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Chapter 11:

Off-Farm Employment Opportunities and Educational Attainment in Rural China

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Introduction

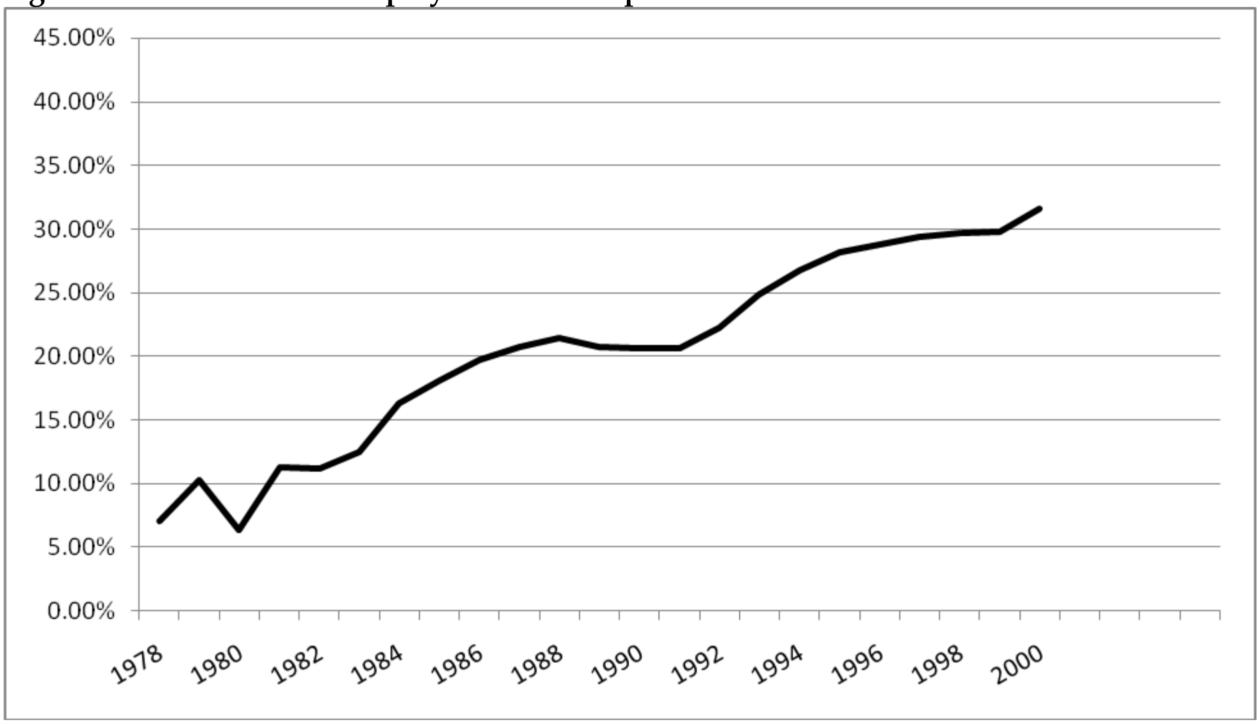
The objective of this chapter is to investigate the relationship between the growth of off-farm employment opportunities and educational attainment in rural China. Since the beginning of the reform era in the late-1970's off-farm employment has surged and education levels have risen dramatically. However, a persistent gap has formed between rural and urban areas, both in terms of income and educational achievement. Despite the existence of positive returns to education in the off-farm labor market (Yang, 1997; Johnson and Chow, 1997), rural children spend significantly less time in school than their urban counterparts. (Connelly and Zheng, 2003; Zheng, 2007) In a recent study de Brauw and Giles (2006) suggest that the increased incidence of rural-urban migration, which has accompanied the growth of off-farm employment, may be partly to blame for discouraging enrollment in upper middle school in rural areas. If this is true, then the growth of off-farm employment opportunities may actually harm long-term development prospects in rural areas by discouraging investment in human capital.

The research reported here examines how a child's potential earnings and ability to participate in the off-farm labor market influence the household's willingness to allocate their children's time to education. Income and participation in each of three major sectors of the rural economy are modeled using data taken from the rural sample of the China Household Income Project (CHIP). We estimate the returns to education and the influence of these returns on the allocation of time to education by young household members. By performing this task, we gain insight into the relationship between employment opportunities and the likelihood of dropping out of school.

Background

Figure 1 shows the growth of the rural off-farm labor force over time. According to the figure, 28% of the rural labor force was employed off the farm when the CHIP surveys were taken in 1995. de Brauw et al. (2002) corroborate this observation, reporting that approximately 32% of the contemporary rural labor force (corresponding to some 154 million rural laborers nationally) was employed off-farm in 1995. Many of these workers were employed in local Township and Village Enterprises (TVEs), but TVEs have not grown fast enough to absorb China's enormous rural labor force. This is partly due to an urban bias in the provision of credit services by China's state-owned financial system (Woo, 2001).

Figure 1: Rural Off-Farm Employment as a Proportion of the total Rural Labor Force



Source: China SSB

Rural-urban migration has become the fastest growing component of off-farm labor in rural China (de Brauw et al., 2002). Before the reform era, internal migration in China was strictly controlled by an internal passport system known as *hukou* (Chan and Zhang, 1999). Each person was assigned a registration status based on their place of birth, and it was nearly impossible to live or work in an area without local *hukou*. In 1988, the *hukou* system was reformed to allow rural residents to apply for temporary work permits in urban areas (de Brauw and Giles, 2006). These permits made it possible for migrants to work in urban areas, but they still did not qualify for the subsidized health care or education benefits provided to residents with urban *hukou*. Workers with rural *hukou* were also often relegated to transient and labor intensive occupations such as construction when they reached the cities.

Hukou restrictions have led to a circular pattern of internal migration, wherein migrants tend to return home periodically only to leave again once they are no longer needed in farm work or local employment. It is difficult to find precise measurements of the incidence of internal migration in China, but according to de Brauw et al. (2002), 54 million of the 154 million rural laborers who found work off the farm in 1995 found it outside their own village. More recently, Omelaniuk (2005) put the number of internal migrants in China above 100 million.

The reform era has also seen several important changes in China's educational policy. In 1986, the National People's Congress (NPC) passed China's first compulsory education law (NPC, 2005). All children were required to complete a minimum of nine years of formal schooling beginning at age six. Some leeway was given to areas where the local level of development made it difficult to provide comprehensive public education, and it is still not clear how strictly the law was enforced in more remote rural areas. Local governments became responsible for ensuring that all children within their jurisdiction achieved the state-mandated level of education, but these localities were also not allowed to charge tuition. To make up for the lack of funds, rural schools charged "fees" instead of tuition and rural households were still forced to fund their child's compulsory education. The result has been persistent rural-urban inequality in China's educational system (Zheng, 2007). While 75% of primary school students are enrolled in rural schools, these schools receive only 50% of total government expenditures on primary education. Despite the passage of the compulsory education law, the average education level of the rural work force in 2000 was 7.33 years, 28% lower than the average education level of the urban work force. The relatively high cost of education imposed on rural households is a likely a cause of lagging educational attainment among rural households compared to those in urban areas.

Literature Review

The existing literature provides some evidence for the existence of positive returns to education in every sector of China's rural economy, but these returns have not yet been fully incorporated into the study of rural educational attainment. Much of the prior research on the relationship between employment and education in rural China focuses on the role of education in the determination of earnings and participation in a given sector. Many studies have examined the role of education as a determinant of migration, with inconclusive results. Liang, Chen and Gu. (2002) and Zhao (1999a) found a positive relationship between the probability of migration and education, However, Zhao (1999b) reports that the household's average level of schooling is negatively related to the probability that that household would produce a migrant, despite the fact that migrants tended to have a higher level of education than the general rural population. Zhao (2002), Meng (1996), and Rozelle, Li, Shen and Hughart (1999) all report no significant relationship between education and the probability of migration.

Few studies have actually attempted to calculate the rate of return to education for migrant labor. Zhao (1997), however, calculates a full rate of return to education for migrant labor by multiplying the additional income expected in the migrant destination by the marginal contribution of education to the probability of migration. This quantity is then divided by the opportunity cost of the time spent on education, yielding a benefit-cost ratio for educational investment with respect to migration. Because migrant earnings can seldom be observed directly, Zhao (1997) uses the prevailing urban wage rate to calculate expected migrant income. This method ignores the fact that temporary migrants rarely hold the same kinds of jobs as workers with urban *hukou*.

The relationship between education and participation in the local wage earning sector has received less attention than has the relationship between schooling and migration, but there is a consensus that higher levels of education are positively associated with the probability of participating in the local wage earning sector (Zhang and Li ,2001; de Brauw et al., 2002; and Knight and Song, 2003), and several studies have found positive returns to education in the local wage earning sector (Yang, 1997; Johnson and Chow, 1997). Parish et al. (1995) report positive returns to education in the local wage earning sector both in terms of increased likelihood of participation and higher wages. de Brauw and Rozelle (2006) report a similar result and improve upon the method used in Parish et al. (1995) by using the Heckman two-step procedure to correct for negative selectivity bias leading to underestimation of the returns to education in local employment.

In order to estimate the influence of growth in off-farm employment on the household demand for education it is necessary to estimate the return to schooling in on-farm employment, which so far we have assumed, is lower than in off-farm employment. Empirically, it is difficult to estimate the returns to education in household farming because an individual's contribution to household farm income cannot be observed directly. Several studies have addressed this problem by using either the average household level of education or the education level of a household "manager" as their measurement of human capital. Yang (1997) found positive returns to household manager education in household farming while Li and Zhang (1998) found positive returns to both the average household level of schooling and the household manager's level of schooling.

Yang (1997) found that the returns to household manager education in household farming were actually higher than the returns to individual education in the local wage earning sector. The author attributes this result to the household head's increased ability to efficiently allocate household resources between farm and off-farm employment, given that he found that the average level of schooling of farm households had no significant effect on household farm value added. Li and Zhang (1998) found significantly lower returns to education than those found in Yang (1997). The returns to household head education and average level of education never exceeded one percent across several different econometric specifications.

Several studies of countries other than China have explored the role of income and participation in a particular sector of the economy as a determinant of educational attainment. Kochar (2004) models household schooling decisions in rural India as a function of the rate of return to education in the urban labor market. Parents choose either a high or a low level of education for their child based on the difference between the probability weighted sums of the returns to high and low education in the urban and rural labor markets. Empirical difficulties preclude calculating the return to education in the rural labor market, but the study finds that higher urban rates of return encourage parents to choose higher levels of schooling for their children. Migration is treated very simplistically, ignoring considerations of distance and the importance of migrant networks. Furthermore, the study ignores the returns to education in farming and the local wage earning sector.

Brown and Park (2001) examine the effects of poverty, school quality and intra-household bargaining on school enrollment decisions and school performance in rural China. They use of the proportional hazards model with cross-sectional survey data to study education decisions in rural China, but the theoretical model focuses more on household budget constraints and the dynamics of intra-household bargaining than on the effects of off-farm employment opportunities. The study models the education decision as the outcome of bargaining between the mother and the father and it specifies a simple rate of return to human capital without specifying from which sector(s) this rate was derived.

Cox and Ureta (2003) use a proportional hazards model is used to study education decisions in rural El Salvador, but no compelling theoretical model is presented to explain the determinants of household demand for education. The study focuses mainly on budget constraints and demographic characteristics of households and individuals as determinants of the education decision. The study makes special reference to the role of migration in education decisions, but only insofar as remittances provide extra income for households to fund education.

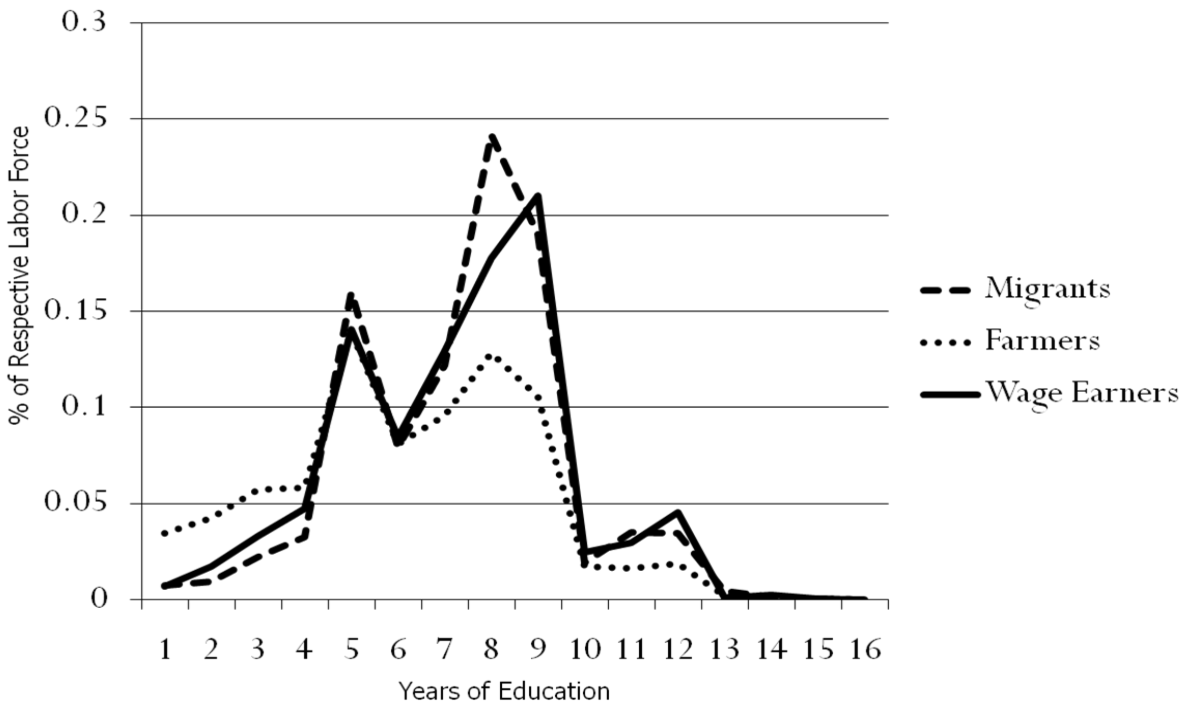
Cox and Ureta's (2003) discussion of the advantages and disadvantages of using proportional hazards models to study education with cross-sectional data is particularly informative. Hazard models calculate the contribution of each covariate to the risk of an individual dropping out of the sample at a given grade level conditional upon the individual having completed the previous grade level. They automatically correct for the incidence of censored observations, which can become a serious problem at higher education levels. Hazard models also permit the inclusion of individuals who have not yet completed their education, which avoids some sample-selection problems. One major drawback of using the proportional hazards model with cross-sectional data is that it forces the researcher to assume that none of the covariates included in the regression have changed over time. For example, the model would attribute the same set of conditions to an individual who dropped out of ninth grade in the current period and someone who had dropped out of ninth grade four years earlier. This problem can be addressed by using a panel data set instead of a cross-section,

de Brauw and Giles (2006), model the effect of the local migrant network on educational attainment explicitly. The local labor market is ignored and it is assumed that positive returns to education only exist in the migrant labor market. The results show that larger migrant networks tend to discourage enrollment in upper middle school, suggesting that increased migration might alleviate income inequality between rural and urban areas in the short run, but also may contribute to educational inequality between rural and urban communities in the long run.

Data

The data used in the empirical analysis come from the rural sample of the 1995 China CHIP. The CHIP was conducted as a joint effort between the China Academy of Science, the Institute of Economics, the Asian Development Bank and the Ford Foundation. The original purpose of the survey was to measure the composition and distribution of income in both rural and urban areas, so it represents a rich source of data on incomes as well as individual, household and community characteristics. The rural sample includes 7,998 households comprising 34, 739 individuals. Surveys were conducted in 113 counties spread out over 19 provinces.

Figure 2: Distribution of Laborers in Each Sector by Education Level



The data summarized in Figure 2 show that education levels in all three labor categories tend to cluster around five, eight and twelve years. These levels correspond to the end of elementary school, lower middle school and upper middle school respectively. The distribution of local wage earners and migrant workers seem to be more concentrated around the higher levels of schooling, while farmers cluster around lower levels. The positive relationship between the level of education and participation in non-farm work suggests that the returns to education are lowest in farming. It appears that workers participating in the local wage earning sector tend to be slightly more educated than migrant workers. A higher proportion of the migrant labor force left school after lower middle school, while a higher proportion of local wage graduated from upper middle school.

Table 1 shows the correlation between the proportion of the local labor force engaged in a particular kind of off-farm employment and several measures of the local level of education. Taken together, these correlations support the hypothesis that the returns to education are higher in off-farm employment and highest of all in the local wage earning sector. The correlations indicate that the incidence of migrant labor is negatively related to local levels of education while the size of the local wage earning sector is positively related to local levels of education. The results are strongest at the province level.

Table 1: Correlations between Off-Farm Employment and Educational Attainment

Province Level Correlations

	Average Years of Schooling	% College and Professional Students	% College, Professional and Technical Students
Migrant Workers (% of Labor Force)	-0.37	-0.455	-0.40
Local Wage Earners (% of Labor Force)	0.81	0.52	0.80

County Level Correlations

	Average Years of Schooling	% College and Professional Students	% College, Professional and Technical Students
Migrant Workers (% of Labor Force)	-0.12	-0.15	-0.17
Local Wage Earners (% of Labor Force)	0.42	0.05	0.36

These correlations may be spurious; it may simply be that households in more developed areas, where the local labor market is larger, are better able to afford education, while households in poorer areas with large numbers of migrant workers pull their children out of school earlier because of binding budget constraints. Deriving the true relationship between local employment opportunities and education requires more sophisticated empirical analysis controlling for various individual, household and community characteristics.

Analysis

We assume that the head of the household maximizes a multi-period household utility function such that time is allocated to education until the marginal benefits equal the marginal costs, where the marginal benefits are defined as the increase in future income resulting from an additional year of schooling and the marginal costs are the direct costs of tuition, books, etc. and forgone labor income opportunities. In any given period t, a worker earns income by allocating time among three sectors: farming (*f*), local wage earning (*l*) and migrant labor (*M*). Income in a given period can be expressed as,

$$(1) \qquad w_{a,t} = t_{f,t} \times w_{a,t}^{f}\left(H_{a,t}\alpha_f, \mathbf{Z}\right) + t_{l,t} \times w_{a,t}^{l}\left(H_{a,t}\alpha_l, \mathbf{Z}\right) + t_{M,t} \times w_{a,t}^{M}\left(H_{a,t}\alpha_M, \mathbf{Z}_M\right).$$

Total labor income (w_a) is determined by the time allocated to each sector (t_f, t_l, t_M), the unique returns to education paid in each sector ($\alpha_f, \alpha_l, \alpha_M$), the individual's current level of education ($H_{a,t}$) and a vector of sector-specific determinants **Z**. We assume that workers know how much work-time they will allocate to each sector in any given period, but that the household head is uncertain as to how the child will allocate his work-time in the future. The existence of unique returns to education and labor in each sector suggests that labor is not free to move between each sector; otherwise the returns in each sector would have been equalized. The high incidence of migrant labor in conjunction with differences in returns among employment sectors further suggests that there is excess supply of labor to local wage earning jobs, which must then be rationed according to some non-price mechanism. The household head calculates a child's expected future earnings as,

$$(2) \qquad \mathrm{E}\left[w_{c,t}\right] = \mathrm{E}\left[t_{ft}\right] \times w_{c,t}^{f}\left(H_{c,t}\alpha_f, \mathbf{Z}\right) + \mathrm{E}\left[t_{l,t}\right] \times w_{c,t}^{l}\left(H_{c,t}\alpha_l, \mathbf{Z}\right) + \mathrm{E}\left[t_{M,t}\right] \times w_{c,t}^{M}\left(H_{c,t}\alpha_M, \mathbf{Z}_M\right).$$

The expectations parameter on child income (w_c) in (2) reflects the household head's perception of the child's possible labor force outcomes. When the household head decides how much time to allocate to education in a given period, he must do so based on the child's potential earnings in each sector as well as his expectation of the child's ability to allocate time to each sector. Based upon these expectations, the household head will allocate the child's time to balance the marginal increase in future expected earnings and the child's forgone expected earnings. This implies that modeling the household's education decision first requires modeling the relationship between education, income, and participation in each sector.

Off-Farm Employment: Income in the local wage earning sector will be estimated using the Heckman two-step procedure as in de Brauw and Rozelle (2006). Here, the local wage earning sector refers exclusively to employment in a local TVE. The Heckman procedure corrects for possible selection bias and separates each determinant's effect on earnings from its effect on the probability of participation. The first step in the Heckman procedure involves estimating a probit function for participation.

The probit function used to estimate participation in the local wage earning sector is,

$$Z = \alpha + \beta_1 SchYrs + \beta_2 Female + \gamma_1 PartyinHH + \gamma_2 LandPerCap + \gamma_3 FlatLand + \gamma_4 K_F PerCap + \delta_1 Impov + \delta_2 MigPctLF + \delta_3 LWEPctLF + \varepsilon . \tag{3}$$

Definitions and summary statistics for each of the variables are presented in Table 2.[1] The probit function is used to calculate an Inverse Mill's Ratio (IMR), which is then used as a regressor in the income equation to correct for selection bias. Estimating the probit function is roughly analogous to estimating E[t_l] from equation 2, but instead of estimating the contribution of each variable to the length time allocated to a given sector, it estimates each variable's contribution to the likelihood of allocating positive time to a given sector. Estimating t_l directly be more informative, but the large number of censored observations for t_l precludes a reliable OLS estimate. Therefore, a tobit function is estimated using the same set of regressors described in (3). This function allows us to observe each variable's effect on time allocated to local wage earning. These results are also reported in Table 2.

In the second step of the Heckman procedure, an income equation is estimated using the IMR derived from the probit estimation. The income equation estimated for the local wage earning sector is,

$$\ln(DW) = \alpha + \tau_1 SchYrs + \tau_2 Exp + \tau_3 Exp^2 + \tau_4 Female + j_1 PartyinHH + \omega_1 \lambda + \varepsilon. \tag{4}$$

Based on Figure 2, years of schooling should be positively associated with income and participation in the local wage earning sector. We would also expect off-farm work experience to be positively related to income, and a quadratic term is included to capture diminishing returns to experience. We include a dummy variable for gender to capture any bias against females in terms of both income and participation in the local wage earning sector. Communist Party membership should increase the likelihood of local wage earning employment and income thanks to the social network it creates. Party membership is likely one of the non-price rationing mechanisms used to distribute the scarce local wage earning jobs. Per capita land and agricultural capital are included along with a dummy variable for land quality (*FlatLand*) to capture the effect of higher household farming productivity.

[1] Due to inconsistencies in the data reported in the survey, many local wage earners had to be eliminated from the sample. The summary statistics presented in Table 2 may not be representative of the sample as a whole, but they do accurately represent the sample used for estimation.

Table 2: Definitions and Summary Statistics for the Off-Farm Income and Participation Model Variables

Variable Name	Definition	Local Wage Earners		Migrants	
		Avg	Std Dev	Avg	Std Dev
SchYrs	Individual's total years spent in school	6.84	2.75	7.13	2.57
Exp	Years since individual took off-farm employment as their main job	3.88	5.50	2.07	3.16
Female	Is the individual female? (1/0)	0.29	0.45	0.27	0.45
PartyinHH	Is there a Communist Party member in the household? (1/0)	0.28	0.45	0.16	0.37
LandPerCap	Household land not used for homestead divided by total household population	1.31	1.11	1.49	1.33
FlatLand	Is the land on which the household sits flat? (1/0)	0.70	0.46	0.35	0.48
K_FPerCap	Total current value of household physical agricultural capital divided by total household population	196.29	322.83	271.79	438.86
Impov	Has the county been designated as impoverished? (1/0)	0.09	0.29	0.32	0.47
MigPctLF	Percent of the local labor force reporting migrant activity	5.12	5.75	12.33	9.01
LWEPctLF	Proportion of the local labor force reporting participation in local wage earning (%)	32.46	24.69	8.83	9.16
DW	Total wage income divided by days allocated to local wage earning	32.52	78.72		
R	Total income remitted by an individual to the household divided by days allocated to migrant labor			4.96	9.26

These land-related variables reflect the opportunity cost of time spent working in an off-farm sector and should be negatively related to participation in local wage earning. The dummy variable *Impov* is included to capture the local level of development. More developed areas should have better developed and higher paying local wage earning sectors, so this variable should be positively related to participation in local wage earning. The last two variables included in the probit function measure the size of the county's local wage earning sector and migrant networks. The size of the local migrant network represents the opportunity cost of working in the local wage earning sector and should be negatively related to participation. Assuming that local wage earning jobs are rationed, then the estimated coefficient on the IMR (ω_1) should be negative, indicating that there exist unobserved variables increasing the likelihood of selection as well as a lower than average reported daily wage.

The econometric results are presented in Table 3. The significant, negative coefficient estimate on the IMR is evidence that negative selection bias was present in this sample. This selectivity bias probably reflects the non-price rationing of local wage employment. Education and experience were positively related to income. The estimated return to education in a local non-farm job is approximately two percent. This is significantly lower than the results found in de Brauw and Rozelle (2006). The presence of a party member in the household was negatively related to income but positively related to participation. The positive coefficient on party membership in both the probit and tobit functions suggests that the negative coefficient on party membership in the income equation is the result of a specification error. Females participated in local wage earning less frequently than men, but gender had no significant effect on earnings. The indicators of household farm productivity, with the exception of land quality, were negatively related participation with the exception of the *FlatLand*. This may be because areas with higher quality land are more likely to be developed and thus more likely to offer greater off-farm employment opportunities. The explicit measure of the size of the local wage earning sector (*LWEPctLF*) was positively associated with participation in the local wage earning sector. The same is true for the size of the local migrant network (*MigPctLF*), but the coefficient estimated in the tobit function was insignificant.

Migrant Labor: Workers employed as migrant laborers also earn wage income, and under ideal circumstances the Heckman procedure would also be applied to this sector. However, migrant income is not observed directly in the CHIP data set. The best available proxy for migrant income is the amount of money each migrant remitted back to their household.

Table 3: Estimation Results for Local Wage Earning Income and Participation

	Local Wage Earning		
	DV=ln(*DW*)	Probit	Tobit
SchYrs	0.02 (2.05)*	0.001 (3.88)**	9.63 (4.15)**
Exp	0.06 (4.73)**		
Exp2	-0.002 (-4.13)**		
Female	-0.05 (0.69)	-0.03 (-13.62)**	-196.55 (-12.69)**
PartyinHH	-0.19 (-2.71)**	0.009 (3.90)**	63.04 (3.93)
LandPerCap		-0.002 (-2.74)**	-22.24 (-3.49)**
FlatLand		0.003 (1.76)+	34.05 (2.05)*
K_F*PerCap*		-.000008 (-3.13)+	-0.06 (-3.23)**
Impov		0.001 (0.41)	-4.88 (-0.21)
MigPctLF		0.0003 (1.80)+	1.87 (1.31)
LWEPctLF		0.002 (21.95)**	12.05 (19.73)**
λ	-0.41 (-5.39)**		
	P> chi^2 = 0		Psuedo R^2=.10

T-statistics are shown in parentheses.
**,*,+ represent significance at the 1, 5, and 10% levels respectively
Includes province level dummies (not shown).
Probit estimate reports marginal effects.
Dependent variable in the income equation is average income remitted daily.

This is not a perfect substitute for migrant income, especially since it forces us to assume that, all migrants of equal levels of education remit an equal proportion of their income. However, using remittances instead of income may actually be more appropriate if we assume that the household head maximizes the income of the household under his control. If this is the case, then his maximization problem would include remitted income rather than total migrant income.

Using remittances instead of income presents several other empirical problems. When estimating a normal income equation, one could plausibly exclude anyone who reported positive time allocated to a wage earning sector but zero income derived from that sector. However, it would not be legitimate to exclude individuals who report positive time allocated to migration but zero remittances. These individuals may have earned positive income but chose not to send any of it home. Unfortunately, it is impossible to distinguish individuals who genuinely remitted no income from individuals who filled out the survey incorrectly, and approximately 50 percent of self-reported migrants reported no remittances. This represents a significant source of error. The high incidence of zero remittances also means that income cannot be estimated using the semi-log specification in (4).

The migrant income equation estimated using the Heckman procedure. The probit function for migrant labor force participation is estimated as,

$$\begin{aligned}(5)\qquad \boldsymbol{Z} = {} & \alpha + \beta_1 SchYrs + \beta_2 Female + \gamma_1 PartyinHH + \gamma_2 LandPerCap + \gamma_3 FlatLand \\ & + \gamma_4 K_F PerCap + \delta_1 Impov + \delta_2 MigPctLF + \delta_3 LWEPctLF + \varepsilon.\end{aligned}$$

Again, a tobit model is estimated to more accurately show the effect of each variable on the individual's t_M.

The IMR derived from the probit function is included as a regressor in the income equation,

$$(6)\qquad DR = \alpha + \tau_1 SchYrs + \tau_2 Exp + \tau_3 Exp^2 + \tau_4 Female + \omega_1 \lambda + \varepsilon.$$

The hypothesized signs of the estimated coefficients are similar to those for the local labor market participation equation. Schooling is expected to be positively related to both income and participation while females are expected to spend less time and earn less income as migrants. The indicators of household agricultural productivity should be negatively related to migrant labor force participation, as should household Party membership. If Party members are better able to find scarce local employment for their family members, then households with a Party member should be less likely to produce a migrant. Off-farm employment experience should raise income. Individuals from impoverished counties should be more likely to migrate because their home villages present fewer opportunities to earn income. The size of the local migrant labor force (*MigPctLF*) should be positively related to participation in that sector, reflecting migrant network effects. The size of the local wage earning sector (*LWEPctLF*) should be negatively related to participation in the migrant labor force because it represents an opportunity cost of time spent migrating.

The econometric results for the migrant labor equations are presented in Table 4. The estimation results for the participation functions mostly conformed to expectations. Schooling and the size of the local migrant labor force was positively related to participation in migrant labor. Individuals in households with higher potential agricultural productivity spent less time migrating, as did individuals in counties with larger local wage earning sectors. Party membership and the local level of development had no significant effect on time allocated to migration.

The estimated income function produced several counterintuitive results. Gender and off-farm experience appears to have no effect on the level of remittances. Surprisingly, an individual's level of schooling is negatively related to the amount remitted. Evaluated at the mean, an additional year of schooling lowers remittances by .02%, but schooling is positively associated with migrant labor force participation. Furthermore, a simple OLS regression on the sample of migrants who reported positive income yields an insignificant, but still negative, coefficient estimate for years of schooling. These counter-intuitive results suggest that using remittances to proxy for income is not a good idea.

Household Farming: Despite the rapid growth of off-farm employment in recent years, household farming remains an important source of income for many households. Of the 7, 998 households included in the CHIP rural sample, only 71 households derived no income from household farming. Estimating the returns to education in farming should allow us predict how households with high agricultural productivity will allocate time to education. Estimating an income function at the household level is not the ideal way to derive the returns to education in household farming, but the data set does report each individual's contribution to farm income. Including the average level of education among all household farm laborers may provide a general idea of the relationship between education and farm income, but it is problematic to calculate a return to education that can be readily compared to the returns calculated in the off-farm sectors.

Table 4: Estimation Results for Migrant Income and Participation

	Migrant Labor		
	DV = DR	Probit	Tobit
SchYrs	-0.20 (-2.36)*	0.01 (16.09)**	25.03 (16.33)**
Exp	-0.07 (-0.51)		
Exp2	0.007 (0.98)		
Female	-0.55 (-1.05)	-0.06 (-17.50)**	-145.88 (-15.86)**
PartyinHH		-0.006 (-1.33)	-4.58 (-0.41)
LandPerCap		-0.003 (-2.00)*	-8.22 (-2.19)**
FlatLand		-0.008 (1.95)+	-19.94 (-1.96)*
K_FPerCap		-.000004 (-1.15)	-0.01 (1.09)
Impov		0.0007 (0.16)	-1.07 (-0.10)
MigPctLF		0.006 (21.90)**	15.66 (21.05)**
LWEPctLF		-0.001 (-3.00)**	-1.35 (-2.60)**
λ	-3.63 (4.75)**		
	P> chi² = 0		Psuedo R^2=.05

T-statistics are shown in parentheses.
**,*,+ represent significance at the 1, 5, and 10% levels
Includes province level dummies (not shown).
Probit estimate reports marginal effects.
Dependent variable in the income equation is average daily income remitted.

Inclusion of the total days allocated to farming by household members in the farm value added equation introduces endogeneity into the value added function. Households expecting higher returns to labor are likely to allocate more time to farming. To control for this endogeneity, farm income is estimated using two-stage least squares. The first stage estimates the expected days allocated to farming using the number of household workers, the presence of a Party member in the household, *LWEPctLF* and *MigPctLF* as instruments. Including the number of household workers controls for the size of the household labor force while Party membership, *LWEPctLF* and *MigPctLF* represent household members' off-farm employment opportunities. The two-stage value added function is specified as,

Farm Income:

$$\begin{aligned}\ln(V) = \alpha &+ \psi_1 FarmDays + \psi_2 AvgSchYrs + \psi_3 Land \\ &+ \psi_4 FlatLand + \psi_5 K_F + \psi_6 PctLandIrr + \varsigma_1 Impov + \varepsilon,\end{aligned} \tag{7}$$

where time is allocated according to,

$$\begin{aligned}\mathrm{FarmDays} = \alpha &+ \varphi_1 AvgSchYrs + \varphi_2 Land + \varphi_3 FlatLand + \varphi_4 K_F \\ &+ \varphi_5 Workers + \varphi_6 PartyinHH + \varphi_7 PctLandIrr + \varsigma_1 Impov + \varsigma_3 MigPctLF \\ &+ \varsigma_4 LWEPctLF + \varepsilon.\end{aligned} \tag{8}$$

Summary statistics for each variable are presented in Table 5. We would expect the direct inputs of farming, including time, land, irrigation, agricultural capital and land quality to be positively related to farm value added and time allocated to farming. Following Yang (1997) and Li and Zhang (1998), education is expected to be positively related to farm income (holding constant the amount of time allocated). Figure 2 shows that farmers tend to be the least educated workers, so we would expect households with higher levels of education to allocate more time to other sectors. The development dummy (*Impov*) should be negatively related to value added but positively related to participation in farming. This would reflect lower prices for agricultural output sold in local markets and the absence of alternative employment opportunities. Party membership and the size of both local off-farm sectors measure the household's off-farm employment opportunities, so they should be negatively related to the time allocated to farming.

The estimation results are presented in Table 6. Average schooling is positively related to value added, but the estimated return is only 0.5%. This is not directly comparable to the two percent return found in the local wage earning sector, but it suggests that the returns paid to individual years of schooling on the farm are much lower than the returns paid in the local wage earning sector. The negative coefficient on the household's average level of schooling in the time allocation function further suggests that the returns to education are higher off the farm, though the estimate is insignificant. All of the agricultural inputs included in the model were positively related to both farm income and time allocated to farming.

Table 5: Definitions and Summary Statistics for the Farm Income and Participation Model Variables

Variable	Definition	Avg	St Dev
V	Total household farm value added in a year including the value of crops consumed by the household (Yuan)	7132.05	4695.67
FarmDays	Total household days allocated to farming	330.61	221.85
AvgSchYrs	Average years of schooling among household members working on the household farm	5.82	2.41
Land	Household land not used for homestead	7.18	6.13
FlatLand	Is the land on which the household sits flat? (1/0)	0.46	0.50
K_F	Current value of household agricultural capital (100 Yuan)	12.29	20.82
Impov	Has the county been designated as impoverished? (1/0)	0.23	0.42
Workers	Number of household members working on the household farm	2.71	1.12
PartyinHH	Is there a Communist Party member in the household? (1/0)	0.16	0.37
MigPctLF	Proportion of the local labor force reporting migrant activity (%)	7.28	6.74
LandPctIrr	Percent of the household's farmland that is irrigated	0.51	0.50
LWEPctLF	Proportion of the local labor force reporting participation in local wage earning (%)	11.75	13.82

Although the estimation results mostly conformed to expectations, there is a potential source of bias built into the model. Twelve percent of the households included in the sample substituted hired labor for household labor. The amount paid to these laborers was netted out of gross farm income, but the hours contributed by hired laborers were not reported in the survey. This would artificially inflate the annual farm value added of households that did not hire labor. This could be resolved by subtracting the imputed opportunity cost of the time household members spent farming from annual value added, but household farming's role as an occupation of last resort makes it difficult to find the appropriate opportunity cost of a household farm worker's time.

Table 6: Estimation Results for Farm Income and Participation

	DV = ln(*V*)	DV = *FarmDays*
FarmDays	0.0009 (16.33)**	
AvgSchYrs	0.005 (2.10)*	-0.54 (-0.64)
Land	0.03 (22.42)**	3.22 (8.03)**
LandPctIrr	0.08 (5.48)**	16.49 (3.64)**
FlatLand	0.16 (11.26)**	17.83 (3.83)**
K_F	0.003 (9.40)**	0.45 (4.43)**
Impov	-0.20 (-11.63)**	43.04 (7.91)**
Workers		95.22 (53.18)**
PartyinHH		-11.93 (-2.23)*
MigPctLF		.05 (0.14)
LWEPctLF		-3.74 (-18.18)**
Adj r^2	0.27	0.41

T-statistics are shown in parentheses.
**,*,+ represent significance at the 1, 5, and 10 percent levels
Includes province level dummies (not shown).
Dependent variable in the income equation is annual farm value-added.
Dependent variable in the time allocation equation is total days allocated to household farming by household members.

Education: Positive returns to education were found in both household farming and the local wage earning sector, and our analysis shows that the returns to education are lower in household farming than in local wage earning. However, the returns to education in the migrant labor market are still unknown. Education is positively associated with the likelihood of participation in both local wage earning and migration, but negatively associated with time allocated to farming. This suggests that the returns to education are higher in the migrant labor market than in household farming, but it is still not clear whether higher returns to education are received by migrants or local wage earners. Figure 2 shows that local wage earners tend to be more educated than migrants, suggesting that the returns to migrant education fall somewhere between those paid to local wage earners and household farmers, but we can not know the actual size of these returns without more data on migrant income.

Assuming that the returns to education are highest in the local wage earning sector, followed by the migrant labor market and household farming, we would expect individuals with relatively higher potential earnings and expected time allocation to local wage earning to spend the most time in education. Similarly, individuals with relatively higher potential earnings and expected time allocation to household farming should spend the least amount of time in education. Individuals with higher expected earnings and time allocation in the migrant labor sector would spend more time in education than a potential farmer but less time than a potential local wage earner.

These expectations cannot be translated directly into hypothesized signs on coefficients in an education demand function because the potential benefits of an additional year of education depend on an individual's subjective discount rate. However, prior research suggests that the discounted returns to education in areas with large migrant networks are such that students are more likely to drop out at the lower middle school level (de Brauw and Giles, 2006). This implies that higher potential earnings and expected participation in the migrant labor sector would have a negative effect on educational attainment at the lower middle school level and above. Assuming that the returns to education are lower in household farming than in migrant labor, we would expect the opportunity cost effect for potential farmers to dominate at even earlier ages.. Higher potential earnings and expected participation in household farming would have a negative effect on educational attainment beginning in elementary school. If the returns to education in the local wage earning sector are higher than those paid in the migrant labor market, then it may be that the returns to education in local wage earning are sufficiently high to encourage investment in education through the end of upper middle school.

These hypotheses can be tested using a proportional hazards model as in Brown and Park (2002) and Cox and Ureta (2003). The general form of the hazard model is:

$$h_i(t) = h_0(t)\exp(\boldsymbol{\beta V}). \tag{9}$$

The term $h_i(t)$ in equation (9) represents the individual's probability (hazard) of dropping out of the sample at time t as a function of the baseline hazard function $h_0(t)$ and a vector of covariates (***V***) with their corresponding estimated coefficients (**β**). The estimation of the baseline hazard function will account for the natural tendency of individuals to drop out around the fifth, ninth and twelfth years, net the estimated effect of the covariates. Using the proportional hazards model forces us to assume that the covariates do not change over time. This could be a significant source of error. In order to adjust for this error, all individuals who dropped out school more than four years before the survey was taken were eliminated from the sample.

An individual's potential earnings and participation in each sector is incorporated into the education model by including the determinants of participation and income from the previous section as covariates. Some of the determinants, such as education level and years of off-farm labor experience, cannot be used in the model. Other variables, such as gender, have the same relationship with participation and income in more than one sector. Identifying the effect of earnings opportunities in a given sector requires finding significant, positive determinants of either income or participation in only one sector. If such a positive determinant of income or participation increases an individual's hazard of leaving school, the returns to education in that sector are too low to induce household investment in education. Similarly, if a positive determinant of income in a given sector decreases an individual's hazard of leaving school, then the returns to education in this industry are sufficiently high to induce household investment in education.

The size of the local wage earning sector and Party membership will be used to identify the effect of local wage earning opportunities. The size of the local migrant network will be used to identify the effect of migrant labor opportunities. Per capita household levels of the agricultural inputs K_F and *Land* along with *FlatLand* and *LandPctIrr* will be used to identify the effect of potential household farming employment. The model will also include, the individual's gender, net household income, average parental level of schooling and the local level of development, though they cannot be used to identify the effect of employment in a particular sector.

Table 7: Summary Statistics and Definitions for the Education Model Variables

Variable	Definition	Avg	St Dev
SchYrs	Individual's total years spent in school	5.79	2.88
Impov	Has the county been designated as impoverished? (1/0)	0.22	0.41
NetHHInc	Net household income in 1995 (Yuan)	7503.02	6168.92
AvgPrntSch	Average schooling level of parents	5.65	2.44
K_F*/Capita*	Current value of physical agricultural capital divided by the household population	314.72	516.10
Land/Capita	Land not used for homestead divided by household population	1.61	1.31
LandPcntIrr	Percent of the household's farmland that is irrigated	0.47	1.37
FlatLand	Is the surrounding land flat? (1/0)	0.48	0.50
MigPctLF	Percent of the local labor force reporting migrant activity	7.53	6.94
PartyinHH	Is there a Communist Party member in the household? (1/0)	0.17	0.38
LWEPctLF	Percent of the local labor force reporting participation in the local wage earning sector	11.16	12.59
Female	Is the individual female? (1/0)	0.46	0.50

Summary statistics for each variable are presented in Table 7. The determinants of income and participation in farming and migrant labor should increase the risk of dropping out of school while the determinants of income and participation in local wage earning should decrease the risk of dropping out. Females and individuals in impoverished regions should be more likely to drop out of school. The parents' average level of schooling and net household income should decrease the hazard of dropping out.

The estimation results are presented in Table 8. Column (1) presents the results for grades one through twelve combined. The estimation results indicate that a one percentage point increase in the proportion of the local labor forced engaged in migrant labor increases the risk of dropping out of school by approximately two percent. The size of the local wage earning sector appears to have no significant effect on the risk of dropping out, but party membership decreases the risk of dropping out by 16%. The results for the household farming variables were mixed. Most of the farming variables had a positive effect on the risk of dropping out, but only the per capita level of agricultural capital had a significant effect. As predicted, females were more likely to drop out and higher levels of parental schooling reduced the risk of dropping out.

Table 8: Estimation Results for the Proportional Hazards Education Model

	(1)	(2)
	Years 1-12	Years 5-10
Impov	0.977	0.983
	(-0.31)	(-0.20)
NetHHInc	1.000	1.00
	(-0.92)	(-0.13)
AvgPrntSch	0.906	0.915
	(-8.87)**	(-7.30)+
K_FPerCapita	1.000	1.000
	(2.18)*	(1.54)
LandPerCapita	1.006	1.035
	(0.25)	(1.44)
LandPcntIrr	0.980	0.988
	(-1.29)	(-0.67)
FlatLand	1.07	1.136
	(1.11)	(1.91)+
MigPctLF	1.018	1.024
	(3.55)**	(4.58)**
PartyinHH	0.840	0.87
	(-2.51)*	(-1.81)+
LWEPctLF	0.997	0.998
	(-0.87)	(-0.50)
Female	1.32	1.287
	(5.42)**	(4.56)**
	P>chi^2 = 0.00	P>chi^2 = 0.00

Z-statistics are shown in parentheses.
**,*,+ represent significance at the 1, 5, and 10% levels
Estimations included province level dummies (not shown)

The estimation results may have been weaker than expected because the sample included individuals from lower grade levels, where drop-outs are relatively scarce. Table 9 shows the drop-out rate for a given interval of school years. According to the table, drop-outs tend to occur between grades five and ten. Examining this subset of the student population may yield more precise estimates. Column (2) presents the results for the education model using only individuals in grades five through ten. The estimation results closely resemble those for the whole sample. Higher levels of parental schooling reduced the risk of dropping out while females were more likely to drop out. The size of the local wage earning sector still had an insignificant effect on the risk of dropping out, but Party membership reduced the risk of dropping out by 13%. The results for the farm-related variables were still weak; only *FlatLand* had a significant effect on the risk of dropping out. Most importantly, a one percentage point increase in the size of the local migrant labor force increased the risk of dropping out by 2.4%.

Table 9: Drop-Outs by School Year for the Education Hazard Model

School Year Interval		Drop-Outs
1	2	28
2	3	30
3	4	27
4	5	28
5	6	121
6	7	118
7	8	127
8	9	480
9	10	474
10	11	30
11	12	51

Conclusions

The analysis presented here suggests that positive returns to education exist in every sector of the rural economy. The returns to education could only be calculated directly for household farming and local wage earning, but the strong positive correlation between education and participation in both of the off-farm labor markets suggests that the returns to education are higher in the off-farm sectors than on the farm. The estimated hazard ratios in the educational attainment model indicate that individuals with higher potential earnings and expected participation in migrant labor market to drop out of school earlier. Household farm productivity and potential local wage employment appeared to have no effect on educational attainment, but the error inherent in using a hazard model with cross-sectional data may be clouding the results.

These results could have serious implications for the long-term development of China's rural areas. As the migrant labor force grows, the growth of local migrant networks could create a preemptive "brain drain" effect, whereby the high opportunity cost of migrant labor income discourages households from investing in higher levels of education. While migrant labor may be appealing as a mechanism for overcoming rural-urban income inequality in the short-run, its negative effect on the growth of human capital may impede the development of China's rural areas.

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