Credit Programs for the Poor and the Nutritional Status of Children in Rural Bangladesh

by

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January 16, 1998

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This research was funded by the World Bank project "Impact of Targeted Credit Programs on Consumption Smoothing and Nutrition in Bangladesh" under research grant RPO 681-09.

Abstract

The impact of group-based credit programs on the nutritional status of children by gender in rural Bangladesh is evaluated. Lacking exclusion restrictions of the usual sort, the effect of credit program participation by gender of participant is identified by imposing a factor structure on the regression errors. Women's credit is found to have a large and statistically significant impact on two of three measures of the nutritional well-being of both boy and girl children. Credit provided men has no statistically significant impact and the null hypothesis of equal credit effects by gender of participant is rejected.

JEL Classification I1,O1,C3
Keywords: micro-finance, rural credit, child health, nutrition, Bangladesh, gender

1. Introduction

This paper evaluates the effects of three group-based credit programs (Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board's (BRDB) Rural Development RD-12 program) by gender of program participant on the nutritional status of children by gender in rural Bangladesh. These programs are the major small-scale credit programs in Bangladesh that provide production credit and other services to the poor. The largest group of program participants have been women, most of whom had no direct contact with the credit market prior to participating in these programs. The self-employment activities financed by these credit programs can affect the nutritional status of children through the standard income and substitution effects, as well as by increasing the role and power of women in the household resource allocation process. Earlier work on the effect of these credit programs on other behaviors (Pitt and Khandker (1998), Pitt *et. al.* (1997) and McKernan (1996)) has demonstrated that the magnitude of the impact of borrowing on labor supply, expenditure, assets, schooling of children, fertility, contraceptive use, and self-employment profits, depends on the gender of credit program participant. In this paper we extend those results by not only asking if the size of the effect of program participation on nutritional outcomes depends upon the sex of the program participant, but also whether the effects on boy and girl children differ.

In recent years, governmental and non-governmental organizations in many low income countries have introduced credit programs such as these targeted to the poor. Many of these programs specifically target women based on the view that women are more likely to be credit constrained than men, have restricted access to the wage labor market, and have an inequitable share of power in household decision-making. Many of these programs earmark loans for production purposes only. The Grameen Bank of Bangladesh is perhaps the best-known example of these small-scale production credit programs for the poor. The Grameen Bank, founded in 1976 by Muhammad Yunus, an economics professor, provides financing for non-agricultural self-employment activities. By the end of 1994, it had served more than 2 million borrowers of whom 94% were women. With loan recovery rates of over 90%, the Grameen Bank has been touted as among the most successful credit programs for the poor and its model for group lending has been used for delivering credit in over 40 countries.

All three of the Bangladesh programs examined below exclusively work with the rural poor. Although the sequence of delivery and the provision of inputs vary some from program to program, all three programs essentially offer production credit to the landless rural poor (defined as those who own less than half an acre of land) using peer monitoring as a substitute for collateral.[1] For example, the Grameen Bank provides credit to members who form self-selected groups of five. Loans are given to individual group members, but the whole group becomes ineligible for further loans if any member defaults. The groups meet weekly to make repayments on their loans as well as mandatory contributions to savings and insurance funds. The Grameen Bank, BRAC, and BRDB also provide non-credit services in areas such as consciousness-raising, skill development training, literacy, bank rules, investment strategies, health, schooling, civil responsibilities, and altering the attitudes of and toward women.[2]

The research results presented below are based upon a 1991/92 survey of 1798 households in 87 villages in rural Bangladesh. The earlier studies, cited above, that used these survey data confirm that program participation by households is self-selective. The estimation method used by these earlier studies corrects for the potential bias arising from unobserved individual- and village-level heterogeneity by taking advantage of a quasi-experimental survey design to provide statistical identification of program effects. The survey design covers one group of households which has the choice to enter a credit program and which may alter their behavior in response to the program, and a "control" group which is not given the choice of entering the program but whose behavior is still measured. Similarly, the identification of these programs' impact by the gender of the participant is accomplished based on the comparison between groups of each gender with and without the choice to participate. These programs, whose professed goal is to better the lives of the poor, may have chosen villages in a conscious manner based on their wealth, attitudes or other attributes. To deal with the possibility of endogenous program placement, these studies couple the quasi-experimental design with village-level fixed-effects to sweep out village unobservables that might bias estimates of the impacts of these credit programs.

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[1]Theoretical aspects of targeted group-based lending to the poor are well summarized in Rashid and Townsend (1993). Some nonproduction lending does take place. In the Grameen Bank, for example, a group fund, financed by the weekly contributions of group members, is used to make consumption loans to group members. More recently, Grameen has offered housing loans to group members as well.

[2] As part of Grameen Bank's social development program, all members are required to memorize, chant, and follow the "Sixteen Decisions". These decisions include "We shall keep our families small", "We shall not take any dowry in our sons' wedding, neither shall we give any dowry in our daughters' wedding", "We shall not practice child marriage", and "We shall educate our children". See Khandker *et. al.* (1995) for details on the operation of the Grameen Bank.

The 1991/92 survey included a special nutritional status module that collected anthropometric measures of nutritional status for all children under the age of 15 years in 15 of the 87 villages surveyed. Unfortunately, only villages with a credit program and only households who were eligible to participate in the programs were included in the nutritional module, making identification via the quasi-experimental survey design impossible. Another identification strategy is required.[3] Unfortunately, as Pitt and Khandker (1998) have argued at length, an instrumental variable approach based upon exclusion restrictions is not applicable because there are unlikely to be valid identifying instruments; that is, exogenous variables affecting credit program participation (by sex) that do not also affect resource allocations to children conditional on participation. This is related to the well known "more goods than prices" problem that naturally arises in the study of intra-household resource allocation. Pitt (1997) reviews some of the approaches to estimating the demand for goods within the household conditional on some individual- or household-specific endogenous choice, and suggests cross-person restrictions on demands within the household as one possible direction.[4] For example, Pitt and Rosenzweig (1990) use cross-person restrictions on regression parameters to estimate the effect of infant illness on the time allocation of the male and female teenage siblings and mother of the infant. The estimated conditional demand equations in that paper, the time allocation of male and female teenagers conditional on the health of an infant sibling, have the same structure as our, the health of the male and female children conditional on the credit program participation of an adult household member. The idea is to estimate the differenced male-female equation conditional on the health of the infant sibling. If the effects of some subset of exogenous regressors (prices) on time allocation conditional on infant health are restricted to be the same for male and female teenagers, these

[3]In an earlier paper produced as part of the original project, Pitt and Khandker (1996) estimated models of anthropometric nutritional outcomes relying solely on the nonlinearity resulting from an assumption that the errors of the nutritional outcome equation and the program participation program equation are distributed as bivariate normal. This approach is unsatisfactory for two reasons. First, no theory of behavior in the social sciences delivers as an implication the distribution of errors. The choice of normality is made simply for computational convenience, and yet, it was used as the sole source of parameter identification. Second, this nonlinearity, even if justified, was seemingly insufficient to numerically identify the effects of credit program participation on these health outcomes with the data. Perhaps the reason large or statistically significant credit program effects were not found is precisely because the model was so poorly identified.

[4]The problem with applying household fixed effects estimation is that one cannot identify the level parameters of household-specific (as opposed to person-specific) regressors. Credit program participation by the either the father or mother of the children in a household is a household-specific variable from the perspective of the individual children in the household, who are the units of observation in the estimation.

regressors became available as identifying instrumental variables for infant health in the differenced regression. However, applied to our problem, this method would only identify the differential effects of credit program participation on the nutritional status of boys and girls, not their level effects. That is, we could learn whether credit program participation augmented the nutritional status of girls relative to boys, but not whether the total effect for any sex was positive or negative, or the magnitude of the effect.

In order to estimate the level effects of credit programs by gender of the credit program participant on individual-specific nutritional indicators of well-being, we propose a set of restrictions on the error covariances on a set of gender-specific health behaviors and the decision to participate in a credit program. Chamberlain (1976, 1977a, 1977b) and Chamberlain and Griliches (1975) first demonstrated how to identify the parameters of a structural equation model from restrictions on error covariances. Extending their approach to our estimation problem permits identification of the level effects of credit program participation by gender of participant without requiring the imposition of difficult to justify zero restrictions which are inconsistent with a general household model, without making cross-equation restrictions on regression parameters, or by relying exclusively on arbitrary assumptions about the distribution of errors. It does, however, require restrictions on the nature of the regression errors. The idea is to place a factor-analytic structure on the residuals of a set of equations for female and male credit program participation and a set of nutritional status outcomes, which in our study are arm circumference, body mass index and height-for-age. In the estimation of the determinants of these nutritional outcomes, the residual includes left-out household- and individual-specific variables such as relative bargaining power in the household, innate healthiness (health endowments), and preferences. These omitted variables may affect the nutritional (and other) resources allocated to boy and girl children, but not necessarily in the same way.

The imposition of a factor-analytic structure can identify structural parameters with a single cross-section of data providing that i) we jointly estimate the determinants of a sufficiently large number of nutritional outcomes that are likely to be influenced by a common latent factor, and ii) we have a sufficient number of households in the sample with more than one child and with children of more than one sex. As we demonstrate below, both conditions are satisfied by our data. In addition, we have data on nutritional status at two points in time for each sampled household. Adding a time-period variance-components structure to the factor-analytic structure adds additional identifying restrictions to the residual covariance matrix (as in Hsiao, 1986).[5] Estimation is by maximum-likelihood.

Our results are striking. After taking into account the endogeneity of individual participation in these credit programs and the placement of these credit programs across areas, we find that women's credit has a large, positive and statistically significant impact on two of three measures of the nutritional well-being of both boy and girl children. Credit provided to men has no statistically significant impact. These patterns are not apparent when credit program participation is treated as exogenous in the determination of nutritional well-being.

Section 2 of this paper outlines an economic theory of household allocation to guide in the interpretation of the empirical results. Section 3 describes the estimation and identification of structural equations with covariance restrictions based upon regression errors with a factor-analytic structure. The precise form of the log-likelihood maximized is fairly messy and its derivation is relegated to an appendix. Section 4 describes the 1991/92 Bangladesh micro-credit survey and the data used in the estimations. Section 5 presents and interprets the parameter estimates of our structural model and compares these estimates to those obtained from models which alternatively assume that household participation in these credit programs is exogenous and that credit programs are randomly placed across villages. Section 6 summarizes our results.

2. Theory

To motivate the evaluation of the effects of group-based credit program participation on the nutritional status of children, consider a simple one period model that generates an efficiency argument for targeted credit for the rural poor. In order to illustrate the impact of credit program participation on child quality in the simplest manner, we treat the credit program as an exogenous endowment of specific capital. The model characterizes the allocation of child quality (health) to children distinguished by gender, and of women's time, while allowing for the preferences of men and women to differ within the household. Assume that households consist of a boy and a girl child and two

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[5] The panel nature of the data suggests that individual fixed-effects estimation may be another approach to dealing with heterogeneity bias. Unfortunately, the two survey rounds are quite closely spaced, only 6 months apart. It is well known that the signal-to-noise ratio can get dangerously low in this case leading to severe attenuation bias. Moreover, the endogenous regressor, participation in a group-based credit program, changed only slightly, if at all, for most households over this short period of time.

working age adults -- the male head and his wife. The adults each have preferences described by person-specific utility functions

$$u_s = u_s(h_b, h_g, Q, \ell_m, \ell_f), \quad s = m, f \qquad \textbf{(1)}$$

where h_b and h_g are the quality (health) of the boy and girl child, respectively, Q is a set of jointly consumed market goods, and ℓ_m and ℓ_f are the leisure of the male and female adult household members, respectively. The household's social welfare is some function of the individual utility functions $U=U(u_f, u_m)$, a simple form of which is

$$U = \lambda u_f + (1-\lambda) u_m, \qquad 0 \leq \lambda \leq 1 \qquad \textbf{(2)}$$

in which λ is the weight given to women's preferences in the household's social welfare function. Browning and Chiappori (1996) have shown that if behavior in the household is Pareto efficient, the household's objective function takes the form of a weighted sum of individual utilities as in equation (2). The parameter λ can be thought of as representing the bargaining power of the female household members relative to the male household member in determining the intrahousehold allocation of resources. When $\lambda=0$ female preferences are given no weight and the household's social welfare function is identically that of the male. We will not explicitly model the process by which λ is determined, but, in accord with much of the literature, we presume that it is increasing in the relative value of the adult female's assets and time.[6] To the extent that participation in a group-based credit program increases the value of assets and time of the participator it also increases the participator's preference weight in (2).

The household produces the child quality good h provided to each child according to

$$h_s = h_s(L_{fhs}, F_s), \quad s = b, g \qquad \textbf{(3)}$$

where L_{fhs} is time devoted to the production of h for children of sex s by females, and F_s is a purchased

[6]The reader is referred to McElroy (1990), McElroy and Horney (1981), and Manser and Brown (1989) for a formal exposition of game theoretic approaches to household decision making.

input (food). It is assumed that males do not supply time to the production of the child quality good h_s.

Very few rural women work in the wage labor market in Bangladesh. It is a conservative Islamic society which encourages the seclusion of women. Lacking other opportunities, women are engaged in the production of household goods to the exclusion of employment in market activities. These effects are magnified if λ is small and male preferences tend to favor production of certain kinds of household goods intensive in the time of women.

There are also economic activities that produce goods for market sale that are not culturally frowned upon. These activities, which produce what we refer to as Z-goods, do not require that production occur away from the home and permit part-day labor for those who reside at the workplace. Although some of these production activities can be operated at low levels of capital intensity, for many Z-goods a minimum level of capital is needed. This minimum is often the result of the indivisibility of capital items. For example, dairy farming requires no less than one cow while hand-powered looms have a minimum size. For other activities where the indivisibility of physical capital is not an issue, such as paddy husking, transactions costs and the high costs of information place a floor on the minimal level of operations. In many societies these indivisibilities may be inconsequential, but household income and wealth among the rural poor of many developing countries including Bangladesh is so low that the cost of initiating production at minimal economic levels are quite high. At very-low levels of income and consumption, reducing current consumption to accumulate assets for this purpose may not be optimal because it may seriously threaten health (and production efficiency) and life expectancy, as shown in Gersovitz (1983).

Formally, we represent the production function for the Z goods as

$$Z = Z(K, L_{mz}, L_{fz}^{*}, A) \quad \textbf{(4)}$$

where L_{mz} is the time of the male devoted to the production of Z, L^{*}_{fz} is efficiency units of labor time of the female (defined below) devoted to the production of Z, K is capital in Z production, and A is a vector of variable inputs. Positive production requires a minimal level of capital K_{min} such that $K \geq K_{min}$. The production function (4) can be operated at a nonzero level when L_{mz} or L^{*}_{fz} are zero, but not when both are zero. For example, in the case of milk production, although at least one cow is required, any person's labor can be used to obtain the milk.

There is jointness between the production of the good Z and the production of the per-child quality good h. This jointness is simply represented here by an equation defining efficiency units of women's time devoted to the production of Z

$$L_{fz}^{*} = L_{fz} + \omega L_{fh}, \quad 0 \leq \omega \leq 1 \qquad \textbf{(5)}$$

where $L_{fh} = L_{fhb} + L_{fhg}$, and L_{fz} is time spent exclusively on the production of Z.[7] This formulation allows for time devoted to producing a good for the market in the home (Z) to also jointly produce the child good (h) albeit at possibly reduced efficiency. If ω =0, the production of h and Z are nonjoint in that the reallocation of a unit of women's (clock) time from the production of h to the production of Z reduces the production of h by the marginal product of labor. In contrast, if ω = 1, h and Z are maximally joint in that reallocating a unit of (clock) time from producing h to producing Z (all else being the same) has no effect on the quantity of efficiency time devoted to producing h and hence the output of h remains unchanged. The time reallocated to the production of Z by women has zero opportunity cost in terms of h.

Households maximize utility subject to the budget constraint

$$Q + p_F(F_b + F_g) = v + L_m w_m + p_z Z - p_A A \qquad \textbf{(6)}$$

where the jointly consumed market good Q is the numeraire; p_A, p_F and p_z are the prices of A (inputs to the Z-good), the purchased input F used to produce child quality, and the Z-good, respectively; v is nonearnings income; w_m is the male wage, and the last term, $p_z Z - p_A A$, gross profit in the production of good Z, disappears if $K < K_{min}$, that is, no one in the household participates in the credit program. Both adults are endowed with time L. Men's time is allocated to wage labor L_{mw}, the production of the Z-good, L_{mz}, and to leisure, ℓ_m:

$$L = L_{mw} + L_{mz} + \ell_m. \qquad \textbf{(7)}$$

Women's time is spent in the production of the h-good (which may be joint with the production of the

[7] Since males devote no time to producing h, their efficiency time in the production of Z is $L_{mz}^{*} = L_{mz}$.

Z good), L_{fh}, the exclusive production of the Z-good, L_{fz}, and in leisure, ℓ_f :

$$L = L_{fhb} + L_{fhg} + L_{fz} + \ell_f \tag{8}$$

The full effect of credit (in the form of an endowment K_{min}) on the level of child quality produced and its allocation across children by sex consists of three components. First, the use of female labor to produce the good Z for sale in the market increases household full income. If child quality h is a normal good for both boys and girls, then the income effect will increase child quality for both sexes. If the relative equality of allocations to boys and girls increases with income ("gender equality is a normal good") as in Behrman (1986), then girls are likely to benefit more than boys.

Second, the increase in the value of women's time will increase the cost of producing child quality h. In the absence of sufficient capital (K_{min}) to operate the Z activity the necessary first-order conditions are

$$\frac{\partial U}{\partial h_i}\frac{\partial h_i}{\partial L_{fhi}} = -\frac{\partial U}{\partial h_j}\frac{\partial h_j}{\partial L_{fhi}} - \frac{\partial U}{\partial l_f}\frac{\partial l_f}{\partial L_{fhi}} \qquad i,j=b,g \tag{9}$$

and when K exceeds K_{min}

$$\frac{\partial U}{\partial h_i}\frac{\partial h_i}{\partial L_{fhi}} = -\frac{\partial U}{\partial h_j}\frac{\partial h_j}{\partial L_{fhi}} - \frac{\partial U}{\partial l_f}\frac{\partial l_f}{\partial L_{fhi}} + (1-\omega)\delta p_z\frac{\partial Z}{\partial L_{fz}^*} \qquad i,j=b,g \tag{10}$$

where δ=marginal utility of income. The shadow cost of producing child quality with women's time is higher in (10) as a result of the last term on the right-hand side of (10) which reflects the utility of the foregone income from Z-good production when a marginal unit of women's time is shifted to the production of child quality. However, this term is zero in the limiting case in which time devoted to the production of Z is maximally joint with the production of h (ω=1). In this special case, there is no substitution effect resulting from an increase in the value of women's time resulting from the production of the Z-good since all time devoted to producing h also produces the Z good with the same efficiency as time devoted exclusively to the production of Z. If $\omega<1$ we have the usual case of increased labor market opportunities for women, including wage labor market opportunities, increasing the shadow cost of household goods such as child quality.

Third, endowing women with productive assets (K_{min}) to be combined with their otherwise unmarketable labor to produce goods for sale in the market will result in an increase in the preference weight λ of the collective utility function (2) if women's power in household decision-making is increasing in their assets and the value of their time endowment. If women tend to prefer child quality more than their husbands (*maternal altruism*), and if husband's preference for h_b compared to h_g is relatively greater than his wife's, then the increased power of women in the household will tend to increase production of child quality, and quality of girls in particular.

The net effect of undertaking production of the Z good on the demand for child-quality is indeterminate because of the negative substitution effect arising from the increase in the value of women's time when there is less than perfect jointness between time allocated to Z-good production (L_{fz}) and child quality (L_{fh}). However, if $\omega=1$ and h_b and h_g are normal goods then child quality will rise even if women's preference weight λ is fixed.

3. Structural equation estimation identified with covariance restrictions

a. Structural estimation with sibling data

We begin by specifying a model in which a set of child-specific health behaviors depend, in part, on a common latent variable that also determines the value of a household-specific behavior, credit program participation. Consider a sample of households indexed by i consisting of siblings indexed by j for whom we observe three related behaviors, h_{ij}, m_{ij} and f_{ij}, in addition to the value of a household-specific endogenous variable y_i. Unobserved heterogeneity that affects y_i is also believed likely to affect these child-specific health behaviors conditional on y_i. As a result, estimating the determinants of these three behaviors conditional on the household-specific variable raises issues of heterogeneity bias. However, if there is a common source or sources to this heterogeneity, it is possible to estimate the parameters of the conditional demand equations by estimating the reduced forms imposing this *factor structure* on the residual covariance matrix. We write the conditional demand equations for the three behaviors h_{ij}, m_{ij} and f_{ij}, conditional on a household choice variable y_i (credit program participation):

$$h_{ij} = X_{ij}\beta_h + \delta_h y_i + \lambda_h \mu_i + \epsilon_{ij} \qquad \textbf{(11)}$$

$$m_{ij} = X_{ij}\beta_m + \delta_m y_i + \lambda_m \mu_i + \eta_{ij} \qquad \textbf{(12)}$$

$$f_{ij} = X_{ij}\beta_f + \delta_f y_i + \lambda_f \mu_i + \upsilon_{ij} \qquad \textbf{(13)}$$

and the reduced form household demand for y_i:

$$y_i = X_{ij}\beta_y + \lambda_y \mu_i + \xi_i,\ i=1,..,n \qquad \textbf{(14)}$$

where h_{ij} is the value of the behavior h for the jth sibling (brother) in the ith household, similarly for m_{ij} and f_{ij}, X_{ij} is a set of exogenous regressors not all of which necessarily vary across siblings in the same household, μ_i is the unobserved source of household heterogeneity having unit variance, ϵ_{ij} is an error term uncorrelated with μ_i, and the β and δ, and *factor-loadings* λ are parameters to estimate. To simplify exposition, we begin by assuming that the only source of correlation among these conditional demand equations is the μ component and that the errors ϵ, η, ν and ξ are uncorrelated across behaviors and individuals.[8] In the context of the theoretical model presented in Section 2, the factor μ can be thought of as preference heterogeneity, perhaps heterogeneity in the determination of the female preference weight λ. The probability that a woman will join a credit program (which precludes her husband from joining) quite likely depends on her power in household decision making λ. In addition, the maternal altruism hypothesis argues that women prefer investments in children more than men and are less likely to favor boys, so that nutritional outcomes by gender are also likely to be correlated with

[8]This restriction is made only to simplify the demonstration of identification and is relaxed in the empirical implementation.

unobserved components of λ.[9]

Estimation of equations (11) - (13) that does not take into account the correlation between the right-hand-side regressor y_i and the common source of error correlation, μ_i, will result in biased estimates of the δ parameters, the effects of y_i on the other behaviors. We can substitute equation (14) into the conditional demand equations (11) - (13)

in order to get the reduced form demand equations for h, m and f:

$$h_{ij} = X_{ij}\tilde{\beta}_h + \tilde{\lambda}_h\mu_i + \tilde{\epsilon}_{ij} \quad \textbf{(15)}$$

$$m_{ij} = X_{ij}\tilde{\beta}_m + \tilde{\lambda}_m\mu_i + \tilde{\eta}_{ij} \quad \textbf{(16)}$$

$$f_{ij} = X_{ij}\tilde{\beta}_f + \tilde{\lambda}_f\mu_i + \tilde{\upsilon}_{ij} \quad \textbf{(17)}$$

where

$$\begin{aligned} \tilde{\beta}_k &= \beta_k + \delta_k\beta_y, \quad k=h,f,m \\ \tilde{\lambda}_k &= \lambda_k + \delta_k\lambda_y, \quad k=h,f,m \end{aligned} \quad \textbf{(18)}$$

and

$$\begin{aligned} \tilde{\epsilon}_{ij} &= \epsilon_{ij} + \delta_h\xi_i \\ \tilde{\eta}_{ij} &= \eta_{ij} + \delta_f\xi_i \\ \tilde{\nu}_{ij} &= \nu_{ij} + \delta_m\xi_i \end{aligned} \quad \textbf{(19)}$$

These reduced forms are correlated with each other through the common error components μ_i and ξ_i and have a variance-covariance matrix of the form:

[9] In addition, the factor μ_i may reflect the family health endowment. Poor health may alter the ability of parents, women in particular, to engage in time-consuming self-employment activities, and also affect the nutritional status of children.

$$\Sigma = \begin{pmatrix} \Sigma_h & \Sigma_{hm} & \Sigma_{hf} \\ \Sigma_{hm}^{/} & \Sigma_m & \Sigma_{mf} \\ \Sigma_{hf}^{/} & \Sigma_{mf}^{/} & \Sigma_f \end{pmatrix} \tag{20}$$

with diagonal sub-matrices of the form:

$$\Sigma_m = \begin{pmatrix} \tilde{\lambda}_m^2\sigma_\mu^2 + \sigma_\eta^2 & \tilde{\lambda}_m^2\sigma_\mu^2 \\ \tilde{\lambda}_m^2\sigma_\mu^2 & \tilde{\lambda}_m^2\sigma_\mu^2 + \sigma_\eta^2 \end{pmatrix} = \begin{pmatrix} \sigma_{mv}^2 & \sigma_{mc} \\ \sigma_{mc} & \sigma_{mv}^2 \end{pmatrix} \tag{21}$$

and off-diagonal sub-matrices of the form:

$$\Sigma_{hm} = \begin{pmatrix} \tilde{\lambda}_h\tilde{\lambda}_m\sigma_\mu^2 & \tilde{\lambda}_h\tilde{\lambda}_m\sigma_\mu^2 \\ \tilde{\lambda}_h\tilde{\lambda}_m\sigma_\mu^2 & \tilde{\lambda}_h\tilde{\lambda}_m\sigma_\mu^2 \end{pmatrix} = \begin{pmatrix} \sigma_{hm} & \sigma_{hm} \\ \sigma_{hm} & \sigma_{hm} \end{pmatrix} \tag{22}$$

In households containing two children of the same gender (brothers), there are 13 unique variance-covariance terms which are functions of 11 free parameters. Thus, there are two over-identifying restrictions. Consider the <u>unique</u> variance-covariance terms:

$$
\begin{aligned}
\sigma_{hv}^2 &= \tilde{\lambda}_h^2 + \sigma_\epsilon^2 + \delta_h^2\sigma_\xi^2 \\
\sigma_{mv}^2 &= \tilde{\lambda}_m^2 + \sigma_\eta^2 + \delta_m^2\sigma_\xi^2 \\
\sigma_{fv}^2 &= \tilde{\lambda}_f^2 + \sigma_\nu^2 + \delta_f^2\sigma_\xi^2 \\
\sigma_{hc} &= \tilde{\lambda}_h^2 + \delta_h^2\sigma_\xi^2 \\
\sigma_{mc} &= \tilde{\lambda}_m^2 + \delta_m^2\sigma_\xi^2 \\
\sigma_{fc} &= \tilde{\lambda}_f^2 + \delta_f^2\sigma_\xi^2 \\
\sigma_{hm} &= \tilde{\lambda}_h\tilde{\lambda}_m + \delta_h\delta_m\sigma_\xi^2 \\
\sigma_{hf} &= \tilde{\lambda}_h\tilde{\lambda}_f + \delta_h\delta_f\sigma_\xi^2 \\
\sigma_{mf} &= \tilde{\lambda}_m\tilde{\lambda}_f + \delta_m\delta_f\sigma_\xi^2 \\
\sigma_y^2 &= \lambda_y^2 + \sigma_\xi^2 \\
\sigma_{hy} &= \tilde{\lambda}_h\lambda_y + \delta_h\sigma_\xi^2 \\
\sigma_{my} &= \tilde{\lambda}_m\lambda_y + \delta_m\sigma_\xi^2 \\
\sigma_{fy} &= \tilde{\lambda}_f\lambda_y + \delta_f\sigma_\xi^2
\end{aligned}
\qquad \textbf{(23)}
$$

where σ_y^2 is the variance of the composite regression error for the reduced form determinants of y_i given by equation (14).

A solution for δ_h, the effect of y_i, credit program participation, can be obtained from this set of moment conditions. To demonstrate that this is so, we consider below an instrumental variables interpretation of identification with this factor-analytic structure.

b. Purged instrumental variables estimate

Instrumental variable estimation of the system of equations (11) through (14) can proceed as follows. First, eliminate the household-effect μ_i from equation (11) by solving equation (12) for μ_i and substituting this expression into (11). Equation (12) solved for μ_i is:

$$\mu_i = (m_{ij} - X_{ij}\beta_m - \delta_m y_i - \eta_{ij})/\lambda_m \qquad \textbf{(24)}$$

and substituting this expression into (12) yields:

$$h_{ij} = X_{ij}(\beta_h - \lambda_h \frac{\beta_m}{\lambda_m}) + (\delta_h - \lambda_h \frac{\delta_m}{\lambda_m})y_i + \frac{\lambda_h}{\lambda_m} m_{ij} + (\epsilon_{ij} - \lambda_h \frac{\eta_{ij}}{\lambda_m}) \qquad \textbf{(25)}$$

In equation (25), the variable y_i is no longer correlated with the error since the sole source of its correlation with the residual of (11), μ_i, has been purged. On the other hand, the health behavior m_{ij} now appears on the right-hand-side of (25) and it is correlated with the residual through the error component η_{ij}. However, valid instruments for m_{ij} exist. The values of m_{ik}, h_{ik} and f_{ik} for all siblings of brother j ($k \neq j$) are correlated with m_{ij} through the common component μ_i but are uncorrelated with the error in equation (25). Note that this model is identified by the purged instrumental variables even if the child-specific error components of equations (11) to (13) are correlated, that is, $E(\epsilon_{ij}, \eta_{ij}) \neq 0$, $E(\epsilon_{ij}, \nu_{ij}) \neq 0$ and $E(\eta_{ij}, \nu_{ij}) \neq 0$. This other source of error correlation is permitted in the estimation reported below. It is clear that we can estimate the complete set of child-specific health outcome equations corresponding to equations (11) through (13) by purging the μ_i component of each equation, as above, and identify the parameters of interest, δ.

c. Estimation: maximum likelihood and generalized method of moments

The estimation problem described above is one of generalized least squares with an unknown error covariance matrix $\Sigma = \sigma^2 \Omega$.[10] If Ω contains a sufficiently small number of parameters θ such that $\Omega = \Omega(\theta)$, then this is feasible generalized least squares. The reduced form model described by equations (14) through (17) can be estimated by maximum likelihood. If the disturbances are distributed as multivariate normal, the log-likelihood for a household is

$$\ln L = -\frac{n}{2} \ln(2\pi) - \frac{1}{2} \ln|\sigma^2 \Omega(\theta)| - \frac{1}{2} \zeta'(\sigma^2 \Omega(\theta))^{-1} \zeta \qquad \textbf{(26)}$$

where ς represents the stacked vector of residuals of equations (14) through (17). In the two brother example n=7 because there are six child-specific behavioral equations: three health behaviors for each of two brothers plus the household-specific behavior (credit program participation). All of the estimates

[10] The parameter σ^2 is not a new unknown parameter since the unknown matrix Ω can be scaled arbitrarily. It's introduction is in keeping with the common nomenclature of the least squares literature.

reported below were obtained by the method of maximum likelihood which estimates the covariance parameters θ simultaneously with the regression parameters $\hat{\beta}$.

This is a problem in generalized method of moments (GMM) estimation. The moment conditions, given by equation (23), define $\Omega(\theta)$, the relationship between elements of $\sigma^2\Omega$ and the parameters θ. The moment conditions of the feasible generalized least squares estimator are

$$E[X'\Omega^{-1}\zeta] = 0 \tag{27}$$

with sample analog of

$$\frac{1}{n} X'\Omega^{-1}\hat{\zeta} = 0 \tag{28}$$

In our model, there are more moment conditions than free parameters in θ. The model is over-identified. Just as in any other over-identified model, the estimation procedure chooses the unique parameter values that maximize the criterion function, in this case, the log-likelihood.

Alternatively, one could simply estimate the parameters $\hat{\beta}$ of equations (14) through (17) one equation at a time by OLS without imposing $\Omega=\Omega(\theta)$. The covariance terms that make up Ω can be computed from the OLS parameter estimates. In the over identified case, the number of these covariance terms, say L, exceed the number of parameters in θ, say K. This implies a set of L equations $\psi_i(\theta)$ in K unknowns, which generally does not have a unique solution. A consistent estimator of θ can be obtained by minimum distance estimation that minimizes a criterion function

$$q = \bar{\psi}(\theta)' A \bar{\psi}(\theta) \tag{29}$$

where $\bar{\psi}$ is the sample mean of the L moment equations, and A is a positive definite matrix. An efficient choice for A is the inverse of the covariance matrix of the moments (Hansen 1982) so that (29) is essentially weighted least squares.

While the likelihood given by (26) illustrates the general principal and method used, the actual likelihoods maximized have been altered to take into account six other features of the data. The first is the limited dependent variable nature of the endogenous credit variables. There is a substantial mass at zero for both men’s and women’s program credit. The likelihood (26) has been appropriately altered to treat the reduced form demands for credit as Tobits.

Second, the sample design is choice-based (see Section 4 below). In particular, program participants are purposely over-sampled. The Weighted Exogenous Sampling Maximum Likelihood (WESML) methods of Manski and Lerman (1977) were grafted onto the maximum likelihood method described above in the estimation of both parameters and the parameter covariance matrix.

Third, the model estimated allows for the conditional demand equations (11) - (13) to vary between boys and girls. Not only are the regression parameters allowed to vary freely but the parameters that describe the residual variance-covariance matrix are allowed to vary. In models of this sort, distinguishing among more member-types within the household, while adding many new parameters to be estimated, can in fact aid in identification as long as the same latent factor structure underlies the behavior of these member-types.

Fourth, we use data from both survey rounds in the estimation. Doing so aids in identification but requires that we add a time-varying error component to the model to be estimated. Thus, the child-specific error associated with each nutritional outcome is allowed to be imperfectly correlated across rounds.

Fifth, the number of boy and girl children in each household varies across households resulting in an “unbalanced” design. The likelihood is tailored to include all sampled children and not just a fixed number per household.

Finally, in line with our earlier work, we do not assume that the placement of these group-based credit programs across the villages of Bangladesh is exogenous. Program officials note that they often place programs in poorer and more flood prone areas, as well as in areas in which villagers have requested program services. Treating the timing and placement of programs as random can lead to serious mismeasurement of program effectiveness (Pitt, Rosenzweig and Gibbons (1993)). Consider the implications of a program allocation rule that was more likely to place credit programs in poorer villages than in richer ones. Comparison of the two set of villages as in a treatment/control framework would lead to a downward bias in the estimated effect of the program on household income and wealth (and other outcomes associated with income and wealth) and could even erroneously suggest that credit programs reduce income and wealth if the positive effect of the credit program on the difference between "treatment" and "control" villages did not exceed the negative village effect that induced the nonrandom placement. Village fixed-effects estimation, which treats the village-specific component of the error as a parameter to be estimated, eliminates the endogeneity caused by unmeasured village attributes including nonrandom program placement. [11]

4. Survey Design and Description of the Data

A multi-purpose quasi-experimental household survey was conducted in 87 villages of 29 thanas in rural Bangladesh during the year of 1991-92. The sample consists of 29 thanas (subdistricts) randomly drawn from 391 thanas in Bangladesh, of which 24 had one (or more) of the three credit programs under study in operation, while 5 thanas had none of them.

Three villages in each program thana were randomly selected from a list of villages, supplied by the program's local office, in which the program had been in operation at least three years. Three villages in each non-program thana were randomly drawn from the village census of the Government of Bangladesh. A household census was conducted in each village to classify households as target (i.e., those who qualify to join a program) or non-target households, as well as to identify program participating and non-participating households among the target households. A stratified random sampling technique was used to over-sample households participating in the credit programs and target nonparticipating households. Of the 1,798 households sampled, 1,538 were target households and 260 non-target households. Among the target households, 905 households (59 percent) were credit program participants.

Indicators of each individual's anthropometric status - height, weight, and arm circumference - were collected from 15 of these villages. Collecting such information at the individual level is costly and time consuming; therefore, the study was limited to a subsample of the original 1,798 households. The anthropometric data was collected from 3 villages in five program thanas chosen at random. Two of the five thanas (Patuakhali and Shakhipur) contain a Grameen Bank, two (Rangpur Sadar and Habgianj Sadar) contain a BRAC program, and one (Matbaria) contains a BRDB program. Households were

[11] One important drawback of estimating program impacts from this approach is the possible misinterpretation of the village fixed effects. It is possible that credit programs can alter village attitudes and other village characteristics, perhaps through *demonstration or spillover effects*, and thus the attitudes of those who do not participate in the credit programs as well as those that do. These spillover effects are captured by the fixed effects and not appropriately credited as a result of the program. It is generally not possible to estimate the village externality from a single cross-section of data. This issue is discussed in more detail in Pitt and Khandker (1998).

randomly selected to be anthropometrically measured within each of the 15 villages based on a village census and the sample selection rules detailed in Khandker, *et al.* (1994), altered to increase the sample size to approximately 20 households per village instead of 17 in all other sampled villages. Although the original household survey design called for anthropometric measures of individuals residing in non-target households, the final survey included only those residing in target households. This precluded the use of the quasi-experimental survey design used to identify program effects in Pitt and Khandker (1998) and Pitt *et. al.* (1997).

The rural economy in Bangladesh revolves around agricultural activity. Both economic welfare and food consumption are highest after the major rice crop, aman, is harvested and are at their lowest just prior to the harvest. To avoid confounding seasonal effects with actual credit effects, anthropometric measures were collected twice; during the peak consumption period (January to April 1992) and during the lean period (September to November 1992).

The measure of credit used below is the natural logarithm of the amount borrowed separately by male and female program participants (in constant taka) plus one. The measures of nutritional status for children under the age of 15 are the natural logarithms of arm circumference (in centimeters), body mass index (weight in kilograms divided by height in centimeters squared), and height (in centimeters) for age (in years). All regression equations also include a number of exogenous characteristics of households -- the age, gender, and sex of the head of the household, the amount of land owned, and the highest education level achieved by any male and any female household resident -- as well the ages of individual children. Table 1 presents the weighted means and standard deviations of all these variables.

As noted above, eight equations are jointly estimated -- six equations for the anthropometric status of boys and girls, and two credit equations for males and females. There are 65 parameters associated with exogenous variables (see Table 1) to be estimated, in addition to 21 factor loadings, and 12 structural parameters (credit effects). Introducing thana fixed effects adds 40 additional parameters, while introducing village fixed effects adds an extra 120 parameters. In total, there are a total of 138 parameters jointly estimated for the thana fixed effects model and 218 for the village fixed effects model.

How many covariance restrictions are required to estimate these models and how many are actually made? The answer depends crucially on the demographic characteristics of the sample. The best identified case is for households with two or more boys and two or more girls surveyed in both rounds. Having more than two children of any gender does not add to identification since the error covariance between brother A and brother B is not different from the error covariance between brother A and brother C or between brother B and brother C. Our data represent an unbalanced random effects design in that households have differing numbers of sons and daughters, and in some cases anthropometric measurement was not taken in each round.

Table 2
Sample Size by Household Type
(total of both periods)

Number of Boys	Number of Girls		
	0	1	2 or more
0	34	73	63
1	101	93	35
2 or more	50	15	2

Table 2 presents a tabulation of our sample by number of boy and girl children less than 15 years of age. Only 2 household observations had the maximum possible identification -- two or more boys and two or more girls. However many household observations had at least two children of one gender. Table 3 present the number of covariance restrictions imposed as well as the number of parameters that they identify, tabulated for households by demographic composition, under the assumption that two rounds of data are available. With the covariance restrictions associated with the factor structure of residuals as described in Section 3 and the appendix, the number of parameters we need to identify is smaller than the number of covariance matrix elements in every case. Since, the difference between the two numbers is the number of over-identifying restrictions, our model is over-identified in every case.

5. Results

In this section we present and interpret the parameters of conditional demand equations of the form given by equations (11) through (13) for three child-specific outcomes: the natural logarithms of arm circumference, body mass index (BMI) and height-for-age. In addition to estimates based upon the covariance restrictions described in Section 3, we present alternative estimates which do not fully treat credit program placement and participation as endogenous. These alternative estimates are presented to illustrate the importance of heterogeneity bias. The alternative methods of estimation ignore self-selection into credit programs, treating it as exogenous, or treat village program placement as random, and thus do not include fixed effects, or do both.[12] In all cases, eight equations are jointly estimated by maximum likelihood— the reduced form determinants of male and female program credit borrowing and the conditional demands for each of the three nutritional indicators for boys and girls separately. In limiting cases of exogeneity (see below), this is equivalent to maximum likelihood (unrestricted) random effects least squares estimation of the conditional demand equations with two random effect components, one reflecting the non-independence of errors across survey rounds, and the other non-independence across behaviors within the household.

Tables 4 through 6 present the parameter estimates of interest. The λ's in the third row are factor-loadings for the household-specific error μ_i that generates a correlation between program credit and the anthropometric outcomes.[13] A sufficient condition for credit to be exogenous in the determination of child health is that all the factor loadings on μ_i, the λ parameters, are zero. Formally, a test of exogeneity requires that the correlation coefficients (ρ) between the errors of the credit reduced form equation and the health behavior equation errors are zero. Estimates of the ρ's are presented in the last row of Tables 4 through 6, as well as approximate t-statistics constructed by the delta method.

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[12]Hausman-like tests of the consistency of the models without location fixed effects were attempted but the covariance matrices of the differences in the parameter vectors were not positive definite in every case tried. This problem is not uncommon in estimation problems of this kind. The test statistic computed is:

$$\left(\hat{\beta}_{FE}-\hat{\beta}\right)' \left(\hat{\Sigma}_{FE}-\hat{\Sigma}\right)^{-1} \left(\hat{\beta}_{FE}-\hat{\beta}\right)$$

where β_{FE} and β (Σ_{FE} and Σ) refer to the fixed effects and no fixed effects parameter vectors (covariance matrices) respectively. Typically, the problem is that one or more of the diagonal elements of the covariance matrix (Σ_{FE} - Σ) are very close to zero, and sometimes negative. Pitt and Khandker (1998) provides further statistical evidence of the bias imparted by treating village effects as random with these data. They regress village fixed effects on the regressors of the credit demand equations and find that fixed effects from the credit demand equations are significantly (at the 0.05 level) correlated with these regressors.

[13]These tables present only a subset of the parameters estimated. Factor-loadings representing other sources of error correlation, as well as parameters on a set of included exogenous variables -- the age, gender, and sex of the head of the household, the amount of land owned by the household, and the highest education level achieved by any male and any female household resident, as well the ages of individual children -- are not shown but are available from the authors.

The last two sets of estimates in Table 4 through 6 treat both credit program participation and program placement as endogenous. One set of estimates uses thana fixed effects and the other set uses village fixed effects. There are three villages in each of the five thanas in the sample. Inspection of Tables 4 - 6 suggests that there is not much difference between thana and village fixed effects, so we will concentrate discussion on the more efficient thana fixed effects estimates.[14]

The preferred model with endogenous credit and thana fixed effects rejects the restriction that all the λ factor-loadings are jointly zero. Table 7 presents joint tests on the statistical significance of these factor-loadings. A joint test that the unobserved determinants of credit program participation by both sexes, such as heterogeneous gender preferences, are not also determinants of all three anthropometric measures for both sexes of children is strongly rejected ($\chi^2(6)=68.205$, $p=0.000$). For the individual nutritional status measures, zero factor-loadings are rejected for arm circumference ($\chi^2(2)=15.732$, $p=0.000$) and height-for-age ($\chi^2(2)=45.683$, $p=0.000$), but not for BMI ($\chi^2(2)=0.207$, $p=0.902$). Moreover, the factor-loadings are statistically different from zero for the three measures of boys health ($\chi^2(3)=12.764$) and girls health ($\chi^2(3)=30.121$).

Table 8 presents joints test of the exogeneity of male and female program credit on the three health outcomes of boys and girls. Credit program participation is endogenous in the determination of child health. The bottom row of that table provides test statistics for the null hypothesis that the correlation coefficients ρ between the errors of all three measures of health and the determinants of women's and men's credit program participation are jointly zero. In all cases the null hypothesis is firmly rejected. The last column of the table presents test statistics for each individual health measure. Only in the case of BMI can we not reject the null hypothesis of exogeneity.

Table 4 presents estimates of the impact of program credit received by males and females on the arm circumference of boy and girl children separately. The preferred model with endogenous credit and thana fixed effects estimates significant and large positive effects of female credit on girl's arm circumference, and somewhat smaller positive effects of female credit on boy's arm circumference and of male credit on girl's arm circumference. Joint tests presented in Table 9 reject the null hypothesis that female credit has no effect on arm circumference at the 0.05 level ($\chi^2(2)=8.347$, $p=0.015$) but cannot reject the same null hypothesis for male credit ($\chi^2(2)=3.066$, $p=0.216$). As the anthropometric measures

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[14]A Hausman test of village fixed effects versus thana fixed effects could not be performed because the covariance matrix for the parameter differences was not positive definite, as before.

and credit are both measured in log form, the parameters can be interpreted as elasticities with respect to latent credit. Thus, a 10 percent increase in (latent) credit provided to females increases the arm circumference of their daughters by 6.1 percent (t=2.52), twice the increase that would be expected from a similar proportionate increase in credit provided to men. At the means, a 10 percent increase in female credit increases the arm circumference of girl's and boy's by 0.44 cm. and 0.33 cm., respectively. Female credit also has a positive but somewhat smaller effect on the arm circumference of sons, although this parameter is not precisely estimated. The same percentage increase in male credit increases arm circumference for girl's by 0.21 cm. and reduces that of boy's by 0.11 cm.

The first two columns of Table 4 provide estimates for a model that imposes exogenous self-selection of households into the credit program and random (exogenous) placement of credit programs across villages. It is equivalent to a random effects regression of the arm circumference of children by sex on a set of household and individual attributes (see Table 1) and the borrowing of male and female adults in the household. Among the four credit effects, only one, the effect of credit received by men on the arm circumference of girls, seems to have a significant (and positive) effect. This model seriously underestimates the effect of female credit on girl's and boy's arm circumference, and overestimates the effect of male credit on boy's arm circumference. The next two columns of the table present estimates with exogenous credit and thana fixed effects. These again are essentially linear random effect estimates. Here again, only the effect of men's credit on girl's arm circumference is significant. Treating credit as endogenous but program placement as exogenous yields fairly large effects for female credit on boy and girl arm circumference, but now male credit effects are much smaller and even negative in the case of boy's arm circumference.

Table 5 presents parameter estimates of the effects of program credit on log BMI. This is the one measure of nutritional status for which the exogeneity of credit hypothesis cannot be rejected. The various alternative estimators provide roughly similar estimates of program effects. The only parameter close to significance is the (positive) effect of male credit on girl's BMI (t=1.75) with an elasticity of 0.288.

Table 6 presents parameter estimates of the effects of program credit on log height-for-age. As in the case of arm circumference, the exogeneity of credit is strongly rejected in this case (see Table 8 for a joint test). Female credit is estimated to have large, positive and statistically significant effects on the height-for-age of both boys and girls. The relevant elasticities are 1.42 (t=2.94) for boys and 1.16

(t=2.16) for girls. A 10 percent increase in female credit increases the height of girl's and boy's by 0.37 and 0.46 centimeters, respectively, at the mean. Male credit effects have negative point estimates, although neither is significantly different from zero. A 10 percent increase in male credit reduces the height of girl's and boy's by 0.16 and 0.10 centimeters, respectively, at the mean. A joint test (Table 9) cannot reject the null hypothesis of no effect of male credit on height-for-age ($\chi^2(2)$=2.546, p=0.280), but strongly rejects the null for female credit ($\chi^2(2)$=15.088, p=0.001).

Table 10 summarizes a set of statistical tests on the effect of program credit on the nutritional status of children by sex of children, and for all children. The Wald test statistics presented in the last column of Table 10 demonstrate that program credit is a significant (at the 0.05 level) determinant of arm circumference, height-for-age and the full set of anthropometric measures taken together, but not of BMI. Program credit is a significant (and always positive) determinant of girl's arm circumference and height-for-age, but does not have a statistically significant effect on boy's nutritional status except height-for-age. The test statistics of Table 9 demonstrate that only credit provided women significantly affects the nutritional status of children ($\chi^2(3)$=27.039, p=0.000). Men's credit is not a significant determinant of any of the three anthropometric measures or of the three taken together ($\chi^2(3)$=10.712, p=0.098). It is thus not surprising that the null hypothesis of equal credit effects by gender of participant is decisively rejected in Table 9 ($\chi^2(3)$=19.85, p=0.003). The bottom line is that there is strong evidence that only women's participation in group-based credit programs, as measured by total borrowing, has a large and important positive effect on the nutritional status of both boys and girls.

6. Summary

This paper evaluates the effects of three group-based credit programs in rural Bangladesh on the nutritional status of children by gender. These programs are the major small-scale credit programs in Bangladesh that provide production credit and other services to the poor. The data come from a 1991/92 survey that includes a special nutritional status module with anthropometric measures of nutritional status for children under the age of 15 years of age in 15 villages. In the nutritional module, only villages with a credit program and only households who were eligible to participate in the programs were sampled, making identification via the quasi-experimental survey design used in previous work impossible.

Lacking exclusion restrictions of the usual sort required for instrumental variables estimates, we identify the effects of credit program participation by gender of participant by placing restrictions on the covariance structure of the regression errors. In addition, we have data on nutritional status at two points in time for each sampled household that adds additional identifying restrictions to the residual covariance matrix. The idea is to place a factor-analytic structure on the residuals of a set of equations for female and male credit program participation and a set of nutritional status outcomes, which in our study are arm circumference, body mass index and height-for-age. In doing, we are assuming that there is a latent unobserved factor that influences both credit program participation and three measures of child health, and that this factor is the sole source of the correlation of credit equation errors with the child health errors. In the estimation of the determinants of these nutritional outcomes, the residual includes left-out household-specific variables such as relative bargaining power in the household, preference hetergeneity and innate healthiness. These omitted variables may affect the nutritional (and other) resources allocated to boy and girl children, but not necessarily in the same way.

We estimate eight equations simultaneously -- three nutritional outcomes separately for boys and girls plus credit program participation for men and women -- by maximum-likelihood. Our results are striking. After taking into account the endogeneity of individual participation in these credit programs and the placement of these credit programs across areas, we find that women's credit has a large and statistically significant impact on two of three measures of the nutritional well-being of both boy and girl children. Credit provided men has no statistically significant impact and we are able to reject the null hypothesis of equal credit effects by gender of participant. A 10 percent increase in (latent) credit provided to females increases the arm circumference of their daughters by 6.1 percent, twice the increase that would be expected from a similar proportionate increase in credit provided to men. Female credit also has a positive but somewhat smaller effect on the arm circumference of sons, although this parameter is not precisely estimated. Female credit is estimated to have large, positive and statistically significant effects on the height-for-age of both boys and girls. The relevant elasticities are 1.42 for boys and 1.16 for girls. Male credit effects have negative point estimates, although neither is significantly different from zero. We find no significant effects of female or male credit on the logarithm of the Body Mass Index (BMI) of boys or girls. Taken together, this is persuasive further evidence that these credit programs have important effects on household well-being particularly if the program participant is a woman.

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Table 1
Summary Statistics

Variables	Observations	Mean	Standard Deviation
Value of program borrowing by females (Taka)	105	9675.951	9712.942
Value of program borrowing by males (Taka)	76	9586.895	10182.8
Girls' weight (in kg, ages 0-14)	401	12.398	4.379
participants	260	13.239	4.350
non-participants	141	11.713	4.294
Boys' weight (in kg, ages 0-14)	375	12.776	4.163
participants	286	12.960	4.202
non-participants	89	12.510	4.113
Girls' height (in cm, ages 0-14)	401	94.239	18.145
participants	260	97.899	17.361
non-participants	141	91.261	18.275
Boys' height (in cm, ages 0-14)	375	95.09	16.587
participants	286	95.701	16.598
non-participants	89	94.204	16.612
Girls' arm circumference (in cm, ages 0-14)	401	14.138	1.511

Variables	Observations	Mean	Standard Deviation
participants	260	14.417	1.556
non-participants	141	13.911	1.439
Boys' arm circumference (in cm, ages 0-14)	375	14.204	1.265
participants	286	14.222	1.257
non-participants	89	14.178	1.283
Girls' Body Mass Index (ages 0-14)	401	0.001	0.0002
participants	260	0.001	0.000
non-participants	141	0.001	0.000
Boys' Body Mass Index (ages 0-14)	375	0.001	0.0001
participants	286	0.001	0.000
non-participants	89	0.001	0.000
Girls' height-for-age (ages 0-14)	401	31.545	21.593
participants	260	27.424	18.532
non-participants	141	34.898	23.323
Boys' height-for-age (ages 0-14)	375	30.768	19.041
participants	286	30.632	19.588
non-participants	89	30.967	18.216
Girls' age (in years)	401	4.517	2.902
Boys' age (in years)	375	4.385	2.745

Variables	Observations	Mean	Standard Deviation
Education by head of household (in years)	233	2.048	3.154
Age of head of household (in years)	233	38.975	10.391
Sex of head of household (1 = male)	233	0.949	0.22
Maximum amount of education by any female in household (in years)	233	1.49	2.712
Maximum amount of education by any female in household (in years)	233	2.671	3.408
Land owned by household (in decimals)	233	53.637	552.184

Table 3

Covariance Restrictions by Household Type
Assuming Two Endogenous Regressors
and Two Time Periods

Number of Boys	Number of Girls					
	0		1		2	
	unique terms in covariance matrix	parameters to be identified by covariance matrix	unique terms in covariance matrix	parameters to be identified by covariance matrix	unique terms in covariance matrix	parameters to be identified by covariance matrix
0	--	--	21	18	27	18
1	21	18	48	33	54	33
2	27	18	54	33	60	33

Table 4
Alternative Estimates of the Impact of Credit on
Boys' and Girls' Arm Circumference

Variable	Exogenous Credit No FE		Exogenous Credit Thana FE		Endogenous Credit No FE		Endogenous Credit Thana FE		Endogenous Credit Village FE	
	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl
male credit	0.0048 (0.063)	0.1908 (1.825)	0.0779 (0.503)	0.3879 (2.032)	-0.1514 (-1.331)	0.1161 (0.927)	-0.1565 (-0.756)	0.3017 (1.459)	-0.0503 (-0.290)	0.2827 (1.328)
female credit	-0.1622 (-0.473)	-0.0842 (-0.300)	-0.0635 (-0.402)	0.0298 (0.191)	0.4519 (1.674)	0.5012 (2.112)	0.4734 (1.534)	0.6146 (2.519)	0.4395 (1.442)	0.5685 (2.482)
λ_{arm}					-4.3289 (-2.230)	-5.4028 (-3.054)	-3.8159 (-1.757)	-5.5295 (-3.320)	-3.3828 (-1.666)	-4.7398 (-3.673)
ρ(m,arm)					0.2375 (0.9635)	0.2712 (1.7831)	0.1865 (0.6575)	0.2385 (1.2844)	0.1317 (0.5183)	0.1678 (0.6484)
ρ(f,arm)					-0.3278 (-2.0818)	-0.3742 (-2.0902)	-0.3179 (-1.5142)	-0.4066 (-2.7288)	-0.2867 (-1.0977)	-0.3654 (-1.5736)

Asymptotic t-ratios in parenthesis.

Table 5

Alternative Estimates of the Impact of Credit on
Boys' and Girls' Body Mass Index

Variable	Exogenous Credit No FE		Exogenous Credit Thana FE		Endogenous Credit No FE		Endogenous Credit Thana FE		Endogenous Credit Village FE	
	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl
male credit	-0.0215 (-0.192)	0.1586 (1.749)	-0.1203 (-0.446)	0.2992 (1.838)	0.0053 (0.053)	0.1639 (1.690)	-0.0594 (-0.251)	0.2878 (1.745)	-0.0776 (-0.370)	0.2120 (1.198)
female credit	-0.1276 (-0.429)	-0.2130 (-0.599)	-0.1644 (-0.981)	-0.1085 (-0.663)	-0.1834 (-0.612)	-0.2325 (-1.022)	-0.2837 (-0.803)	-0.1851 (-0.831)	-0.2666 (-0.690)	-0.1562 (-0.636)
λ_{BMI}					0.8883 (0.380)	0.6213 (0.419)	1.0275 (0.454)	0.2383 (0.169)	0.7828 (0.333)	0.5495 (0.411)
ρ(m,bmi)					-0.0423 (-0.3014)	-0.0311 (-0.2920)	-0.0430 (-0.2843)	-0.0109 (-0.0871)	-0.0255 (-0.1460)	-0.0191 (-0.1649)
ρ(f,bmi)					0.0583 (0.3459)	0.0430 (0.3483)	0.0733 (0.4065)	0.0186 (0.1274)	0.0556 (0.2247)	0.0417 (0.2423)

Asymptotic t-ratios in parenthesis.

Table 6

Alternative Estimates of the Impact of Credit on
Boys' and Girls' Height-for-Age

Variable	Exogenous Credit No FE		Exogenous Credit Thana FE		Endogenous Credit No FE		Endogenous Credit Thana FE		Endogenous Credit Village FE	
	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl
male credit	0.0090 (0.067)	-0.1699 (-0.991)	0.1941 (0.680)	-0.3775 (-1.243)	-0.3154 (-1.766)	-0.3138 (-1.689)	-0.2979 (-1.001)	-0.4921 (-1.469)	0.0065 (0.022)	-0.1315 (-0.377)
female credit	0.0737 (0.164)	-0.2097 (-0.567)	0.1757 (0.700)	0.0415 (0.190)	1.345 (2.694)	0.9085 (1.739)	1.4185 (2.944)	1.1627 (2.161)	1.3726 (2.893)	1.1484 (2.075)
λ_{height}					-9.9711 (-3.559)	-9.5997 (-3.344)	-8.9989 (-3.254)	-9.2758 (-2.987)	-8.0763 (-3.754)	-9.1642 (-3.603)
ρ(m,height)					0.3004 (5.9993)	0.2652 (7.7185)	0.2459 (3.5192)	0.2282 (4.9599)	0.1737 (1.9504)	0.1748 (2.2019)
ρ(f,height)					-0.4146 (-10.9719)	-0.3660 (-12.0708)	-0.4191 (-10.2439)	-0.3890 (-11.9503)	-0.3783 (-6.1040)	-0.3807 (-6.7201)

Asymptotic t-ratios in parenthesis.

Table 7
Joint Tests of Factor Loadings on the Common Factor in the Determination of Children's Health

Anthropometric Measure	Boys	Girls	Boys & Girls
Arm Circumference	3.087 (p = 0.079)	11.022 (p = 0.001)	15.732 (p = 0.000)
BMI	0.206 (p = 0.650)	0.029 (p = 0.865)	0.207 (p = 0.902)
Height-for-Age	10.589 (p = 0.001)	8.922 (p = 0.003)	45.683 (p = 0.000)
All Anthropometric Measures	12.764 (p = 0.005)	30.121 (p = 0.000)	68.205 (p = 0.000)

Table 8

Joint Tests of the Exogeneity
of Credit in the Determination of Children's Health

Anthropometric Measure	Boys			Girls			Boys & Girls		
	Male	Fem	Both	Male	Fem	Both	Male	Fem	Both
Arm Circumference	0.43 (0.51)	2.29 (0.13)	4.25 (0.12)	1.65 (0.20)	7.45 (0.01)	7.51 (0.02)	1.66 (0.44)	13.96 (0.00)	39.91 (0.00)
BMI	0.08 (0.78)	0.17 (0.68)	0.81 (0.67)	0.01 (0.93)	0.02 (0.90)	0.53 (0.78)	0.08 (0.96)	0.17 (0.92)	3.73 (0.44)
Height-for-Age	12.38 (0.00)	104.93 (0.00)	148.20 (0.00)	24.59 (0.00)	142.80 (0.00)	186.69 (0.00)	26.20 (0.00)	240.54 (0.00)	380.88 (0.00)
All Anthropometric Measures	60.25 (0.00)	170.30 (0.00)	257.25 (0.00)	62.82 (0.00)	226.82 (0.00)	343.65 (0.00)	119.79 (0.00)	338.29 (0.00)	580.34 (0.00)

Chi-squared p-values in parenthesis.

Table 9

Wald Tests for the Joint Significance of Credit
on Children's Health by Gender of Participant

Anthropometric Measure	Men	Women	Men & Women
Arm Circumference	3.07 (p = 0.22)	8.35 (p = 0.02)	10.31 (p = 0.04)
BMI	3.05 (p = 0.22)	0.85 (p = 0.66)	4.87 (p = 0.30)
Height-for-Age	2.55 (p = 0.28)	15.09 (p = 0.00)	19.07 (p = 0.00)
All Anthropometric Measures	10.71 (p = 0.10)	27.04 (p = 0.00)	39.47 (p = 0.00)
Equality of Credit Effects on All Anthropometric Measures	19.85 (p = 0.00)		

Table 10

Wald Tests for the Joint Significance of Credit
on Children's Health by Gender of Child

Anthropometric Measure	Boys	Girls	Boys & Girls
Arm Circumference	2.40 (p = 0.30)	8.33 (p = 0.02)	10.31 (p = 0.04)
BMI	0.65 (p = 0.72)	4.02 (p = 0.13)	4.87 (p = 0.30)
Height-for-Age	9.14 (p = 0.01)	7.31 (p = 0.03)	19.07 (p = 0.00)
All Anthropometric Measures	11.7 (p = 0.07)	19.50 (p = 0.00)	39.47 (p = 0.00)

Appendix

The general model contains $k1$ outcome equations for two types of people - boys and girls - and are functions of $k2$ endogenous variables.[1]

Explicitly, the model for a single cross-section is

$$y_{bih}^{s} = X_{ih}\alpha_{b}^{s} + Z_{h}\gamma_{b}^{s} + \Sigma_{r=1}^{k2}\delta_{bt}^{s}E_{h}^{r} + \lambda_{b}^{s}\mu_{h} + \xi_{b}^{s}\epsilon_{bih}^{s} \tag{1}$$

$$y_{gih}^{s} = X_{ih}\alpha_{g}^{s} + Z_{h}\gamma_{g}^{s} + \Sigma_{r=1}^{k2}\delta_{gt}^{s}E_{h}^{r} + \lambda_{g}^{s}\mu_{h} + \xi_{g}^{s}\epsilon_{gih}^{s} \tag{2}$$

$$E_{h}^{r} = Z_{h}\gamma^{r} + \lambda^{r}\mu_{h} + \theta^{r}\omega_{h}^{r} \quad , \tag{3}$$

where i indexes individuals; h indexes households; b and g represent boy and girl; y^s, $s = 1, ..., k1$, are the outcomes; X is a matrix of individual characteristics; Z is a matrix of hh characteristics; E^r, $r = 1, ..., k2$, are the endogenous variables; μ is a household random effect; ϵ, ω are individual shocks; and, all variances are normalized to one.

Substituting in for E_h^r and collecting terms yields the following reduced form outcome equations, where $k = b, g$ indexes the equations for boys and girls

$$y_{kih}^{s} = X_{ih}\alpha_{k}^{s} + Z_{h}[\gamma_{k}^{s} + \Sigma_{r=1}^{k2}\delta_{kt}^{s}\gamma^{r}] + [(\lambda_{k}^{s} + \Sigma_{r=1}^{k2}\delta_{kt}^{s}\lambda^{r})\mu_{h} + \Sigma_{r=1}^{k2}\delta_{kt}^{s}\theta^{r}\omega_{h}^{r} + \xi_{k}^{s}\epsilon_{kih}^{s}] \quad . \tag{4}$$

In more concise notation,

$$y_{kih}^{s} = X_{ih}\alpha_{k}^{s} + Z_{h}\Psi_{k}^{s} + [,\, {}_{k}^{s}\mu_{h} + \Sigma_{r=1}^{k2}\delta_{kt}^{s}\theta\omega_{h}^{r} + \xi_{k}^{s}\epsilon_{ihk}^{s}] \quad , \tag{5}$$

where we adopt the normalization $\theta^r = \theta$.

Prior to obtaining the covariance matrix for a household, several assumptions are made:

- $E\mu_h\mu_{h'} = \begin{cases} 1 & if \quad h = h' \\ 0 & otherwise \end{cases}$
- $E\mu\epsilon = E\mu\omega = 0$

[1]The model can easily be extended to incorporate more than two types of people.

- $E\epsilon^s_{kih}\epsilon^s_{ki'h} = \begin{cases} 1 \quad if \quad i = i' \\ 0 \qquad otherwise \end{cases}$

- $E\epsilon^s_{bih}\epsilon^{s'}_{gi'h} = 0 \ \ \forall s, s'$

- $E\omega^r_h\omega^{r'}_{h'} = \begin{cases} 1 \quad if \quad r = r', \quad h = h' \\ 0 \qquad otherwise \end{cases}$

Each household covariance matrix consists of five sub-matrices: covariances between a given boy's equations, covariances between a given girl's equations, covariances between a pair of brothers, covariances between a pair of sisters, and covariances between any opposite-sex sibling pair.

Under the assumptions made, the sub-matrices take on the following form, where the four equations correspond to outcomes s and s' and endogenous variables r and r':

- Covariances for a given *individual*

$$\begin{bmatrix} \begin{matrix}(,{}^s_k)^2 + (\xi^s_k)^2 \\ +\Sigma^{k2}_{r=1}(\delta^s_{kr}\theta^r)^2\end{matrix} & \begin{matrix},{}^s_k ,{}^{s'}_k \\ +\Sigma^{k2}_{r=1}\delta^s_{kr}\delta^{s'}_{kr}(\theta^r)^2\end{matrix} & \begin{matrix}\lambda^r ,{}^s_k \\ +\delta^s_{kr}(\theta^r)^2\end{matrix} & \begin{matrix}\lambda^{r'} ,{}^s_k \\ +\delta^s_{kr'}(\theta^{r'})^2\end{matrix} \\ & \begin{matrix}(,{}^{s'}_k)^2 + (\xi^{s'}_k)^2 \\ +\Sigma^{k2}_{r=1}(\delta^{s'}_{kr}\theta^r)^2\end{matrix} & \begin{matrix}\lambda^r ,{}^{s'}_k \\ +\delta^{s'}_{kr}(\theta^r)^2\end{matrix} & \begin{matrix}\lambda^{r'} ,{}^{s'}_k \\ +\delta^{s'}_{kr'}(\theta^{r'})^2\end{matrix} \\ & & (\lambda^r)^2 + (\theta^{r'})^2 & \lambda^r\lambda^{r'} \\ & & & (\lambda^{r'})^2 + (\theta^{r'})^2 \end{bmatrix}$$

- Covariances between any pair of *same-sex siblings*

$$\begin{bmatrix} \begin{matrix} (,{}^{s}_{k})^2 \\ +\Sigma_{r=1}^{k2}(\delta^{s}_{kr}\theta^{r})^2 \end{matrix} & \begin{matrix} ,{}^{s}_{k},{}^{s'}_{k} \\ +\Sigma_{r=1}^{k2}\delta^{s}_{kr}\delta^{s'}_{kr}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s}_{k} \\ +\delta^{s}_{kr}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r'},{}^{s}_{k} \\ +\delta^{s}_{kr'}(\theta^{r'})^2 \end{matrix} \\ & \begin{matrix} (,{}^{s'}_{k})^2 \\ +\Sigma_{r=1}^{k2}(\delta^{s'}_{kr}\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s'}_{k} \\ +\delta^{s'}_{kr}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r'},{}^{s'}_{k} \\ +\delta^{s'}_{kr'}(\theta^{r'})^2 \end{matrix} \\ & & (\lambda^{r})^2+(\theta^{r'})^2 & \lambda^{r}\lambda^{r'} \\ & & & (\lambda^{r'})^2+(\theta^{r'})^2 \end{bmatrix}$$

- Covariances between any pair of *opposite-sex siblings*

$$\begin{bmatrix} \begin{matrix} ,{}^{s}_{b},{}^{s}_{g} \\ +\Sigma_{r=1}^{k2}\delta^{s}_{br}\delta^{s}_{gr}(\theta^{r})^2 \end{matrix} & \begin{matrix} ,{}^{s}_{b},{}^{s'}_{g} \\ +\Sigma_{r=1}^{k2}\delta^{s}_{br}\delta^{s'}_{gr}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s}_{b} \\ +\delta^{s}_{br}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s}_{b} \\ +\delta^{s}_{br'}(\theta^{r'})^2 \end{matrix} \\ \begin{matrix} ,{}^{s}_{g},{}^{s'}_{b} \\ +\Sigma_{r=1}^{k2}\delta^{s}_{gr}\delta^{s'}_{br}(\theta^{r})^2 \end{matrix} & \begin{matrix} ,{}^{s'}_{b},{}^{s'}_{g} \\ +\Sigma_{r=1}^{k2}\delta^{s'}_{br}\delta^{s'}_{gr}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s'}_{b} \\ +\delta^{s'}_{br}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s'}_{b} \\ +\delta^{s'}_{br'}(\theta^{r'})^2 \end{matrix} \\ \begin{matrix} \lambda^{r},{}^{s}_{g} \\ +\delta^{s}_{gr}(\theta^{r})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s'}_{g} \\ +\delta^{s'}_{gr}(\theta^{r})^2 \end{matrix} & (\lambda^{r})^2+(\theta^{r})^2 & \lambda^{r}\lambda^{r'} \\ \begin{matrix} \lambda^{r},{}^{s}_{g} \\ +\delta^{s}_{gr'}(\theta^{r'})^2 \end{matrix} & \begin{matrix} \lambda^{r},{}^{s'}_{g} \\ +\delta^{s'}_{gr'}(\theta^{r'})^2 \end{matrix} & \lambda^{r}\lambda^{r'} & (\lambda^{r})^2+(\theta^{r})^2 \end{bmatrix}$$

Assuming all of the equations are continuous, the likelihood is obtained using the multivariate normal density function. Explicitly,

$$lnL = \frac{1}{2}ln|\Omega_h^{-1}| - \frac{1}{2}(y_h - X_h\alpha - Z_h\Psi)'\Omega_h^{-1}(y_h - X_h\alpha - Z_h\Psi) \ . \quad (6)$$

However, this is not always the case. In the model presented in the paper, E^r, $r = 1, 2$, are truncated from below at zero. Thus, it becomes necessary to estimate these equations as tobits. To accomplish this, factor the likelihood as the product of a conditional and a marginal density, where now the truncated endogenous regressors are estimated conditional on the remaining continuous equations. Now, the likelihood becomes

$$lnL = ln(\Phi_j(\Xi_E)) + \frac{1}{2}ln|\tilde{\Omega}_h^{-1}| - \frac{1}{2}(y_h - X_h\alpha - Z_h\Psi)'\tilde{\Omega}_h^{-1}(y_h - X_h\alpha - Z_h\Psi) \;, \qquad (7)$$

where Φ_j is a j-dimensional normal cumulative denisty function and j is the number of endogenous variables truncated at zero, Ξ_E is a j-dimensional vector of conditional means standardized by their conditional standard devitations, and $\tilde{\Omega}_h$ is the covariance matrix for the continuous equations.

The general model can be extended to allow for multiple time periods. Re-writing the model to incorporate this new dimension, it becomes

$$y^s_{biht} = \eta^s_b t + X_{iht}\alpha^s_b + Z_h\gamma^s_b + \Sigma^{k2}_{r=1}\delta^s_{bt}E^r_h + \lambda^s_b\mu_h + \pi^s_b\nu_{bih} + \xi^s_b\epsilon^s_{biht} \qquad (8)$$

$$y^s_{giht} = \eta^s_g t + X_{iht}\alpha^s_g + Z_h\gamma^s_g + \Sigma^{k2}_{r=1}\delta^s_{bt}E^r_h + \lambda^s_g\mu_h + \pi^s_g\nu_{gih} + \xi^s_g\epsilon^s_{giht} \qquad (9)$$

$$E^r_h = Z_h\gamma^r + \lambda^r\mu_h + \theta^r\omega^r_h \qquad (10)$$

and the reduced form outcome equations are

$$y^s_{kiht} = \eta^s_k t + X_{iht}\alpha^s_k + Z_h[\gamma^s_k + \Sigma^{k2}_{r=1}\delta^s_{kt}\gamma^r] + [(\lambda^s_k + \Sigma^{k2}_{r=1}\delta^s_{kt}\lambda^r)\mu_h + \Sigma^{k2}_{r=1}\delta^s_{kt}\theta^r\omega^r_h + \pi^s_k\nu_{kih} + \xi^s_k\epsilon_{kiht}] \;. \qquad (11)$$

In more concise notation,

$$y^s_{kiht} = \eta^s_k t + X_{iht}\alpha^s_k + Z_h\Psi^s_k + [\Gamma^s_k\mu_h + \Sigma^{k2}_{r=1}\delta^s_{kt}\theta\omega^r_h + \pi^s_k\nu_{kih} + \xi^s_k\epsilon^s_{kiht}] \;, \qquad (12)$$

where we again adopt the normalization $\theta^r = \theta$.

When obtaining the covariance matrix in a model with multiple time periods, one additional assumption is made:

- $E\nu_{kih}\nu_{k'i'h} = \begin{cases} 1 \quad if \quad k = k',\ i = i' \\ 0 \qquad otherwise \end{cases}$

Given this assumption, only the sub-matrix for a given *individual* will change since the individual random effects do not correlate across members within a household. The new version takes the following form, where the four equations correspond to outcomes s and s' at time t and outcomes s and s' at time t'[2]:

$$\begin{bmatrix} \begin{array}{c}(\pi_k^s)^2 \\ +(\Gamma_k^s)^2+(\xi_k^s)^2 \\ +\Sigma_{r=1}^{k2}(\delta_{kr}^s)^2(\theta^r)^2\end{array} & \begin{array}{c}\pi_k^s\pi_k^{s'} \\ +\Gamma_k^s\Gamma_k^{s'} \\ +\Sigma_{r=1}^{k2}\delta_{kr}^s\delta_{kr}^{s'}(\theta^r)^2\end{array} & \begin{array}{c}(\pi_k^s)^2+(\Gamma_k^s)^2 \\ +\Sigma_{r=1}^{k2}(\delta_{kr}^s)^2(\theta^r)^2 \\ \ \end{array} & \begin{array}{c}\pi_k^s\pi_k^{s'} \\ +\Gamma_k^s\Gamma_k^{s'} \\ +\Sigma_{r=1}^{k2}\delta_{kr}^s\delta_{kr}^{s'}(\theta^r)^2\end{array} \\ & \begin{array}{c}(\pi_k^{s'})^2 \\ +(\Gamma_k^{s'})^2+(\xi_k^{s'})^2 \\ +\Sigma_{r=1}^{k2}(\delta_{kr}^{s'}\theta^r)^2\end{array} & \begin{array}{c}\pi_k^s\pi_k^{s'} \\ +\Gamma_k^s\Gamma_k^{s'} \\ +\Sigma_{r=1}^{k2}\delta_{kr}^s\delta_{kr}^{s'}(\theta^r)^2\end{array} & \begin{array}{c}(\pi_k^{s'})^2+(\Gamma_k^{s'})^2 \\ +\Sigma_{r=1}^{k2}(\delta_{k1}^{s'}\theta^r)^2 \\ \ \end{array} \\ & & \begin{array}{c}(\pi_k^s)^2 \\ +(\Gamma_k^s)^2+(\xi_k^s)^2 \\ +\Sigma_{r=1}^{k2}(\delta_{kr}^s\theta^r)^2\end{array} & \begin{array}{c}\pi_k^s\pi_k^{s'} \\ +\Gamma_k^s\Gamma_k^{s'} \\ +\Sigma_{r=1}^{k2}\delta_{kr}^s\delta_{kr}^{s'}(\theta^r)^2\end{array} \\ & & & \begin{array}{c}(\pi_k^{s'})^2 \\ +(\Gamma_k^{s'})^2+(\xi_k^{s'})^2 \\ +\Sigma_{r=1}^{k2}(\delta_{kr}^{s'}\theta^r)^2\end{array} \end{bmatrix}$$

The likelihood does not change with the addition of multiple time periods; only the dimension of the covariance matrix.

[2]The covariance between the outcomes and the endogenous variables does not change from the cross-section model and are therefore omitted.