Education, Labour Supply and Market Development in Rural Peru

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Abstract

This paper examines the channels through which education affects household earnings in environments where wages are unobserved. Utilizing data from rural Peru, the empirical strategy decomposes the earnings returns to education into various wage-dependent and labour supply parameters. Geographic variation of market development inherent in the Peruvian Andes assists in the identification of unobserved wages. Results indicate that education affects earnings disproportionately more than hours, implying strong wage effects of education. This paper provides evidence that education gives rural households access to better, more lucrative, jobs characterized by fewer hours. This effect is more pronounced in more developed market environments.

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1 Introduction

In many rural areas, economic activity is largely driven by household rather than individual level activities. In addition, job rationing in the non-farm sector, a common source of market imperfection in such areas, creates a wedge between actual and desired hours worked. Furthermore, wages do not always reflect the marginal productivity of labour, nor are they always observable in these settings. These characteristics of rural economic activity complicate the analysis of labour supply behaviour.

Typically, the assessment of labour supply behaviour rests on wage-dependent parameters, such as the wage elasticity of labour supply. Thus, the primary challenge in adapting the labour supply model to the rural case is to tackle the problem of identifying the wage. Many empirical studies overcome these complications by identifying rural shadow wages using the neoclassical family labour supply model approach and the implied marginal productivity of labour.[1] While an excellent approach to a number of identification issues for rural labour markets, these attempts often suffer from a number of shortcomings. First, the identification of wages often relies on the assumed functional form of agricultural production. This technique is computationally demanding when households diversify their economic activity. Second, the identification of wages relies mostly on the supply side and often remains mute on the demand side. The level of local market development is an important determinant of the local demand for labour and must not be ignored. Third, for ease of computation, agricultural household models must often make strong sample restrictions regarding household structure.[2] Utilizing schooling as an instrument,

[1] See Jacoby (1993) and Newman and Gertler (1994) for examples using Peruvian data.
[2] Jacoby (1993) includes only households where at least one male and one female household member works on the family farm and Newman and Gertler (1994) include only households with land tenure greater than 0.01 hectares. Dropping households with little or no farm production may lead to biased inferences of labour supply behaviour.

this paper fills a number of gaps in the identification of labour supply behaviour when wages are unobserved.

First, schooling influences household earnings through increased productivity, the efficient allocation of factors of production and knowledge spillovers within the household (Welch 1970, Schultz 1975 and Basu et al. 2001). There is little evidence, meanwhile, indicating whether the gains to earnings from increased schooling are driven by schooling's effect on labour supply or by its effect on the marginal returns to work.[3] This paper seeks evidence on the relative importance of these two effects. In a relatively homogeneous and well-behaved labour market, holding hours worked constant, an additional year of schooling increases wages insofar as it increases labour's productivity. In more complex labour markets, such as in rural areas, schooling may also affect hours worked. Schooling provides households with increased labour market opportunities and thus educated household members can allocate labour to where it is more productive.

Second, Rosenzweig (1995) stresses the importance of technological change and the role of markets in the determination of the returns to education. Many studies find that the only way to experience strong returns to education in traditional farming is to combine schooling with modern inputs.[4] As markets begin to diversify through increased investment in non-farm sectors, higher wage jobs become available to an educated workforce, permitting the returns to education to rise. As markets continue to develop and more lucrative opportunities abound, the role of education in affecting earnings is eventually reduced. This study attempts to quantify more

[3] See Abowd and Card (1989) for a seminal study on the covariance of hours and earnings for the US. They show that changes in earnings are mostly driven by changes in hours. There exists nonetheless evidence that education leads to changes in labour allocated to different activities (see Jolliffe (2004) for a developing country case and Huffman (1980) for a developed country case).

[4] E.g. Schultz,(1975), Lockheed et al. (1980), Cotlear (1989), Moock (1989), Yang (1997), Rosenzweig (1995), Foster and Rosenzweig (1996).

precisely the role of market development in the returns to education and exploits geographic variation in these markets in the identification strategy.

This paper investigates the relationship between schooling and household earnings utilizing data from Peru. Most households in rural Peru are engaged in either farming or household self-employment ventures (or both). As a result, marginal wages are rarely observed. In addition, the wage may be a function of hours worked: for example, hours dedicated to a self-employment venture may influence the marginal returns to this enterprise (see Lemieux et al. 1994 and Oettinger 1999). Easily observable demand shifters identify the labour supply elasticity and the marginal returns to work. Since the level of market development is correlated to the level of market demand for good and services, as long as markets clear, it is likely that there exist some demand side variables that influence the returns, but not hours worked.[5]

A two-stage approach estimates schooling's effect on household labour supply and on the marginal returns to work when the latter are unobserved. The first stage estimates a reduced form simultaneous equations error components model of hours and earnings with unobserved wages. The second stage then applies a minimum distance estimator to solve the structural parameters. The technique utilized here has many salient advantages. First, it permits the identification of the own price elasticity of labour supply as well as the independent effect of education on hours worked and on the marginal returns to work when wages are unobservable. Second, it is possible to identify the effects of local market development on both hours worked and marginal returns to work. Third, this technique permits the identification of these structural parameters when the marginal returns to work are endogenous to hours worked. Fourth, it does not require stringent

[5] This is particularly important for the non-farm self-employed. See Oettinger (1999) for a discussion on the importance of utilizing demand level variables in estimating labour supply elasticities in the case of baseball stadium vendors. Card (2001) also emphasizes the need to appeal to both the supply and the demand side in the estimation of returns to education.

sample restrictions. Finally, the methodology developed here allows ready comparison of alternative models of labour supply behaviour.

Results indicate that schooling affects earnings disproportionately more than hours worked: more schooling within the household raises the marginal returns to work while seemingly not affecting hours worked. Nonetheless, once the direct effect of schooling on hours worked is accounted for, the wage elasticity of labour supply is negative: once schooling permits households to obtain better, more lucrative employment, households are able to enjoy more leisure. Education affects occupational choice, as more educated households are capable of substituting away from subsistence farming to better paying non-farm activities. The degree to which this occupational shift occurs depends largely on how well developed markets are. As the occupational shift occurs, earnings rise and households' labour supply behaviour is dominated by an income effect. This effect is particularly acute in more developed areas. In well-developed areas, education increases the likelihood of finding a better job, which is accompanied by both better wages and better hours. The results provided here suggest that the demand side variables are indeed significant determinants of labour supply behaviour in this rural economy (both in terms of hours and wages). These effects suggest that rural labour markets in Peru are indeed characterized by job rationing, since hours worked respond to local market conditions, holding wages fixed.

2 The Model

2.1 An Empirical Model of Household Labour Supply

The model borrows from the static neoclassical labour supply model for individuals.[6] This analysis, however, shifts the unit of observation from the individual to the household. Household

[6] See Killingsworth (1983) and Pencavel (1986) for a comprehensive look at the static labour supply model.

members in rural areas often engage in joint production, both on and off the farm. Thus, analyses at the individual level might not capture much of the intrahousehold allocation of labour. In addition, earnings from such ventures are often observed at the household rather than the individual level. In this time allocation model, households maximize their utility function subject to both a budget and a time constraint. Utility is defined over consumption goods (c) and leisure (l), both assumed normal goods, for given taste-shifting parameters collected in vector **Z**: $U = u(c, l; \mathbf{Z})$. Normalizing the price of consumption goods, agents are faced with the following full income budget and non-negativity constraints:

$$c + wl = A + wT \tag{1}$$

$$c \geq 0; \quad \text{and} \quad T \geq l \geq 0 \tag{2}$$

where w is the wage rate, A is non-labour income and T is the agent's time endowment.[7] The optimization problem is to maximize utility subject to (1) and (2). The optimal quantity of hours supplied (h) is obtained by subtracting optimal leisure demanded $l^* = l(w, A, T; \mathbf{Z})$ from the time endowment T:

$$h^* = T - l(w, A, T; \mathbf{Z}) = h(w, A, T; \mathbf{Z}) \tag{3}$$

One key theoretical parameter of this model is the wage elasticity of labour supply that measures the responsiveness of hours supplied to changes in the wage. A second parameter of interest, implicit in (3), is the return to education - the responsiveness of the wage to increases in individual schooling levels.[8] The usefulness of equation (3) in policy making depends on the extent to which the wage elasticity of labour supply and the returns to education can be identified and estimated. Policy makers might be interested in using schooling as a means to raise

[7] This representation assumes homogeneous labour such that each hour of labour supplied by the household is compensated by the same wage. An extension in section 6 of this paper relaxes this assumption.
[8] See Becker (1967), Mincer (1958, 1974) and Card (1999) for the human capital investment model and the returns to education.

household earnings. Since earnings are a function of hours and wages, the effect of schooling on earnings is dependent on the wage return to education and the responsiveness of hours worked to changes in the wages. Unfortunately, most household data sets for developing countries do not consistently report hourly wages for each economically active individual within the household.

The self-employment nature of rural economic activity necessitates some departures from standard estimation of the relationships implicit in (3). First, household surveys typically report total earnings or profits from these activities, not hourly wages. In the presence of measurement error, dividing earnings by hours to obtain average wages leads to an attenuation bias in the estimation of the wage elasticity of labour supply (Borjas 1980). In addition, these earnings are not always directly proportional to hours worked.[9] As a result, obtaining the marginal returns to work becomes quite difficult and requires a great deal of information relating to farm and off-farm production.[10] Second, using the household as the unit of observation eliminates a potential source of self-selection bias often present at the individual level: most households in rural Peru have at least one household member working, so that very few observations have hours or earnings taking the value zero. Finally, since earnings are the product of hours and the marginal returns to work, any framework employed to analyse labour supply behaviour utilizing these types of data sets must account for the determination of both hours worked and wages, a non-trivial task when marginal wages are unobserved.

Consider the following log-linear approximation form of equation (3):

$$\log h = a + \eta \log w + \mathbf{Z}'_{\mathbf{h}} \boldsymbol{\gamma}_{\mathbf{h}} + e \qquad (4)$$

[9] See Lemieux et al (1994) and Oettinger (1999) for excellent illustrations of endogenous wages: for the self-employed, wages - or the marginal returns to work - are likely a function of hours actually worked.
[10] Such is the approach in Jacoby (1993).

The parameter η represents the wage elasticity of labour supply, the vector $\mathbf{Z}_h$ includes demographic, market and regional characteristics affecting labour supply and e is a stochastic disturbance term. The marginal returns to work are approximated by the following log-linear wage structure:

$$\log w = b + \mu S + \mathbf{Z}'_{\mathbf{w}} \boldsymbol{\gamma}_{\mathbf{w}} + u \tag{5}$$

where μ represents the wage return to household schooling (S), the vector $\mathbf{Z}_w$ includes demographic, market and regional characteristics affecting wages, and u is a stochastic disturbance term. While schooling is observed at the individual level, the analysis will consider an aggregate measure of household schooling. I begin by utilizing average household schooling. The empirical work that follows will conduct some sensitivity analysis using alternative aggregates for household schooling (see section 6.2). Household earnings (E) are represented by:

$$\log E = \log h + \log w \tag{6}$$

Though wages are unobserved, the econometrician observes both earnings and hours. Using the relationship in (6), the structural model can thus be reinterpreted as follows with (5) being a latent wage process, where schooling acts as an `instrument' for unobserved wages:

$$\log h = a + \eta \log \widetilde{w} + \mathbf{Z}'_{\mathbf{h}} \boldsymbol{\gamma}_{\mathbf{h}} + e \tag{7}$$

$$\log E = a + (1+\eta) \log \widetilde{w} + \mathbf{Z}'_{\mathbf{h}} \boldsymbol{\gamma}_{\mathbf{h}} + e \tag{8}$$

$$\log \widetilde{w} = b + \mu S + \mathbf{Z}'_{w} \boldsymbol{\gamma}_{w} + u \tag{9}$$

Equations (7) through (9) provide the basic structural model, with the structural parameters μ (the wage return to schooling) and η (the labour supply elasticity) to be estimated with a two-stage approach described in section 3. In other words, $\log \widetilde{w}$ in equation (9) is approximated by a function of schooling and other controls. Conceptually, this method amounts to using schooling as an instrument for the wage.[11]

2.2 Returns to Education in the Basic Model

To use education as a policy tool in raising household earnings, it is necessary to identify the derivative of household earnings with respect to schooling. Since earnings are a function of hours and wages, the earnings returns to education is a function of the wage returns to education. Since wages are presumably affected by schooling, earnings are also sensitive to the responsiveness of hours worked to changes in wages. Using equations (7) to (9), the earnings return to schooling in total household earnings can be shown to be a function of the wage return to education (μ) and the wage elasticity of labour supply (η):

$$r = \frac{\partial \log E}{\partial S} = \frac{\partial \log h}{\partial S} + \frac{\partial \log w}{\partial S} = \mu(1+\eta) \tag{10}$$

Consider a positive estimate of r. If the wage elasticity of labour supply is negative (i.e. households are behaving on the backward bending portion of their labour supply curves), then it must be that households face large wage returns to schooling allowing more leisure consumption. If the wage elasticity of labour supply is instead positive (i.e. households are behaving on the upward sloping portion of their labour supply curve), then the wage return to schooling must be small relative to the earnings return to schooling.

[11] See Becker (1967), Mincer (1958, 1974), Schultz (1975) and Welch (1970) for more on the effect of education on the wage. In other words, schooling is a major determinant of the wage, either through its effect on productivity or through its effect on occupational choice. Ham and Reilly (2002) also use schooling as an instrument for the wage (see the literature that they cite for additional examples).

2.3 Multiple Effects Model

Schooling may have two separate effects on household hours. First, schooling's effect on hours works through its effect on the wage: higher schooling means higher wages and thus changes in hours. Second, it is also possible that schooling has an effect on a household's supply of hours, independently of its effect on the wage. There are a number of reasons why this second effect of schooling might be present. More educated households may work more hours because of the occupations in which they engage, as they have access to more lucrative jobs. In order to keep these jobs, they might provide extra time and effort to ensure tenure or permanence in the occupation. Moreover, these jobs might instead be less physically intensive or spread out over more hours. Thus, increased schooling may provide households with opportunities characterized by different hours requirements. Alternatively, schooling can improve a household's allocation of labour to various activities. Finally, schooling may affect attitudes towards work and thus desired hours. If schooling has a direct effect on hours, equation 7) must be revised as:

$$\log h = a + \eta \log \tilde{w} + \varphi S + \mathbf{Z}'_{\mathbf{h}} \boldsymbol{\gamma}_{\mathbf{h}} + e \qquad (11)$$

The structural parameter φ represents schooling's direct effect on hours worked, independent of its effect through wages. The structural model with multiple effects of schooling is thus given by equations (8), (9) and (11). Using this system, it can be shown that the earnings returns to education are now:

$$r = \mu(1+\eta) + \varphi \qquad (12)$$

The earnings return to schooling can thus be decomposed into three effects - the wage elasticity of labour supply, the wage return to schooling and schooling's direct effect on hours. Intuitively, the wage return to schooling is a downward biased approximation of the earnings return to education if hours respond positively to increased schooling, independently of its effect through the wage. To illustrate, increased schooling may lead to households improving their labour market "opportunities": a household engaged predominantly in small scale farming might dedicate more hours to a non-farm self-employment venture had it acquired more education. The types of occupations these households engage in is related to the level of schooling that they have obtained, occupations with different (and perhaps fewer) hours requirements.

2.4 Endogenous Wage Model

Alternatively, the types of activities that rural households engage in might be characterized by endogenous wages: the marginal wage might not be constant and instead be a function of hours worked. Endogenous wages are likely to occur in farm and non-farm self-employment activities: marginal wages - the opportunity cost of time - is dependent on the amount of time, care and effort that goes into production. Given the small scale nature of self-employment and subsistence farming production, the marginal product of labour is likely very sensitive to the amount of hours worked.[12] The present framework is easily adaptable to account for the potential endogeneity of wages. Let the latent process in (9) be transformed as the following function of hours:

$$\log \widetilde{w} = b + \mu S + \psi \log h + \mathbf{Z}'_w \boldsymbol{\gamma}_w + u \tag{13}$$

The system described by (7), (8) and (13) defines the structural model with endogenous wages. The structural parameter ψ represents labour supply's effect on wages. More specifically, ψ is a measure of the marginal product of labour. If ψ is negative, then the endogenous wage process is characterized by a diminishing marginal product of labour.[13] In this model, it can be shown that the earnings returns to education are calculated as:

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[12] Lemieux et al. (1994) and Oettinger (1999) provide excellent examples of endogenous wages for workers in the underground economy and of stadium vendors, respectively.
[13] Consider the following simplification of (13): $\log\widetilde{w} = \log A + \psi \log h$ where A is some constant. Then, $\widetilde{w} = Ah^{\psi}$. If $\psi < 0$, then the endogenous wage has the same form as that assumed in Lemieux et al. (1994).

$$r = \frac{\mu \cdot (1+\eta)}{1-\eta\psi} \tag{14}$$

3 Empirical Strategy

3.1 Joint Estimation of the Reduced form model

The first stage in this approach is to estimate the reduced form of the structural model in equations (7) to (9). The reduced form is obtained by substituting the latent wage equation (9) into the labour supply equation (7) and the earnings equation (8), yielding:

$$\log h = \beta_{10} + \beta_{11} S + \mathbf{Z}' \beta_{1Z} + \varepsilon_1 \tag{15}$$

$$\log E = \beta_{20} + \beta_{21} S + \mathbf{Z}' \beta_{2Z} + \varepsilon_2 \tag{16}$$

The reduced form model is best estimated using a systems approach such as Zellner's seemingly unrelated regression equations (SURE) (Zellner 1962). This estimation method allows the error term to be correlated across equations, which is likely in this case as there is a proportional relationship between the dependent variables in the two equations.

The SURE estimates provide some insight into the returns to education. Mainly, these estimates identify the returns to education in total household earnings. The reduced form parameter β_{21} identifies the left hand side of equation (10); that is, the earnings return to education. The degree to which we are able to identify the structural parameters from section 2 depends largely on which structural model we are estimating. Note that any of the models from section 2 have the reduced form as in (15) and (16). The control variable vectors in both the hours and the wage equations will contribute to the identification of the structural parameters.

3.2 Identification of Structural Parameters

The structural model in section 2 assumes that hours and wages are determined by different control variables, such that $\mathbf{Z}_h \neq \mathbf{Z}_w$. In fact, if there are no common variables in the two vectors, the system described in (15) and (16) is underidentified. A reasonable point of departure is to assume that $\mathbf{Z}_h \equiv \mathbf{Z}_w \equiv \mathbf{Z}$. Interpreting the estimated coefficients $\hat{\beta}_{1Z}$ and $\hat{\beta}_{2Z}$ becomes straightforward. To illustrate, if $\hat{\beta}_{2Z}$ is positive and $\hat{\beta}_{1Z}$ is indistinguishable from zero, we can assume that $\mathbf{Z}$ affects wages and not hours.

Suppose that the variables that make up $\mathbf{Z}$ include both supply and demand side variables. A reasonable test of the channels through which these variables affect earnings is to exploit several exclusion restrictions. These exclusion restrictions are ex ante obtained by our beliefs about whether the control variables affect hours or wages or both in the structural model.[14] For instance, the level of market development may be correlated with the size of the local demand base. As such, households selling farm output or their non-farm self-employment product face higher returns where the demand for these products is greater. Thus, one hypothesis posits that the local demand conditions affect wages not hours. The hypothesis is easily verified by testing the validity of the restriction that the coefficients on $\mathbf{Z}_h$ are jointly zero. The structure of the reduced form system in (15) and (16) is invariant to the exclusion of $\mathbf{Z}_h$ in the structural model. Nonetheless, the reduced form coefficients (and the implied functions of structural parameters) provide exclusion restrictions that allow us to test the specification of the underlying structural model. Not only do these exclusion restrictions assist in the identification problem, but they also

[14] The control variables appear in both the hours and the earnings reduced form equations. The exclusion restrictions pertain to the structural model.

assess the role of the supply and the demand side variables in establishing the returns to work, the returns to schooling, and the labour supply responses of both these returns.

3.2.1 Basic Model

The full basic model assumes that $\mathbf{Z}_h \equiv \mathbf{Z}_w \equiv \mathbf{Z}$. That is, the non-schooling control variables are common to both the hours and the wage processes. The vector $\boldsymbol{\theta}$ collects the structural parameters to be identified:

$$\boldsymbol{\theta} = \left[a, \quad \eta, \quad \boldsymbol{\gamma}_{\mathbf{h}}, \quad b, \quad \mu, \quad \boldsymbol{\gamma}_{\mathbf{w}}\right]' \tag{17}$$

The reduced form estimates, gathered in vector $\hat{\boldsymbol{\beta}}$, are functions of the parameters in $\boldsymbol{\theta}$:

$$\hat{\boldsymbol{\beta}} - f(\boldsymbol{\theta}) = 0 \tag{18}$$

These moment conditions are summarized in table 1. The first column maps the reduced form estimates into their functions of the structural parameters in the basic model with full controls. In this case, the number of structural parameters equals the number of reduced form parameters and so the dimension of $\boldsymbol{\theta}$ is the same as the dimension of $\hat{\boldsymbol{\beta}}$ and the system is exactly identified. Given that this model is exactly identified, the parameters in $\boldsymbol{\theta}$ are simply estimated by an Indirect Least Squares method that solves equation (18):

$$\hat{\boldsymbol{\theta}} = f^{-1}\left(\hat{\boldsymbol{\beta}}\right) \tag{19}$$

These expressions are collected and summarized in the first column of table 2.

It remains possible that $\mathbf{Z}_h \neq \mathbf{Z}_w$ that hours and wages are not affected by the same controls. In particular, we might be interested in determining whether hours are affected by household and regional characteristics while the wage is only affected by the household's schooling. To illustrate, let the level of market development affect hours worked but not the wage. In isolated areas with low levels of economic development, households may dedicate a lot of their time to subsistence agriculture (this is particularly likely in hostile environments for agriculture such as in the Andes). A better environment and better access to infrastructure are both correlated with increases in the level of market development, thus reducing the need to work as many hours even at constant 'wages'. In this case, we may want to investigate an extreme version of the basic model using controls on only the hours process. Schooling is thus conjectured to be a sufficient statistic for the marginal returns to work. This model implies that the level of market development is a constraint on hours worked but does not affect the wage.

The model with controls on hours only is overidentified: the dimension of the structural form parameter vector $\boldsymbol{\theta}$ (denoted by k) is smaller than the dimension of the reduced form estimates in vector $\hat{\boldsymbol{\beta}}$ (denoted by j):

$$\theta = \left[a, \eta, \gamma_h, b, \mu\right]' \tag{20}$$

As a result, there are multiple solutions. The moment equations and a solution for the structural parameters are provided in the second column of tables 1 and 2, respectively. Since the model is overidentified ($j>k$), table 2 also provides the overidentification restriction that can then be tested across the reduced form equations to check whether the exclusion restrictions are reasonable. Similarly, we might be interested in a model in which hours are purely a function of the wage and where the household and regional controls operate only through wages. This case is presented in the third column of tables 1 and 2, and is also overidentified since ($j>k$). The structural parameters of this model are presented in this vector:

$$\theta = \left[a, \eta, b, \mu, \gamma_w\right] \tag{21}$$

3.2.2 Multiple Effects Model

The moment equations and the identification of the structural parameters of this model are represented in the second last column of tables 1 and 2. This model is also overidentified as *j*>*k*.[15] In this case, the earnings returns to education β_{21} is also a function of schooling's direct effect on labour supply, φ:

$$\beta_{21} = (1+\eta)\mu + \varphi \tag{22}$$

Conditional on the indirect effect through wages, φ measures the direct effect of household schooling on household labour supply. Ignoring this direct effect would lead to an upward bias in the estimated wage return to schooling. The vector of structural parameters is thus:

$$\theta = [a, \eta, \varphi, b, \mu, \gamma_w]' \tag{23}$$

3.2.3 Endogenous Wage Model

The moment equations and the implied structural parameters in the endogenous wage model are presented in the last column of tables 1 and 2. Since the number of reduced form parameters exceeds the number of structural parameters (*j*>*k*), this model is also overidentified, and the overidentification restrictions are also provided in the last row.[16] In the endogenous wage model, the earnings returns to education are also a function of the endogenous wage parameter. For instance, it is possible that the marginal returns to work are decreasing with hours worked, as would be expected if these occupations were characterized by diminishing marginal product. The methodology utilized here allows us to test whether wages are characterized by diminishing

[15] In order to identify this model, controls are only included in the wage process. Otherwise the model with multiple effects is underidentified. In an extension, I relax this restriction by instead considering the interaction between schooling and the demand side variables.

[16] As in the multiple effects model, the control variables are only included in one of the two processes. Otherwise the model is underidentified.

marginal product by simply estimating the structural parameter ψ. A non-negative estimate of ψ rejects diminishing marginal product of labour. The structural parameters are as follows:

$$\theta = [a, \eta, \gamma_h, b, \mu, \gamma_w, \psi]' \tag{24}$$

3.3 Minimum Distance Estimation

The models described above are identifiable to a certain degree. The basic model is exactly identified such that the structural parameters are induced by indirect least squares. Four of the five models are however overidentified. In these cases, there exist multiple solutions for the structural parameters. That is, there exists multiple $\hat{\boldsymbol{\theta}}$ that satisfy equation (19). The Minimum Distance Estimator, a Generalized Method of Moments estimator, 'picks' the $\hat{\boldsymbol{\theta}}$ that minimizes the distance represented by the moment equations in (18).[17]

The objective is to minimize the distance between the reduced form estimates and the corresponding functions of the structural parameters. That is, minimum distance estimation finds the $\hat{\boldsymbol{\theta}}$ that minimizes the moments in (18) by solving the following optimization problem:

$$\hat{\boldsymbol{\theta}}_{\mathbf{MDE}} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \left(\hat{\boldsymbol{\beta}} - f(\boldsymbol{\theta})\right)' \left(\hat{\boldsymbol{\beta}} - f(\boldsymbol{\theta})\right) \tag{25}$$

This minimum distance estimator, named equally weighted minimum distance, shares all of the usual GMM properties. If the system is exactly identified (j=k) then $\hat{\boldsymbol{\theta}}_{\mathbf{MDE}} = \hat{\boldsymbol{\theta}}_{\mathbf{ILS}}$ where

[17] This method has been developed by Chamberlain (1984). Most applications of the minimum Distance estimator have been in the empirical labour literature (Abowd and Card 1984, Benjamin 1995, Kimhi and Lee 1996 and Deschênes 2001).

$\hat{\boldsymbol{\theta}}_{\mathbf{ILS}}$ is the indirect least squares estimator of the structural parameter that is the unique solution to (18).[18]

This identification technique has several desirable properties. First, it allows for the identification of key parameters belonging to a latent process. If a structural, theoretical, process is unobservable, this two-stage procedure identifies all structural parameters, even when the reduced form model is overidentified. Second, this technique identifies the structural parameters under alternative models. Third, this technique does not require the assumption that the instrument in the latent wage equation be orthogonal to the error terms in the observed equations. Finally, this technique does not suffer from the measurement error bias often encountered in labour supply estimation: measurement error of the dependent variable is only problematic if the dependent variable also appears as a regressor.[19]

4 Data

The primary source of data utilized in this paper is the 1991 round of the Peruvian Living Standards Survey (PLSS), a Living Standards Measurement Study household survey administered by a Peruvian non-profit organization, Instituto Cuánto S.A., with assistance (technical and financial) from the World Bank. Additional data are drawn from two separate and

[18] There may be instances where the EWMD estimator is not efficient. Altonji and Segal (1996) state that "the EWMD estimator is not efficient if the elements of ε [the error term] are heteroscedastic or correlated" (p. 354). since the reduced form estimates are generated by a simultaneous system, it is possible the estimated $\hat{\boldsymbol{\beta}}$ is contaminated by heteroscedasticity. There exists a correction for heteroscedasticity in minimum distance analogous to Generalized Least Squares (GLS). The Optimal Minimum Distance (OMD) estimator minimizes the objective function in (4.23) using a weighting matrix $\mathbf{W} \neq \mathbf{I}$ (Abowd and Card 1989, Benjamin 1995, Altonji and Segal 1996 and Deschênes 2001). There are however two disadvantages to using the OMD relative to the EWMD. First, Altonji and Segal (1996) demonstrate that the EWMD dominates the OMD estimator in small samples. The small sample bias in their paper is likely to be present here. Second, EWMD dominates the OMD in the simple pragmatic reason that it is computationally easier to estimate.

[19] Since I do not approximate wages by average hourly earnings, there is no attenuation (see Borjas 1980). Thus, any measurement error in hours is absorbed by the regression error term (Greene 1993).

independent sources: Instituto Cuánto S.A. and the Instituto Nacional de Estadística e Información (INEI).[20] While 70% of the country's population resides in the area covered by the 1991 PLSS, the survey is not nationally representative (World Bank (1993)).[21] The rural sample of the PLSS includes 585 households. However, the analysis in this paper includes only 423 households. The remaining households were dropped because the districts in which they live are not represented in all of the three other data sets used in this study (district level data on local market development described below are drawn from an earlier 1985/86 PLSS, Instituto Cuánto and the INEI).

Table 3 summarizes and describes the data.[22] Household hours aggregate annual hours over all working household members and includes both paid and unpaid work. Total household paid hours are also shown and account for 93 percent of households.[23] Total household hours are also shown by activity (farm and non-farm). Farm activities are broadly considered as all production (wage- or self-employment) of raw agricultural products (subsistence, small scale farming, cash crops or livestock). Non-farm activities cover all remaining activities (wage- or self-employment). The hours variables are transformed by taking logarithms.[24] Rural households spend the majority of their time in farm activities and derive the majority of their earnings from

[20] The details of the survey and the additional sources can be found in World Bank (1991 and 1993).
[21] The rural sample is comprised of three domains (Mountain North, Mountain Centre and Mountain South). The sample is representative within, but not across domains. Some departments (Ayacucho, Apurimac and Huancavelica, as well as departments in the Selva) were excluded from the 1991 PLSS because of terrorist activity or for being too isolated (and thus fieldwork too costly). The sample frame is large, but it is based on a 1981 National Census of Population and Dwellings. See World Bank (1993) for details on the survey design.
[22] The means are probability weighted to account for different expansion factors in the survey design (see World Bank (1991a) for these expansion factors). The means are also adjusted to account for the stratification and clustering of the data.
[23] The remaining 7 percent of households have positive hours supplied, but none that are remunerated. These hours correspond to unpaid hours in the family business or family farm.
[24] Rather than dropping observations with zero paid hours, I transform the paid hours and earnings by adding one prior to the logarithmic transformation (see Jacoby 1993). Mean values of these variables are relatively unchanged with this transformation. I rerun the relevant regressions in this paper that make use of these variables over the relevant sample. Though not shown here, the results are not sensitive to the transformation.

these activities as well. Earnings include the value of home consumption of agricultural output, evaluated at local market prices by the respondent.

The relationship between hours and earnings becomes apparent when looking at mean activity level values of the dependent variables (conditional on positive). Households engaged in non-farm activities work slightly fewer hours than households engaged in farm activities, on average. Average household earnings in non-farm activities are higher than in farm activities, indicating that the former are more lucrative than the latter.

The primary independent variable is the schooling variable. Given the household level analysis, the natural candidate is a household aggregate for schooling: average years of schooling of household members aged 15 and above.[25] Table 3 also provides this variable expressed as activity specific aggregates for non-farm and farm activities. The average years of schooling of household members in non-farm activities is higher than in farm activities. This pattern is consistent across alternative measures of household schooling (such as the maximum years of schooling within the household). These alternative measures of household schooling will be utilized to check for robustness of the empirical analysis in section 6. A measure of household capital stock is constructed from various parts of the PLSS. The value of total household capital stock includes business assets from the self-employment venture, farm equipment, the stock of fertilizers, seeds and pesticides, household durables and livestock.

This paper exploits easily observable demand side variables to assist in the identification of the key theoretical parameters. This approach is also utilized in Oettinger (1999) and Ham and Reilly (2002). Since many households derive incomes from self-employment ventures and farming, simply utilizing supply side household variables such as schooling, demographics and

[25] To reduce the likelihood of an endogeneity bias between earnings and schooling, this aggregate excludes the education of those household members presumably in school or of school age. The results presented next are nonetheless checked for robustness by relaxing this restriction.

other household production variables will lead to biased estimates of parameters such as the return to education and the wage elasticity of labour supply. The marginal return to work in these activities is likely influenced by the prevailing market conditions. There is a large regional variation in the level of market development in rural Peru, a source of variation that is very useful in identifying the structural parameters.

Unlike Oettinger's study, there is no single, obvious demand variable.[26] Combining the various sources of data provides us with several variables that proxy for the level of market demand and development: altitude, the density of the rural population, the number of populated centres in the district, the number of hostel beds in the region and the distance to the nearest post office. For example, closer markets suggest lower transaction costs in accessing a demand base. The density of the rural population, the number of populated centres in the district and the number of hostel beds in the region imply a larger demand base. District altitude is correlated as well with the level of market development. Rural settlements in the Peruvian Andes are scattered at many different altitudes.[27] Very elevated districts are less likely to support large populations or dynamic market centers.[28]

[26] Oettinger (1999) studies the labour supply behaviour of baseball vendors and utilizes ‘exogenous game-to-game variation’ such as game attendance.

[27] The household's location decision is potentially dependent on the ecological (and thus elevation) zone, especially for farm households.

[28] With the exception of the relatively flat highland districts in the Altiplano in the south of the country, ‘modern’ economic activity is more likely concentrated in the valleys than the highlands.

5 Results

5.1 Seemingly Unrelated Regression Equations Results

Table 4 presents the reduced form results from the first stage of the estimation strategy corresponding to equations (15) and (16).[29] The results reveal that the average years of household schooling affects only earnings, suggesting that the wage returns to schooling are large. This finding provides preliminary evidence that schooling is a reasonable instrument for wages as it affects earnings disproportionately more than hours. The schooling coefficient in the earnings equation provides an estimate of the earnings return to education of 5.18 percent. This estimate is only a summary statistic for education's role in household earnings (r). On its own, it does not provide any indication whether the effect is working through the wage return (μ), the wage elasticity of labour supply (η) or schooling's direct effect on hours (φ). For instance, the coefficient of schooling on hours may be driven by opposing effects working through η and φ (see equation (12)). In this particular case, an insignificant coefficient on hours can be misinterpreted as evidence that schooling is a good instrument of wages as it is likely correlated with the error term in (7).

Household size, plot size and capital stock give us some indication of the importance of supply side effects. First, household size is positively related to both hours and earnings. This relationship is consistent with intuition: larger households have more workers, so they supply more hours and earn more than smaller households. The effect on earnings is however much smaller than the effect on hours. This result suggests that larger households earn less per hour

[29] Ideally, these regressions would include cluster fixed-effects to account for the survey design. Including cluster fixed effects would however preclude the inclusion of district-level variables proxying for the level of market development, since each cluster corresponds to a different district. However, some sensitivity analysis was conducted. I estimated the model (excluding the district-level variables) with and without cluster fixed-effects. The results were robust - the patterns of significance were unaffected by the inclusion of the cluster fixed-effects.

than smaller households. Second, there is a positive estimated effect of total plot area on household earnings. A natural interpretation of this correlation is that larger landholdings imply more total agricultural output. However, agricultural plots in the Andes may be difficult to cultivate because of the slope of the plot as well as its elevation. As a result, households may need to be compensated for the low quality of the lands by the quantity of the land.[30] A more likely interpretation is that large landholdings are indicative of wealth (particularly inherited wealth), and this wealth may be correlated with household earnings through other channels - notably schooling.[31] Plot area does not affect total household hours: on average, having more land does not mean that households work more. Total household capital stock is also a significant predictor of both household hours and household earnings. In fact, it is a stronger predictor of earnings than of hours, suggesting that its effect works mostly through the 'wage' equation.

The remaining variables point to the role of local market development and demand side effects. The overall picture is consistent with a story in which household earnings are positively, but household hours negatively, related to the level of local market development. This pattern suggests that an important benefit of more developed markets is higher hourly returns to work. As the level of market development rises, household activity becomes more profitable and households are able to find more lucrative employment. In light of the effects on hours, more lucrative employment means that households enjoy more leisure. To illustrate, district elevation is positively correlated with hours worked, but negatively related to household earnings. More elevated areas are on average more isolated and economic activity is concentrated in subsistence

[30] Interacting total plot size with altitude positively affects earnings but not hours, thus substantiating the quantity versus quality trade-off (results not shown here).
[31] Interacting schooling with total plot size, however, negatively affects hours worked but not earnings (results not shown here).

types of production such as cropping of basic staples (potatoes and other tubers) and livestock tending that require a great deal of labour input to maintain a minimum standard of living. At lower altitudes, there is an increasing participation in non farm activities including non-farm self-employment. These activities are more lucrative and require less labour input. The estimated effect of the distance to the nearest post office provides a similar story: the more remote the household, the higher the hours worked as being in remote areas increases the probability that the household is engaged in predominantly subsistence production. However, this variable does not seem to affect earnings.

Finally, table 4 provides some goodness of fit measures and a Breusch-Pagan test of independence. The Chi-squared tests are statistically significant in both equations, indicating that the hypothesis that all coefficients are zero is safely rejected. The Breusch-Pagan test of independence is statistically insignificant, thus failing to reject the hypothesis that the two equations are independent of each other. The cross-equation error correlation is low at 0.0627.

To summarize, the reduced form estimates presented in table 4 suggest that schooling's effect on earnings is attributable to its effect on wages. The result that schooling has no reduced form effect on hours worked might overlook possible opposing effects caused by a labour supply response to wages. In addition, the demand side variables that proxy for the level of market development have statistically different effects on hours and earnings. The following section scrutinizes these effects and identifies more conclusively where the effects originate. In particular, the minimum distance estimates decompose schooling's effect on hours into a direct effect and an indirect effect through labour supply elasticity.

5.2 Minimum Distance Estimates of the Structural Model

Table 5 presents the structural form results from the equally weighted minimum distance estimation for the basic model. The basic model with full controls estimates a statistically significant negative wage elasticity of labour supply, suggesting that Peruvian households behave on the backwards bending portion of their labour supply schedules. The overall pattern of significance of the key structural parameters is invariant to excluding the controls on hours worked in the basic model. The exclusion of the supply or demand side variables from the wage equation does not affect the labour supply elasticity or the wage returns to education. In the third column, excluding the controls on hours produces different estimates of one of the key structural parameters: the wage elasticity becomes larger in magnitude while the wage returns are similar as before.

A negative labour supply elasticity might at first glance seem counter-intuitive for poor rural households. Intuition, backed by standard labour economics textbook discussions with respect to labour supply behaviour, suggests that at low wage levels, a wage increase would lead to a dominating substitution effect and thus leisure consumption would decrease. While this may be true for many scenarios under which the standard labour supply model is applied, the story may be quite different in poor rural areas of developing countries. In particular, many of these households live in a subsistence economy where the wage is significantly lower than the low wage considered in most developed countries or in more urban developing country settings. In the absence of social welfare programs, these households work very long hours to meet subsistence needs. For these households, a wage increase will allow meeting subsistence needs (and possibly much more) while permitting household members to enjoy some consumption of leisure. The alternative models estimated next show how schooling might enable this transition.

The most striking results from the EWMD estimates of the key structural parameters are found in the alternative models (Table 6). In particular, controlling for schooling's direct effect on hours in the multiple effects model, the wage elasticity of labour supply is statistically significant and negative. Together with the first stage results, the EWMD estimates support the story in which increased schooling permits households to enjoy more leisure. Fafchamps and Quisumbing (1999a) attribute this negative wage elasticity to the omission of socially productive activities: more educated individuals are more likely engaged in 'information gathering and community building (p. 27)', activities that may not be recorded as productive, though they are. The present analysis provides a somewhat different interpretation. As households become more educated, they are able to find more lucrative employment outside of subsistence agriculture. With more lucrative employment, there is less need to work in subsistence agriculture that may require substantial labour input to meet basic needs.

To gain additional credibility, this effect would be more pronounced where labour market opportunities abound. The level of market development would thus have a larger effect on hours than on wages. Though unidentifiable from the multiple effects model, the basic model (with full controls) estimates that the demand side control variables have different effects on wages than on hours. Households in more elevated areas work longer hours and earn lower wages - this pattern is consistent with the notion that elevated areas are predominantly characterized by subsistence types of activities that involve long hours and little pay. The number of population centers in the district and the number of beds in hostels in the region provide an approximation of the level of regional market demand - a larger regional market is correlated with a larger regional demand base and thus higher wages. With fewer hours worked these results point to a dominating income effect. The greater the distance to the nearest post office, the more hours households work and the lower their wages. Thus, more developed areas provide households with improved opportunities allowing them to enjoy more leisure. In the basic model excluding the controls on wages, the more isolated the household is, the more hours it is likely to work, reflecting the high degree of subsistence or small scale agriculture relative to remunerated work in remote areas. Taken together with the reduced form results presented earlier, the effects of the demand side variables indicate dominating income effects.

The three supply side variables (household size, the total plot size and total capital stock) have positive effects on household hours worked - larger households work more hours than do smaller households, as do households with more agricultural land and with more capital stock. The effects of these three variables on wages are consistent with intuition. Larger households earn less per hour, while households with more land or more capital earn more. The effects of land size and capital stock on earnings seem to be working through wages as the magnitudes of their coefficients are stronger than their counterparts in the hours equation. This conclusion reiterates the results from the reduced form estimates in table 4.[32]

5.3 Hypothesis Testing

The tests provided in tables 7 and 8 make use of the overidentification restrictions described in tables 1 and 2. The first test (I) rejects the hypothesis that the coefficients across the two simultaneous equations in table 4 have the same effect: the two equations (hours and earnings) are statistically different from each other. The second hypothesis (II) tests the first over-identification restriction that would be compatible with the controls on hours version of the basic model and corresponds to the overidentification restriction in the second column of table 1.[33] The statistic tests the joint hypothesis that the effect of the supply and demand side controls is the same on the hours and earnings regression. The test safely rejects the overidentification restrictions, indicating that the basic model with controls on hours only is rejected. This is

[32] The SURE and EWMD results are robust to amending the schooling variable to include the years of schooling of children in the household.
[33] This tests the validity of the exclusion restriction that the controls have no effect on the system through wages.

evidence that the control variables are likely affecting the wages more than hours, thus rejecting the exclusion restriction. By turning our attention to each control individually, the cross-equation tests (III) suggest that only one variable is consistent with the basic model with controls on hours only. Notably, it is not possible to reject that the density of the rural population has the same statistical effect across both equations. Hypothesis tests for the basic model with controls on wages only are reported in rows (IV) and (V). The overall test of the overidentification restriction for this model (IV) cannot be rejected. However, the individual tests in (V) do reject that some of the cross-products are the same across both reduced form equations. Nonetheless, based on the tests pertaining to the identification restrictions in the basic model, the evidence suggests that the best model is the one in which the control variables affect wages rather than hours.

The hypotheses tested in (VI) in table 7 and (VII) in table 8 relate to the last two models: the multiple effects model and the endogenous wage model, corresponding to the overidentification restrictions in the last two columns of table 1.[34] While the test statistic in (VI) rejects the null hypothesis, fewer than two fifths of these tests are statistically significant at the 10% level, fewer still at the 5% level and only one at the 1% level (table 8 provides the statistics for the separate hypotheses that make up the joint test in (VI)). The evidence presented in this table puts some weight on the multiple effects and the endogenous wage model. The over-identification restrictions, however, do not permit a way to test which of these two models dominates the other. In other words, the hypothesis tests provide weak evidence in support of either the multiple effects model with exclusion restrictions on hours or the endogenous wage model with exclusion restrictions on wages. If we were to judge the two models according to the

[34] Note that the degrees of freedom in (VI) are different than the number of individual tests in (VII): some of the individual tests are redundant.

minimum distance estimates, the Chi-square statistic for the goodness of fit in the multiple effects model is slightly larger than in the endogenous wage model and the value of the minimized objective function is much lower. Though not conclusive on their own, these results put additional weight on the multiple effects model.

6 Other Considerations

6.1 Relative Returns

Section 5 reveals that schooling affects earnings by influencing both wages and hours worked. In particular, the results indicate that education allows households to find 'better', more gainful, jobs, possibly with fewer hours. Given the aggregate nature of the previous analysis, these conclusions provide only first order evidence that education's effect on earnings might largely be driven by its effect on occupational choice. A disaggregated approach may help in reinforcing this result. In other words, are the hour supply responses and effects of schooling reacting in the same way for all activities? Or, does employment in farming respond differently to changes in schooling than employment in non-farm activities?

Ideally, one would repeat the empirical strategy in section 3 by disaggregating all income-generating activities in which the household engages. Such an exercise would lead to more precise estimates of the rates of return to schooling in different activities, and would provide an abundance of own and cross-wage elasticities. Though certainly an informative exercise, estimation of such a model is tedious. The structural framework described in this paper is easily amended to account for multiple activities. The empirical implementation, however, involves computationally intensive methods to estimate the maximum likelihood function of a system of equations of truncated dependent variables: the estimation technique would have to contend with as many self-selection corrections as there are activities.[35] Instead, estimating relative returns and relative labour supply behaviour may be as informative.

Section 5 highlights the role of schooling in permitting households to work in more lucrative, non-farm, activities. For this to be the case, the marginal returns to non-farm work relative to farm work should be dependent on schooling. Furthermore, given the results in the multiple effects model, schooling would also provide a differential effect on household hours supplied to non-farm relative to farm employment. Suppose that the household engages in either or all of two activities: farm work (*f*) and non-farm (*nf*) work (see section 4 for a discussion of the difference between the two sectors). The basic model from section 2 can be modified as follows:

$$\log h_i = a_i + \eta_i \log \widetilde{w}_i + \mathbf{Z}'_{\mathbf{h}i}\boldsymbol{\gamma}_{\mathbf{h}i} + e_i \tag{26}$$

$$\log E_i = a_i + (1+\eta_i)\log \widetilde{w}_i + \mathbf{Z}'_{\mathbf{h}i}\boldsymbol{\gamma}_{\mathbf{h}i} + e_i \tag{27}$$

$$\log \widetilde{w}_i = b_i + \mu_i S + \mathbf{Z}'_{\mathbf{w}i}\boldsymbol{\gamma}_{\mathbf{w}i} + u_i \tag{28}$$

where $i = \{nf, f\}$. Letting $\mathbf{Z}_{\mathbf{h}nf} = \mathbf{Z}_{\mathbf{h}f} = \mathbf{Z}_{\mathbf{h}}$, $\mathbf{Z}_{\mathbf{w}nf} = \mathbf{Z}_{\mathbf{w}f} = \mathbf{Z}_{\mathbf{w}}$ and substituting (28) into (26) and (27) for each *i*, then taking the difference of the non-farm and the farm equations yields the following reduced form system of 'relative' equations:

$$\begin{aligned}\log h_{nf} - \log h_f = a_{nf} - a_f + \left(\eta_{nf} b_{nf} - \eta_f b_f\right) + \left(\eta_{nf}\mu_{nf} - \eta_f \mu_f\right)S \\ + \mathbf{Z}'_{\mathbf{w}}\left(\eta_{nf}\boldsymbol{\gamma}_{\mathbf{w}nf} - \eta_f \boldsymbol{\gamma}_{\mathbf{w}f}\right) + \mathbf{Z}'_{\mathbf{h}}\left(\boldsymbol{\gamma}_{\mathbf{h}nf} - \boldsymbol{\gamma}_{\mathbf{h}f}\right) + \zeta_1\end{aligned}$$

$$\begin{aligned}\log E_{nf} - \log E_f = a_{nf} - a_f + \left((1+\eta_{nf})b_{nf} - (1+\eta_f)b_f\right) + \left((1+\eta_{nf})\mu_{nf} - (1+\eta_f)\mu_f\right)S \\ + \mathbf{Z}'_{\mathbf{w}}\left((1+\eta_{nf})\boldsymbol{\gamma}_{\mathbf{w}nf} - (1+\eta_f)\boldsymbol{\gamma}_{\mathbf{w}f}\right) + \mathbf{Z}'_{\mathbf{h}}\left(\boldsymbol{\gamma}_{\mathbf{h}nf} - \boldsymbol{\gamma}_{\mathbf{h}f}\right) + \zeta_2\end{aligned}$$

or:

$$\Delta \log h = \Delta a + \Delta(\eta b) + \Delta(\eta\mu)S + \mathbf{Z}'_{\mathbf{w}}\Delta(\eta\boldsymbol{\gamma}_{\mathbf{w}}) + \mathbf{Z}'_{\mathbf{h}}\Delta\boldsymbol{\gamma}_{\mathbf{h}} + \zeta_1 \tag{29}$$

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[35] This is left for future research. This particular research avenue would deal with a concern in Glewwe (2002) that assessing the returns to education for the self-employed requires a careful treatment of self-selection effects.

$$\Delta \log E = \Delta a + \Delta((1+\eta)b) + \Delta((1+\eta)\mu)S + \mathbf{Z}'_{\mathbf{w}}\Delta((1+\eta)\boldsymbol{\gamma}_{\mathbf{w}}) + \mathbf{Z}'_{\mathbf{h}}\Delta\boldsymbol{\gamma}_{\mathbf{h}} + \zeta_2 \qquad (30)$$

where the λs are the reduced form moments representing functions of the structural parameters in (26) to (28). Table 9 provides the SURE results of the system in (29) and (30). The most striking result that is revealed in this exercise is that increased education is correlated with a substitution away from farm activities to non-farm activities: the estimated schooling coefficients in the system described by (29) and (30) are statistically significant (at the 1% level) and positive for both the labour supply and the earnings equations. More educated households dedicate more hours to non-farm relative to farm activities and derive more earnings from non-farm sources relative to farm sources.

Household capital stock does not affect the difference in hours dedicated to non-farm relative to farm work, but it reduces the earnings gap between the two activities. If hours differentials are unresponsive to capital stock, then its effect on earnings differentials must be driven by its effect on the relative wages: the wage gap between non-farm and farm work is lower for households with larger capital stock. This is likely reflecting the notion that farms with large physical capital stock are less likely engaged in subsistence production, and the shadow wage in farming is likely higher in these cases than in subsistence cases. The estimation of the relative returns and hours supplied reveals that hours are also more responsive to differences in the market environment as proxied by district elevation. District elevation has an estimated negative effect on the difference in hours supplied: households in more elevated districts supply less labour to non-farm activities than to farm activities. This negative effect is smaller (and statistically different) in the earnings equation.

6.2 Robustness of the Household Education Variable

The measure of household schooling utilized thus far is an average for all household members that have presumably completed their formal human capital investment. Since this variable is an aggregate, it is possible that much information is lost. Numerous papers discuss some of the advantages and disadvantages in using such a measure and highlight the fact that it is not clear whose education within the household really matters.[36]

Table 10 presents the point estimates of the schooling coefficients corresponding to the SURE model in (15) and (16) using alternative aggregates of household schooling. Though only the schooling coefficients are shown here, the coefficients on the control variables remain relatively unchanged across estimations. The first set of results indicates that there is little difference between the estimated schooling coefficients using the years of schooling of the most educated household member and the average years of household schooling.[37] Taken with table 4, these results indicate that it is indeed the education of the most educated household member that really matters most.

The second set of results repeats the analysis using instead the years of schooling of the household head to account for the possibility that it is the education of the primary decision maker within the household that matters. These results are strikingly different from those found using the previous two measures of household schooling. The years of schooling of the household head negatively influences the hours supplied by the household and its effect on household earnings is substantially (and statistically) smaller than the average or maximum household measures. This pattern suggests that the household head is most likely not the most educated person in the household.[38]

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[36] See Moock et al. (1989), Vijverberg (1995), Taylor and Yuñez-Naude (2000) and Jolliffe (2002).

[37] The results in table 4 using average years of household schooling are the benchmark for comparison in this section.

[38] Jolliffe (2002) finds a similar result for Ghana.

The last two sets of results use activity specific aggregate measures of schooling. The average years of schooling of household members that are engaged in non-farm activities has a significantly positive effect on household earnings, suggesting that much of the effect is working through the wage, as in table 4. In contrast to table 4, the magnitudes of these effects are stronger using the non-farm activity specific average years of schooling than the average household measure. This result provides additional evidence that schooling causes households to allocate their labour resources towards more lucrative employment. To strengthen this result further, the results using the farm activity specific measure of schooling show that the effect of `farm schooling' on household hours and earnings is insignificant. These results corroborate the notion that there are little (if any) returns to education in farming.[39]

7 Conclusions

A simple effect conceptually, the empirical identification of the returns to education is clouded both by data related problems of observation and by the many (and possibly opposing) effects of schooling on earnings. In many micro data sets, marginal wages are often unobservable: the wage sector is small relative to the non-wage sector in many developing countries, particularly in rural areas where most economic activity is self-employment. With data on hours and total earnings, the empirical strategy formulated in the present paper outlines how it is possible to back out key parameters of interest pertaining to unobserved wages.

The strategy begins with reduced form estimation of a simultaneous equation error components model. The identification of wage-dependent structural parameters is possible by appealing to minimum distance estimation and utilizing schooling as an instrument for the

[39] It is widely accepted that for schooling to affect the marginal returns to work in farming, human capital must be combined with a more modern technology. See for example Schultz (1975), Lockheed et al. (1980), Cotlear (1989), Moock et al. (1989), Rosenzweig (1995) and Yang (1997).

unobserved wages. The framework also permits the estimation of these parameters when schooling has an effect on hours worked independent of its effect on wages. The empirical strategy allows the decomposition of the earnings returns to schooling into various components relating to the wage, hours worked and schooling. Furthermore, the framework allows for a potential endogeneity of wages. Various structural models are estimated and the exclusion restrictions are exploited to gather evidence on the relative validities of these models.

Results indicate that an increase in household schooling raises household earnings disproportionately to its effect on hours, suggesting positive wage returns to education. In addition, once the direct effect of education on hours worked is controlled for, the results indicate that the wage elasticity of labour supply is negative. Education thus permits households to find more lucrative employment opportunities that allow them to enjoy more leisure.

In addition to the identification of the key labour supply and returns to education parameters, the paper investigates the importance of local market demand variables and their interaction with schooling in affecting household labour supply behaviour. While it is widely accepted that the role of education in affecting earnings in farming is limited, the results in this paper are encouraging. Education, when combined with local market development, leads to increases in rural standards of living as evidenced by increased marginal returns to work and increased consumption of leisure. In particular, educated households in developed areas are likely to generate a large proportion of their labour incomes from lucrative non-farm sources. There is thus an impetus for policies that promote human capital investment in conjunction with improved access to markets in rural areas.

Appendix

The SURE system described in (7) and (8) can be rewritten as:

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon$$

corresponding to a structural equations error components model with unobserved wages, where $\mathbf{y} = [h, E]'$, $\beta = [\beta_1, \beta_2]'$, $\mathbf{X} = [\mathbf{X}_h, \mathbf{X}_w]'$, and to keep matters simple, the error term is assumed to have the following distributional property:[40]

$$\boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Sigma})$$

where $\boldsymbol{\Sigma}$ is the variance-covariance matrix of the reduced form simultaneous equations model:[41]

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{11}\mathbf{I} & \sigma_{12}\mathbf{I} \\ \sigma_{12}\mathbf{I} & \sigma_{22}\mathbf{I} \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix} \otimes \mathbf{I} = \boldsymbol{\Sigma}_{\mathbf{c}} \otimes \mathbf{I}$$

Zellner (1962) shows that the SURE variance-covariance matrix is as follows:

$$\mathbf{V}(\hat{\boldsymbol{\beta}}) = (\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1} = \begin{bmatrix} \sigma^{11}\mathbf{X}_h'\mathbf{X}_h & \sigma^{12}\mathbf{X}_h'\mathbf{X}_w \\ \sigma^{21}\mathbf{X}_w'\mathbf{X}_h & \sigma^{22}\mathbf{X}_w'\mathbf{X}_w \end{bmatrix}$$

where σ^{ij} is the ij^{th} element of $\boldsymbol{\Sigma}_c^{-1}$. This allows cross-equation hypothesis testing, a feature that will be exploited in evaluating the models outlined above. This variance-covariance matrix is indispensable to the second stage of the estimation procedure.

The standard errors are given by the following variance covariance matrix:

$$\mathbf{V}(\hat{\boldsymbol{\theta}}_{\mathbf{MDE}}) = (\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}'\mathbf{V}(\hat{\boldsymbol{\beta}}_{\mathbf{SURE}})\mathbf{G}(\mathbf{G}'\mathbf{G})^{-1}$$

where $\mathbf{G}$ is the Jacobian of the objective function in (25). Newey (1985) shows that the following is a chi-squared distributed goodness of fit statistic for this estimation method:

$$(\hat{\boldsymbol{\beta}} - f(\hat{\boldsymbol{\theta}}_{\mathbf{MDE}}))'\mathbf{R}^{-}(\hat{\boldsymbol{\beta}} - f(\hat{\boldsymbol{\theta}}_{\mathbf{MDE}})) \sim \chi^2(j-k)$$

where $\mathbf{R}^{-}$ is the generalized inverse of $\mathbf{R} = \mathbf{PV}(\hat{\boldsymbol{\beta}}_{\mathbf{SURE}})\mathbf{P}'$ and where $\mathbf{P} = \mathbf{I} - \mathbf{G}'(\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}$.

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[40] Note that the ε_i (i=1,2) are functions of the 'structural error terms' (e and u) in equations (7) to (9).

[41] Note that the variance-covariance matrix is symmetric. See Kinal and Lahiri (1993) for a similar application of the simultaneous equation with error components.

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Table 1: Moment Equations

	Basic Model			Multiple Effects Model	Endogenous Wage Model
Moment	**Full controls**	**Controls on hours**	**Controls on wages**	**Controls on wages**	**Controls on hours**
β_{10}	$a+\eta b$	$a+\eta b$	$a+\eta b$	$a+\eta b$	$\frac{a+\eta b}{1-\eta\psi}$
β_{11}	$\eta\mu$	$\eta\mu$	$\eta\mu$	$\eta\mu+\varphi$	$\frac{\eta\mu}{1-\eta\psi}$
β_{1i}	$\gamma_{hi}+\eta\gamma_{wi}$	γ_{hi}	$\eta\gamma_{wi}$	$\eta\gamma_{wi}$	$\frac{\gamma_{hi}}{1-\eta\psi}$
β_{20}	$a+(1+\eta)b$	$a+(1+\eta)b$	$a+(1+\eta)b$	$a+(1+\eta)b$	$\frac{a(1+\psi)+(1+\eta)b}{1-\eta\psi}$
β_{21}	$(1+\eta)\mu$	$(1+\eta)\mu$	$(1+\eta)\mu$	$(1+\eta)\mu+\varphi$	$\frac{(1+\eta)\mu}{1-\eta\psi}$
β_{2i}	$\gamma_{hi}+(1+\eta)\gamma_{wi}$	γ_{hi}	$(1+\eta)\gamma_{wi}$	$(1+\eta)\gamma_{wi}$	$\frac{(1+\psi)\gamma_{hi}}{1-\eta\psi}$
	Exactly identified	Over-identified	Overidentified	Overidentified if i>1	Overidentified if i>1
Over-id. Restrict.		$\beta_{1i}=\beta_{2i}$	$\beta_{11}\beta_{2i}=\beta_{21}\beta_{1i}$	$\beta_{1j}\beta_{2i}=\beta_{2j}\beta_{1i}$	$\beta_{1j}\beta_{2i}=\beta_{2j}\beta_{1i}$

Table 2: Identification of Structural Parameters

	Basic Model			**Multiple Effects Model**	**Endogenous Wage Model**
Parameter (θ)	**Full controls**	**Controls on hours**	**Controls on wages**	**Controls on wages**	**Controls on hours**
a	$\frac{\beta_{10}\beta_{21}-\beta_{11}\beta_{20}}{\beta_{21}-\beta_{11}}$	$\frac{\beta_{10}\beta_{21}-\beta_{11}\beta_{20}}{\beta_{21}-\beta_{11}}$	$\frac{\beta_{10}\beta_{21}-\beta_{11}\beta_{20}}{\beta_{21}-\beta_{11}}$	$\frac{\beta_{10}\beta_{2i}-\beta_{1i}\beta_{20}}{\beta_{2i}-\beta_{1i}}$	$\frac{\beta_{10}\beta_{21}-\beta_{11}\beta_{20}}{\beta_{21}-\beta_{11}}$
η	$\frac{\beta_{11}}{\beta_{21}-\beta_{11}}$	$\frac{\beta_{11}}{\beta_{21}-\beta_{11}}$	$\frac{\beta_{11}}{\beta_{21}-\beta_{11}}$	$\frac{\beta_{1i}}{\beta_{2i}-\beta_{1i}}$	$\frac{\beta_{11}}{\beta_{21}-\beta_{11}}$
γ_{hi}	$\frac{\beta_{1i}\beta_{21}-\beta_{11}\beta_{2i}}{\beta_{21}-\beta_{11}}$	β_{1i}			$\frac{(\beta_{1i}\beta_{21}-\beta_{11}\beta_{2i})}{\beta_{21}-\beta_{11}}$
φ				$\frac{\beta_{11}\beta_{2i}-\beta_{1i}\beta_{10}}{\beta_{2i}-\beta_{1i}}$	
b	$\beta_{20}-\beta_{10}$	$\beta_{20}-\beta_{10}$	$\beta_{20}-\beta_{10}$	$\beta_{20}-\beta_{10}$	$\frac{\beta_{1i}\beta_{20}-\beta_{10}\beta_{2i}}{\beta_{1i}}$; $\forall i \geq 2$
μ	$\beta_{21}-\beta_{11}$	$\beta_{21}-\beta_{11}$	$\beta_{21}-\beta_{11}$	$\beta_{21}-\beta_{11}$	$\frac{\beta_{1i}\beta_{21}-\beta_{11}\beta_{2i}}{\beta_{1i}}$; $\forall i \geq 2$
γ_{wi}	$\beta_{2i}-\beta_{1i}$		$\frac{\beta_{1i}(\beta_{21}-\beta_{11})}{\beta_{11}}$	$\frac{\beta_{1j}(\beta_{2i}-\beta_{1i})}{\beta_{1i}}$	
ψ					$\frac{\beta_{2i}-\beta_{1i}}{\beta_{1i}}$
	Exactly identified	Overidentified	Overidentified	Overidentified if i>2	Overidentified if i>2
Over-id restrictions		$\beta_{1i}=\beta_{2i}$	$\beta_{11}\beta_{2i}=\beta_{21}\beta_{1i}$	$\beta_{1j}\beta_{2i}=\beta_{2j}\beta_{1i}$	$\beta_{1j}\beta_{2i}=\beta_{2j}\beta_{1i}$

Table 3: Descriptive Statistics

Variables	Mean	Std. Error.	% >0	Mean if >0	Std. Error	Source
Total Hhld Hours (inc. unpaid hours)	4447.49	212.00	100	4447.49	212.00	1991 PLSS
Total Hhld Paid Hours	2459.61	118.31	93	2656.01	117.08	1991 PLSS
Total Hhld Paid Hours in NF	906.26	99.16	45	2051.71	97.77	1991 PLSS
Total Hhld Paid Hours in F	1553.35	124.80	75	2069.77	124.38	1991 PLSS
Hhld Earnings (incl. subsistence)	335.90	25.52	100	335.90	25.52	1991 PLSS
Hhld Earnings	271.55	23.29	99	276.06	24.55	1991 PLSS
Hhld Earnings in NF	129.77	20.49	45	293.79	34.29	1991 PLSS
Hhld Earnings in F	93.03	11.51	75	123.96	15.04	1991 PLSS
Avg Yrs of Hhld Schooling (Ages 15+)	4.98	0.29	92	5.40	0.29	1991 PLSS
Avg Yrs of Ed of Hhld Members in NF	3.57	0.16	42	6.50	0.38	1991 PLSS
Avg Yrs of Ed of Hhld Members in F	2.71	0.28	65	5.51	0.23	1991 PLSS
Max Yrs of Ed in Household	5.80	0.26	83	6.95	0.29	1991 PLSS
Max Yrs of Ed of Hhld Members in NF	4.07	0.17	42	7.59	0.43	1991 PLSS
Max Yrs of Ed of Hhld Members in F	3.16	0.34	65	6.28	0.26	1991 PLSS
Years of Ed of Household Head	4.93	0.27	83	5.95	0.26	1991 PLSS
Household Size	4.85	0.11	100	4.85	0.11	1991 PLSS
Total Plot Area	1.86	0.32	95	1.95	0.34	1991 PLSS
Value of Total Capital Stock	1262.61	130.81	99	1265.74	133.11	1991 PLSS
Altitude (km above sea level)	3.13	0.06	100	3.13	0.06	INEI
Density of the Rural Population	56.37	10.39	100	56.37	10.39	INEI
# of Popul. Centres in the District (/1000)	0.07	0.01	100	0.07	0.01	INEI
# of Hostel Beds in the Region (/1000)	7.22	0.26	100	7.22	0.26	Cuánto
Km to the Nearest Post Office (/1000)	0.12	0.02	100	0.12	0.02	1985 PLSS

Population weights are including corresponding to the expansion factors (see World Bank 1991a). These sample means and mean standard errors account for the stratified and clustered design of the PLSS. N=423.

Table 4: Zellner's Seemingly Unrelated Regression Estimates

Dependent Variable	**Log Household Hours**	**Log Household Earnings**
Average Years of Household Education	-0.0073	0.0518***
	(0.010)	(0.015)
Household Size	0.1312***	0.0348***
	(0.014)	(0.022)
Total Plot Size (Hectares)	0.0002	0.0154**
	(0.004)	(0.007)
Log Total Capital Stock (Soles)	0.0819***	0.2014***
	(0.023)	(0.037)
Altitude (Kilometres above Sea Level)	0.3976***	-0.3248***
	(0.053)	(0.085)
Density of Rural Population in the District	0.0008*	0.0003
	(0.000)	(0.001)
Number of Populated Centers in the District	-0.7549	1.1769
	(0.584)	(0.946)
Number of Beds in Hostels in the Region	-0.0844***	0.0262
	(0.018)	(0.030)
Distance to Nearest Post Office (Km)	1.0196***	-0.6389
	(0.307)	(0.497)
Constant	6.3373***	5.8305***
	(0.229)	(0.371)
R-Squared	0.3250	0.1883
LR $\chi^2(8)$	203.64***	98.14***
Cross-Equation Error Correlation Coefficient	0.0627	
Breusch-Pagan Test of Independence	1.665	

Notes: ***significant at 1%, ** at 5% and * at 10%. N=423. Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto (see table 3). (Std. err. in brackets). The estimation used weights corresponding to the expansion factor to account for the non-representativeness of the survey. N=423.

Table 5: EWMD Estimates of Structural Form Model – Basic Model

	Full Controls	Controls on Hours	Controls on Wages
Key Structural Parameters			
Wage Elasticity of Household Labour Supply (η)	-0.1240	-0.1240	-0.4888
	(0.013)	(0.011)	(0.018)
Household Wage Returns to Schooling (μ)	0.0592	0.0592	0.0601
	(0.000)	(0.018)	(0.000)
Effect of Control Variables on Labour Supply			
Household Size	0.1192	0.0830	
	(0.000)	(0.000)	
Total Plot Size (Hectares)	0.0021	0.0078	
	(0.000)	(0.000)	
Total Capital Stock (Log Soles)	0.0967	0.1417	
	(0.000)	(0.000)	
Altitude (Meters above Sea Level)	0.3079	0.0364	
	(0.008)	(0.001)	
Density of Rural Population in the District	0.0008	0.0005	
	(0.000)	(0.000)	
Number of Populated Centers in the District	-0.5153	0.2110	
	(0.160)	(0.163)	
Number of Beds in Hostels in the Region	-0.0707	-0.0291	
	(0.000)	(0.000)	
Distance to Nearest Post Office (Km)	0.8139	0.1904	
	(0.000)	(0.045)	
Effect of Control Variables on Wages			
Household Size	-0.0964		-0.0926
	(0.000)		(0.000)
Total Plot Size (Hectares)	0.0152		0.0155
	(0.000)		(0.000)
Total Capital Stock (Log Soles)	0.1195		0.1258
	(0.001)		(0.001)
Altitude (Meters above Sea Level)	-0.7224		-0.4120
	(0.005)		(0.005)
Density of Rural Population in the District	-0.0006		-0.3882
	(0.000)		(0.000)
Number of Populated Centers in the District	1.9318		1.9403
	(0.583)		(0.588)
Number of Beds in Hostels in the Region	0.1106		0.1092
	(0.001)		(0.001)
Distance to Nearest Post Office (Km)	-1.6586		-1.6492
	(0.161)		(0.163)
Value of Minimized Objective Function	0.0000	3.5204	0.3253
Goodness of Fit Statistic c^2(d.f.)	0.00	101.21	143.92
d.f.	0	8	8
Implied *r*	0.0518	0.0518	0.0307

Notes: Standard Errors are in brackets. Optimization of equation (25) used the Newton-Raphson algorithm for all five models. Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto (see table 3).

Table 6: EWMD Estimates of Structural Form Model – Alternative Models

	Multiple Effects	Endogenous Wage
Key Structural Parameters		
Wage Elasticity of Household Labour Supply (η)	-0.4872	-0.1764
	(0.047)	(0.647)
Household Wage Returns to Schooling (μ)	0.0586	0.0843
	(0.000)	(0.000)
Direct Effect of Schooling on Labour Supply (φ)	-0.0215	
	(0.000)	
Endogenous Wage Parameter (ψ)		-0.7835
		(0.391)
Effect of Control Variables on Labour Supply		
Household Size		0.1166
		(0.007)
Total Plot Size (Hectares)		-0.0001
		(0.000)
Total Capital Stock (Log Soles)		0.0697
		(0.003)
Altitude (Meters above Sea Level)		0.3608
		(0.071)
Density of Rural Population in the District		0.0007
		(0.000)
Number of Populated Centers in the District		-0.6902
		(0.472)
Number of Beds in Hostels in the Region		-0.0758
		(0.004)
Distance to Nearest Post Office (Km)		0.9480
		(0.679)
Effect of Control Variables on Wages		
Household Size	-0.0883	
	(0.000)	
Total Plot Size (Hectares)	0.0159	
	(0.000)	
Total Capital Stock (Log Soles)	0.1332	
	(0.011)	
Altitude (Meters above Sea Level)	-0.7188	
	(0.030)	
Density of Rural Population in the District	-0.0005	
	(0.000)	
Number of Populated Centers in the District	1.9521	
	(0.371)	
Number of Beds in Hostels in the Region	0.1078	
	(0.000)	
Distance to Nearest Post Office (Km)	-1.6400	
	(0.126)	
Value of Minimized Objective Function	0.2223	2.8972
Goodness of Fit Statistic χ^2(d.f.)	8.62 (7)	67.54 (7)
Implied *r*	0.0086	0.0806

Notes: Standard Errors are in brackets. Optimization of equation (25) used the Newton-Raphson algorithm for all five models. Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto (see table 3).

Table 7: Cross-Equation Hypothesis Tests (From SURE Estimates)

Hypothesis		**Test (d.f.)**	**Statistic**
I. Joint Hypothesis that all coefficients are identical across equations		Wald $\chi^2(9)$	109.16***
II. Joint Hypothesis that $\beta_{1i}=\beta_{2i}$ for all i		Wald $\chi^2(8)$	101.08***
III. Separate Hypotheses that $\beta_{1i}=\beta_{2i}$ for each i			
***i* =**	Household Size	Wald $\chi^2(1)$	14.55***
	Total Plot Size (Hectares)	Wald $\chi^2(1)$	3.49*
	Total Capital Stock (log Soles)	Wald $\chi^2(1)$	7.86***
	Altitude (Kilometres above Sea Level)	Wald $\chi^2(1)$	55.17***
	Density of Rural Population in the District	Wald $\chi^2(1)$	0.40
	Number of Populated Centers in the District	Wald $\chi^2(1)$	3.20*
	Number of Beds in Hostels in the Region	Wald $\chi^2(1)$	10.58***
	Distance to Nearest Post Office (Km)	Wald $\chi^2(1)$	8.54***
IV. Joint Hypothesis that $\beta_{11}\beta_{2i}=\beta_{21}\beta_{1i}$ for all i		Wald $\chi^2(8)$	11.51
V. Separate Hypothesis that $\beta_{11}\beta_{2i}=\beta_{21}\beta_{1i}$ for each i			
***i* =**	Household Size	Wald $\chi^2(1)$	10.73***
	Total Plot Size (Hectares)	Wald $\chi^2(1)$	0.19
	Total Capital Stock (log Soles)	Wald $\chi^2(1)$	4.32**
	Altitude (Kilometers above Sea Level)	Wald $\chi^2(1)$	6.09**
	Density of Rural Population in the District	Wald $\chi^2(1)$	2.39
	Number of Populated Centers in the District	Wald $\chi^2(1)$	0.75
	Number of Beds in Hostels in the Region	Wald $\chi^2(1)$	6.39**
	Distance to Nearest Post Office (Km)	Wald $\chi^2(1)$	4.15**
VI. Joint Hypothesis that $\beta_{1j}\beta_{2i}=\beta_{1i}\beta_{2j}$ for all i		Wald $\chi^2(13)$	51.03***
VII. Separate Hypothesis that $\beta_{1j}\beta_{2i}=\beta_{1i}\beta_{2j}$ for each i		See Table 8	

Notes: ***significant at 1%, ** at 5% and * at 10%. N=423. Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto

Table 8: Cross-Equation Hypothesis Tests (From SURE Estimates)

	H_0: $\beta_{1j}\beta_{2i}=\beta_{1i}\beta_{2j}$	*j=* Hhld Size	Total Plot Size	Total Capital Stock	Altitude	Rural Density	Popul. Centers in District	Beds in Hostels in Region
	Total Plot Size	4.39**						
	Total Capital Stock	14.83***	1.14					
	Altitude	15.10***	3.24*	25.47***				
i=	Rural Density	0.00	1.79	1.21	1.08			
	Populated Centers in District	2.06	0.98	3.07*	0.26	0.90		
	Beds in Hostels in Region	2.17	3.66*	12.82***	1.34	0.44	0.81	
	Distance to Nearest Post Office	3.08*	2.92*	9.70***	3.09	0.61	0.42	0.27

Notes: All test statistics are distributed Wald $\chi^2(1)$, ***significant at 1%, ** at 5% and * at 10%. N=423.
Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto

Table 9: Sure Results for Relative Labour Supply and Relative Returns
(Non-Farm Versus Farm)

Dependent Variable	**Difference in Log Household Paid Hours (Non-Farm vs. Farm)**	**Difference in Log Household Earnings (Non-Farm vs. Farm)**
Average Years of Household Education	0.3889***	0.3168***
	(0.066)	(0.061)
Household Size	0.0222	0.0892
	(0.094)	(0.087)
Total Plot Size (Hectares)	-0.0574*	-0.0574**
	(0.030)	(0.028)
Total Capital Stock (Log Soles)	0.0058	-0.3376**
	(0.158)	(0.147)
Altitude (Kilometres above Sea Level)	-2.5762***	-1.6246***
	(0.362)	(0.336)
Density of Rural Population in the District	0.0011	0.0004
	(0.003)	(0.003)
Number of Populated Centers in the District	7.9167**	6.6326*
	(4.015)	(3.725)
Number of Beds in Hostels in the Region	0.1382	0.0150
	(0.126)	(0.117)
Distance to Nearest Post Office (Km)	0.2238	1.8557
	(2.110)	(1.958)
Constant	0.0811	1.5426
	(1.574)	(1.461)
R-Squared	0.1627	0.1155
LR $\chi^2(8)$	88.22***	55.26***
Cross-Equation Error Correlation Coefficient	0.9024	
Breusch-Pagan Test of Independence	344.84	

Notes: ***significant at 1%, ** at 5% and * at 10%. N=423. Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto

Table 10: SURE Results with Different Schooling Measures

Dependent Variable	**Log Household Hours**	**Log Household Earnings**
a. Measure of Schooling:		
Years of Schooling of the Most Educated Household Member	0.0034	0.0658***
	(0.007)	(0.010)
R-Squared	0.3245	0.2384
LR $\chi^2(9)$	203.16***	132.42***
b. Measure of Schooling:		
Years of Schooling of the Household Head	-0.0175**	0.0205*
	(0.007)	(0.012)
R-Squared	0.3331	0.1724
LR $\chi^2(9)$	211.30***	88.12***
c. Measure of Schooling:		
Average Years of Schooling of Household Members Working in Non-Farm	0.0059	0.1064***
	(0.007)	(0.011)
R-Squared	0.3251	0.3294
LR $\chi^2(9)$	203.76***	207.77***
d. Measure of Schooling:		
Average Years of Schooling of Household Members Working in Farm	-0.0087	-0.0047
	(0.008)	(0.013)
R-Squared	0.3260	0.1670
LR $\chi^2(9)$	204.57***	84.81***

Notes: ***significant at 1%, ** at 5% and * at 10%. N=423. Calculations based on the 1991 PLSS, 1985/86 PLSS, INEI and Instituto Cuánto (see table 3). (Std. err. in brackets). The estimation used weights corresponding to the expansion factor to account for the non-representativeness of the survey. N=423.