Migrant Opportunity and the Educational Attainment of Youth in Rural China*

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Abstract

In this paper, we investigate how reductions of barriers to migration affect the decision of middle school graduates to attend high school in rural China. Change in the cost of migration is identified using exogenous variation across counties in the timing of national identity card distribution, which make it easier for rural migrants to register as temporary residents in urban destinations. We make use of a large panel household and village data set supplemented by an original follow-up survey, and find a robust negative relationship between migrant opportunity and high school enrollment. This effect is consistent with our finding of low returns to high school education among migrants from surveyed villages.

Key Words: Migration, Educational Attainment, Rural China

JEL Codes: O12, O15, J22, J24

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1 Introduction

Throughout the developing world, promoting higher levels of educational attainment and improving education quality figure prominently among priorities of policy makers. The focus on improving educational attainment is well-founded: a substantial body of research confirms the benefits of human capital accumulation for long-run economic growth, and emphasizes the contribution of educational attainment to higher wages and the improvement of other human development outcomes. However, the decision to enroll a child in school will be influenced by financial constraints that affect a family's ability to cover education-related costs, by the opportunity cost of attending school, and by the expected returns to investment in education. If new off-farm opportunities develop and wages for unskilled labor increase as economies grow, families may find that the costs dominate the real or perceived returns to further schooling. New wage-earning opportunities may lower poverty incidence and improve household welfare in the short-term, but worsen distributional outcomes in the long-term as families in poor areas choose employment over investment in education.[1] Understanding how new opportunity in off-farm labor markets affects family educational investment decisions is important for policy makers charged with considering appropriate subsidies for tuitions and other costs associated with different levels of schooling.

In this paper we examine how changing opportunities in the migrant labor market affect the decisions of families in rural China to enroll middle school graduates in high school. Whereas middle school completion is mandated by policy in China (Tsang, 1996), high school education is neither compulsory nor heavily subsidized in rural areas. High school tuitions can be a substantial share of household annual income, and credit constrained families may be unable to enroll children in school. Increasing wealth associated with migrant or other off-farm employment opportunities may ease credit constraints and lead to higher enrollment rates (Edmonds, 2004; Glewwe and Jacoby, 2004). In addition, if returns to high school education either locally (Foster and Rosenzweig, 1996) or in migrant destinations (Kochar, 2004) are increasing then we might expect to find increases in the probability that families will enroll children in high school.

In China, improved migrant opportunities reduce the effect of credit constraints on high school

[1] The trade off between short-run benefits of wage employment to poor households (who potentially face credit constraints) and long-run benefits associated with educational investment has been emphasized recently by Rosenzweig (2003) and Glewwe and Jacoby (1998).

enrollment, but they also raise the net return to migrant employment and therefore the opportunity cost of remaining in school. In this paper, we find that a decline in the cost of participating in migrant employment leads to a decrease in the probability that children will attend high school in rural China. The magnitude of the estimated effects are fairly large, and can be explained by increases in off-farm opportunities in migrant destinations with referral through the migrant network. The effect is plausibly reinforced by higher returns to local wage employment in home communities as the size of the local labor force declines through out-migration.

One drawback to much of the literature on the effects of migration on source communities in China is that migrant opportunity is difficult to identify in a clean and convincing way. An important contribution of the paper lies in the development of an instrumental variables approach that may be useful for identifying the impact of migration on a range of outcomes in source communities in rural China. We use a reform in the residential registration system that made it easier for rural migrants with national identification cards (IDs) to live legally in cities after 1988. National IDs had not been distributed to all rural counties as of 1988, and we exploit differences in the timing of access to IDs to identify the cost of migrating to cities. We assume that the size of the village migrant network living in cities is related to the time since residents of a county received IDs. We show that the instrument is both related to the size of the migrant network from a village and plausibly exogenous to the school enrollment decision.

After showing the negative impact of migrant opportunity on high school enrollment, we examine economic channels through which this effect operates. We estimate migrant labor wage regressions and show that returns to a year of schooling in the migrant labor market are indeed positive but nonlinear: returns to elementary and middle school are positive and significant, but point estimates of returns to a year of high school are low and do not differ significantly from zero. Finally, a larger migrant network outside villages implies a smaller labor force. Thus, with the expanding migrant labor market, the opportunity cost of high school may rise both because the net return from migrant employment is increasing and because depletion of the local labor market with migration leads to an increase in returns to relatively unskilled employment locally. We find that as the size of the migrant labor network increases, the probability that high school age children are employed in either the migrant or local off-farm employment also increases.

The paper proceeds as follows. In the next section, we provide background on rural-urban migration in China and on the demographic and educational profile of rural migrants from other research and data sources. We next introduce the data sources that we will use for our analyses and provide descriptive evidence on cohort trends in educational attainment and age of first-time out-migrants. Section 3 briefly discusses theoretical background, and section 4 introduces our empirical strategy. In section 5, we present our results and robustness checks, and section 6 concludes.

2 Background

Rural-Urban Migration in China

During the 1990s, China's labor market experienced a dramatic change with rapid growth in the volume of rural migrants moving to urban areas for employment. Estimates using the one percent sample from the 1990 and 2000 rounds of the Population Census and the 1995 one percent population survey suggest that the inter-county migrant population grew from just over 20 million in 1990 to 45 million in 1995 and 79 million by 2000 (Liang and Ma, 2004). Surveys conducted by the National Bureau of Statistics (NBS) and the Ministry of Agriculture include more detailed retrospective information on past short-term migration, and suggest even higher levels of labor migration than those reported in the census (Cai, Park and Zhao, 2004).

Before labor mobility restrictions were relaxed, households in remote regions of rural China faced low returns to local economic activity, raising the possibility that they were stuck in geographic poverty traps (Jalan and Ravallion, 2002). A considerable body of evidence suggests that the growth and scale of rural migrant flows in China make migrant opportunity an important mechanism for poverty reduction in China. Studies of the impact of migration on source communities suggest that opportunities to migrate are contributing to growth in rural incomes (Taylor, Rozelle and de Brauw, 2003), easing problems of risk-coping and risk-management (Du, Park and Wang, 2004; Giles, 2005; Giles and Yoo, 2005), and possibly leading to higher levels of local investment in productive activities (Zhao, 2003).

Institutional changes, policy signals and the high return to labor in urban areas each played a role in the expansion of migration during the 1990s. An early reform of the household registration (*hukou*) system in 1988 first established a mechanism for rural migrants to obtain legal temporary residence in China's urban areas (Mallee, 1995). In order to take advantage of this policy change, rural residents required a national identity card to obtain a legal temporary worker card (*zanzu zheng*), but not all rural counties had distributed IDs as of 1988.[2] As China recovered from its post-Tiananmen retrenchment, some credit a series of policy speeches made by Deng Xiaoping in 1992 as signaling renewed openness toward the marketization of the economy, including employment of migrant rural labor in urban areas (Chan and Zhang, 1999). Combined with economic expansion, these institutional and policy changes led to increased demand for construction and service sector workers, and catalyzed the growth in rural-urban migration that continued throughout the 1990s.

The use of migrant networks and employment referral in urban areas are important dimensions of China's rural-urban migration experience. Rozelle et al (1999) emphasize that villages with more migrants in 1988 experienced more rapid migration growth by 1995. Zhao (2003) shows that number of early migrants from a village is correlated with the probability that an individual with no prior migration experience will choose to participate in the migrant labor market. Meng (2000) further suggests that variation in the size of migrant flows to different destinations can be partially explained by the size of the existing migrant population in potential destinations.[3]

Additional descriptive evidence from a survey of migrants living in cities underscores the likely importance of migrant networks in lowering the cost of finding employment in urban areas. In Table 1 we present descriptive evidence from a survey of rural migrants conducted in five of China's largest cities in late 2001.[4] More than half of the rural migrants in the urban survey secured employment

[2] Legal temporary residence status does not confer access to the same set of benefits (e.g., subsidized education, health care, and housing) typically associated with permanent registration as a city resident.

[3] Referral through one's social network is a common method of job search in both the developing and developed world. Carrington, Detragiache, and Vishnawath (1996) explicitly show that in a model of migration, moving costs can decline with the number of migrants over time, even if wage differentials narrow between source communities and destinations. Survey-based evidence suggests that roughly 50 percent of new jobs in the US are found through referrals facilitated by social networks (Montgomery, 1991). In a study of Mexican migrants in the US, Munshi (2003) shows that having more migrants from one's own village living in the same city increases the likelihood of employment.

[4] We use the migrant sub-sample of the China Urban Labor Survey (CULS), which was conducted in late 2001 by the Institute for Population and Labor Economics at the Chinese Academy of Social Sciences (CASS-IPLE) working in collaboration with local National Bureau of Statistics Survey Teams. Researchers from Michigan State University and the University of Michigan collaborated in funding, designing, implementing and monitoring the survey. Using the 2000 Population Census as a guide, neighborhoods were selected using a proportional population sampling procedure. Sample frames were then assembled from residents' committee records of migrant households, and public security bureau records of migrants living on construction sites. Very short-term migrants are unlikely to have made it into the sample frame.

before their first migration experience, and more than 90 percent moved to an urban area where an acquaintance from their home village lived. Notably, before migrating over half of migrants surveyed had a member of their extended family living in the city, and over 65 percent knew hometown acquaintances other than a family member in the city.[5]

The Rural Educational System and the Age and Educational Attainment of Rural-Urban Migrants

In rural China, education became compulsory through middle school after passage of the Law on Compulsory Education in 1986 (Tsang, 1996). In practice, some rural areas took considerable time to meet this standard, and many rural areas still provide only five years of elementary education instead of the mandated six years. Thus, children completing middle school in some rural areas have eight years of formal schooling, while in other areas a middle school graduate has nine years of education. After middle school, children may take admissions tests for academic or vocational-technical high schools, but families of students who pass examinations are required to pay substantial tuition before they can enroll.

Prior research on rural-urban migrants has found a positive correlation between years of schooling and the ability to participate in migrant labor markets.[6] Much of this research has been conducted in China's poorer areas (e.g., Du, Park and Wang, 2004), where educational attainment often falls short of compulsory education through middle school (Brown and Park, 2002). Therefore these studies may pick up the effect of completing additional years of middle school on the ability to migrate. Descriptive information on migrants in CULS cities reinforces the idea that migrants do not require high school education to find employment in urban areas (Table 2, Panel A). Of the rural-urban migrants surveyed in the CULS, nearly 82 percent had a middle school education or less. While migrants with a high school education may earn higher wages, it is not evident that high school graduation is necessary to find a job as a migrant. If a bias exists in the CULS, it picks up more educated migrants who are successful at finding employment in larger cities and have established a stable long-term residence. The CULS data are consistent with information on interprovincial migration from the 1990 and 2000 Population Census (Table 2, Panel B). Over 75

[5] Categories of acquaintance type shown in Table 1 are not exclusive because many migrants were preceded to cities by both family members and other hometown acquaintances.

[6] More generally, Yang (2004) finds that prior household educational attainment helped to facilitate the adjustment to use of goods and factor markets during transition.

percent of migrants from RCRE provinces have a middle school education or less. This figure does not provide a clear picture of the share of rural migrants with a middle school education or less, as the Census data pool urban and rural migrants and therefore include a large number of college educated, urban-urban migrants. Nonetheless, the data sets confirm that though some education may be useful for migration, education beyond middle school may not be necessary for most jobs in which migrants are employed.

Evidence on Educational Attainment and Age of Migration from the RCRE Supplemental Survey

For our primary analysis, we use household and village surveys conducted in fifty-two villages of four provinces from August to October 2004 in collaboration with the Research Center for Rural Economy (RCRE) at the Ministry of Agriculture. All 3999 households in the most recent wave of RCRE's panel for these four provinces were enumerated, allowing us to match villages and households from the 2004 supplemental survey with a historical panel of villages and households that RCRE has surveyed annually from 1986 to 2003.[7] One unique feature of the supplemental survey is that education level, birth year, current occupations, work and migration history and residence locations were enumerated for all children and other current and former residents (including deceased former residents) of households in the survey. This survey design eliminates the selection bias that would occur if household survey data with only current household residents were used to study educational attainment.

We summarize different aspects of educational attainment by cohort in Figures 1 through 3 for individuals born after 1940 and residing (or previously residing) in RCRE households. The RCRE supplemental survey data suggest that cohorts from RCRE villages have educational attainment levels consistent with those found in the census.[8] Educational attainment is rising over time, and the educational attainment of girls and boys converges by the 1975 birth cohort.

In the RCRE survey, summary statistics on the age of first migration are consistent with surveys of migrants in urban areas. Between 1987 and 2004 the number of migrants of all ages increased

[7] A detailed discussion of a larger nine-province sample from the RCRE panel dataset, including discussions of survey protocol, sampling, attrition, and comparisons with other data sources from rural China, can be found in the data appendix of Benjamin, Brandt and Giles (2005). This paper makes use of village and household data from the four provinces where the authors conducted a follow-up survey, which are Shanxi, Jiangsu, Anhui and Henan.

[8] See Hannum et al (2004) for a discussion of evidence on rural educational attainment using information from the 2000 Population Census.

while the average age of first migration remained fairly constant at 20 years of age (Figure 4). Individuals over 30 or 35, however, might reasonably be considered outliers who keep the average age of migration constant when it would otherwise decline due to increasing migration among teenagers. Figure 5 shows lowess estimates of the share of three teen cohorts engaged in temporary or long-term migrant employment outside of their home counties. While it is clear that the share of 15 and 16 year olds in migrant employment is increasing, the rate of increase does not appear dramatic, and the level of migration is low enough that it would not necessarily require a decline in high school enrollment. The shares of 17 and 18 year olds and 19 and 20 year olds working in migrant jobs are increasing at a much faster rate. It is important to note that these effects are averaged across individuals in many villages, and once we control for village fixed effects in our analyses the increase in teenagers migrating for employment reasons may be substantial in some villages. Given that much migration occurs after employment has been secured through referral, it is also possible that potential migrants go through a period of waiting after completion of middle school before departing to work in an urban area.

3 Theoretical Framework

Below we present a simple model to frame the potential effects of expanding migrant opportunity on the decision to enroll a child in high school. The model illustrates the relationship between the cost of participating in migrant labor markets, expected returns to high school attainment, and the opportunity cost of schooling, as credit constraints are eased. We focus our discussion of the model on the high school enrollment decision.[9]

Assume that in each period households may choose to invest in human capital, H_t, and physical capital K_t used in agricultural or non-agricultural household self-employment activity. Human capital is accumulated when a child attends school for e_t share of his or her time during the year, with a cost of P_t^e for tuition, books, supplies, and other costs associated with schooling. The household accumulates human capital according to:

[9] Glewwe and Jacoby (2004) and Kochar (2004) both present models with these basic features. We follow Glewwe and Jacoby in our derivation but allow for the possibility of migrant wage employment where returns in the migrant market are dependent on size of the village migrant network and accumulated human capital.

$$H_{t+1} = H_t + \psi_t G(e_t) \tag{1}$$

where G is a concave production function and ψ_t is a learning productivity parameter reflecting school quality, child ability and factors that affect the motivation and effort of the child.

Households earn income from some or all of the following activities: agricultural production, non-agricultural self-employment and employment in migrant labor markets. Home production may utilize physical capital and labor of both children and adults, $y_t^h = \theta_t F\left(K_t, L_t^{a1}, L_t^{c1}\right)$, where θ_t is a multiplicative productivity shock with a mean of one, K_t is the current stock of capital, and L_t^{a1} and L_t^{c1} are adult and child labor used in self-employment activities, respectively. Household income from the migrant labor market will be $y_t^m = w(H_t^a, M_{jt})L_t^{a2} + w(H_t^c, M_{jt})L_t^{c2}$, where L_t^{a2} and L_t^{c2} are adult and child labor used in migrant employment, and $w(H_t^a, M_{jt})$ and $w(H_t^c, M_{jt})$ are the wages that can be earned in the migrant labor market by adults and older children, respectively. We treat wages in the migrant market as net returns to the household from migrant employment, and are a function of human capital, H_t^a and H_t^c, and the effect of the migrant network, M_{jt}, from village j on the cost of migrating.[10] We assume that as M_{jt} increases, the cost of migrating falls. The household will thus accumulate physical capital according to

$$K_{t+1} = K_t + \theta_t F\left(K_t, L_t^{a1}, L_t^{c1}\right) + w(H_t^a, M_{jt})L_t^{a2} + w(H_t^c, M_{jt})L_t^{c2} - c_t - P_t^e e_t \tag{2}$$

We further restrict $K_t, K_{t+1} \geq 0$, which amounts to a credit constraint that affects the ability of the household to borrow against future income for current expenditures on consumption, tuition and education related expenses.

Households have a given number of school-age children at time $t = 0$. From periods $t = 0$ to $t = T - 1$ children are eligible for school. In period T and beyond, children are no longer eligible for school and returns to educational investment through period T are realized. We assume that if school age children are employed in farm production or off-farm activities, they perform unskilled tasks for which human capital is unimportant. The utility of human and physical capital stocks

[10] The migrant network may influence net income from migration by both lowering the cost of migration and by facilitating matches to higher quality jobs. These effects will be observationally indistinguishable, as they both raise the net return to participating in the migrant labor market.

accumulated by period T over the remaining life of the household can be written as a terminal value function, $\Phi(K_T, H_T)$, which represents the uncertain future utility of the household and incorporates expected consumption and financial benefits from educated children. Current utility is an additively separable concave function of consumption c_t, the leisure of adults and children ($l_t^a = 1 - L_t^{a1} - L_t^{a2}$ and $l_t^c = 1 - L_t^{c1} - L_t^{c2}$, respectively) and the current school enrollment of a school-age child, e_t. The household's objective function is to maximize

$$E_0 \left[\sum_{t=0}^{T-1} \delta^t U\left(c_t, l_t^a, l_t^c, e_t\right) + \Phi\left(K_T, H_T\right) \right] \tag{3}$$

subject to equations (1) and (2) and the borrowing constraint, where δ^t is the subjective discount factor and E_0 is the expectations operator. Households are uncertain about future values of ψ_t, θ_t, $w(\cdot,\cdot)$, P_t^e, and Φ.

The first-order conditions for an interior solution are:

$$U_c(t) = \lambda_t \tag{4}$$

$$U_{l^a}(t) = \lambda_t \left(\theta_t F_{L_t^{a1}}(t) + w(H_t^a, M_{jt}) \right) \tag{5}$$

$$U_{l^c}(t) = \lambda_t \left(\theta_t F_{L_t^{c1}}(t) + w(H_t^c, M_{jt}) \right) \tag{6}$$

$$U_e(t) + \mu_t \psi_t G_e(t) = \lambda_t \left(\theta_t F_{L_t^{c1}}(t) + w(H_t^c, M_{jt}) - P_t^e \right) \tag{7}$$

where μ_t and λ_t are time-varying shadow values of physical and human capital that will be scaled by the discount factor, δ^t. Solving the system of equations yields an enrollment demand function of the form:

$$E_t^* = E^* \left(\lambda_t, \mu_t, \psi_t, \theta_t F_{L_t^{c1}}(t), \theta_t F_{L_t^{a1}}(t), w(H_t^a, M_{jt}), w(H_t^c, M_{jt}), P_t^e \right) \tag{8}$$

Because preferences are additively separable, current period decisions depend on past decisions and expected future prices only through the shadow prices of physical and human capital, μ_t and λ_t. Further, after controlling for λ_t, the borrowing constraint will only influence intertemporal decisions through the intertemporal Euler equation and have no affect on intratemporal decisions.

Using equations (4)-(7), we can trace out the potential effect of an increase in the village migrant labor network, M_{jt}, on high school enrollment decisions. First, since income earned in the off-farm market will increase, the shadow price of physical assets, λ_t, will fall. The wealth effect eases credit constraints associated with paying high school tuition, and may facilitate school high school enrollment.

Second, an increase in M_{jt} affects the shadow price of human capital, μ_t. The shadow price can be thought of as the expected "return to schooling," since the terminal condition requires that $\mu_T = \frac{\partial \Phi}{\partial H_T}$, and it can be shown that $\mu_t = \mu_T$. The actual functional form of the terminal condition will affect whether or not the return to schooling rises with human capital investment. If $\frac{\partial w}{\partial H_t^c} > 0$ and is of significant magnitude when children complete middle school, the return to schooling will be positive.[11]

The third and fourth effects of an increase in the village migrant network size operate through the shadow prices of adult and child time. Since w will increase with an increase in M_{jt}, the net income potentially earned in the migrant market given the child's current stock of human capital also increases. Therefore the value of the child's time increases, decreasing the likelihood of further school enrollment. An increase in M_{jt} also raises the value of parent time in the migrant labor market and has a cross-price effect in equation (8) that is difficult to sign. The net effect of migrant opportunity on high school enrollment is a combination of all four of these effects and cannot be signed a priori.

We further simplify the enrollment demand functions that we will estimate by recognizing that farm productivity will be a function of potentially time varying household endowments and other characteristics, $\mathbf{X}_{ht}$, that affect wealth and family preferences for education. Among these characteristics are parent human capital, which also affect the potential returns that parents may earn both in the labor market and through household activities. We thus simplify the enrollment

[11] As we will see below, this is an empirical matter and may be influenced by the nature of institutions that affect the segmentation of rural and urban laborers in China's cities.

demand function to:

$$E_t^* = E^*\left(\lambda_t, \mu_t, \psi_t, \theta_t, \mathbf{X}_{ht}, M_{jt}, P_t^e\right) \tag{9}$$

where enrollment demand is now a function of the shadow price of physical assets, the expected return to schooling (or shadow price of schooling), child ability, productivity shocks, household endowments and characteristics, migrant opportunity as proxied by the size of the village migrant network, and the tuition and other costs associated with high school enrollment.

4 Empirical Methodology

To understand how migrant opportunity affects the decision to enroll middle school graduates in high school, we need to control for such factors as lifetime wealth, preferences, prices and unobserved ability that might covary with the probability of school enrollment and off-farm opportunities. From arguments of the enrollment demand function in equation (9), a reduced form model of the discrete decision of household h to enroll child i in high school can be written:

$$E_{it} = \beta_0 + \beta_1 M_{jt} + \mathbf{Z}_{jt}'\beta_2 + \mathbf{X}_{ht}'\beta_3 + \mathbf{u}_j + \mathbf{v}_t + \nu_i + e_{ihjt} \tag{10}$$

where E_{it} is 1 if an individual completing middle school in year t enrolls in high school in year $t+1$, and 0 otherwise. M_{jt} is the number of village residents with employment as migrants outside the home county, and proxies for size of the migrant network. $\mathbf{Z}_{jt}$ are other time-varying village characteristics that potentially affect local returns to high school education and alternative activities (the shadow value of schooling, μ_t, in equation (9)), and local factors influencing credit constraints faced by all households. Household characteristics, $\mathbf{X}_{ht}$, are introduced in some models to control for family preferences for education, factors affecting lifetime household wealth, and the likelihood that the household faces credit constraints. Some important village characteristics, like location, do not vary over time but have considerable influence over both labor market returns and the cost of obtaining education, and so we include $\mathbf{u}_j$, a vector of village fixed effects, in all models. Price levels, macroeconomic shocks and trends can also affect family income, the cost of education, and the demand for migrant labor, and we control for these effects with year dummy variables,

$\mathbf{v}_t$. The ability of individual middle school graduates, ν_i, is unobserved but important for high school enrollment decisions, and reflects the education productivity parameter, ψ_t, in equation (9) above. In particular, students must test into high schools and it is likely that examinations are more competitive in settings where the local supply of spaces in high school is more constrained. In models that include household information, we include the parents' years of schooling as proxies for dimensions of ability picked up from the family, but other dimensions will remain unobserved. In order to identify the impact of migrant opportunity on enrollment decisions, instruments for endogenous migrant network size must be plausibly unrelated to unobserved individual ability.

We assume an error term, e_{ihjt}, that allows for correlation of errors among individuals from the same village, but is independent across village clusters. Although we only observe individuals in the year that a family makes a decision about high school enrollment, the decisions are made at different points in time from 1986 to 2003. Village migrant network size, time-varying village effects and instruments for migrant network size all have a village level time component. Correlation in the errors with which these variables are measured can introduce correlation in the error term, and so our estimator must allow for correlation of errors within the village.[12]

Since E_{it} is a binary variable, one might consider using a non-linear model such as a probit to estimate equation (10). However, we are concerned with the endogeneity of migrant network size, M_{jt}, and implementing an "instrumental variables" probit estimator requires uncomfortable joint normality assumptions about the error terms. We choose to work with the linear probability model because it allows us to implement a linear instrumental variables estimator, and the mean conditional probability that a middle school graduate will enroll in high school is nearly 0.5. In this situation the marginal effects are unlikely to differ significantly from those calculated from a probit.[13]

We use an instrumental variables generalized method of moments (IV-GMM) estimator to obtain efficient estimates of (10) while allowing for correlation within village clusters. For computational purposes, we control for village fixed effects by calculating village means for all variables and then

[12] Kedzi (2003) emphasizes the importance of calculating standard errors robust to serial correlation of errors in fixed effects models. Bertrand, Duflo and Mullainathan (2004) show that failure to consider serial correlation in differences-in-differences analyses may lead to estimates of standard errors that are too small.

[13] Nonetheless, we estimated equation (10) using an instrumental variables probit model (Rivers and Vuong, 1988), and the signs and statistical significance of the estimated marginal effects are consistent with the coefficients on linear probability models that we present here.

demeaning. We then follow a procedure outlined in Wooldridge (2002, p. 193) to obtain consistent coefficient estimates and estimates of the variance-covariance matrix robust to arbitrary forms of heteroskedasticity and serial correlation.

Identification Strategy

Estimating equation (10) using OLS would almost certainly introduce endogeneity bias because our proxy for the migrant network reflects factors that influence both the demand for and supply of migrants from the village. A persistent disruption to the local economy, for example, could limit the ability of parents to cover tuition costs while raising the relative return to migrant employment in more distant destinations, inducing a negative relationship. On the other hand, positive correlation between migrant network size and unobservables affecting high school enrollment could exist if increases in household wealth or expanded high school capacity (and lower test scores for competitive admission) occurred simultaneously with growing access to migrant employment. To identify the effect of the migrant network and the higher net return from migration that comes with referral, we must find an instrumental variable that is correlated with the share of migrants living outside the village but unrelated to unobserved individual, household and community factors affecting high school enrollment.

We make use of two policy changes that, working together, affect the strength of migrant networks outside home counties, but are plausibly unrelated to the demand and supply for schooling. First, a new national ID card (*shenfen zheng*) was introduced in 1984. While urban residents received IDs in 1984, residents of most rural counties did not immediately receive IDs. In 1988, a reform of the residential registration system made it easier for migrants to gain legal temporary residence in cities, but a national ID card was necessary to obtain a temporary residence permit (Mallee, 1995). While some rural counties made national IDs available to rural residents as early as 1984, others distributed them in 1988, and still others did not issue IDs until several years later. The RCRE follow-up survey asked local officials when ID cards had actually been issued to rural residents of the county. In our sample, about half of the counties issued cards in 1988 (25 of 52), but cards were issued as early as 1984 in one village and as late as 1996 in another. It should be emphasized that ID cards were not necessary for migration, and large numbers of migrants live in cities without legal temporary residence cards. However, migrants with temporary residence cards have a more secure position in the destination community, hold better jobs, and make up part of the long-term migrant network within a city. Migrant networks take time to build up and time-since-IDs-were-issued has an apparent non-linear relationship with the size of the migrant network. We experimented with quadratic, cubic and quartic functions of time-since-IDs-issued, and settle on the quartic function for our instruments because we find it fits the pattern of expanding migrant networks better than the quadratic or the cubic functions.

Though this policy change is plausibly exogenous to schooling decisions, it does not provide us with an ideal identification strategy. In a perfect world, a randomly implemented policy would exist that affected the ability to migrate from some counties but not others. As the distribution of ID cards was not necessarily random, we must be concerned that counties with specific characteristics were singled out to receive ID cards earlier than other counties, or that features of counties receiving IDs earlier are systematically correlated with trends in educational attainment.[14]

In order to assess the possibility of endogenous placement bias in the distribution of ID cards, to control for this endogeneity, and then to determine the likelihood that our results are biased by endogenous placement, we proceed as follows. First, we split the sample into early, middle and late adopters and examine lowess plots and average characteristics across groups to identify obvious evidence of bias. Next, in our estimation we include village fixed effects to control for unobserved village characteristics that may lead to endogenous placement, and check the robustness of our results to inclusion of additional time-varying village variables that proxy for time-varying village level unobservables that may be related to the timing of ID card distribution. Finally, we perform a Hahn-Hausman test (Hahn and Hausman 2002). If our estimates fail the Hahn-Hausman test, one possible implication would be that our instruments are correlated with the unobservables in equation (10). In the remainder of this section, we present descriptive evidence that is largely supportive of our identification strategy. In our discussion of results in section 5, we assess the robustness of our estimates and perform the Hahn-Hausman test.

The Plausibility of the Years-Since-ID Instrument

To evaluate the plausibility of using years-since-ID-card-distribution as an instrument, we first categorize villages as receiving cards prior to 1988, in 1988, or after 1988, and look for significant

[14] The new ID card was implemented by provincial offices of the Ministry of Civil Affairs.

differences in observable average village characteristics measured in 1988 (Table 3). Although some differences appear between early and late villages, few are statistically significant. For example, although early adopters were more likely to be near cities, they were not all near cities. The only statistically significant difference at the ten percent level was between mean income per capita in villages receiving ID cards before 1988 and other villages.

Even if villages that issued ID cards early are not observably different than other villages, one should be concerned that the timing of ID card receipt was endogenous. Local demand for migration may have led county officials to issue ID cards in response to a sharp rise in migration from the village, and in this case, issuing ID cards would have little to do with new migration, but may have simply been correlated with migration flows already occurring. To consider whether demand for migration drove distribution of IDs, we plot the log number of migrants in the village workforce against the years since ID cards were issued (Figure 6). The lowess plot through the data indicates that migration appears to rise immediately after or as ID cards are issued, accelerates and then slows to a plateau about 10 years after ID cards are issued. To ensure that our results are not driven by the twenty-five counties receiving IDs in 1988, we plot the figure with these villages removed in Figure 7.

Finally, one might worry that our instruments are correlated with differing trends in enrollment prior to distribution of IDs. To examine whether enrollment trends obviously differed prior to ID distribution, we plot the share of individuals entering high school who are of age to do so by birth year cohort and by the timing of ID card distribution in the county (Figure 8). We find that in general there are no significant differences in trends prior to the 1973 birth cohort, whose parents would have been making the high school enrollment decision around 1988. We also plot the same figure conditional on middle school completion (Figure 9), and again find no apparent differences in trends prior to the 1973 birth cohort. Note, however, that in villages receiving IDs after 1988, enrollment growth in high school was faster for birth cohorts after 1973 than in those villages with IDs by 1988. Considering the long-term growth in incomes in rural China, this pattern is consistent with a positive wealth effect dominating in villages with smaller off-farm migrant networks.

The Timing of the High School Enrollment Decision

In order to estimate equation (10) we need to make two final assumptions about the timing of school enrollment and years of primary school. Although the supplementary survey implemented by RCRE provides us with an individual's age and years of schooling completed by 2004, we do not know the precise age at which each individual started school. To inform our assumption about the age at which children enter school, we use a survey conducted by the Center for Chinese Agricultural Policy (CCAP) in late 2000.[15] In addition to explicit questions about educational attainment, the CCAP survey asked specifically about the age at which individuals entered and left school. We find that among individuals aged 16 to 34, a slight majority of children began school at age 7 (Table 4). Therefore we assume that individuals begin school at age 7, and test whether our results are robust to this assumption.[16]

To construct our sample, we have to make one more assumption. In some parts of rural China, primary school lasts five years, whereas in other places primary school lasts six years. The supplemental survey did not directly ask whether villages in the RCRE survey have five or six year primary schools. However, when we examine completed years of schooling at the village level, it is fairly straightforward to discern whether completed schooling patterns are consistent with five or six year primary schools. We found that in some villages most children completed 6, 9 or 12 years of school; as middle and high school each last three years, and these patterns were consistent with six year primary schools. In other villages, most children completed 5, 8, or 11 years of schooling, consistent with five year primary schools.[17] Using this information, we coded all of the villages as five or six year primary school villages. To illustrate our assumption, we show average enrollment rates for each grade level in five and six year primary school villages conditional on completing the previous grade (Table 5). The most significant decision is clearly either the decision to move from grade 8 to grade 9 (in five year villages) or from grade 9 to grade 10 (in six year villages). We measure the decision to enroll in high school with a variable that includes the decision to enter grade 10 conditional on completing grade 9 for six year primary school villages and the decision to enter grade 9 conditional on completing grade 8 for five year primary school villages.[18]

[15] See de Brauw et al (2002) for a description of the CCAP survey.

[16] We tested whether our main results are robust to this assumption by assuming that children enter school at either age 6 or age 8, and found that the signs and relative magnitudes of our main results did not change.

[17] In the one village in which our method was indeterminate, we assume that the village has a five year primary school. Our results are robust to recoding the village as one with a six year primary school.

[18] All of our estimation results are robust to studying the grade 9 enrollment decision conditional on grade 8 completion, as well as to analyzing the grade 10 enrollment decision conditional on grade 8 completion.

One final concern may involve the way that repeats or skipped grades are handled. Although the supplemental survey did not ask explicitly about repeats or skips, the protocol for the supplemental survey required respondents to report years of schooling completed and the common interpretation is to answer in terms of the level of schooling completed. Examination of the CCAP data, which asked explicitly about skips and repeats, suggests their inclusion does not affect the general distribution of educational attainment. Therefore our findings should be robust to any errors in the measurement of schooling attainment.

5 Results

The First-Stage

Before estimating equation (10), we first establish that our instruments, a polynomial function of the years since ID cards were issued in the county, are significantly related to size of the migrant labor force. We first estimate the relationship as a quadratic, cubic, and quartic function of the years since IDs were issued (Table 6, columns 1a through 1c), with only year and village dummies as controls. Even after controlling for economic growth and macroeconomic shocks, we find a strong relationship between years-since-IDs were distributed and the size of the migrant network, regardless of specification. We favor the quartic function for the remainder of our estimation for two reasons. First, it allows for the most flexibility in determining the effects of ID card distribution on the migrant network.[19] Second, the partial R^2 increases significantly from the quadratic to the quartic, which reduces the potential for bias in instrumental variables regression.[20]

In most of the remainder of our regressions, we control for several village economic conditions that vary over time. The vector $\mathbf{Z}_{vt}$ in models 2 through 5 includes economic indicators controlling for wealth, the local agricultural environment, potential credit constraints and size of the local market. To control for the average village wealth level, we include the logarithm of average income per capita. To control for opportunity costs in agriculture, we include the average land per capita and the share of land in the village that is cultivable. The cultivable land Gini coefficient controls for

[19] The quartic was first favored in studies of empirical age earnings profiles as far less restrictive than the typical second order polynomial in age (Murphy and Welch, 1990).

[20] Since the bias in instrumental variables estimation is inversely proportional to the partial R^2, a higher partial R^2 also implies lower bias so long as each additional instrument is strongly correlated with the endogenous variable.

underlying inequality in the village and may affect credit constraints in the informal credit market.[21] Alternatively, a measure of within village inequality may pick up differences across villages in the willingness to provide local public goods, like an elementary school, that are correlated also with likelihood of testing into high school. Finally, to control for the size of markets within the village, we include the size of the village labor force.

Because we are concerned about introducing unobservable heterogeneity into our models from individual or household level variables in our second stage, we next include only the village level controls in the first stage (Table 6, column 2). We again find that the instruments jointly have a significant effect on the number of migrants from the village; in this case, the F-statistic is 10.06. As we add the individual and household level controls (models 3 through 5) to pick up effects of average village-wide variation in these variables, the instruments remain jointly significant, with F-statistics that range between 9.98 and 10.19.[22]

The Effect of Migrant Networks on High School Enrollment

We initially investigate the relationship between migrant opportunity and high school enrollment by estimating equation (10) using OLS with village demeaned data to control for fixed effects and year dummies (Table 7, column 0). We estimate a coefficient of -0.001 on the migration opportunity variable, and the estimate is not statistically different than zero. Without controlling for the endogeneity of migration, there seems to be no relationship between high school enrollment and migration. However, factors such as expanded capacity in high schools or a decline in the cost of attending high schools through improved roads and public transportation may well be endogenous with factors simultaneously lower the cost of participating in the off-farm market.[23]

When we estimate the determinants of high-school enrollment after controlling for the endogeneity of migration, we find that the number of migrants from the village has a negative, statistically

[21] Under some assumptions, a higher Gini coefficient would be correlated with more severe constraints on access to credit. Banerjee and Newman (1993), for example, provide a model suggesting that underlying wealth distribution and the nature of credit constraints may have an impact on occupational choice.

[22] Our dependent variable and many regressors for the first stage are at the village-level, and some readers may prefer to assess significance of our instruments in a village level regression. In Appendix Table A.2, we reproduce Table 6 for corresponding models in which each observation represents a village-year average.

[23] In Appendix Table A.1, we present descriptive statistics for all variables used in our estimation. These descriptive statistics show average characteristics for individuals completing middle school and making the decision whether or not to enter high school in the following year. We show averages over all years and selected years in three year intervals.

significant effect on high school enrollment (Table 7, columns 1 through 5). Holding only village and year effects constant, an additional ten migrants from a village is associated with a 2.9 percent decrease in the probability that an individual graduating from middle school will enroll in high school in the following year. The estimate is significant at the 5 percent level. As migration networks increase in strength, the net return to migrating and the opportunity cost of staying in school rises enough that we observe a substantial decline in high school enrollment.

To account for time varying village economic conditions, we add the village controls to equation (2) (Table 7, column 2). We find only one coefficient that is significantly different from zero; individuals in villages with larger labor forces are more likely to enroll in high school. Larger villages are more likely to have supported their own elementary school when high school age children were younger, so children from these villages may have found it systematically less costly to obtain quality early education when younger. The inclusion of these variables does not change our conclusion about the association between migration opportunity and high school enrollment. In this specification, the estimated coefficient on the number of migrants increases in absolute magnitude, now implying that an increase of ten migrants from a village is associated with a 4.9 percent decrease in the probability that a middle school graduate will enroll in high school. In elasticity terms, at the mean migration network size in the sample the effect of migrant opportunity on the probability of migration is -0.441; a one percent increase in the size of the network implies that students are 0.441 percent less likely to enroll in high school.

Individual and parental characteristics may also affect the decision to go to high school by contributing to differences in levels of household wealth or family preferences for education. Therefore, we add selected characteristics to the model (Table 7, columns 3 through 5). One might be concerned that unobserved heterogeneity related to individual characteristics may be related to the years since IDs became available, so we add these variables gradually while paying attention to changes in overidentification test statistics. First, we add gender, an indicator variable for the first born child to the model, and an indicator variable for households in which the first born child was male (column 3). We find that gender does not affect the probability of enrolling in high school. Since educational gender gaps have been narrowing in much of rural China (e.g. Hannum, 2004), this finding is not surprising. Whereas birth order might be a significant determinant of educational attainment if parents face credit constraints, restrictions on fertility make it unsurprising that the estimated coefficient on the first born child indicator is also statistically insignificant.

We further add parental characteristics that reflect innate ability, proxy for wealth, and the ability to participate in migration, and continue to find that migration opportunities negatively affect high school enrollment (columns 4 and 5). Both the father's and mother's years of schooling have a positive effect on an individual's likelihood of attending high school (column 4). Families with more education are likely to be wealthier, more active in encouraging the child's study, or have preferences for more school. We add measures of the number of potential male and female migrants in the household (column 5), which are the number of children in the household over the age of 16, we find both have negative, statistically significant effects on high school enrollment. When more individuals in a household are of the age to migrate, households may have more information about jobs and therefore be less likely to send children to high school.

Finally, we are concerned that other time-varying village characteristics that affect market development may affect the relationship between migrant networks and high school enrollment decisions. If local economic or other activities are facilitated by ID card issuance, our estimates could be biased. For example, if IDs make it easier for local firms to trade with more distant partners, make it easier for families to claim benefits (e.g., health insurance) or register children for school, then issuing IDs may affect other activities that also have an influence on migration. Most stories one could think of, however, are likely to bias against migration by increasing profitability of local enterprise or lowering the cost of obtaining benefits locally. Furthermore, with or without an ID migrants cannot register children for subsidized education outside of their home counties. To account for characteristics related to market development and the local impact of state intervention, we include another vector of time varying village level variables in our model (column 6). The average share of grain sold at quota prices is included to pick up the extent to which grain policy is binding in the village. Variables reflecting the distribution of land among different uses other than crop production (share of land allocated to aquaculture, the share of land allocated to forestry, and the share of land allocated to orchards) control for the extent of specialization in and marketization of the agricultural economy. Average household wealth per capita (housing, durable goods, savings and other financial wealth) provides an additional control for the average level of credit constraints, and finally the average proportion of households with some non-agricultural self-employment picks up the effect of local household businesses. We test the estimated coefficients on these variables and find that we cannot reject the hypothesis that they are jointly insignificant, and further, inclusion of these variables has no impact on the coefficient on M_{jt}. Since inclusion of additional village level controls does not affect our coefficient of interest, we believe it unlikely that time-varying unobservables related to market development bias our results. We exclude this vector from our remaining analyses because these variables introduce additional noise and their inclusion has no impact on the coefficient on migrant network size.

Controlling for individual characteristics, the estimated effect of larger village networks does not change. In each case, the coefficient estimate is between -0.045 and -0.049, and significant at the 5 percent level. We also perform over-identification tests on the quartic in time-since-IDs were distributed, and results from these tests offer further support that the instruments are not systematically related to unobservables influencing both migrant opportunity and enrollment in high school.[24]

Additional Robustness Checks

Before concluding that increasing migration opportunity causes a decrease in the probability of high school enrollment, we perform a number of robustness checks on our result. First, we want to be sure that our instruments are not weak, which could lead to difficulties in statistical inference. Next, we ensure that our results are robust to the inclusion of wealth shocks.

Weak instruments affect the sampling distribution of point estimates and therefore hypothesis tests in GMM estimators (Stock, Wright, and Yogo, 2002), so we want to ensure that our instruments are not weak and that second-order bias in IV estimation can be ignored. At first glance, we may not have much reason for concern; the F-statistics are over 10 in most specifications of our model. However, as discussed by Hahn and Hausman (2003), potential bias in IV estimation is also affected by correlation between the error terms in the first and second stage equations. As the F-test does not account for this correlation, our estimates could be substantially biased if unobservables still exist that affect both migrant networks and high school enrollment.

[24] To test for overidentification, we use the Hansen J-Statistic. It is similar to the more commonly used Sargan test but robust to heteroskedasticity (Baum, Schaffer, and Stillman, 2003).

Hahn and Hausman (2002) devise an alternative to the F-test which assumes that instruments are strong and that the second-order bias in IV estimates is zero. If the Hahn-Hausman test is rejected, one can conclude that either the instruments are weak, or that they are correlated with unobservables in ways that introduce bias. In a model with one endogenous variable and strong instruments, the estimated relationship between the dependent variable and the endogenous variable should not depend on the choice of dependent variable. Partialing out all other coefficients, the inverse of β_1 is implied by the equation:

$$M_{vt} = \alpha_1 E_{it} + u_{ihvt} \tag{11}$$

where u_{ihvt} is an error term, and we test the null hypothesis that $\beta_1 = \frac{1}{\alpha_1}$. If the null hypothesis is rejected, then the instruments are weak and inference using those instruments is almost certainly incorrect.

We performed the Hahn-Hausman test using the bias corrected 2SLS estimator developed by Donald and Newey (2001) and suggested by Hahn and Hausman as appropriate for implementation of their test. In each specification in Table 7, we find that we cannot reject the null hypothesis that the forward and reverse regressions imply the same coefficient estimate.[25] Therefore we can conclude that the quartic function of the years since ID cards were issued are sufficiently strong instruments for the number of migrants from a village and that our estimates are unbiased.

Second, we examine the effect of wealth shocks on school enrollment decisions (Table 8). One might be concerned that, in spite of our IV strategy, unobserved wealth shocks may drive the decisions to leave school and to participate in the migrant labor market. We add a variable measuring village rainfall shocks lagged one year to the specification in column 5 of Table 7 in order to capture unexpected shocks to income and wealth.[26] We also interact the rainfall shock variables with an indicator variable for households in which the father has completed high school,

[25] The coefficient estimated using 2SLS is nearly identical to the coefficient reported from the IV-GMM estimator. This should not be surprising as the IV-GMM estimator was used primarily to provide robust, efficient estimates of the variance-covariance matrix, whereas coefficient estimates from either estimator are consistent.

[26] The rainfall shocks are measured as the squared county level deviation from the long-term mean rainfall between July and November of the previous year. Giles and Yoo (2005) show that deviations in rainfall between July and November matter most for crop production in these villages as it has a significant impact on the following Spring's winter wheat crop.

which is strongly correlated with whether or not the father holds off-farm employment, to determine whether or not village-wide wealth shocks have different impacts on households with and without off-farm income (columns 2). We also test whether birth order matters, by explicitly including the birth order (column 3) and an interaction with the first born child indicator (column 4). We do not find that the father's education matters, but we do find that when wealth shocks are larger the first born is less likely to enroll in high school. In all cases, the estimated coefficient on migrant network size decreases to -0.025, but it is still significant at the 10 percent level and not significantly different from the coefficient in our base model. Therefore we conclude that our result is robust to the inclusion of wealth shocks.

Low Returns to High School Education in Migrant Labor Markets

In order to understand how returns in the labor market influence decisions about enrollment in high school, we use a module added to the 2003 round of the RCRE survey designed to study the returns in migrant labor markets. For individuals who had out-migrated from RCRE households in 2003, the RCRE survey collected information on earnings, the cost of migration and the number of days individuals worked as migrants. Using a sample of all adult children of the household head and spouse who were between 15 and 50 years old, we estimate the net returns to education for migrants using a Heckman selection model (Table 9). Our objective here is not to provide a separate study of returns to education in which we carefully identify education from unobserved ability bias. We are simply interested understanding whether returns to education in the migrant labor market are consistent with an observed decline in high school enrollment with expanding migrant opportunity. For the selection equation, we use household land per capita and demographic characteristics (e.g. household size, number of laborers, number of elderly in the household, the household dependency ratio, the male/female ratio and number of children under 5). On average, we find that an additional year of education has a return in the migrant labor market of 2.9 percent (model 1).

To separately estimate the returns to years of schooling for primary and middle school, high school, and post-high school education, we introduce a linear spline in model 2. We find a higher return to primary, middle school and post-secondary years of schooling than to high school. Specifically, we estimate an average return of 4.0 percent to primary and middle school, but only a statistically insignificant 0.3 percent return to a year of high school (model 2).[27] The return to post-secondary education, consistent with findings reviewed by Cai, Park and Zhao (2004), is higher than that for other types of education 4.7 percent, but also statistically insignificant.[28]

Moreover, the selection coefficient on years of high school education is negatively related to whether an individual is a migrant or not, implying that going to high school makes an individual more likely to stay in the village. Returns to high school for rural migrants in urban areas are low, while individuals with a high school education in rural areas are able to qualify for more lucrative positions in village or township government or as managers (or owners) of local enterprises.

Effects in Local Labor Markets: The Activities of High School Age Children

With the growth of migrant networks from the village and depletion of the local labor force, the local labor market may also experience general equilibrium effects that increase the opportunity cost of enrolling in high school. As migrants leave the village, the local labor force decreases in size, which in turn may increase the return to labor in home production (agricultural or non-agricultural family businesses) or local off-farm wage employment sufficiently to dissuade teenagers from attending high school.[29] While we lack individual information on daily earnings over time, we can investigate the effects of migrant networks on the activity choices of individuals of the age to enter high school and in the two years after they would normally have enrolled in high school. We expect that as the size of the migrant network increases, the local labor force is depleted and, as a result, we may observe that teenagers are more likely to participate in local labor market activities.

In Table 10 we show the coefficients on migrant network size from the IV-GMM linear probability model estimates and marginal effects from IV-Probit estimates (Rivers and Vuong, 1988) of individual activity choice. The IV-Probit models are included because the percentage of individuals actually entering the migrant or local off-farm labor markets is somewhat low, and we are worried that the implied marginal effects from the IV-GMM linear probability model may be

[27] In the spline model we estimate returns to education for years greater than or equal to 9 through 12 in order to make sure that we are picking up returns to years of high school education for this range. Villages with five year primary schools will have one year of high school pooled with grades 0 to 8.

[28] The estimated returns to schooling here are much lower than recent estimates of returns to urban workers. This may reflect measurement error bias, measurement problems in the calculation of net daily migrant wages, or reflect bias against rural migrants in urban labor markets.

[29] Figure 10, for example, shows suggestive trends indicating increases in long-term employment within the county of high school age cohorts.

biased. We observe that implied marginal effects are quite similar across the two models, and we thus prefer the IV-GMM results because these are again estimated with cluster corrected standard errors robust to within village correlation.

The results imply that general equilibrium effects may be taking place. As the size of the migrant network expands, high school age individuals are more likely to be employed in both local off-farm and migrant destinations. The increase in the probability they will be employed locally off-farm can be explained by the reduction in the size of the local labor force. Moreover, the size of the coefficients increase for individuals one or two years out of high school. We do not observe an increase in provision of labor on the family farm or in family businesses, but this activity choice may be subject to greater error in reporting than wage employment.

6 Conclusions

The movement of rural laborers out of agriculture into urban and coastal areas has been an important feature of China's economic transition. While the opportunity to migrate has been important for raising living standards in many areas of rural China, access to migrant opportunity appears to create a disincentive for continued increases in educational attainment of rural youth. In this paper, we show that relatively low returns to high school education for migrant workers provides a possible explanation for the negative relationship. Since relatively high wages are available for middle school graduates in migrant destinations with little increase in compensation for additional education, families considering enrolling their children in high school find the opportunity cost to be too high.

It is plausible that institutional features of China's economy continue to influence relative returns to education for urban and rural registered residents and shape the disincentives for enrollment in high school. Many cities still explicitly reserve some occupational categories for registered urban residents, and even where this practice has been relaxed there is often *de facto* segregation of rural residents into service sector, construction and other relatively low skill jobs that are unwanted by urban residents.[30] To the extent that migrant employees can earn significantly higher wages in

[30] See Meng and Zhang (2001) for an empirical analysis on the Shanghai labor market and Solinger (1999) for a description of the differences in treatment of migrant rural and urban residents in Wuhan.

relatively unskilled employment in urban areas, the opportunity cost of high school enrollment may well be higher than the returns to high school education. Given that an increasing share of urban residents are completing university, the gap in educational attainment between youth growing up in urban and rural areas is likely to reinforce barriers to economic mobility for rural residents and their families even after they migrate to cities. Ending restrictions on the occupational categories in which rural migrants may be employed may create frictions between urban and rural registered migrants in the short-term, but may raise returns to high school education for rural youth and have the salutary effect of facilitating greater intergenerational economic mobility in the future.

The growing cost of university education and the lack of a well-functioning student loan program may also contribute to a decline in the perceived return to high school education. The returns to education in urban China are non-linear and driven primarily by increases in the returns to college education (Cai, Park and Zhao, 2004; Heckman and Li, 2004). In fact, the primary return to high school education may be as an input for post-secondary education (e.g. Appleton, Hoddinott, and Knight, 1996). Combined with credit constraints and increasing college tuitions, the possibility of college entrance may be perceived as extremely remote in rural areas, implying an even lower expected return to enrollment in high school.

At present there is considerable concern about the potential consequences of growing inequality across China's regions and between rural and urban areas. The results presented in this paper suggest that institutional features creating low returns to high school education for rural registered families may contribute to persistence in unequal outcomes even as urbanization proceeds. In order to avoid long-term distributional consequences of low returns to high school enrollment for rural residents, China's government should consider expanding subsidies for high school education in rural areas and ending formal restrictions on occupational categories for employment of rural registered individuals in urban areas. Finally, developing a more flexible student loan system to facilitate paying college tuitions may alter expectations regarding ability to enroll in college and thus change incentives for high school enrollment in rural areas.

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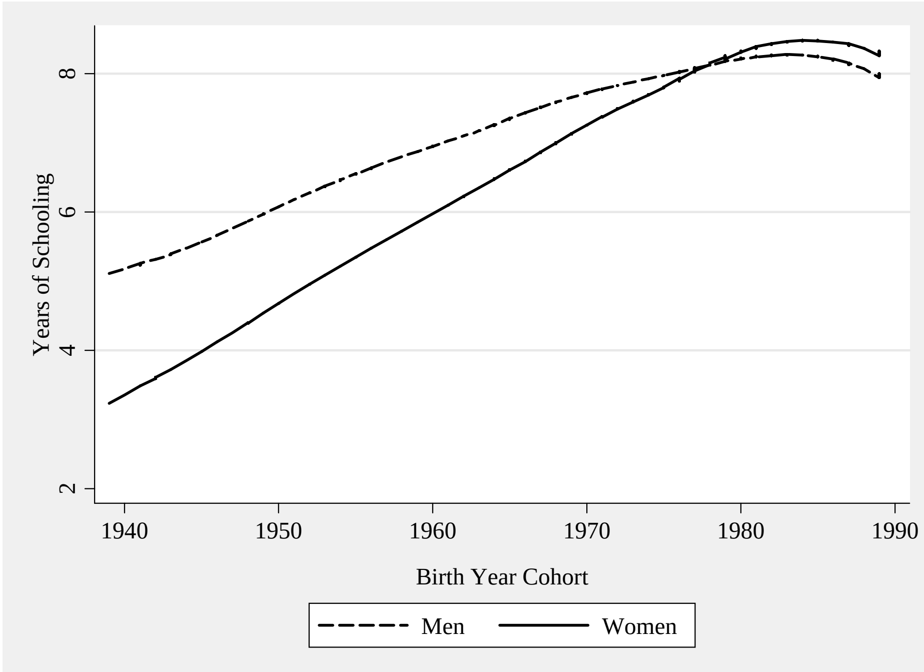
Figure 1
Cohort Average Educational Attainment
Lowess Fit

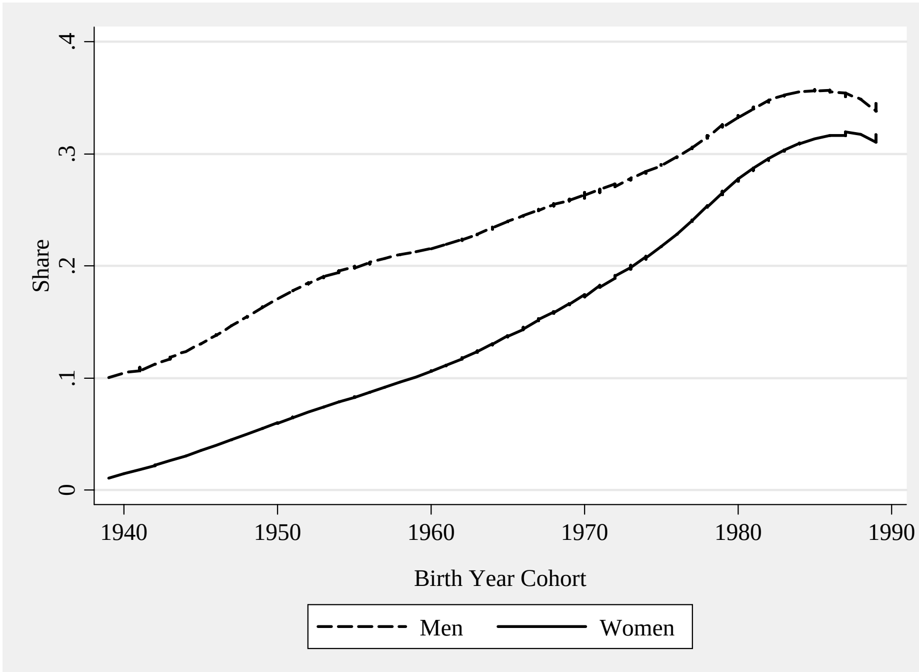


Source: RCRE Supplemental Survey (2004).

Figure 2
Share of Cohort Completing Middle School by Gender
Lowess Fit

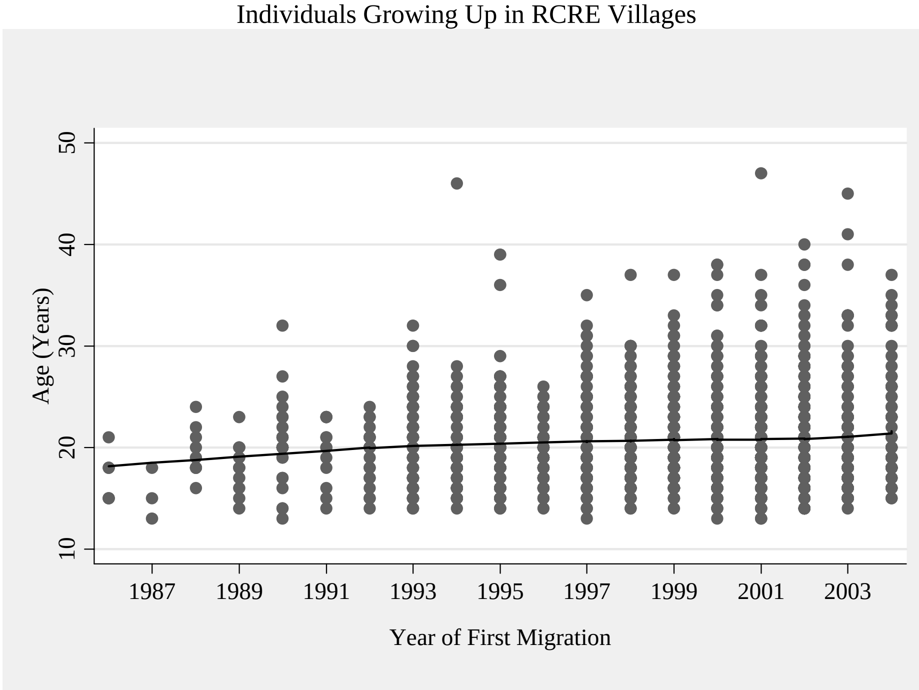
Source: RCRE Supplemental Survey (2004).

Figure 3
Share of Cohort Entering High School by Gender
Lowess Fit



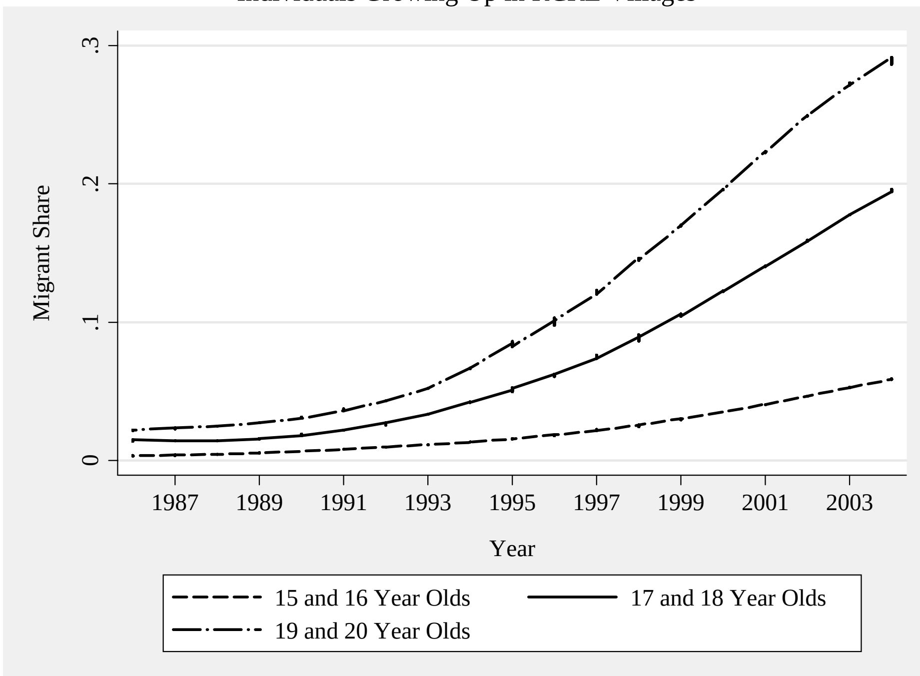
Source: RCRE Supplemental Survey (2004).

Figure 4
Age at Time of First Migration Experience
Individuals Growing Up in RCRE Villages



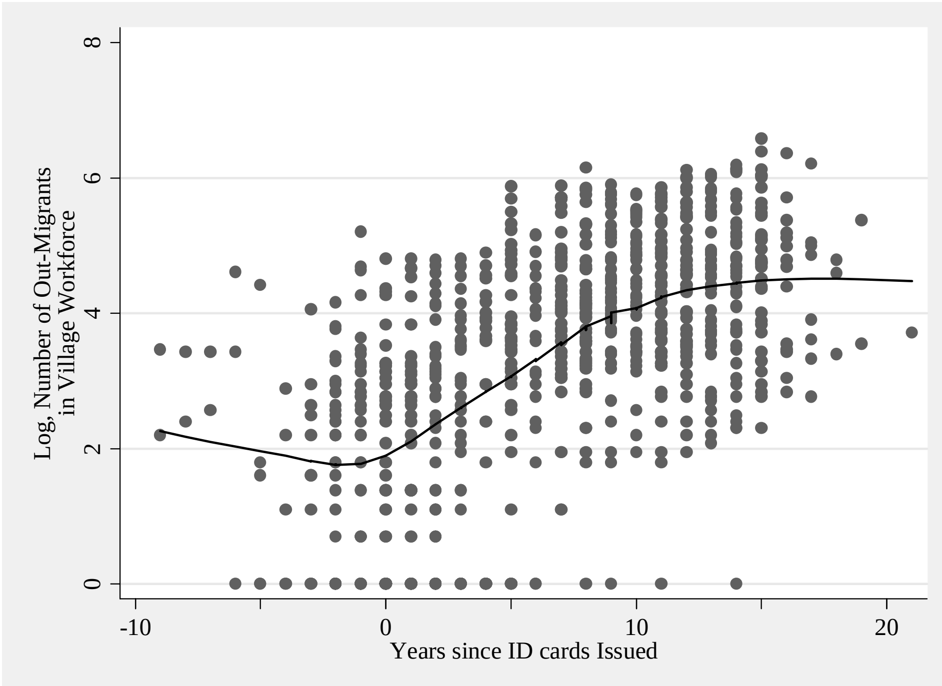
Source: RCRE Supplemental Survey (2004).

Figure 5
Share of Age Group with Temporary or Long-Term Migrant Employment
Individuals Growing Up in RCRE Villages



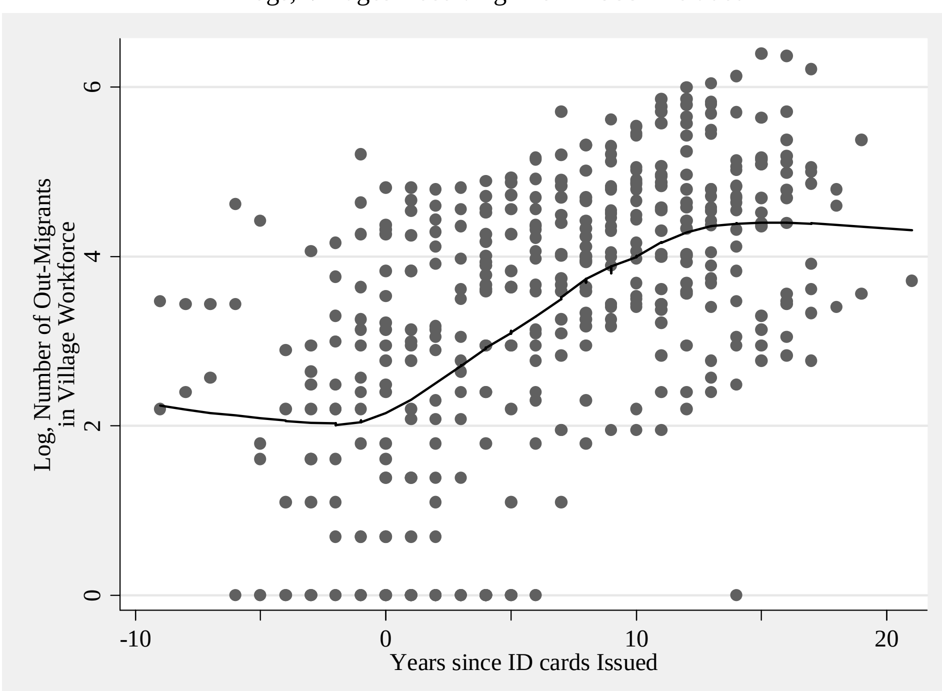
Source: RCRE Supplemental Survey (2004).

Figure 6
Working Age Laborers from Village Employed as Migrants
In Logs



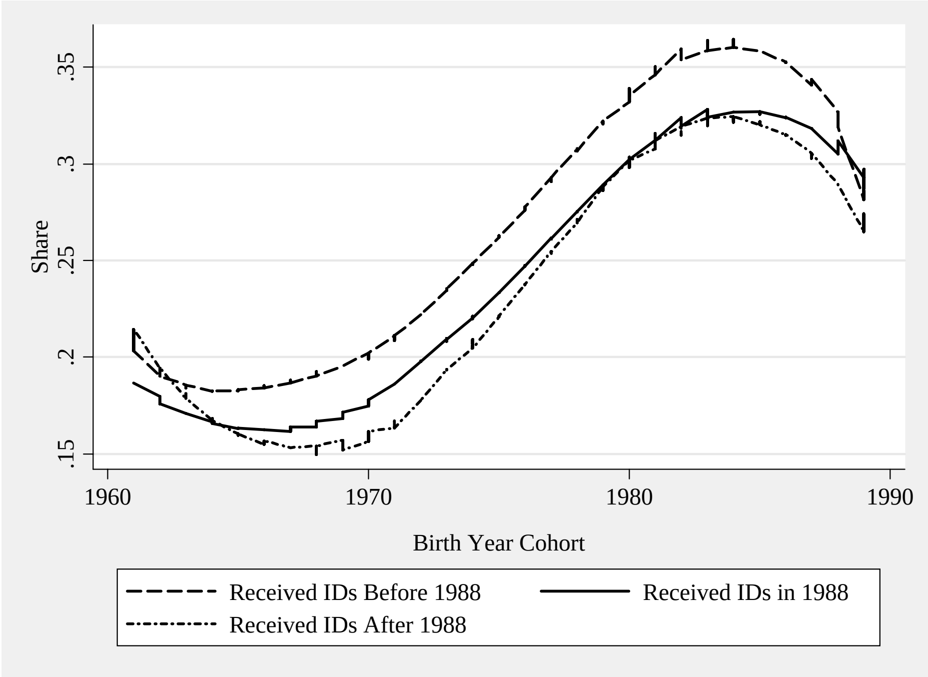
Source: RCRE Village Surveys (1986-2003), RCRE Supplemental Village Survey (2004).

Figure 7
Working Age Laborers from Village Employed as Migrants
In Logs, Villages Receiving IDs in 1988 Excluded



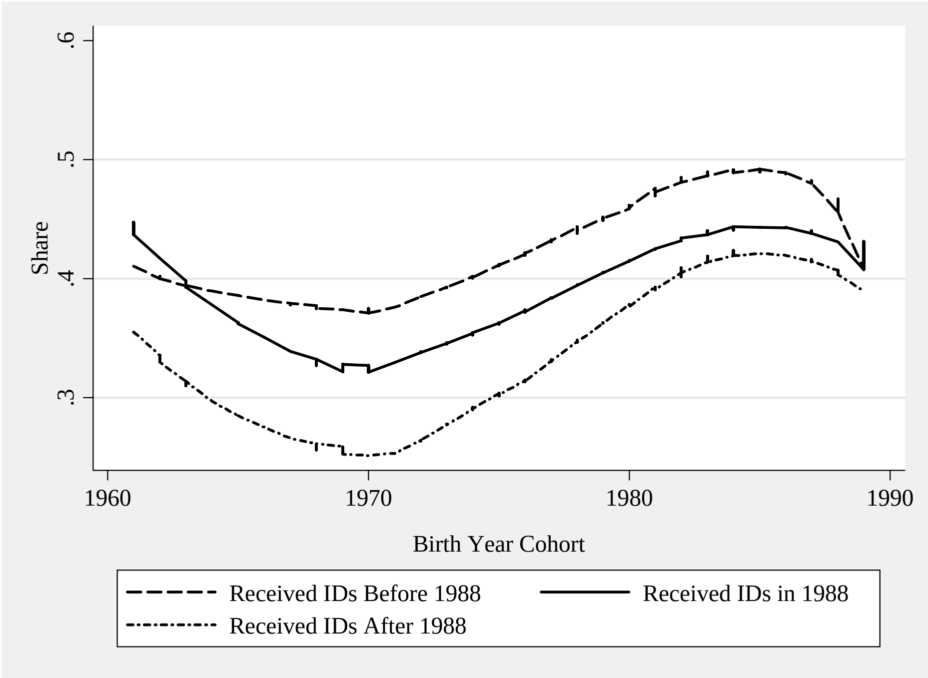
Source: RCRE Village Surveys (1986-2003), RCRE Supplemental Village Survey (2004).

Figure 8
Share of Age Cohort Entering High School
by Timing of ID Card Receipt
Lowess Fit



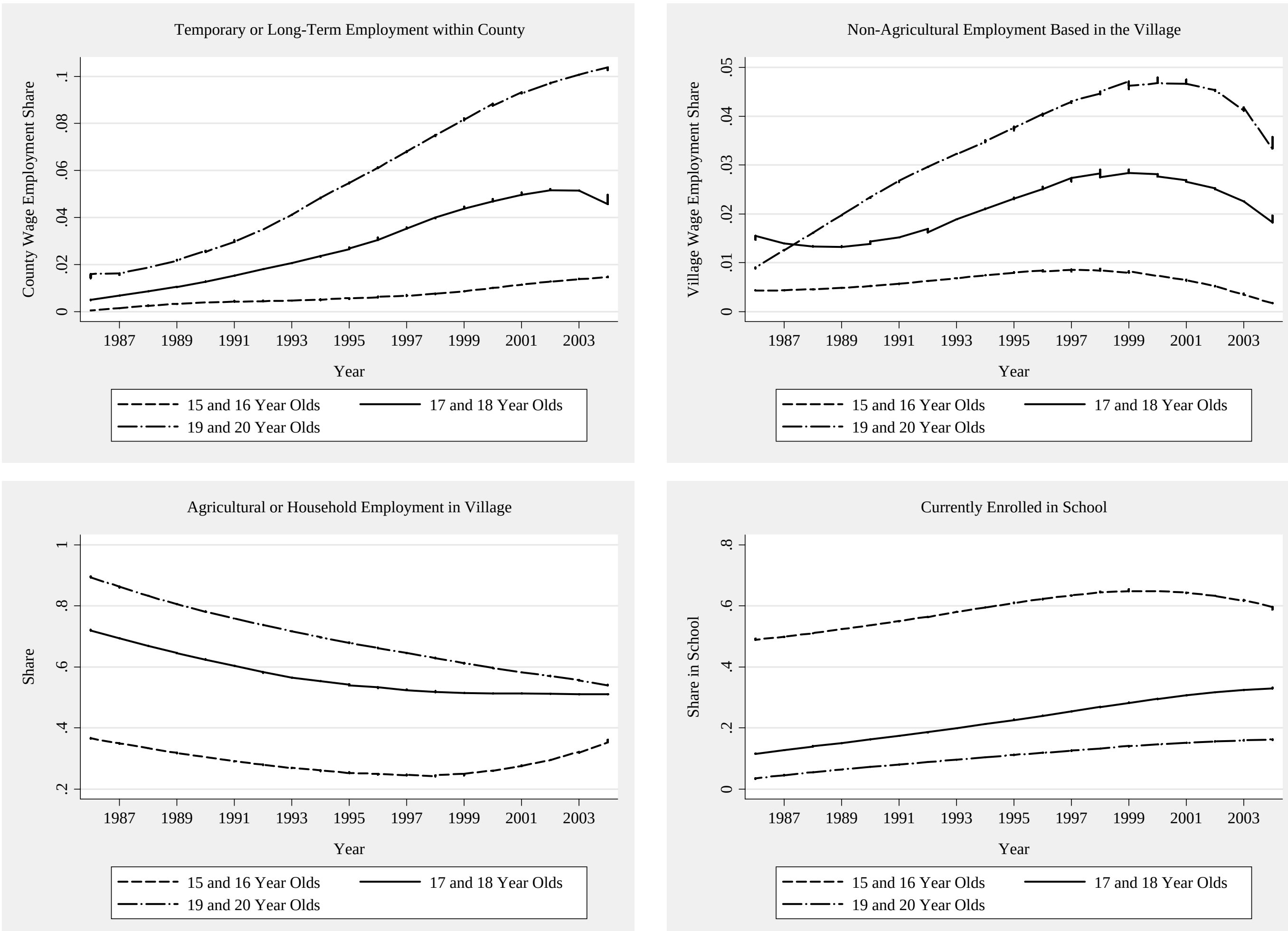
Source: RCRE Supplemental Surveys (2004).

Figure 9
Share of Middle School Graduates Entering High School
By Timing of ID Card Receipt
Lowess Fit



Source: RCRE Supplemental Surveys (2004).

Figure 10
Share of Young Pursuing Activities other than Migrant Employment
Lowess Fit



Source: RCRE Supplemental Surveys (2004).

Table 1
Local Networks of Rural-Urban Migrants at Time of Migration
Five-City CULS Migrant Survey*

	Source Community Location	
	All Provinces	4 RCRE Provinces
Share of Migrants with:		
Job Arranged Before *First* Migration Experience	0.52	0.57
Job Arranged Before *Current* Migration Experience	0.53	0.56
Some Acquaintance from Home Village in City Before Migrating	0.91	0.94
**Close Family Member in City Before Migration	0.35	0.35
**Extended Family Member in City Before Migration	0.52	0.58
**Hometown Acquiantances	0.65	0.67
Five or Fewer Hometown Acquaintances	0.39	0.44
More than Five Hometown Acquaintances	0.27	0.24
At Least One Local Acquaintance	0.09	0.08
Number of Migrants	2,463	481

*Respondents are holders of rural registration (*hukou*). The survey was conducted in Fuzhou, Shanghai, Shenyang, Wuhan and Xian during late 2001. Sample frames were assembled using information on distribution of migrants within cities from the 2000 Population Census. After selecting neighborhoods through a proportional population sampling procedure, sample frames were assembled using residents' committee records of migrant households and registers of migrants living on construction sites and held by local by police stations. Very short-term migrants, who lack a residence that falls under the jurisdiction of either of these authorities, are unlikely to have made it into the sample frame.
**A *close family member* is adult sibling or member of nuclear family (e.g., spouse, child, parent). An *extended family member* refers to cousins or other relatives. *Hometown acquaintances* are unrelated, but known by the respondent. Note that migrants may have acquaintances in several categories, so that subcategories of acquaintances will add to more than 100.

Table 2
Educational Attainment of Migrants

Panel A. Education Attainment and Age at First Migration of Rural-Urban Migrants from Five-City CULS Migrant Survey*

	Source Community	
	All Provinces	4 RCRE Provinces
Education		
Elementary or Less	0.247	0.220
Some Middle School	0.086	0.096
Middle School	0.485	0.501
Some High School	0.039	0.045
High School	0.120	0.120
Some Post Secondary	0.009	0.011
College	0.010	0.012
Number of Observations	2,463	481

*Source: China Urban Labor Survey (see discussion on note of Table 1).

Panel B. Evidence on Educational Attainment of Cross-Province Migrants from the 1990 and 2000 Population Census

	Source Community	
	All Provinces	4 RCRE Provinces
Educational Attainment of Individuals Migrating from the Province Between 1985 and 1990		
Less than Middle School	0.348	0.317
Middle School	0.341	0.411
High School	0.162	0.158
College or Higher	0.148	0.114
Educational Attainment of Individuals Migrating from the Province Between 1995 and 2000		
Less than Middle School	0.245	0.249
Middle School	0.462	0.518
High School	0.154	0.132
College or Higher	0.148	0.101

*Source: One Percent Sample of the 1990 and 2000 Population Census. Includes cross-province migrants from both urban and rural areas.

Table 3
Average Village Characteristics in 1988
by Timing of ID Card Distribution

		Year ID Cards Were Issued		
		prior to 1988	in 1988	after 1988
Share of Productive Assets Owned by the Village Collective	mean	0.399	0.242	0.246
	std. dev	0.277	0.189	0.276
Mean Consumption Per Capita	mean	414.3	349.3	405.1
	std. dev	154.6	131.6	86.9
Mean Income Per Capita*	mean	627.2	481.5	558.1
	std. dev	243.3	183.5	162.4
Cultivable Share of Total Land Area	mean	0.691	0.546	0.512
	std. dev	0.277	0.273	0.309
Share in Mountains	mean	0.14	0.24	0.3
	std. dev	0.36	0.43	0.48
Share Near a City	mean	0.21	0.04	0.08
	std. dev	0.43	0.20	0.28
Cropped Land Gini Ratio	mean	0.21	0.15	0.17
	std. dev	0.07	0.05	0.05
Average Household Size	mean	4.40	4.72	4.68
	std. dev	0.66	0.47	0.53
Total Village Land	mean	4508	4633	7676
	std. dev	4694	4676	9401
Male Share in Population	mean	0.51	0.51	0.50
	std. dev	0.02	0.02	0.02
Share of Labor Force Earning Wage Locally	mean	0.27	0.14	0.16
	std. dev	0.21	0.12	0.22
Village Population	mean	1646	1284	1501
	std. dev	1089	548	925
Village Consumption Per Capita Gini	mean	0.18	0.16	0.16
	std. dev	0.03	0.03	0.03
Village Income Per Capita Gini	mean	0.23	0.22	0.21
	std. dev	0.07	0.05	0.07
Average Years of Schooling, aged 18-22	mean	8.75	7.56	7.50
	std. dev	3.44	2.02	2.03
Share of 15-18 Year Olds Enrolled in High School	mean	0.41	0.35	0.31
	std. dev	0.25	0.16	0.16
Observations		14	25	13

Notes:
*Indicates difference is statistically signicant at the 10th Percentile.
1. Consumption and income per capita are reported in 1986 RMB Yuan.
2. Sources: RCRE Household and Village Surveys (1986 to 2003), and RCRE Supplemental Surveys (2004).

Table 4

Reported Age Starting Primary School

Individuals Age 10 to 34 in 2000

Age	Number	Share
4	6	0.002
5	56	0.021
6	530	0.198
7	1336	0.499
8	639	0.239
9	83	0.031
10	18	0.007
11	6	0.002
12	2	0.001
13	2	0.001
14	1	0.000

Source: China Center for Agricultural Policy (CCAP) Data Set, 2000. See the Appendix of de Brauw et al (2003) for a description of the CCAP survey.

Table 5
Proportion of Individuals Staying in School
by Grade and Primary School Type

	Six Year Primary Schools		Five Year Primary Schools	
Grade	Proportion	N	Proportion	N
2	1.00	1310	1.00	4193
3	1.00	1310	0.99	4186
4	1.00	1296	0.99	4118
5	0.99	1285	0.98	4019
6	0.98	1257	0.91	3904
7	0.95	1211	0.95	3484
8	0.92	1122	0.87	3238
9	0.90	1011	0.43	2712
10	0.47	877	0.68	1134
11	0.95	388	0.84	729
12	0.91	351	0.62	574
13	0.36	305	0.59	329
14	0.91	100	0.81	183
15	0.83	83	0.58	138
16	0.36	61	0.32	74
17	0.40	20	0.21	24
18	0.80	5	0.50	4
19	0.00	3	0.50	2
20	0.00	0	0.00	1

Notes: Proportions are conditional on school enrollment the previous year.
Assumes children start school at age 7 and do not skip.
Source: RCRE Supplemental Survey (2004).

Table 6
What Factors Determine the Size of the Village Migrant Network?
First-Stage Regression Using the Sample of Individuals Completing Middle School, 1986-2003

	Dependent Variable: Number of Registered Village Residents Working as Migrants						
Model	1a	1b	1c	2	3	4	5
Years Since IDs issued	0.721 (0.122)	-0.016 (0.225)	-0.720 (0.367)	-0.629 (0.332)	-0.621 (0.333)	-0.632 (0.333)	-0.631 (0.333)
Years Since IDs Issued Squared	-0.041 (0.007)	0.074 (0.030)	0.277 (0.089)	0.266 (0.081)	0.264 (0.081)	0.267 (0.081)	0.267 (0.081)
Years Since IDs Issued Cubed		-0.004 (0.001)	-0.022 (0.008)	-0.024 (0.007)	-0.024 (0.007)	-0.024 (0.007)	-0.024 (0.007)
(Years Since IDs Issued)^4			0.005 (0.002)	0.006 (0.002)	0.006 (0.002)	0.006 (0.002)	0.006 (0.002)
Ln(Village Average Income Per Capita)				0.447 (0.627)	0.430 (0.626)	0.393 (0.627)	0.387 (0.627)
Total Land in Village (Mu)				0.019 (0.016)	0.019 (0.016)	0.018 (0.016)	0.018 (0.016)
Cultivable Land Gini Coefficient				3.520 (2.143)	3.560 (2.147)	3.631 (2.147)	3.661 (2.149)
Size of Village Workforce				0.074 (0.006)	0.074 (0.006)	0.075 (0.006)	0.075 (0.006)
Cultivable Share of Village Land				3.094 (1.462)	3.103 (1.462)	3.068 (1.463)	3.061 (1.464)
Gender (1=male, 0=female)					-0.479 (0.238)	-0.509 (0.238)	-0.503 (0.239)
First Born? (1=yes, 0=no)					-0.067 (0.232)	-0.066 (0.234)	0.023 (0.352)
First Born in Household is Male? (1=yes, 0=no)					0.140 (0.258)	0.156 (0.258)	0.102 (0.286)
Father's Years of Schooling						-0.076 (0.050)	-0.076 (0.050)
Mother's Years of Schooling						0.088 (0.054)	0.088 (0.054)
Number of Potential Migrants, Male							0.117 (0.259)
Number of Potential Migrants, Female							0.010 (0.220)
Number of Observations	3160	3160	3160	3068	3068	3068	3068
r2	0.419	0.422	0.423	0.451	0.452	0.453	0.453
F-Statistic on Instruments	18.3	17.28	14.46	10.06	9.98	10.2	10.19
Partial r2, Instruments	0.011	0.016	0.018	0.013	0.013	0.013	0.013

Notes: Columns 1c through 5 are the first stage of instrumental variable regressions shown in models 1 to 5 of Table 7. The F-statistic tests the hypothesis that the estimated coefficients on the instruments are zero. All F statistics are significant at the one percent level. All regressions control for village fixed effects (using a village demeaned specification) and include year dummy variables. Models 1c through 2 are estimated at the village level in Appendix Table A.2

Table 7
Determinants of High School Enrollment
Conditional on Completing Middle School, 1986-2003

	Dependent Variable: Enroll in High School Next Year = 1						
Model	0	1	2	3	4	5	6
	OLS	IV-GMM	IV-GMM	IV-GMM	IV-GMM	IV-GMM	IV-GMM
(Number of Migrants from Village)/10	-0.001	-0.029	-0.049	-0.048	-0.047	-0.047	-0.045
	(0.002)	(0.012)	(0.020)	(0.020)	(0.019)	(0.019)	(0.034)
Gender (1=male)				0.025	0.032	0.030	0.035
				(0.027)	(0.027)	(0.027)	(0.031)
First Born (1=yes)				0.028	0.005	-0.045	-0.057
				(0.025)	(0.024)	(0.031)	(0.037)
First Born in Household was Male (1=yes)				-0.058	-0.069	-0.059	-0.058
				(0.023)	(0.023)	(0.025)	(0.029)
Father's Years of Schooling					0.021	0.021	0.022
					(0.005)	(0.005)	(0.005)
Mother's Years of Schooling					0.033	0.033	0.033
					(0.005)	(0.005)	(0.006)
Number of Potential Migrants, Household, Male						-0.048	-0.056
						(0.022)	(0.025)
Number of Potential Migrants, Household, Female						-0.030	-0.036
						(0.015)	(0.017)
ln(Village Mean Income Per Capita)			0.051	0.050	0.043	0.044	0.000
			(0.176)	(0.172)	(0.172)	(0.173)	(0.189)
Village Total Land			-0.024	-0.021	-0.014	-0.026	-0.023
			(0.349)	(0.345)	(0.348)	(0.349)	(0.530)
Village Cultivable Land Per Capita Gini			0.001	0.001	0.002	0.002	0.002
			(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
(Village Labor Force)/10			0.004	0.004	0.004	0.004	0.003
			(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Cultivable Share of Village Land			0.363	0.375	0.291	0.296	0.397
			(0.279)	(0.274)	(0.258)	(0.259)	(0.426)
Additional Time-Varying Village Variables?	no	no	no	no	no	No	yes
Chi-Square Test, Time-Varying Village Variables							1.41
p-value, Chi-Square Test							0.965
Over-ID Test: Hansen J-Statistic		0.449	0.765	1.186	1.253	1.321	1.820
P-value, J-statistic		0.930	0.858	0.756	0.740	0.724	0.611
F-Test		14.46	10.06	9.98	10.2	10.19	4.42
P-value, F-statistic		0	0	0	0	0	0.015
Partial r2		0.018	0.013	0.013	0.013	0.013	0.006
Hahn-Hausman test, t statistic		-0.69	-0.83	-0.75	-0.79	-0.78	-0.41
Hahn-Hausman, p value		0.490	0.407	0.453	0.430	0.435	0.682
Number of Obs.	3160	3160	3068	3068	3068	3068	3068

Notes: In parentheses, we show robust standard errors that allow for arbitrary correlation within villages. All regressions control for village fixed effects and include year dummies. The additional time varying village level variables include the average proportion of households with non-agricultural self-employment, the share of grain sold at quote, the logarithm of average household wealth, the share of land allocated to aquaculture, the share of land allocated to forestry, and , the share of land allocated to orchards. Models 1-6 are estimated using instrumental variables generalized method of moments.

Table 8
Is the Effect of Migrant Opportunity on High School Enrollment Robust to Unexpected Shocks to Wealth?

	Dependent Variable: Enroll in High School Next Year = 1			
Model	1	2	3	4
(Number of Migrants from Village)/10	-0.029	-0.029	-0.028	-0.029
	(0.017)	(0.017)	(0.017)	(0.017)
July-November Lagged Rainfall Shock Squared	0.002	0.002	0.001	0.006
	(0.003)	(0.003)	(0.004)	(0.002)
Lagged Rainfall Shock*(Father has High School Education)		-0.004		
		(0.736)		
Lagged Rainfall Shock Squared * Birth Order			0.001	
			(0.001)	
Lagged Rainfall Shock Squared * First Born				-0.008
				(0.002)
Instruments:	ID Cards	ID Cards	ID Cards	ID Cards
Over-ID Test: Hansen J-Statistic	3.793	3.793	3.839	3.632
J-Statistic, P-value	0.285	0.285	0.279	0.304
F-Test	11.92	11.85	11.91	11.91
F-Probability	0.000	0.000	0.000	0.000
Number of Obs.	2786	2786	2786	2786

Notes: In parentheses, we show robust standard errors that allow for arbitrary correlation within villages. All regressions control for village fixed effects and include year dummies and the village and individual level controls listed in column 5 of Table 7. All models are estimated using instrumental variables generalized method of moments.

Table 9
Returns to Education Among Migrants from RCRE Villages in 2003
Heckman Selection Models

	Model 1		Model 2	
	ln(Daily Migrant Wage)	Migrant? (1= Yes)	ln(Daily Migrant Wage)	Migrant? (1= Yes)
Years of Schooling	0.029	-0.007	--	--
	(0.012)	(0.014)		
0<=Years of Schooling <9	--	--	0.040	0.072
			(0.019)	(0.022)
9<=Years of Schooling <12	--	--	0.003	-0.126
			(0.034)	(0.036)
Years of Schooling>=12	--	--	0.047	-0.029
			(0.059)	(0.068)
Age	0.146	0.285	0.149	0.286
	(0.041)	(0.043)	(0.034)	(0.042)
Age Squared	-0.003	-0.005	-0.002	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.213	0.311	0.217	0.307
	(0.053)	(0.061)	(0.052)	(0.061)
Fathers Years of Education	-0.013	-0.0283	-0.012	-0.027
	(0.010)	(0.011)	(0.009)	(0.011)
Mothers Years of Education	0.008	-0.005	0.008	-0.005
	(0.010)	(0.012)	(0.010)	(0.011)
Household Size	--	-0.010	--	-0.020
		(0.044)		(0.044)
Number of Adult Laborers	--	0.054	--	0.057
		(0.046)		(0.046)
Household Land Per Capita	--	-0.115	--	-0.126
		(0.052)		(0.052)
Number of Elderly in Household	--	-0.054	--	-0.045
		(0.038)		(0.038)
Dependency Ratio	--	-0.079	--	-0.087
		(0.178)		(0.179)
Male/Female Ratio	--	-0.354	--	-0.317
		(0.202)		(0.202)
Number of Children Under 5	--	-0.197	--	-0.203
		(0.068)		(0.069)
Number of Observations	3880		3880	
Censored Observations	3101		2101	
Uncensored Observations	779		779	

Notes: Individual information necessary to estimate daily returns to education from migrant employment are only available for the 2003 survey. We estimate returns to education in migrant employment for children of the household head and spouse who are under 50 and over 15 years of age. Robust standard errors are shown in parentheses.

Table 10
Effect of Number of Village Migrants on Individual Choice of Activity, by Activity

	In School?	Agricultural or Home Work		Local Wage Employment		Migrant Employment	
Dependent Variable	IV-GMM	IV-GMM	IV Probit	IV-GMM	IV Probit	IV-GMM	IV Probit
Of Age to Start High School This Year	-0.038	0.009	0.003	0.001	0.005	0.004	0.0013
	(0.017)	(0.009)	(0.010)	(0.002)	(0.001)	(0.002)	(0.0006)
Of Age to Have Started High School Last Year	-0.019	-0.0002	0.003	0.008	0.012	0.008	0.002
	(0.010)	(0.010)	(0.012)	(0.006)	(0.003)	(0.004)	(0.006)
Of Age to Have Started High School Two Years Ago	-0.013	-0.004	-0.010	0.013	0.009	0.009	0.0005
	(0.008)	(0.012)	(0.012)	(0.011)	(0.006)	(0.005)	(0.007)

Notes: All explanatory variables in Column 5 of Table 8 included in all regressions. We report coefficients on number of village migrants in models with different activity choices (shown in columns) and for different ages relative to the normal starting age for high school (which is 15 in villages with five years of primary education and 16 in villages with six years of primary education). Standard errors clustered at the village level in IV-GMM estimation and bootstrapped in the IV Probit regressions. Marginal effects are reported for IV probit models.

Appendix Table 1

Descriptive Statistics for Children Graduating from Middle School

Selected Variables, for Selected Years

	All Years	Year 1987	1990	1993	1996	1999	2002
Individual Level Variables							
Enrolled in High School? (1=yes)	0.43	0.32	0.44	0.41	0.42	0.47	0.47
	(0.47)	(0.47)	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)
Gender (1=male)	0.57	0.58	0.60	0.58	0.53	0.53	0.48
	(0.50)	(0.49)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
First Born (1=yes)	0.45	0.47	0.49	0.46	0.52	0.50	0.37
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.48)
Birth Order	1.87	1.92	1.94	1.92	1.76	1.71	1.94
	(1.04)	(1.12)	(1.18)	(1.14)	(1.02)	(0.85)	(0.93)
Household Level Variables							
First Born in Household	0.40	0.28	0.44	0.43	0.38	0.42	0.43
was Male (1=yes)	(0.50)	(0.45)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Father's Years of Schooling	6.39	5.44	5.52	6.25	6.47	7.27	6.79
	(3.21)	(3.28)	(3.28)	(3.32)	(3.16)	(3.06)	(3.04)
Mother's Years of Schooling	4.22	3.30	3.07	3.67	4.23	5.02	5.14
	(3.30)	(3.03)	(2.99)	(3.22)	(3.36)	(3.17)	(3.32)
Number of Potential Migrants,	0.46	0.30	0.47	0.45	0.44	0.45	0.54
Household, Male	(0.62)	(0.48)	(0.58)	(0.61)	(0.59)	(0.62)	(0.62)
Number of Potential Migrants,	0.49	0.25	0.51	0.55	0.52	0.47	0.59
Household, Female	(0.71)	(0.48)	(0.69)	(0.81)	(0.81)	(0.66)	(0.79)
Village Level Variables							
Number of Migrants from	90.5	18.6	18.6	74.0	107.4	99.3	188
Village	(110)	(28.7)	(27.0)	(83.7)	(119.2)	(83.5)	(136)
ln(Village Mean Income Per Capita)	6.42	6.20	6.21	6.22	6.52	6.52	6.66
	(0.39)	(0.32)	(0.35)	(0.31)	(0.32)	(0.38)	(0.31)
ln(Village Mean Wealth Per Capita)	8.80	8.62	8.51	8.69	8.89	8.93	9.07
	(0.55)	(0.48)	(0.57)	(0.48)	(0.50)	(0.50)	(0.45)

Appendix Table 1 Continued on Next Page

Appendix Table 1 (Continued)

	All Years	1987	1990	1993	1996	1999	2002
		Year					
Village Total Land (mu)	5090	4820	5080	4870	5200	5100	5760
	(5710)	(5110)	(5190)	(5500)	(5310)	(6240)	(6460)
Village Cultivable Land Per Capita Gini	0.19	0.19	0.19	0.20	0.20	0.23	0.25
	(0.10)	(0.10)	(0.06)	(0.07)	(0.07)	(0.11)	(0.09)
Village Labor Force	861	780	851	867	899	820	948
	(486)	(352)	(419)	(433)	(470)	(487)	(559)
Cultivable Share of Village Land	0.58	0.60	0.57	0.62	0.55	0.57	0.54
	(0.28)	(0.26)	(0.28)	(0.28)	(0.28)	(0.29)	(0.31)
Years Since IDs Issued	7.37	0.33	2.12	4.86	7.87	11.01	13.86
	(5.11)	(1.02)	(1.65)	(2.07)	(2.20)	(2.23)	(2.28)
Cultivable Share of Village Land	0.58	0.60	0.57	0.62	0.55	0.57	0.54
	(0.28)	(0.26)	(0.28)	(0.28)	(0.28)	(0.29)	(0.31)
Forest Share of Village Land	0.15	0.16	0.16	0.15	0.14	0.16	0.19
	(0.27)	(0.27)	(0.25)	(0.27)	(0.25)	(0.28)	(0.30)
Orchards Share of Village Land	0.04	0.02	0.03	0.04	0.07	0.06	0.06
	(0.07)	(0.03)	(0.05)	(0.06)	(0.10)	(0.10)	(0.09)
Aquaculture Share of Village Land	0.04	0.05	0.05	0.04	0.04	0.04	0.05
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)
Share of Households with Non-Agricultural Self-Employment Income	0.56	0.66	0.66	0.55	0.57	0.49	0.51
	(0.28)	(0.27)	(0.27)	(0.27)	(0.25)	(0.28)	(0.26)
Quota Share of Grain Produced	0.09	0.12	0.12	0.08	0.10	0.07	0.03
	(0.08)	(0.10)	(0.09)	(0.08)	(0.08)	(0.07)	(0.05)
Scaled Lagged July-November Rainfall Shock, Squared	0.15	0.02	0.02	0.02	0.04	0.02	0.02
	(2.12)	(0.04)	(0.07)	(0.02)	(0.05)	(0.05)	(0.05)
Number of Observations	3068	158	162	237	262	238	187

Notes: The first column includes descriptive statistics for all years; the second through seventh columns include descriptive statistics for selected years.

Sources: RCRE Supplemental Survey (2004), Annual RCRE Household and Village Surveys (1986-1991, 1993, 1995-2003).

Appendix Table A2

What Factors Determine the Size of the Village Migrant Network?

First-Stage Regression Using the Sample of Village-Year Observations, 1986-2003

	Dependent Variable: Number of Registered Village Residents Working as Migrants			
Model	1a	1b	1c	2
Years Since IDs issued	1.385	0.417	0.038	-0.156
	0.469	0.702	1.012	0.910
Years Since IDs Issued Squared	-0.041	0.085	0.182	0.224
	0.016	0.070	0.199	0.180
Years Since IDs Issued Cubed		-0.005	-0.013	-0.019
		0.003	0.017	0.015
(Years Since IDs Issued)^4			0.002	0.004
			0.004	0.004
Ln(Village Average Income Per Capita)				0.966
				1.266
Total Land in Village (Mu)				0.029
				0.033
Cultivable Land Gini Coefficient				6.413
				3.965
Size of Village Workforce				0.078
				0.014
Cultivable Share of Village Land				2.529
				3.119
Number of Obs.	762	762	762	739
F-Test	4.62	4.23	3.23	2.78
F-Probability	0.0102	0.0057	0.0121	0.0261
partial r2, Instruments	0.0131	0.0178	0.0182	0.0165

Notes: The F-statistic tests the hypothesis that the estimated coefficients on the instruments are zero. All regressions control for village fixed effects and include year dummy variables.