned} h_w(X_0\beta, \eta_{it}) &= \frac{\partial h(X_0\beta, \eta_{it})}{\partial w} \\ \delta(X_0) &= E_\eta\left[h_w(X_0\beta, \eta_{it})\right] \end{aligned} \tag{20}$$

Given assumption 3, the control function assumption, this expression can be rewritten as

$$\delta(X_0) = E_{\overline{X_i}\gamma}\left[h_w(X_0\beta, \overline{X_i}\widehat{\gamma})\right] \tag{21}$$

(Wooldridge 2002). This function gives estimates of the Frisch elasticity for different values of the structural index, averaged over the marginal utility of wealth. To estimate $\delta(X_0)$, first the wage elasticity is estimated for each individual, at different values of the control function index, by a local linear regression. The wage elasticity at each combination of indices is computed as $\frac{\partial h(X_0\widehat{\beta}, \overline{X_i}\widehat{\gamma})}{\partial\left(X_0\widehat{\beta}\right)} * \widehat{\beta}^{wage}$. Next, the estimated APE of the wage for a given X_0 is the average of these elasticities over the control function.

$$\widehat{\delta}(X_0) = \frac{1}{N}\sum_{i=1}^{N}\widehat{h}_w(X_0\widehat{\beta}, \overline{X_i}\widehat{\gamma}) \tag{22}$$

Given the interest in the literature in the variation of the Frisch elasticity with respect to different levels of wealth, I also compute unconditional wage elasticities. Using the local linear regression estimates of the Frisch elasticity for each individual, without averaging out the individual effect, I examine variation in the elasticity with respect to the control function. This provides an illustration of how different values of marginal utility of wealth impact an individual's responsiveness to changes in the wage.

4 Results

The data are from the Michigan Panel Study of Income Dynamics (PSID) from the years 1984 to 1994. The sample was chosen to most closely match the samples used in the standard papers on life-cycle labor supply, and therefore includes prime-age men, aged 25 – 55, who were employed during each period in the sample. The hours variable used is an individual's annual hours of work. Characteristics in X include marital status, self-reported health status on a scale of 1 to 5, the numbers of total children and young children (under age 6) present in the household, age, age-squared, education, and an interaction between age and education.

Although the control function accounts for endogeneity of the wage due to time-invariant heterogeneity, there is still an important potential source of correlation between the wage term and the error. The typical labor-supply equation uses a measure of hourly earnings that is computed by dividing labor income by the number of hours worked. If hours of work are measured with error, a negative correlation is induced between the measurement error of hours and the measurement error of wages (see Altonji 1986). To avoid this problem, I use data only for workers who report an hourly wage rate. This strategy has the disadvantage of limiting the sample to workers who earn an hourly wage, rather than an annual salary. As these workers are not likely to be a random sample of employees, the results and conclusions below can only be interpreted as statements about prime-age men who work for an hourly wage.

The first column of Table 1 presents the results of estimating the hours equation by OLS. The wage coefficient is -0.011 and significantly different from zero. The third column presents the results of fixed effects estimation, which provides an estimate of the standard Frisch labor supply model, controlling for unobserved marginal utility of wealth with the fixed effect. The signs and significance levels of several of the coefficients change, indicating that the individual effects are in fact correlated with the regressors. The wage coefficient is still negative, but smaller in magnitude than the OLS coefficient and not significantly different from zero. Life-cycle theory predicts that the intertemporal elasticity of substitution, captured here by the wage coefficient, must be positive. Thus the simple fixed effects model seems to fail in this dataset.

Figure 1 presents the estimate of the ASF. The ASF is upward sloping over most of the support of the structural index. It increases from a value of 7.58 to a value of 7.95. The dependent variable is log hours, so these values correspond to annual hours of work ranging from 1,939 to 2,853. Since an increase in the structural index is associated with an increase in the ASF, variables that increase the index can be interpreted as increasing the expected number of hours of work, averaged over the distribution of the marginal utility of wealth.

Table 2 presents the parameter estimates of the structural index. Semiparametric estimates using kernels are identified only up to location and scale. A constant is therefore excluded from each index. The coefficient on age is normalized to one in the structural index, and the coefficient on the average wage is normalized to one in the control function index. Given this normalization, the remaining coefficients can be interpreted in relative terms. All variables have been standardized to have mean zero and standard deviation of one. The log wage, education, number of children, and marital status all enter the index with positive coefficients, and have t-statistics greater than 2. A one standard deviation increase in education, however, has a five times greater impact on the index than a one standard deviation increase in the log wage. A standard deviation increase in the number of children present impacts the index twice as much as education, and a standard deviation increase in marital status contributes by far the most to the index. The coefficient on self-reported health status is also positive, but not significantly different from zero. In contrast to the number of children, which increases the index, the number of young children impacts the index negatively, with a standard deviation increase in each leading to about the same magnitude of impact on hours. The interaction between age and education is also negative and significant, indicating a drop-off to the impact of education as the individual ages. Several of the time dummy variables are significant as well.

Table 3 presents the parameter estimates for the control function index. The mean of income, the mean numbers of children and young children, and mean health status all impact the index negatively and have coefficient estimates that are strongly significantly different from zero. Only the mean of marital status enters with the opposite sign. Standard deviation changes in the means of health and number of children have the greatest impact, with about the same magnitude. The number of young children has about 75% of the impact of the overall number of children, and in this case both move the index in the same direction. The mean of education has the smallest coefficient, and is not significantly different from zero.

The Frisch elasticity is estimated as the Average Partial Effect of the wage on the structural function, and is presented in Figure 2. The estimated elasticity ranges from -0.025 up to 0.0042. While starting out negative and initially increasing, it remains relatively flat over most of the support of the structural index. At the median of the structural index, the Frisch elasticity is estimated to be 0.0005826. This number is lower than MaCurdy's estimate of 0.1, but generally in keeping with the findings in panel data that the Frisch elasticity is positive but small. The semiparametric model is an improvement over the fixed effects model, in that the wage elasticity is positive, as predicted by life-cycle theory. This result suggests that the control function is successfully capturing the impact of the unobserved marginal utility of wealth term, and that allowing the individual heterogeneity to enter the hours equation non-additively significantly improves the estimation.

While there is not a great deal of variation in the wage elasticity with respect to the structural index, it is also instructive to see how it varies with the control function. Figure 3 presents the estimates of the wage elasticity over the support of the control function index, as described above. The wage elasticity decreases as the index increases. The control function captures the individual's marginal utility of wealth, so wealth is decreasing as the index increases. The interpretation of Figure 3 is therefore that wealthier individuals have a greater Frisch elasticity, indicating that they are more flexible in responding to changes in the wage. This result is in agreement with the findings of Ziliak and Kniesner, who also document a higher

Frisch elasticity for wealthier men.

5 Conclusion

This paper contributes to the literature on life-cycle labor supply by estimating a Frisch labor supply equation without requiring additive fixed effects. Allowing fixed effects to enter the hours equation nonlinearly allows for a non-separable, non-quasihomothetic utility function. The Frisch elasticity is found to be positive, at 0.00058, and significantly different from zero. This value is not outside the range of estimates found in the existing literature, although it is quite close to zero. Prime-age men who work for an hourly wage are therefore found to respond very little to changes in the wage when making labor supply decisions. The difference between the linear fixed effects estimate and the semiparametric estimate suggests that an hours equation with additive fixed effects represents a mis-specification of the labor supply function. This result can be interpreted as a rejection of the assumptions on utility that are necessary to generate a labor supply equation with additive fixed effects.

In addition to parameter estimates, the shape of the hours function and its wage derivatives are explored. The Average Structural Function and Average Partial Effects are identified and estimated, with the ASF found to be increasing in the structural index while the APE remains relatively flat. In addition, the wage elasticity is found to be decreasing in the marginal utility of wealth.

6 Chapter 1 Tables

Table 1. OLS and Fixed Effects Estimation

	OLS	T-stat.	Fixed Effects	T-stat.
ln wage	-0.011	(-1.020)	-0.007	(-0.350)
education	-0.032	(-2.740)	0.012	(0.660)
kids	0.009	(2.620)	0.003	(0.550)
youngkid	-0.018	(-2.010)	-0.003	(-0.390)
age	-0.029	(-3.780)	0.002	(0.210)
age2	0.000	(2.990)	0.000	(0.220)
age*ed	0.001	(2.950)	0.000	(-0.720)
health	-0.008	(-1.950)	0.005	(1.160)
married	0.044	(3.740)	0.035	(2.270)
constant	8.400	(42.220)	7.543	(29.500)

Table 2. Structural Index

	Index coeff.	T-stat.
ln wage	0.291	(2.492)
education	1.586	(2.670)
children	3.280	(4.050)
young children	-3.629	(-3.463)
age squared	-0.070	(-0.449)
age*education	-7.075	(-3.193)
health	0.261	(1.439)
married	13.265	(3.257)
year 1985	0.660	(1.665)
year 1986	1.233	(3.076)
year 1987	2.756	(4.605)
year 1988	3.722	(4.624)
year 1989	4.422	(4.422)
year1990	5.398	(4.660)
year 1991	6.689	(4.402)
year 1992	7.496	(4.138)
year 1993	0.729	(1.572)
year 1994	2.466	(5.199)

Table 3. Control Function Index

	Index Coeff.	T-stat.
mean income	-0.771	(-7.088)
mean education	-0.142	(-0.828)
mean children	-2.381	(-9.588)
mean young children	-1.839	(-13.569)
mean health	-2.644	(-12.271)
mean married	1.168	(12.490)

7 Chapter 1 Figures

Figure 1

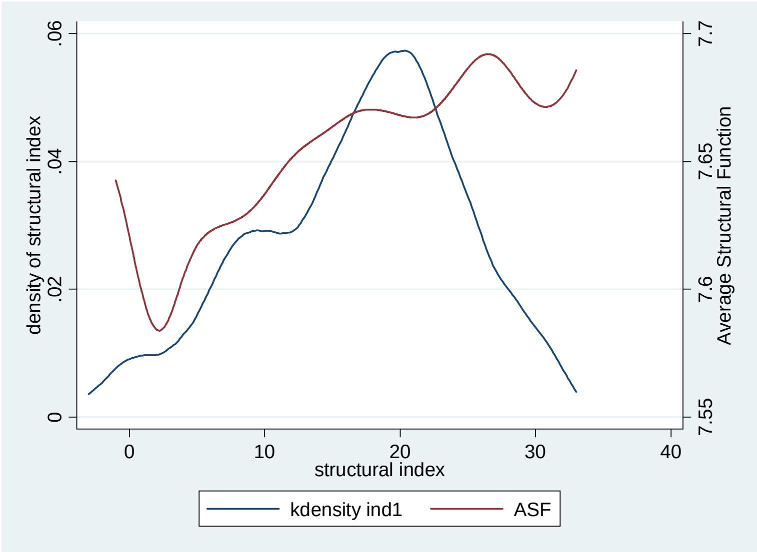


Figure 2

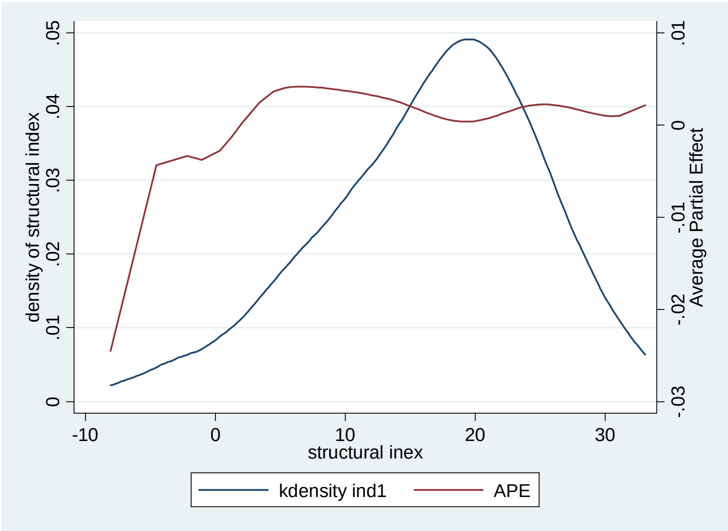
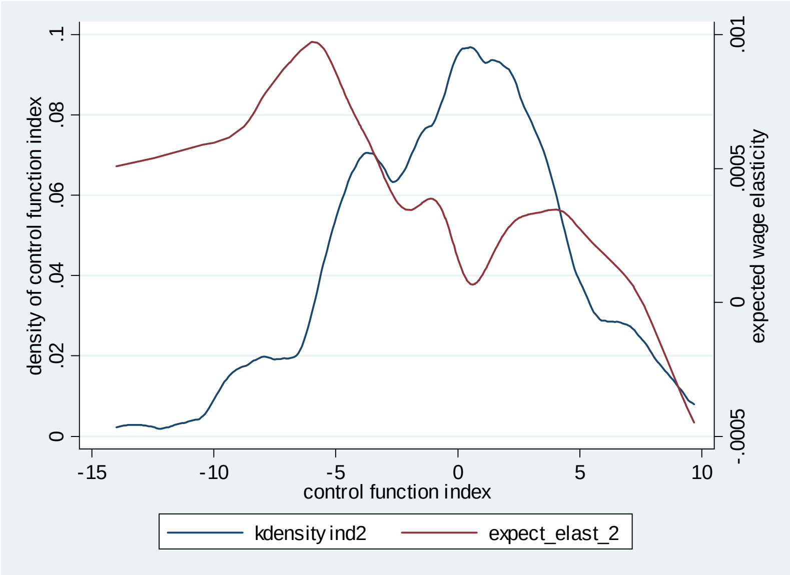


Figure 3



density of control function index
0
.02
.04
.06
.08
.1
expected wage elasticity
-.0005
0
.0005
.001
-15
-10
-5
0
5
10
control function index
kdensity ind2
expect_elast_2

Chapter 2: Dynamic Labor Supply Adjustment with Bias Correction

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, an 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.[2] 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 re-optimize each period in response to changing wages or preference variables. If individuals instead adjust over time, mov-

[2] See Blundell and MacCurdy (1999) for an overview.

ing 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 (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.

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

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

Here, 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 is 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 completely 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 modeling a particular constraint on hours, they introduce a cost to adjusting labor supplied 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. Below, θ is the cost of adjustment, with $0 < \theta \leq 1$.

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

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 view of labor supply is used to generate a dynamic hours 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 θ_t, where $\theta^t = \{\theta_0, ...\theta_t\}$ is the time t contingency. A contract agreed on at time τ 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 a worker's marginal productivity of labor, given by $\psi\left(\theta^t, X_{i,t}\right)$.

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

Beaudry and DiNardo derive a log-linear hours equation from the above 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 θ^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

$$\ln hours_{i,t} = \beta_0 + \beta_1 \ln hours_{i,t-1} + \beta_2 \ln wage_{i,t} + x'_{i,t}\varphi + z'_{it}\delta_1 + \varepsilon^h_{i,t}$$

$$\ln wage_{i,t} = \gamma_0 + \gamma_1 \ln wage_{i,t-1} + x'_{i,t}\pi + z'_{it}\delta_2 + \varepsilon^w_{i,t}$$

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.

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

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

Hours and wages depend on their own lagged values, exogenous individual characteristics, and both time varying and time-invariant unobserved characteristics. Here, α_i^h and α_i^w are treated as fixed effects, potentially correlated with the variables in X. Here, X will incorporate the variables in Z or not, depending on the specification.

Endogeneity of the wage in the hours equation operates through two channels: correlation between α_i^h and α_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. Any individual characteristics that affect wages in every time period (i.e., any components of α_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 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_{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 trade-offs. 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.

Fixed effect estimation controls for one source of endogeneity of the wage, the time-invariant heterogeneity captured by α_i^h and α_i^w. A control function included in the hours equation eliminates the remaining time-varying endogeneity, but introduces an additional source of incidental parameters bias, since the control function depends on the individual effects of the wage equation. Fernandez-Val and Vella (2009) provide a bias-corrected estimator that accounts for this additional source of bias. Their estimator also has the advantage of allowing for predetermined regressors, including lagged dependent variables.

In the first step, the wage equation is estimated by LSDV and the coefficients are corrected for bias. Denoting the bias corrected estimates with "bc," the control function, $\lambda_{i,t}$, is the residual from the estimated wage equation.

$$\lambda_{i,t} = \ln w_{i,t} - \widehat{\gamma}_1^{bc} \ln w_{i,t-1} - x_{i,t}' \widehat{\pi}^{bc} - \widehat{\alpha}_i^w$$

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. 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 β_2. The final estimating equation is:

$$\ln hours_{i,t} = \beta_0 + \beta_1 \ln hours_{i,t-1} + \beta_2 \ln wage_{i,t} + x_{i,t}'\delta + \rho\lambda_{i,t} + \alpha_i^h + \varepsilon_{i,t}^h$$

This hours equation is estimated via fixed effects and the coefficients corrected for bias following Fernandez-Val and Vella.

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. 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. 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 0.414 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 percent.

Table 2 presents the results of the dynamic hours equation estimation under the hours restrictions framework. The first column shows 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 -0.549 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 -0.549 and highly significant in the first column, to 0.1278 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 significant, with a T-statistic of -11.40.

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 .231 to .273. Bias correction also makes a large difference, increasing the control-function adjusted estimate from 0.273 to 0.326.

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 the both 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 -1.142. The coefficient on the control function is -0.469 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 0.271 to 0.308 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 0.31 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.

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 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 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 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 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. 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 0.31 and 0.33. Failure to correct for dynamic panel bias leads to underestimating this effect by more than 15 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 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.

7 Chapter 2 Tables

Table 1. Hours Restrictions Specification

Dependent variable: log wage

	LSDV	LSDV-BiasCorr
lag log wage	0.3499	0.4139
	(33.0521)	(25.8007)
exper	0.2894	0.2497
	(9.2844)	(6.7684)
$exper^2$	-0.2198	-0.1907
	(-6.9811)	(-5.1779)
health	-0.0024	-0.0036
	(-0.3310)	(-0.4800)
married	0.0097	0.0088
	(1.2425)	(0.9802)

T-statistics in parentheses.

Table 2. Hours Restrictions Specification

Dependent variable: log hours of work

	LSDV	LSDV	LSDV - BiasCorr
lag log hrs	0.2305	0.2730	0.3260
	(22.3798)	(25.1092)	(15.6323)
log wage	-0.5492	-0.1075	0.1278
	(-32.6113)	(-2.5486)	(0.7073)
exper	0.2393	0.0208	0.0934
	(4.5164)	(0.3727)	(0.7278)
exper2	-0.1563	0.0043	-0.0956
	(-2.8750)	(0.0770)	(-0.7113)
health	-0.0009	-0.0004	-0.0114
	(-0.0770)	(-0.0370)	(-0.7034)
kids	0.0239	0.0194	0.02179
	(1.5244)	(1.2457)	(1.0357)
young kids	-0.0058	-0.0064	-0.0108
	(-0.5523)	(-0.6192)	(-0.7207)
married	0.0485	0.0403	0.03835
	(3.8050)	(3.1833)	(1.9858)
control fct		-0.5191	-0.7544
		(-11.4018)	(-3.8425)

T-statistics in parentheses.

Table 3. Implicit Contracts Specification

Dependent variable: log wage

	LSDV	LSDV-BiasCorr
lag log wage	0.3395	0.4032
	(31.9465)	(21.4878)
exper	0.3211	0.2806
	(9.9584)	(7.6032)
$exper^2$	-0.1876	-0.1619
	(-5.7283)	(-4.3107)
health	-0.0024	-0.0033
	(-0.3307)	(-0.4169)
married	0.0076	0.0068
	(0.9768)	(0.7757)
tenure	0.1380	0.1292
	(6.3056)	(6.2510)
$tenure^2$	-0.1142	-0.1073
	(-5.4556)	(-5.864)

T-statistics in parentheses.

Includes time and industry effects.

Table 4. Implicit Contracts Specification

Dependent variable: log hours of work

	LSDV	LSDV	LSDV - BiasCorr
lag log hrs	0.2284	0.2709	0.3082
	(22.1562)	(24.8042)	(13.8492)
log wage	-0.5592	-0.1108	-0.1614
	(-32.9633)	(-2.5301)	(-1.1422)
exper	0.2695	0.0322	0.2136
	(4.9210)	(0.5522)	(1.2352)
exper2	-0.1274	0.0039	-0.1874
	(-2.2609)	(0.0687)	(-1.0201)
health	-0.0001	0.0005	-0.0055
	(-0.0106)	(0.0444)	(-0.2752)
kids	0.02526	0.0212	0.0138
	(1.6134)	(1.3662)	(0.5921)
young kids	-0.0086	-0.0087	-0.0203
	(-0.8215)	(-0.8435)	(-1.1040)
married	0.0462	0.0390	0.0492
	(3.6291)	(3.088)	(2.5552)
		(-11.0901)	(-3.0363)

Continued on next page.

Table 4 continued

Dependent variable: log hours of work

	LSDV	LSDV	LSDV - BiasCorr
tenure	0.0797	-0.0228	-0.0951
	(2.2964)	(-0.6409)	(-1.366)
tenure sq	-0.0812	0.0012	0.1527
	(-2.4429)	(0.0361)	(1.6956)
control fct		-0.5217	-0.4689
		(-11.0901)	(-3.0363)

T-statistics in parentheses.

Includes time and industry effects.

Chapter 3: The Impact of Microcredit Borrowing on Household Consumption in Bangladesh

1 Introduction

Microcredit is considered by many practitioners and advocates to be a powerful tool to alleviate poverty. The practice consists of lending small amounts to the very poor for self-employment projects, known as microentrepreneurship, with the intention of allowing households that would otherwise be credit constrained to engage in income-generating activities. The Grameen Bank and its founder, Muhammad Yunus, were awarded the Nobel Peace Prize in 2006 for originating this method of economic development, which has been praised for allowing families to work to end their own poverty. As a result of its perceived success, the Grameen Bank model of lending has spread around the world, reaching millions of people. While microcredit is succeeding at providing access to loans, however, there is little evidence that this lending is achieving the underlying policy goal of poverty reduction.

One of the innovations of the Grameen Bank has been to require borrowers to form small, self-selected groups that accept liability jointly. Much of the literature on microcredit has focused on the potential of this type of group-based lending to overcome credit market imperfections (Stiglitz 1990, Ghatak and Guinnane 1999, Armendariz and Morduch 2005). Traditional banks have historically been unwilling to lend to the rural poor in developing countries, where the high cost of gathering information and enforcing contracts can lead to adverse selection and moral hazard problems. The difficulty in screening potential borrowers is exacerbated by the fact that households lack collateral. The interest rates necessary to compensate for the risk of lending in these areas are high enough to drive away many safe borrowers. Information costs also make it difficult to monitor borrowers' activities after lending. Group lending is designed to overcome these information problems. If one member of the group defaults, the entire group becomes ineligible for further loans. Group members thus have incentives to screen and monitor each other's projects.

There is evidence that this type of microcredit lending is succeeding in extending credit to those who would not otherwise get it. Participation is increasing, with estimates indicating that more than 150 million clients have been reached, over 100 million of whom were counted among the world's poorest (Microcredit Summit Campaign). Repayment rates average over 90 percent (Grameen Foundation). Microfinance institutions are, by these measures, demonstrating an ability to overcome obstacles to providing credit to the rural poor.

The relevant policy question, however, is whether the extension of credit is achieving the original goal, stated by the Grameen Foundation as seeing people "move themselves out of poverty." Most microfinance institutions rely on funding from governments and other donors with anti-poverty agendas, and the amounts are increasing. A survey conducted by CGAP found that leading donors and investors had committed $14.8 billion in active microfinance investments and projects as of December 2008, 63% of which consisted of debt. Critics worry that microcredit programs are essentially untested, however, and might be counterproductive. By pushing loans at high interest rates, microcredit could ultimately make borrowers even poorer. If microentrepreneurs are unable to earn profits, perhaps because unfavorable local economic conditions prevent them from selling what they produce, borrowers may not be able to pay off their loans without selling off assets or receiving help from relatives.

Microfinance institutions often offer an array of training activities in addition to financial services. There are thus a variety of measures of participation and predictions about outcomes that could, in principle, be tested to measure their success. For example, microfinance institutions in Bangladesh provide training in literacy, health, and business skills like accounting, and encourage family planning and childhood education among their members. The extension of credit is the primary flow of services, however, and the question of whether microcredit increases household income and consumption is of particular interest, given the goal of enabling households to escape poverty.

In attempting to answer this question, the literature has focused on household consumption, which is generally taken to be the preferred measure of well-being, or standard of living, in applied work (Ravallion 1992). The measurement of income, and self-employment income in particular, is notoriously inaccurate in surveys in developing countries. Incomes are reported with a high degree of error, and accounting frameworks not employed by the households must be imposed on the data in order to obtain a measure of profit that can be correctly interpreted (Deaton 1997). In addition, poverty in countries such as Bangladesh is often thought of in terms of consumption; households do not have enough to eat. Microcredit is intended to address this type of poverty by increasing the household consumption of participants (Khandker 1998). Consumption expenditure is thus a natural measure of household welfare in Bangladesh, and for these reasons, I focus on consumption as the outcome of interest.

Microcredit borrowing can be expected to increase consumption if households that would profit from choosing microentrepreneurship are constrained from doing so by lack of access to credit. Many of the types of enterprises in question require a fixed investment up-front, before income is generated. For example, self-employment activities in Bangladesh include the production of handicrafts such as weaving, which requires purchase of a loom, or transportation services by van, rickshaw or boat (Khandker 1998). Banerjee, Duflo, Glennerster and Kinnan (2009) outline a two-period model in which households that can invest a minimum amount in an entrepreneurial business during the first period are able to generate income in the second. The presence of microfinance institutions allows more households to meet the minimum capital investment required for production.

This model generates predictions about consumption for new entrepreneurs. Current consumption could increase or decrease upon receipt of a microcredit loan, since investment can be financed partly by the loan and partly by cutting back on consumption. Income is generated in the next period, after borrowing and investment have taken place, allowing for increased consumption as investments pay off. It is also possible that some loan money is being used directly for consumption. Grameen Bank borrowers are expected to monitor other group members, ensuring that loans are invested in business activities. Nevertheless, money is fungible within a household, and an increase in current consumption could be the result of consumption smoothing. A better assessment of the impact of borrowing would therefore look at less immediate outcomes. If microcredit is enabling households to generate enough income to escape poverty, one would expect to see evidence of sustained increases in consumption over time, as households continue to borrow, invest, and produce from year to year. I follow Pitt and Khandker (1998) in examining the impact of the cumulative amount borrowed over the past seven years from microcredit institutions on current household consumption. While it would be desirable to isolate the effects of borrowing in different years, borrowing from year to year is too highly correlated to be able to make any definitive statements about each year separately.

A particularly relevant question for donors and practitioners is how a microcredit loan would affect the consumption of a randomly selected household in the population of interest. Many organizations, including the World Bank, the United Nations and USAID, have stated goals of increasing the usage of microcredit in developing countries. In particular, during the years since the survey data used here were collected in Bangladesh, microcredit institutions have continued to open branches across the country. It is therefore important to ask not just how loans have benefited those who were first to join microcredit groups, but how they can be expected to benefit an average household.

The issue with estimating this effect is that households that have already borrowed are not a random sample of the population. Households decide whether or not to take out a loan and start a business based on unobserved attributes such as entrepreneurial ability. In addition, microcredit institutions are targeted toward poorer households. In the presence of these limitations, various techniques have been employed in the literature to try to identify the expected impact of microcredit borrowing on a random household. Quasi-experimental survey designs have been employed to simulate randomization by creating an appropriate control group of people who were excluded from borrowing (Pitt and Khandker 1998, Coleman 1999). More recently, randomized trials have been developed and implemented (Banerjee, Duflo, Glennerster and Kinnan 2009). Although it is difficult to randomly assign loans by household, it is possible to identify other measures of the impact of microcredit by randomizing the expansion of microcredit programs into new areas.

Rather than relying on randomization, in this paper I adopt a new approach to identify the treatment effect. I estimate the average effect of the amount borrowed from a microcredit institution on per capita household consumption in Bangladesh. Identification relies on the assumption that the conditional correlation between the errors in the borrowing and consumption equations is constant. I outline a plausible error structure that satisfies this requirement. Under this assumption, the model is identified in the presence of heteroskedasticity.

2 Literature

Attempts to model household consumption as a function of microcredit borrowing have focused on ways to overcome the endogeneity of borrowing. Households select into borrowing based not only on their observed characteristics, but also on unobserved traits such as entrepreneurial ability. Microcredit institutions choose where to locate and what type of households to target, perhaps using information that is not observable to the econometrician. These unobserved characteristics can also be expected to affect consumption directly, biasing estimates of the impact of borrowing that do not account for the endogeneity. The empirical literature on this topic has been scarce, reflecting a failure to find instrumental variables that affect borrowing but not consumption.

Pitt and Khandker (1998) was one of the first significant attempts to study of the impact of microcredit borrowing on household outcomes, and their results are often cited by both academics and practitioners. Using the intuition of a regression discontinuity to generate exclusion restrictions, they estimate the impact of borrowing from three different microfinance institutions in Bangladesh: the Grameen Bank, the Bangladesh Rural Advancement Committee (BRAC), and the Bangladesh Rural

Development Board's (BRDB) Rural Development RD-12 program. Estimating the impact of loans from these three institutions to both men and women, they find elasticities of per capita household consumption with respect to the six resulting sources of borrowing ranging between 0.018 and 0.043.

Identification in Pitt and Khandker comes from a lending rule that was, at least nominally, followed by all three microfinance institutions in Bangladesh at the time of the survey. Only households that were "functionally landless," defined as owning less than one-half acre of land, were considered eligible for microfinance loans. The assumption is that there should be a discontinuity in borrowing at one-half acre of land, but no discontinuity in household consumption at the cutoff point, conditional on borrowing. Using this requirement to divide households into groups based on borrowing eligibility, Pitt and Khandker are able to identify the effect of borrowing in a limited-information maximum likelihood estimation. The authors point out that the same identifying assumptions could be used to implement a two-stage least squares estimation, in which a dummy variable for whether a household faced the choice to borrow is interacted with all of the exogenous variables to generate instruments for borrowing.

Concerns have been raised about the validity of this identifying assumption. Morduch and Roodman (2009) perform regression discontinuity analyses on the Bangladesh data and find little evidence of discontinuity at one-half acre of landholding. This result is likely due to substantial mistargeting, in the sense that the landholding rule was not enforced. If there is no discontinuity, the strategy of Pitt and Khandker lacks the power to identify the impact of borrowing. In the two-stage least squares framework, the lack of a substantial discontinuity has the interpretation of the instruments being weak. Morduch and Roodman conclude that Pitt and

Khandker have not succeeded in identifying the endogeneity of borrowing, and leave open the question of whether microcredit is increasing consumption in Bangladesh.

Another example of a quasi-experimental design is Coleman (1999). Survey data was collected from villages in Thailand that were targeted by a microcredit program. In some villages, lending had already taken place. In others, households had selected into borrowing groups, but had not yet received any loans. Coleman estimates the average program effect by regressing household income on the treatment status of a village, given by whether or not loans had been disbursed, and a set of household and village controls. A dummy for whether or not a household had joined a borrowing group is assumed to control for unobserved factors that lead to selection into borrowing. Coleman does not find a significant impact of treatment status on household income, but notes that the population in Thailand is wealthier than that of countries such as Bangladesh, and access to other sources of credit is more widespread.

The implementation of randomized trials is the most recent strategy employed to deal with the endogeneity of borrowing. Banerjee, Duflo, Glennerster and Kinnan (2009) discuss an ongoing experiment in Hyderabad, India, where new microfinance institutions were opened in a randomly selected half of a group of slums. Within each location, households could then endogenously form groups and choose to borrow. The treatment status of a slum provides an exclusion restriction, affecting borrowing, but not consumption conditional on borrowing. The authors estimate the impact of living in a treatment area 15 to 18 months after the branches were opened, and find no effect of access to microcredit on average per-capita expenditure. They did find increases in durable expenditures in households with existing businesses and those that were likely to start a business, however, suggesting that investment is taking place, and that greater impacts may be found as time goes on. Karlan and Zinman conducted a trial in the Philippines, working with a lender to generate exogenous variation in loan approval, a method they previously applied in South Africa (Karlan and Zinman 2008). They find significant benefits from loans in the South African trial, but not in the Philippines. These studies look at consumer credit, however, and may not be directly comparable to results on microentrepreneurial credit in populations like that served by the Grameen Bank.

To draw broader conclusions about the impact of microcredit in different populations in different countries, it would be beneficial to combine the results from these studies with results from a wider range of observational datasets. Comparison of different treatment effects is also of interest. Instruments created by randomization identify local average treatment effects, such as the effect of microcredit loans on those who were moved to borrow by the presence of a new institution. Estimates of average treatment effects can help address questions about the external validity of these studies, and are an important parameter given the interest in expanding microfinance programs. In addition, the ability to use currently available datasets would allow for the comparison of microfinance programs in a variety of countries.

Despite the pioneering status of the Grameen Bank, there is still no consensus on the question of whether or not microcredit in Bangladesh is alleviating poverty by increasing the household consumption of borrowers. I return to the Bangladesh data used by Pitt and Khandker, and Morduch and Roodman, and estimate the impact of borrowing on consumption without imposing the controversial moment conditions on the instruments.

3 Estimation and Identification

A new approach to identifying models in the absence of exclusion restrictions is to make an alternative assumption about the unobservables. In the absence of credible instruments, other literatures have looked for different types of moment conditions that can reasonably be imposed to identify sample selection models. For example, many impact evaluations use propensity score methods to compare people in the treated group to people with similar characteristics who did not receive treatment. Estimation of this type involves assuming that treatment status is independent of the outcome of interest, conditional on the probability of receiving treatment. This assumption is not realistic in the context of microcredit, however, as households select into borrowing based on unobservable characteristics that also affect consumption. Biased estimates of the impact of borrowing will result unless selection on unobservables is also controlled for.

An example from the education literature, Altonji, Elder and Taber (2005), suggests imposing that selection on the observables is equal to selection on the unobservables. Here, the impacts of the observed part of the outcome equation and the unobserved part of the outcome equation on the endogenous variable are assumed to be equal. The authors argue that the assumptions necessary to motivate this condition are no less plausible than the assumption, made when using OLS or probit methods, that selection on the unobservables is zero, and show that estimates using this moment condition can provide a lower bound on the impact of the endogenous variable.

I adapt control function methods, discussed below, by imposing another restriction that has been applied in the education literature. The missing moment condition caused by the endogenous variable is replaced with a condition on the second moments of the errors in the model. This identification strategy, proposed by Klein and Vella (2010), does not require the use of instruments, but instead relies on the presence of heteroskedasticity in the estimating equations. Identification is based on the restriction that the correlation coefficient of the disturbances, conditional on the exogenous regressors, is constant. I outline a plausible error structure that satisfies this requirement below.

Consider the following system of borrowing and consumption equations. Per capita household consumption depends on the amount borrowed, B, and a set of additional household characteristics, X, that are assumed to be exogenous. These include demographic characteristics such as the sex and age of the household head, and the education levels of household members. Borrowing also depends on a set of exogenous characteristics, Z. For expositional puroposes, Z is for the time being allowed to contatin a variable that is excluded from X. Borrowing is censored at the minimum loan amount, $\underline{\mathrm{B}}$, of 1000 taka.

$$C_i = X_i\beta + \delta B_i + u_i \tag{23}$$

$$B_i^* = Z_i\pi + v_i \tag{24}$$

$$B_i = \begin{cases} B_i^* \text{ if } B_i^* > \underline{B} \\ 0 \text{ otherwise} \end{cases} \tag{25}$$

The endogeneity of borrowing arises due to correlation between the error terms, u and v, caused by the unobservable factors that affect both borrowing and consumption.

Models encompassing endogeneity combined with Tobit-type censoring have been considered in the parametric and semiparametric literature. Vella (1993) describes a two-step estimation procedure for estimating the system of equations above, under the assumption that the errors are jointly normally distributed. Taking conditional expectations of equation (1) gives

$$E[C_i|X_i, B_i] = X_i\beta + \delta B_i + E[u_i|X_i, B_i] \tag{26}$$

Using the assumption of joint normality and the law of iterated expectations, the last term can be rewritten.

$$\begin{aligned} E[u_i|X_i, B_i] &= E\left[E[u_i|Z_i, v_i]|X_i, B_i\right] && (27) \\ &= \rho E[v_i|Z_i, B_i] && (28) \end{aligned}$$

where $\rho = \frac{cov(u,v)}{var(v)}$. The equation to be estimated becomes

$$C_i = X_i\beta + \delta B_i + \rho E[v_i|Z_i, B_i] + e_i \tag{29}$$

The remaining error term e, is uncorrelated with v by construction: $e = u - \frac{cov(u,v)}{var(v)}v$. The conditional expectation of v, however, is unobserved and correlated with the other regressors. Employing a consistent estimate of this expectation as a control function removes the impact of v on u, restoring orthogonality of the regressors. Under the normality assumption, equation (3) can be estimated by Tobit, and the appropriate control function is the Tobit generalized residual, given by

$$\widetilde{v} = E[v_i|Z_i, B_i] = -\widehat{\sigma}_v(1 - I_i)\phi_i(1 - \Phi_i)^{-1} + I_i\widehat{v}_i \tag{30}$$

Here, $\widehat{\sigma}_v$ and $\widehat{\pi}$ are the Tobit estimates, ϕ_i and Φ_i are the probability density function and cumulative distribution function of the standard normal distribution evaluated at these estimates, and I_i is an indicator that is equal to one if borrowing is positive. The last term, $\widehat{v}_i = B_i - Z_i\widehat{\pi}$, is the residual for observations with positive amounts of borrowing. Consistent parameter estimates can be obtained by estimating the following equation by least squares.

$$C_i = X_i\beta + \delta B_i + \rho\widetilde{v}_i + e_i \tag{31}$$

In the absence of an exclusion restriction requiring that a variable in Z does not appear in X, this equation is identified only by the nonlinearity of the normal distribution.

A related model is a sample selection model in which consumption is only observed for households that have borrowed positive amounts. This group of households is expected to be different from the full sample. After controlling for the X variables, selection into the positive borrowing group is caused by v, leading to sample selection bias if u and v are correlated. Since the factors in v are responsible for both sample selection and the endogeneity of borrowing, however, one control function can be used to control for both. Equation (9) can be consistently estimated over the subsample of observations with positive amounts of borrowing, noting that the residual for these observations is $\widehat{v}$. The control function purges the error term of the component that is correlated with borrowing, including factors that lead to selection into the positive borrowing group. In this case, however, an exclusion restriction would be necessary. The residual, $\widehat{v}$, would otherwise be a perfect linear combination of the variables in X and the borrowing variable, and the matrix of regressors would not be of full rank.

The assumption that the errors in equations (1) and (2) are normally distributed can be relaxed. Lee and Vella (2006) propose a semiparametric least-squares estimator for this system of equations, which relies on the same idea of removing the impact of v on equation (1) by conditioning on an estimate of its conditional expectation. This approach also requires the assumption of an exclusion restriction.

These control function approaches could be employed in the present application in the presence of an exclusion restriction. However, the scarcity of empirical literature on microcredit so far reflects the failure to find such exclusions. Many of the obvious candidates have been ruled out. Interest rates cannot be used as instruments, since these rates generally do not vary within programs. Community characteristics cannot be used when community-level fixed effects are included to control for nonrandom program placement (Armendariz and Morduch (2005) discuss these points). Finally, there are no obvious household characteristics that can be assumed a priori to affect borrowing but not consumption.

Accordingly, assume that Z=X in equations (1) through (3). The lack of identification in equation (1) is the result of having one more parameter to estimate than moment conditions to impose on the data. Since orthogonality of borrowing and the error term cannot be justified, an additional moment condition is needed to identify the model. The literature on microcredit to date has approached this problem by looking for additional moment conditions involving the first moments of borrowing and consumption, generating instruments either by randomization or survey design.

The strategy of Klein and Vella focuses on second moments. Variation in X provides an additional source of identification when the distribution of the error terms depends on the exogenous variables.

To see how this strategy enables identification, assume the errors are heteroskedastic and can be written as follows.

$$
\begin{aligned}
u &= S_u(X)u^* && (32)\\
v &= S_v(X)v^* && (33)\\
E[u|X] &= E[v|X] = 0 && (34)
\end{aligned}
$$

Here, u* and v* are assumed to be homoskedastic, and the conditional variances are given by

$$
\begin{aligned}
var(u|X) &= S_u^2(X) && (35)\\
var(v|X) &= S_v^2(X) && (36)
\end{aligned}
$$

In equation (7), the impact of the control function on consumption was given by

$$\rho = \frac{cov(u,v)}{var(v)} \tag{37}$$

When the conditional second moments of the errors depend on X, however, the impact of the control function is no longer constant. Define

$$A(X) = \frac{cov\,(u, v|X)}{var\,(v|X)} \tag{38}$$

The equation to be estimated is now identified without exclusion restrictions.

$$C_i = X_i\beta + \delta B_i + A(X)\widehat{v} + \varepsilon \tag{39}$$

Unlike equation (9), the matrix of regressors here is of full rank, as long as the impact of the control varies with X. Equation (17) can be estimated provided consistent estimation of A(X).

Klein and Vella show that estimation is possible when the errors satisfy the following constant correlation condition.

$$E[u^* v^* | X] = E[u^* v^*] \tag{40}$$

When this condition holds, A(X) can be rewritten.

$$A(X) = \rho_0 \frac{S_u(X)}{S_v(X)} \tag{41}$$

where $\rho_0 \equiv \frac{cov(u^*,v^*)}{var(v^*)}$ is constant. Provided consistent estimates of the conditional variances of u and v, the equation of interest can now be estimated as

$$C_i = X_i\beta + \delta B_i + \rho_0 \frac{S_u(X)}{S_v(X)}\widehat{v} + \varepsilon \tag{42}$$

The model is identified as long as $S_u(X)$ and $S_v(X)$ are not identical functions. I assume a reasonable structure for the errors that possesses the constant correlation property, which is discussed in detail below.

Estimation is done in two stages. First, the borrowing equation is estimated over the entire sample of households who faced a choice to borrow. The borrowing equation is estimated by the semiparametric least squares method of Ichimura (1993). This technique allows for censoring without requiring homoskedasticity or normality of the error terms. Ichimura describes how a Tobit-type model can be described as a single-index model, in which the distribution of the error term, v, can depend on the index. The necessary assumption is thus that the same index of characteristics is driving selection into borrowing and the amount borrowed, as well as the heteroskedasticity.[3] Estimates of π in Equation 2 are obtained as:

$$\widehat{\pi} = \arg\min_{\pi} \sum_{i=1}^{n} \left(B_i - \widehat{E}\left[B_i | X_i \pi\right] \right)^2 \tag{43}$$

The operator $\widehat{E}[\cdot]$ is a nonparametric conditional expectation, estimated using a normal kernel. Since these estimators are identified up to location and scale, $X_i\pi$ is an index of the X's in which the constant is normalized to zero, and the coefficient on a continuous variable in X is normalized to one.

The residuals from this estimation are used to compute the conditional variance of the borrowing error. For households with positive amounts of borrowing, the residuals from the first stage estimation are simply $\widehat{v} = X\widehat{\pi}$. Once residuals have been obtained for these households, they are used to estimate S_v^2. This is done by taking the nonparametric expectation of $\widehat{v}^2$ conditional on $X\widehat{\pi}$, in order to maintain the index assumption on the heteroskedasticity.

$$\widehat{S}_{vi}^2 = \widehat{E}\left[\widehat{v_i}^2 | X_i \widehat{\pi}\right] \tag{44}$$

[3] This equation could also be estimated under these assumptions using the symetrically trimmed least squares estimator of Powell (1986), without requiring the heteroskedasticity to be a function of the index. Using this technique resulted in a severe loss of precision, however, due to the amount of data that is thrown out by trimming the positive observations.

In the second stage, the primary equation is estimated over the subsample of households that borrowed positive amounts. The functional form of $\mathrm{S}_u(\cdot)$ is unspecified. Although it is possible to estimate $\mathrm{S}_u(\cdot)$ nonparametrically, it is more practical to assume an index structure, allowing parameters to be well-identified using a reasonable amount of data. The index restriction is that $S_u^2\left(X_i\right) = S_u^2\left(X_i\gamma\right)$.

$$C_i = X_i\beta + \delta B_i + \rho_0 \frac{S_u\left(X_i\gamma\right)}{\widehat{S}_v}\widehat{v_i} + \varepsilon_i \tag{45}$$

Klein and Vella (2010) provide a semiparametric estimation procedure for this equation, which estimates the index parameters of the conditional variance simultaneously with the other parameters of interest. First, define

$$u_i(\beta,\delta) = C_i - X_i\beta - \delta B_i \tag{46}$$

A variance-type estimator is defined as

$$S_{u_i}^2(\beta,\delta,\gamma) = E[u_i^2(\beta,\delta)|X_i\gamma] \tag{47}$$

Notice that at the true parameter values, $u_i(\beta_0,\delta_0) = u_i$ and $S_{u_i}^2(\beta,\delta,\gamma) = S_{u_i}^2(X_i)$. The conditional variance is estimated semiparametrically, where $\widehat{E}[\cdot]$ is once again the nonparametric expectation using normal kernels.

$$\widehat{S}_{u_i}^2(\beta,\delta,\gamma) = \widehat{E}[u_i^2(\beta,\delta)|X_i\gamma] \tag{48}$$

Parameter estimates are obtained selecting β,δ, and γ to minimize the sum of the squared residuals of the resulting consumption equation.

$$C_i = X_i\beta + \delta B_i + \rho_0 \frac{\widehat{S}_{u_i}(\beta, \delta, \gamma)}{\widehat{S}_v} \widehat{v_i} + \varepsilon_i \tag{49}$$

In each step, starting values are given by the OLS estimates, and standard errors are computed by 250 bootstrap repetitions with replacement.

Identification relies on the constant correlation assumption given by equation (17). It is useful to think of potential error structures in the present example under which this assumption would or would not be satisfied. The literature on micro-credit has focused on entrepreneurial ability as the driving force behind selection into borrowing and the endogeneity between borrowing and consumption. (Pitt and Khandker 1998, Coleman 1999, Armendariz and Morduch 2005). Armendariz and Morduch describe the household's endowment of entrepreneurship as "entrepreneurial skills, persistence in seeking goals, organizational ability and access to valuable social networks." Individuals with more entrepreneurial tendencies are likely to borrow more, and also to earn higher incomes regardless of borrowing. Failure to control for entrepreneurial ability might therefore lead to an over-estimation of the effects of borrowing. Armendariz and Morduch cite a finding, from a survey done by Hashemi (1997), that over half of those who chose not to borrow from a microfinance program in Bangladesh did so because they felt that they would not be able to generate sufficient profits to be able to repay the loans. In this sense, households appear to be selecting into borrowing based on their own assessments of their entrepreneurial ability.

One example of an error structure is therefore the assumption that the disturbances are comprised purely of entrepreneurial ability. In this case, the errors described by equations (10) - (12) can be written as follows, where a* denotes unobserved entrepreneurial ability.

$$u = S_u(X)a^* \tag{50}$$

$$v = S_v(X)a^* \tag{51}$$

There are a variety of ways that heteroskedasticity of this form can be expected to arises in the model. Consider the borrowing equation. The impact of entrepreneurial ability on borrowing is likely to be a function of the location variables. A higher variance of borrowing can be expected in locations that have more extensive microfinance institutions that have been in place longer. In these areas, high ability households will have had more opportunities to borrow greater amounts,so the effect of their ability will be magnified by a function of their location, $\mathrm{S}_v(\mathrm{X})$. The availability of outside borrowing options also varies across areas, and can be expected to affect the amount of microcredit borrowing demanded. High ability households may be able to obtain loans from traditional banks. Regional variation in the availability of traditional banks may therefore lead to different variances in the amount of borrowing from microcredit institutions in different areas. Microcredit institutions also increasingly target female borrowers. Thus the impact of high ability would be magnified, as determined by $\mathrm{S}_v(\mathrm{X})$, for households containing an adult woman.

The consumption equation contains potential sources of heteroskedasticity as well. Two households with equal endowments of ability may face different consumption opportunities if one is headed by a man and the other is headed by a woman. The impact of the ability term is magnified or diminished based on the gender of the head of the household, in a manner captured by $\mathrm{S}_u(\mathrm{X})$. Thus a higher variance in consumption might be expected in households headed by men. The set of regressors also includes the number of family members of the household head and spouse who own land, which is a measure of wealth. Having wealthier relatives may have a stabilizing effect that helps to guarantee a minimum amount of consumption, dampening the variance in consumption for those households and minimizing the impact of low ability. In addition, the set of location characteristics includes information that will affect incomes in an area, and households with higher income-generating opportunities will have greater variance in consumption. For example, households with the same endowment of ability can earn higher incomes in areas with higher wages. Among households that produce milk or eggs, for example, those in areas with higher prices for milk and eggs will be able to earn higher incomes, increasing the variance of consumption.

If the unobserved error terms are purely comprised of entrepreneurial ability, as in equations (28) and (29), the constant correlation assumption is satisfied trivially, and we would expect a positive correlation between the error terms. In the data, however, the correlation between u and v is found to be negative, both here and in Pitt and Khandker. A negative correlation between the error terms is also common in the literature on returns to education, where the presence of unobserved ability terms would, on its own, lead to a positive correlation. This suggests that there are other sources of endogeneity in the error terms. In the present application, one such source of unmeasured variation is random shocks to household income. For example, two households with equivalent endowments of ability may make different borrowing decisions if a member of one household becomes sick or injured. Such a shock could also cause a reduction in consumption, leading to correlation between the error terms of the two equations. Similarly, random events such as flooding that destroys crops could also affect both borrowing and consumption. Microcredit programs are specifically designed to appeal to the poorest borrowers, using devices such as small loans sizes and the requirement to enter into joint liability agreements, which households with other resources might find unattractive (Khandker 1998). This targeting will lead to a negative correlation between the unpredictable shock components of the error terms, since events that reduce potential consumption will also increase interest in borrowing. Denoting these shocks ε_1 and ε_2, and assuming a multiplicative structure, the errors become

$$u = S_u(X)a^*\varepsilon_1 \tag{52}$$

$$v = S_v(X)a^*\varepsilon_2 \tag{53}$$

Now ρ_0 in equation (19) will depend on the correlation between the εs, and have a negative sign if this correlation is negative. This structure is the same as the one employed by Klein and Vella's returns to schooling estimation (2009), and satisfies the constant conditional correlation condition under the assumption that the εs are independent of X, as well as independent of a*.

To give some intuition, consider two households in which the head of household suffers a broken leg, reducing his ability to work. The assumption would be that this shock leads to a constant propensity to consume less, and a constant propensity to borrow more. The relationship between the borrowing and consumption propensitites is captured by ρ_0. Each household's actual ability to adjust consumption and borrowing, however, depends on factors such as location. For instance, a household in an area with more access to microcredit could respond by borrowing more; this effect is captured by $S_v(X)$. Thus, while the correlation between ε_1 and ε_2 is constant, the correlation between u and v depends on the functions of X that magnify or diminish the impact of the εs in each equation. The conditional correlation assumption would not be satisfied, then, if failure to control for location effects led to correlation between ε_1 and ε_2 that varied with location, which is potentially related to other variables in X. Below, I control for location effects in the estimation, first by including a set of location fixed effects, and then using a set of village-level characteristics.

4 Empirical Model and Results

The Household Study to Conduct Micro-Credit Impact Studies was carried out by the Bangladesh Institute of Development Studies (BIDS) and the World Bank between 1991 and 1992. The survey sampled 1,798 households drawn from 87 villages of 29 Thanas, or sub-districts, in rural Bangladesh. Out of the 29 Thanas, 24 had microfinance programs in place at the time of the survey. The first stage of estimation is carried out over all households in these 24 program Thanas, resulting in a sample size of 1,461 households. The second stage uses the subsample of 814 households with positive microcredit borrowing. Descriptive statistics are provided in Table 1.

The exogenous variables chosen are the same as those employed by Pitt and Khandker. Household characteristics include the age and sex of the household head, the education level of the household head, and the highest education level achieved by a male and female in the household. Dummy variables for the absence of an adult male and absence of an adult female are included to allow interpretation of these coefficients, as is a dummy for the presence of a spouse. Also included is a set of variables describing whether or not the parents of the household head and spouse own land, and the number of brothers and sisters of the head and spouse who own land. These variables are intended to control for outside opportunities for borrowing or income.

Location characteristics are controlled for in two ways. The first set of results includes a set of Thana dummy variables. The use of Thana dummies is a departure from the Pitt and Khandker model, which includes village fixed effects, but was a necessary reduction in dimensionality for the semiparametric estimations. Location characteristics that may affect both borrowing and consumption include not only observed features like price and infrastructure variables, but unobserved attributes like proximity to an urban area, climate, and local attitudes. The location dummies will also absorb any spillover effects that the presence of a microcredit institution has on all residents, regardless of their borrowing status. It is possible, for example, that some of the increased expenditures by households that borrow will go toward buying goods and services from their neighbors. In this case, the presence of microcredit will raise the average consumption for all residents of a community. The coefficients on borrowing estimated here thus represent the benefit to a household that borrows over and above the benefits from any spillovers.

The second set of results includes a set of village characteristics. These include the average wages for men and women in each village, and a set of goods prices. Also included are variables that describe the local infrastructure, including the distance to a bank and the presence of schools, health clinics, and family planning and midwife services. This specification has the advantage of controlling for some location characteristics at a more local level, but lacks the spillover interpretation given above. In each specification, the heteroskedasticity index for the consumption equation includes the same explanatory variables that appear in the conditional means of both equations.

Table 2 shows the results of testing for heteroskedasticity by regressing the squared residuals from the borrowing and consumption equations onto all the explanatory variables. Test results are reported under both model specifications. In all four cases, the null hypothesis of homoskedasticity is rejected. For the borrowing equation, the evidence of heteroskedasticity is strongest for the Thana dummy specification, indicating that regional variation in program availability and intensity is an important source of heteroskedasticity.

Table 3 presents the results of estimation of the borrowing equation in the Thana dummy specification. As discussed above, one of the index coefficients must be normalized to one. Given this normalization, the coefficients can only be interpreted in relative terms. Here, the coefficient fixed to unity is on the variable that gives the negative of log-landholding, since an increase in landholding is known to reduce the likelihood of borrowing, and the remaining coefficients will therefore have the correct sign. All variables have been standardized to have mean zero and standard deviation equal to one. Thus an increase of one standard deviation in the maximum education of a male in the household is interpreted to have 75% of the impact of a increase of one standard deviation in the maximum education of a female.

Having a male head of household led to a significant reduction in the amount borrowed. This result is expected, since microcredit has become increasingly targeted toward women over the years in Bangladesh. Each borrowing group is required to be single-sex, and female-only groups were more prevalent in the survey areas, compounding the effect of targeting women by providing more opportunities for women to join groups. Households without an adult male or a spouse present borrowed less. This is evidence that entrepreneurship is easier for households that have two working age adults present, a household head and a spouse. The entrepreneurial good may be produced at the same time as home production, such as child care, making entrepreneurship feasible for households in which the spouse of the head does not work outside the home. (Pitt and Khandker 1998 describe such a model of household production.) Households in which the spouse's family members owned land also borrowed less. This confirms the idea that families borrow from each other when they have the opportunity, rather than paying interest rates to outside lenders. Households with more highly educated females borrowed less, which is perhaps an indication that these women were more likely to work before microcredit borrowing, and thus less inclined to microentrepreneurship. In addition, there is evidence that regional variation is an important determinant of borrowing, as several of the Thana dummy variables are significant.

The parameter estimates for the consumption equation are presented in table 3. The first column shows the OLS estimates over the subsample of households with positive borrowing. Column three gives the estimates after inclusion of the control function. Parameter estimates are presented for the non-standardized variables. Several household characteristics had a significant impact on per-capita consumption. The elasticity of consumption with respect to land-holding is 0.311, confirming the expectation that land is an important source of income generation. The lack of an adult female in the household was significant, but increased consumption only slightly, by 0.8%. The variables summarizing the land-holding of the relatives of the household head were also significant, supporting the idea that families help smooth each other's income. Several of the Thana dummies were significant as well.

The coefficient on borrowing estimates the elasticity of per-capita household consumption with respect to borrowing. This coefficient is 0.056 in the OLS estimation with a t-statistic of 3.290. Inclusion of the control function raises the estimate of the borrowing coefficient to 0.193. With a t-statistic of 2.838, this effect is still statistically significant below the 5% level. The increase in the effect of borrowing is due to the negative and significant coefficient on the control function. The significance of this coefficient, with a t-statistic of 3.92 in absolute value, is an indication that the estimation strategy is succeeding in capturing the endogeneity of borrowing. The negative sign is evidence that there is a negative correlation between the random error components, ε_1 and ε_2. Pitt and Khandker also find a negative correlation between the errors, and interpret the sign as an evidence that microfinance programs are successfully targeting poorer clients.

The results of estimating the village-characteristics specification lead to similar conclusions. The estimates for the borrowing equation are presented in table 5, where interpretation is subject to the same normalizations discussed above. Here, a higher level of education for the head of the household led to an increase in borrowing, as did an increase in the age of the head of the household. The absence of an adult male or female decreased the amount borrowed, supporting the idea that microentrepreneurship is easier in a household with two adults. A higher level of female education again decreased borrowing, but in this specification, none of the coefficients on family members' landholding were significantly different from zero. Of the village characteristics, only two were significant. Both the presence of a family planning center and the availability of a wage for females increased the amount borrowed. These variables may be a reflection of gender attitudes in a village. Areas that are in general more supportive of women working outside the home and women's health issues may also be more accepting of women engaging in microentrepreneurship.

Table 6 presents the estimates of the consumption equation under the village characteristic specification. The amount of land held by a household is again found to be significant, although the elasticity is slightly smaller, at 0.218. An additional year of age of the household head is found to reduce per capita consumption by 4.3%. The maximum education of a female in the household is again found to increase consumption, while the absence of an adult female again slightly increases it. Household consumption was lower in villages that had a primary school, a rural health center, or a midwife available. This is perhaps due to households that own more land and are able to generate more income living farther out from town centers, where poverty may be more concentrated.

In the village characteristic specification, the coefficient on borrowing rises from 0.023 to 0.212 after inclusion of the control function, an even greater increase than in the previous specification. The t-statistic is also larger, at 6.793. Once again, the coefficient on the control function is negative and significant, indicating a negative correlation between the error components ε_1 and ε_2.

Tables 3 and 6 present the coefficient estimates for the index of the heteroskedasticity function of the consumption equation in each specification. These parameters have no direct interpretation, other than to note that some of them are significantly different from zero, including the variables capturing the landholding of relatives of household members. More of the coefficients are significant in the village characteristic specification, indicating that this model may better capture the heteroskedasticity present in the consumption equation.

5 Discussion

The rapid spread of microcredit in recent years is an indication that many people believe it can be successful at combating poverty. In finding that microcredit borrowing from the flagship Grameen Bank and other similar institutions raises household consumption, the results of this paper therefore confirm the beliefs of numerous microcredit practitioners and donors, which have so far been based on anecdotal evidence alone. While the scarcity of empirical evidence on this topic to date has raised doubts about the effectiveness of microcredit, the finding that borrowing has a positive and significant impact on consumption is in this sense what many have expected.

Theoretical results also predict that the impact of microcredit could be large. If the principle of diminishing returns to capital holds, microenterprises with relatively little capital should be able to earn high returns on their investments (Armendariz and Morduch). The average size of a loan disbursed by the Grameen Bank is $100. At the average, then, the results above predict that an additional $100 in lending can be expected to increase per-capita household consumption by around 20%. In absolute terms, this is a small amount of consumption, given that the average household income in Bangladesh is around $293 (World Bank). Such small amounts can make a big difference for households that are living in extreme poverty, however.

The elasticities discussed above are larger in magnitude than those found in the previous literature, some of which finds no impact of borrowing on consumption at all. In the case of Banerjee, et. al., who look at consumption a little more than one year after borrowing, the difference in results is in keeping with their model of household investment. As discussed above, the benefits of microcredit borrowing might not be immediately evident, and my estimates incorporate borrowing over a longer span of time. In addition, both Banerjee, et. al. and Coleman estimate intent to treat effects, or the impact on a household of living in a treatment village. Estimates of the average treatment effect presented here, in describing the expected gains from actually borrowing, can be expected to be larger.

A more interesting result is that the elasticity estimates found here are higher than those found by Pitt and Khandker using the same data. While both studies detected positive and significant effects of borrowing, the estimates presented here are larger in magnitude and farther from the OLS estimates. This is evidence that the strategy employed here is more successful at identifying the endogeneity of borrowing. It is clear from the results that failure to appropriately control for the endogeneity of borrowing leads to severe underestimation of the impact of borrowing on consumption, and also that the restrictions imposed above on the conditional second moments of the data are sufficiently informative to identify that endogeneity.

Since the results discussed above provide consistent estimates for the consumption equation, a set of variables that could potentially be used as instruments is identified. In the Thana dummy specification, the variables representing the sex of the household head, the maximum education of a female household member, no adult male present, no spouse present, and the landholding of the spouse's parents and brothers are all significant in the borrowing equation, but not the consumption equation. The estimation was therefore repeated using these variables as exclusion restrictions. While the first stage of estimation was the same as above, in the presence of the exclusion restrictions, the control function used in the second step was simply the residual from the borrowing equation, $\widehat{v}$, and higher order terms $\widehat{v}^2$ and $\widehat{v}^3$. The coefficient on borrowing was found to be 0.12 and significant. The village characteristic specification was estimated in the same way. Here, the variables education of the household head, no adult male present, family planning center present in village, and village average female wage were excluded from the consumption equation. The coefficient on borrowing in this case was 0.04 and not significantly different from zero. These results indicate that the instruments were able to identify the endogeneity of borrowing in the first specification, but not the second. In both cases, the estimated impact of borrowing was lower than the estimates using the control function approach. The conditional second moment restrictions thus appear to be the most informative in this application.

6 Conclusion

This paper estimates the impact of borrowing from a microcredit institution in Bangladesh on per-capita household consumption. By appropriately controlling for the endogeneity of borrowing, I am able to estimate the average effect of a microcredit loan for a randomly selected household in the survey areas. By imposing an assumption that the errors in the model have a constant correlation, conditional on the exogenous variables, I am able to exploit the presence of heteroskedasticity in the model to control for the endogeneity of borrowing.

I find that microcredit loans have a positive and significant impact on consumption, with an elasticity in the range of 0.193 to 0.212. These estimates contribute to the debate over whether microcredit is reducing poverty in Bangladesh by finding that microcredit loans are succeeding in allowing households to raise their levels of consumption.

7 Chapter 3 Tables

Table 1. Summary Statistics

	Mean	Standard Dev.
annual per-capita houshold consumption (taka)	4507.212	2796.714
total borrowng (taka)	2931.259	6843.770
education of head	2.754	3.723
age of head	41.266	13.153
sex of head (male = 1)	0.950	0.219
max education female	1.920	3.306
max education male	3.627	4.234
no adult male present	0.033	0.178
no spouse present	0.117	0.321
no adult female present	0.010	0.101
no adult male present	0.033	0.178
head's parents own land	0.254	0.559
# head's brothers own land	0.805	1.301
# head's sisters own land	0.802	1.256
spouse's parents own land	0.514	0.780
# spouse's brothers own land	0.919	1.437
# spouses's sister's own land	0.764781	1.20497
landholding	137.887	425.389
n = 1457		

Table 2. Heteroskedasticity Tests

		Chi-squared statistic	P-value
Borrowing equation			
	Thana dummy specification	30.93	(0.000)
	village characteristic specification	9.34	(0.0022)
Consumption equation			
	Thana dummy specification	48.37	(0.000)
	village characteristic specification	40.65	(0.000)

Table 3. Dependent variable: log borrowing

	Coeff.	T-stat.
education of head	0.209	(0.609)
sex of head	-5.510	(-6.288)
age of head	0.572	(1.336)
max ed male	-0.377	(-1.184)
max ed female	-0.503	(-3.046)
no adult male present	-0.934	(-6.406)
no adult female present	-0.038	(-0.458)
no spouse present	-0.889	(-4.474)
head's parents own land	0.071	(0.635)
# head's brothers own land	-0.008	(-0.047)
# head's sisters own land	0.113	(1.056)
spouse's parents own land	-0.319	(-2.317)
# spouse's brothers own land	-0.358	(-2.238)
# spouses's sister's own land	0.093	(0.804)
Thana 1	-2.117	(-3.496)
Thana 2	-0.965	(-1.357)
Thana 3	-0.495	(-1.012)
Thana 4	-1.342	(-2.205)
Thana 5	-1.165	(-1.882)
Thana 6	-2.590	(-3.450)

Continued on next page.

Table 3 continued. Dependent variable: log borrowing

	Coeff.	T-stat.
Thana 7	-2.133	(-4.320)
Thana 8	-1.218	(-1.503)
Thana 9	-0.796	(-1.536)
Thana 10	0.444	(0.664)
Thana 11	0.772	(1.505)
Thana 12	-1.044	(-1.747)
Thana 13	-2.398	(-4.015)
Thana 14	-0.991	(-1.294)
Thana 15	-2.191	(-3.421)
Thana 16	2.123	(3.291)
Thana 17	1.031	(1.568)
Thana 18	1.637	(2.868)
Thana 19	0.310	(0.554)
Thana 20	0.504	(0.920)
Thana 21	1.479	(2.141)
Thana 22	0.920	(1.455)
Thana 23	2.084	(3.385)

Table 4. Dependent variable: log per-capita houshold consumption

	OLS Coeff.	T-stat.	CF Method Coeff.	T-stat.
constant	7.894	(32.014)	7.940	(20.262)
log landholding	0.124	(2.429)	0.311	(2.984)
education of head	-0.004	(-0.730)	0.038	(0.277)
sex of head	-0.001	(-0.038)	0.032	(0.860)
age of head	-0.277	(-1.564)	-0.015	(-0.624)
max ed male	0.228	(3.111)	0.070	(0.374)
max ed female	0.006	(2.019)	0.043	(0.574)
no adult male present	-0.002	(-1.111)	0.001	(0.210)
no adult female present	0.020	(4.349)	0.008	(2.722)
no spouse present	0.023	(2.228)	0.002	(0.185)
head's parents own land	0.011	(0.700)	0.020	(1.391)
# head's brothers own land	0.018	(1.092)	0.046	(1.752)
# head's sisters own land	0.016	(1.574)	0.053	(2.122)
spouse's parents own land	0.030	(1.482)	0.009	(0.556)
# spouse's brothers own land	-0.010	(-0.628)	-0.025	(-0.849)
# spouses's sister's own land	0.000	(-0.097)	0.012	(0.501)
Thana 1	0.016	(0.911)	0.016	(0.687)
Thana 2	0.069	(4.532)	0.087	(4.458)
Thana 3	0.027	(1.708)	0.030	(1.514)
Thana 4	0.000	(0.006)	0.002	(0.077)
Thana 5	0.062	(3.641)	0.061	(2.945)

Continued on next page.

Table 4 continued. Dependent variable: log per-capita houshold consumption

	OLS Coeff.	T-stat.	CF Method Coeff.	T-stat.
Thana 6	0.032	(1.991)	0.027	(1.227)
Thana 7	0.056	(3.406)	0.080	(3.957)
Thana 8	0.022	(1.431)	0.010	(0.382)
Thana 9	0.022	(1.488)	0.025	(1.228)
Thana 10	0.017	(1.097)	0.023	(1.385)
Thana 11	0.031	(2.055)	0.032	(1.476)
Thana 12	0.056	(3.040)	0.045	(2.294)
Thana 13	0.024	(1.570)	0.052	(2.493)
Thana 14	0.041	(2.561)	0.040	(2.182)
Thana 15	0.009	(0.607)	0.038	(1.926)
Thana 16	0.041	(2.621)	0.038	(2.228)
Thana 17	0.015	(0.888)	0.015	(0.894)
Thana 18	0.009	(0.616)	-0.007	(-0.392)
Thana 19	0.005	(0.347)	0.007	(0.348)
Thana 20	0.020	(1.187)	0.025	(1.196)
Thana 21	-0.021	(-1.284)	-0.030	(-1.537)
Thana 22	0.055	(3.383)	0.046	(2.331)
Thana 23	-0.033	(-0.399)	-0.006	(-0.296)
borrowing	0.056	(3.290)	0.193	(2.838)
control function			-0.974	-(3.290)

Table 5. Heteroskedasticity index

	Coeff.	T-stat.
education of head	1.050	(1.173)
sex of head	0.048	(0.279)
age of head	0.095	(0.699)
max ed male	-2.020	(-1.764)
max ed female	-0.604	(-1.489)
no adult male present	0.001	(0.059)
no adult female present	0.006	(0.794)
no spouse present	-0.103	(-1.932)
head's parents own land	0.112	(1.575)
# head's brothers own land	0.244	(1.642)
# head's sisters own land	0.393	(2.394)
spouse's parents own land	-0.110	(-1.130)
# spouse's brothers own land	-0.146	(-0.644)
# spouses's sister's own land	0.064	(0.351)
Thana 1	-0.028	(-0.206)
Thana 2	0.048	(0.431)
Thana 3	0.057	(0.588)
Thana 4	-0.066	(-0.616)
Thana 5	0.004	(0.034)
Thana 6	-0.094	(-0.787)

Continued on next page.

Table 5 continued. Heteroskedasticity index

	Coeff.	T-stat.
Thana 7	0.112	(0.922)
Thana 8	-0.106	(-0.876)
Thana 9	-0.011	(-0.098)
Thana 10	0.042	(0.429)
Thana 11	0.021	(0.191)
Thana 12	0.003	(0.027)
Thana 13	0.076	(0.605)
Thana 14	-0.013	(-0.115)
Thana 15	0.165	(1.780)
Thana 16	0.022	(0.193)
Thana 17	0.099	(0.849)
Thana 18	-0.080	(-0.759)
Thana 19	0.055	(0.546)
Thana 20	0.063	(0.621)
Thana 21	0.060	(0.570)
Thana 22	-0.025	(-0.223)
Thana 23	0.046	(0.392)

Table 6. Dependent variable: log household borrowing

	Coeff.	T-stat.
education of head	0.520	(2.688)
sex of head	-0.862	(-1.721)
age of head	1.194	(3.399)
max ed male	-0.492	(-2.418)
max ed female	-0.336	(-2.249)
no adult male present	-0.349	(-3.415)
no adult female present	-0.277	(-4.285)
no spouse present	0.049	(0.447)
head's parents own land	-0.099	(-1.178)
# head's brothers own land	-0.038	(-0.322)
# head's sisters own land	-0.085	(-1.023)
spouse's parents own land	-0.067	(-0.570)
# spouse's brothers own land	0.041	(0.372)
# spouses's sister's own land	0.048	(0.401)
village has primary school	-0.098	(-0.530)
village has rural health center	0.074	(0.714)
village has family planning center	0.290	(2.452)
midwife available in village	0.188	(1.544)
village distance to bank (km)	0.090	(0.718)
village price of rice	-0.118	(-0.859)

Continued on next page.

Table 6 continued. Dependent variable: log household borrowing

	Coeff.	T-stat.
no village female wage	0.233	(1.533)
village price of wheat flour	-0.212	(-1.509)
village price of milk	0.134	(1.091)
village price of hen egg	-0.024	(-0.333)
village price of potato	0.015	(0.147)
village average male wage	0.242	(1.639)
village average female wage	0.333	(2.015)
no village female wage	0.233	(1.533)

Table 7. Dependent variable: log per-capita household consumption

	OLS coeff.	T-stat.	CF method coeff.	T-stat
constant	8.310	(37.811)	7.766	(24.265)
log landholding	0.050	(2.050)	0.218	(2.870)
education of head	-0.014	(-0.153)	-0.130	(-0.950)
sex of head	-0.002	(-0.098)	0.005	(0.185)
age of head	-0.022	(-1.595)	-0.043	(-2.106)
max ed male	0.275	(2.680)	0.258	(1.805)
max ed female	0.094	(1.997)	0.156	(2.382)
no adult male present	-0.002	(-0.800)	-0.002	(-0.401)
no adult female present	0.006	(4.006)	0.006	(2.375)
no spouse present	0.011	(1.883)	0.007	(1.119)
head's parents own land	0.002	(0.297)	-0.001	(-0.099)
# head's brothers own land	0.014	(0.838)	0.042	(1.234)
# head's sisters own land	0.015	(0.937)	0.024	(1.236)
spouse's parents own land	0.011	(0.983)	0.004	(0.241)
# spouse's brothers own land	-0.019	(-0.972)	-0.027	(-1.137)
# spouses's sister's own land	-0.022	(-1.337)	-0.051	(-2.115)
village has primary school	-0.027	(-4.305)	-0.022	(-2.025)
village has rural health center	-0.006	(-1.650)	-0.012	(-2.203)
village has family planning center	0.004	(1.128)	0.008	(1.442)
midwife available in village	-0.015	(-2.700)	-0.018	(-2.204)

Continued on next page.

Table 7 continued. Dependent variable: log per-capita household consumption

	OLS coeff.	T-stat.	CF method coeff.	T-stat
village distance to bank (km)	-0.037	(-1.113)	-0.053	(-1.243)
village price of rice	-0.010	(-0.757)	-0.026	(-1.088)
village price of wheat flour	0.040	(2.549)	0.067	(2.563)
village price of milk	0.007	(0.121)	-0.039	(-0.524)
village price of hen egg	0.003	(0.126)	0.016	(0.621)
village price of potato	0.019	(0.936)	0.011	(0.281)
village average male wage	0.199	(1.461)	0.270	(1.393)
village average female wage	-0.201	(-0.966)	-0.289	(-0.923)
no village female wage	0.001	(0.172)	0.004	(0.267)
log borrowing	0.023	(1.616)	0.212	(6.739)
control function			-0.951	(-3.007)

Table 8. Heteroskedasticity index

	Coeff.	T-stat
education of head	-1.417	(-1.413)
sex of head	-0.022	(-0.156)
age of head	-0.142	(-1.099)
max ed male	-0.406	(-0.347)
max ed female	0.333	(0.624)
no adult male present	-0.033	(-1.200)
no adult female present	-0.003	(-0.234)
no spouse present	-0.026	(-0.390)
head's parents own land	-0.119	(-1.006)
# head's brothers own land	0.853	(3.171)
# head's sisters own land	0.290	(2.183)
spouse's parents own land	-0.293	(-2.461)
# spouse's brothers own land	0.203	(1.030)
# spouses's sister's own land	-0.454	(-2.315)
village has primary school	0.033	(0.374)
village has rural health center	-0.101	(-2.635)
village has family planning center	0.054	(1.354)
midwife available in village	-0.060	(-1.028)
village distance to bank (km)	0.072	(0.202)
village price of rice	-0.317	(-1.979)

Continued on next page.

Table 8 continued. Heteroskedasticity index

	Coeff.	T-stat
village price of wheat flour	0.311	(1.409)
village price of milk	-0.264	(-0.483)
village price of hen egg	0.132	(1.049)
village price of potato	-0.256	(-0.953)
village average male wage	2.054	(1.548)
village average female wage	-0.136	(-0.065)
no village female wage	0.112	(1.249)

References

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

[2] **Altonji, Joseph G.,** "Intertemporal Substitution in Labor Supply: Evidence from Micro Data," *Journal of Political Economy*, 1986, *94 (3-2)*, S176 - S215.

[3] **Altonji, Joseph G., Todd E. Elder and Christopher R. Taber**, "An Evaluation of Instrumental Variable Strategies for Estimating the Effects of Catholic Schools," *Journal of Human Resources*, 2005, *40 (4)*, 791-821.

[4] **Altonji, J. and R. Matzkin,** "Cross Section and Panel Data Estimators for Nonseparable Models with Endogenous Regressors," *Econometrica*, 2005, *73*, 1053-1102.

[5] **Altonji, Joseph G. and Christina H.Paxson,** "Labor Supply, Hours Constraints, and Job Mobility," *The Journal of Human Resources*, 1992, *27 (2)*, 256-278.

[6] **Altug, S. and R. Miller,** "Household Choices in Equilibrium," *Econometrica*, 1990, *58 (3)*, 543-570.

[7] **Armendariz, Beatriz and Jonathan Morduch,** *The Economics of Microfinance*, Cambridge, MA: MIT Press, 2005.

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

[9] **Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan,** "The Miracle of Microfinance? Evidence from a randomized evaluation," *MIT Working Paper Series*, 2009.

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

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

[12] **Biddle, Jeff E.,** "Intertemporal Substitution and Hours Restrictions," *Review of Economics and Statistics*, 1988, *70 (2)*, 347-351.

[13] **Bun, Maurice J.G. and Martin A. Carree,** "Bias-Corrected Estimation in Dynamic Panel Data Models," *Journal of Business and Economic Statistics*, 2005, *23 (2)*, 200 - 210.

[14] **Blundell, R., M. Browning and C. Meghir,** "Consumer Demand and the Life-Cycle Allocation of Household Expenditures," *The Review of Economic Studies*, 1994, *61 (1)*, 57-80

[15] **Blundel, R., V. Fry and C. Meghir**, "Preference Restrictions in Life-Cycle Models," in "Microeconometrics: Surveys and Applications," edited by J. Florens, M. Ivaldi, J. Laffont, and F. Laisney, Basil Blackwell, 1990.

[16] **Blundell, Richard & Ham, John & Meghir, Costas,** "Unemployment and Female Labour Supply," *Economic Journal*, 1987, *97*, 44-64.

[17] **Blundell and T. MaCurdy,** “Labor Supply: A Review of Alternate Approaches,” in "Handbook of Labor Economics," edited by O. Ashenfelter and D. Card, Elsevier, 1999.

[18] **Blundel, R., and C. Meghir**, "The Effects of Male and Female Labor Supply on Commodity Demands," *Econometrica*, 1991, *59 (4)*, 925-951.

[19] **Blundell, R. and J. Powell,** "Endogeneity in Nonparametric and Semiparametric Regression Models," in "Advances in Economics and Econometrics: Theory and Applications," edited by M. Dewatripont, L. Hansen and S.Turnovsky, Cambridge, U.K.:Cambridge University Press, 2003.

[20] **Browning, Martin,** "The Costs of Using Frisch Demand Functions That Are Additive in the Marginal Uility of Expenditure," *Economic Letters*, 1986, *21*, 205-207.

[21] **Browning, Deaton and Irish,** "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle," *Econometrica* , 1985, *53 (3)*, 503-544.

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

[23] **Coleman, Brett E.,** "The Impact of Group Lending in Northeast Thailand," *Journal of Development Economics*, 1999, *60 (1)*, 105-141.

[24] **Das, Mitali, Francis Vella and Whitney Newey,** “Non-parametric Estimation of Sample Selection Models” *Review of Economic Studies*, 2003, *(70)*, 33-58.

[25] **Deaton, A.,** *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, Baltimore:The Johns Hopkins University Press,1997.

[26] **Deaton, A.,** (2009). "Instruments of Development: Randomization in the Tropics, and the Search for the Elusive Keys to Economic Development," *NBER Working Paper,* 2009, #14690.

[27] **Euwals, R., Bertrand Melenberg, and Arthur van Soest,** "Testing the Predictive Value of Subjective Labor Supply Data," *Journal of Econometrics*, 1998,*13 (5)*, 567-585.

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

[29] **Ghatak, Maitreesh and Guinnane, Timothy W.,** "The Economics of Lending with Joint Liability: Theory and practice," *Journal of Development Economics*,1999, *60 (1)*, 195-228.

[30] **Ham, John C.,** "Estimation of a Labour Supply Model with Censoring Due to Unemployment and Underemployment," *The Review of Economic Studies*, 1982, *49 (3)*, 335-354.

[31] —— , "Testing Whether Unemployment Represents Intertemporal Labour Supply Behaviour," *The Review of Economic Studies*, 1986, *53 (4)*, 559-578.

[32] **Ham, John C. and Kevin T. Reilly,** "Testing Intertemporal Substitution, Implicit Contracts, and Hours Restriction Models of the Labor Market Using Micro Data," *The American Economic Review*, 2002, *94 (2)*, 905-927.

[33] **Heckman, J. and T. MaCurdy,** "A Life Cycle Model of Female Labor Supply," *The Review of Economic Studies,* 1980*, 47 (1)*, 47-74.

[34] **Heckman, James J. and Petra E. Todd,** "A Note on Adapting Propensity Score Matching and Selection Models to Choice Based Samples," *Institute for the Study of Labor (IZA) Discussion Paper*, 2009, #4303.

[35] **Holtz-Eakin, Douglas, Whitney Newey, and Harvey S. Rosen,** "Estimating Vectorautoregressions with Panel Data," *Econometrica*, 1988, *56 (6)*, 1371-1395.

[36] **Ichimura, H. and L.F. Lee,** "Semiparametric Least Squares (SLS) and Weighted SLS Estimation of Multiple Index Models: Single Equation Estimation," in "Nonparametric and Semiparametric Methods in Econometrics and Statistics," edited by W. Barnett, J. Powell and G. Tauchen, Cambridge University Press, 1991.

[37] **Imbens, Guido W. and Thomas Lemieux,** "Regression discontinuity designs: A guide to practice," *Journal of Econometrics*, 2008, *142 (2)*, 615-635.

[38] **Karlan, Dean and Jonathan Zinman**, "Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts," *Economic Growth Center, Yale University, Working Paper*, 2007, #956.

[39] **Khandker, Shahidur R.,** *Fighting Poverty with Microcredit: Experience in Bangladesh*, New York:Oxford University Press, 1998.

[40] **Klein, Roger and Francis Vella,** "A Semiparametric Model for Binary Response and Continuous Outcomes Under Index Heteroskedasticity," *Institute for the Study of Labor (IZA) Discussion Paper*, 2006, #2383.

[41] —— **and** ——, "Estimating the Return to Endogenous Schooling Decisions via Conditional Second Moments," *Journal of Human Resources*, 2009, *44 (4)*, 1047-1065.

[42] —— **and** ——, "Estimating a Class of Triangular Simultaneous Equations Models Without Exclusion Restrictions," *Journal of Econometrics*, 2010, *154 (2)*, 154-164.

[43] **Lee, M. J. and Francis Vella,** "A Semiparametric Estimator for Censored Selection Models with Endogeneity," *Journal of Econometrics*, 2006, *130*, 235-252.

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

[45] —— , "A Simple Scheme for Estimating an Intertemporal Model of Labor Supply and Consumption in the Presence of Taxes and Uncertainty," *International Economic Review*, 1983, *24 (2)*, 265-289.

[46] **Maurer, Jurgen, Roger Klein and Francis Vella,** "Health, Demographics and Retirement: Evidence from a Semiparametric Binary Choice Model with Nonadditive Correlated Fixed Effects," *Institute for the Study of Labor (IZA) Discussion Paper*, 2007, #3257.

[47] **Morduch, Jonathan,** "The Microfinance Promise," *Journal of Economic Literature*, 1999, *37*, 1569–1614.

[48] **Pitt, Mark M. and Shahidur R. Khandker,** "The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?" *Journal of Political Economy*, 1998, *106 (5)*, 958-996.

[49] **Ravallion, Martin,** "Poverty Comparisons: A guide to concepts and methods," *World Bank Living Standards Measurement Study Working Paper*, 1992, #88.

[50] **Roodman, David and Jonathan Morduch,** "The Impact of Microcredit on the Poor in Bangladesh: Revisiting the Evidence," *Center for Global Development Working Paper*, 2009, #174.

[51] **Stiglitz, Joseph E.,** "Peer Monitoring and Credit Markets," *World Bank Economic Review*, 1990, *4 (3)*, 351-366.

[52] **Vella, Francis,** "A Simple Estimator for Simultaneous Models with Censored Endogenous Regressors," *International Economics Review*, 1993, *34 (2)*, 441-457.

[53] **Wooldridge, Jeffrey M.,** *Econometric Analysis of Cross Section and Panel Data,* Cambridge, MA: MIT Press, 2002.