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HOW LAND FRAGMENTATION AFFECTS OFF-FARM LABOR SUPPLY IN CHINA: EVIDENCE FROM HOUSEHOLD PANEL DATA

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How land fragmentation affects off-farm labor supply in China: Evidence from household panel data

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Abstract

Research on agricultural development in China has increasingly paid attention to the potentially negative effects of highly fragmented farm structures. This study provides a deeper theoretical understanding of the linkages between land fragmentation and off-farm labor supply and investigates this relationship empirically in a more direct and robust way than in the existing literature. Drawing upon a rural household panel dataset collected in Zhejiang, Hubei and Yunnan provinces from 1995-2002, we estimate the effects in two steps. First, we estimate the effect of land fragmentation on labor productivity using a time-demeaned translog production function. Second, we estimate the effect of land fragmentation on off-farm labor supply using Wooldridge's (1995) panel data sample selection model. The production function results show that land fragmentation indeed leads to lower agricultural labor productivity. It implies that land consolidation will make on-farm work more attractive and thus decrease off-farm labor supply. This conclusion is supported by a direct estimation of the off-farm labor supply function, but only for the group of farmers with the least involvement in off-farm labor. Our analysis suggests that, if more liberal land market policies and hardened property rights will allow more consolidated farmland in the future, this will not trigger a flood of former farmers leaving rural areas in search for alternative incomes. As it makes farm work more productive, it will rather provide an incentive to continue farming and raise agricultural productivity.

Keywords: Land fragmentation, off-farm, labor supply, China

1 Introduction

Research on agricultural development in China has increasingly paid attention to the potentially negative effects of highly fragmented farm structures. Land fragmentation means that a household's land resources are divided in several spatially separated plots (McPherson, 1982). In China, it emerged as a result of egalitarian land redistribution in the aftermath of the Household Responsibility System (HRS) implemented in the late 1970s and early 1980s (Tan et al., 2006). Various researchers pointed out that land fragmentation is causing productivity losses (Nguyen et al., 1996; Wan and Cheng 2001; Chen et al., 2009). It therefore has direct implications for the Chinese government's goal

to foster productivity levels in domestic agriculture. However, changes in land fragmentation may also have consequences for input use in agriculture. The most important input in Chinese agriculture, next to land, is labor. Based on an analysis of labor costs in Chinese farm households, Tan et al. (2008) suggest that more liberal land policies allowing consolidation may release more agricultural surplus labor in the future. If this is true, policies addressing land fragmentation will also affect the steadily increasing number of off-farm employees and rural migrants, and thus one of the most challenging problems of Chinese economic transition.

While Tan et al. (2008) find that fragmented farm structures correlate with higher labor costs, it is not clear why this implies that land consolidation does release rural labor, as the authors do not investigate the actual mechanisms of labor allocation any further. Moreover, other empirical work based on the analysis of household data provides only indirect and mixed evidence on the linkages between land fragmentation and off-farm labor supply in rural China. Wang et al. (2007) found positive effects of village land renting activities, which imply a higher potential for voluntary land consolidation, on household decisions to participate in the off-farm labor market in Zhejiang province. This evidence supports the suggestion by Tan et al. (2008). However, there was no effect on the quantity of households' off-farm labor supply. Wan and Cheng (2001) report that more plots per household increase the marginal product of labor in maize and early rice production (the estimated β_2 parameters in table 5 of their paper), thus implying a lower on-farm labor demand if land is consolidated. However, they found the opposite sign for tuber production. Furthermore, Carter and Yao (2002) found that more land parcels per farm reduce the average labor intensity on-farm in a sample of farmers from Jiangxi and Zhejiang provinces, which contradicts Tan et al. (2008). Similarly, Brosig et al. (2007) show that, in Zhejiang villages with much activity on the land rental market, households display a lower tendency to engage in off-farm labor markets.

In this article, we aim at a deeper theoretical understanding of the linkages between land fragmentation and off-farm labor supply and investigate this relationship empirically in a more direct and at the same time methodologically robust way than in the existing literature. Our theoretical argument is that whether or not land consolidation releases agricultural labor depends on the local shape of the production function and is undetermined a-priori. We develop this argument in the framework of a microeconomic farm household model and show that the critical parameter is the effect of land fragmentation on the marginal product of labor. We then employ a panel set of household data from three Chinese provinces to investigate this issue econometrically. Our empirical strategy consists of two steps. We first estimate the effect of land fragmentation on labor productivity by using a flexible, aggregate production function. We then estimate a labor supply function and test the direct influence of land fragmentation on off-farm labor supply. The available panel data allows us to eliminate unobserved heterogeneity by employing fixed effects techniques, which we adapt to be used in a flexible production function. The effects of the potential endogeneity of labor allocation are considered. In estimating the off-farm labor supply equation, we employ a panel data sample selection model due to Wooldridge (1995) that allows to address problems of unobserved heterogeneity and sample selectivity simultaneously and which has not been used in the agricultural household literature before.

We replicate the conventional wisdom that fragmentation reduces output and hence implies productivity losses. However, we also show that the negative effect of fragmentation on labor productivity is the only channel through which such output reduction occurs. A direct implication is that land consolidation will make on-farm work more attractive and thus decrease off-farm labor supply. This conclusion is supported by our analysis of an empirical off-farm labor supply equation, but only for the group of farmers with the least involvement in off-farm labor. Households already more active in nonfarm work are more likely to face binding constraints on labor expansion, so that the consolidation effects are not visible in the data.

If an increased reliance on voluntary land transactions and the gradual hardening of individual property rights in land markets allow more land consolidation in the future, this will not lead to a flood of labor-seeking migrants from rural areas. Instead, agricultural labor productivity will be increased and farming will become a more attractive occupation.

This paper is structured as follows: first, we analyze the effect of land fragmentation on agricultural labor productivity and off-farm labor supply theoretically; second, we introduce the database; third, we present empirical methodologies to estimate these effects; then we report the results and finally we discuss the results and conclude.

2 Theoretical analysis of the effects of land fragmentation

2.1 The effect of land fragmentation on agricultural labor productivity

We consider a separable farm household model with land fragmentation. The model follows the standard model as presented by Benjamin (1992), which is augmented by a land consolidation parameter α that determines how effectively labor can be used on the land.

We first outline the standard model. The farmer maximizes utility by choosing consumption c and leisure l , subject to a set of household characteristics, a , for example, its demographic composition. The household allocates family labor L to produce an aggregate agricultural output Y . There are other fixed inputs A , so that $Y = Y(L; A)$, with $Y_L > 0$ and $Y_{LL} < 0$. The household may also supply labor off-farm, L^o , which yields an exogenously determined wage w . Total time endowment is $T(a)$. To simplify the exposition, we ignore the possibility that labor may also be hired. Hence, the farmer's problem is as follows:

$$\begin{aligned}
 (1) \quad & \max u(c, l; a) \text{ w.r.t. } c, l, L^o, L \text{ s.t.} \\
 (2) \quad & c = Y(L; A) + wL^o, \\
 (3) \quad & l + L + L^o = T.
 \end{aligned}$$

In this model with an exogenous wage, profits are maximized independent of the household's utility function. The optimal amount of labor supplied on the farm depends only on the production technology and the wage, following the optimality condition $Y_L = w$. Given the leisure choices of the household l , which depend on a , off-farm labor supply $L^o \geq 0$ is determined as a residual. This is shown in Figure 1 (a).

We now introduce an exogenous land consolidation parameter $\alpha \in]0,1]$, which measures the efficiency of labor use on the plot. If α is close to 1, almost all the time allocated to farming is actually spent on the plot. If α is closer to 0, much time is used for travelling to and from the plot, or for other unproductive activities that result from land fragmentation, such as cumbersome water management or less efficient machinery use (Wan and Cheng, 2001). Hence, the amount of labor productively used is reduced. We write $Y = Y(\alpha L; A)$ in the presence of land fragmentation, where αL is the level of effective on-plot labor. As an illustration, consider that L is measured in days spent on-farm, each day covering 10 working hours. If $\alpha = 0.8$, the household spends 2 hours per day for travelling and other non-productive activities, and 8 hours effectively on the plot. If the household chooses to spend many days on-farm, the absolute time spent non-productively will also increase proportionally.

We are interested in the effects of varying α on labor use in the household. If land fragmentation is modeled in the abovementioned way, the first point to note is that more fragmented land unambiguously reduces output. To see this, consider the effect of land fragmentation on output as follows:

$$(4) \quad \frac{\partial Y}{\partial \alpha} = \frac{\partial Y}{\partial \alpha L} L.$$

With $Y_1 > 0$, this effect is unambiguously positive, which implies a negative impact of fragmentation on the absolute level of output.

Secondly, note that *the effect of land fragmentation on the marginal product of on-farm labor is undetermined*. The marginal productivity of labor (MPL) in the model with land fragmentation is given as follows:

$$(5) \quad \frac{\partial Y}{\partial L} = \alpha \frac{\partial Y}{\partial \alpha L}.$$

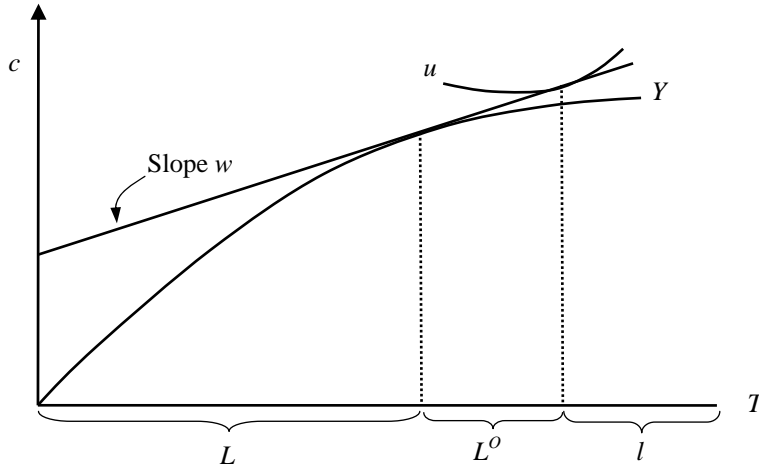
The effect of α on the MPL is then:

$$(6) \quad \frac{\partial^2 Y}{\partial L \partial \alpha} = \frac{\partial Y}{\partial \alpha L} + \alpha L \times \frac{\partial^2 Y}{\partial (\alpha L)^2}.$$

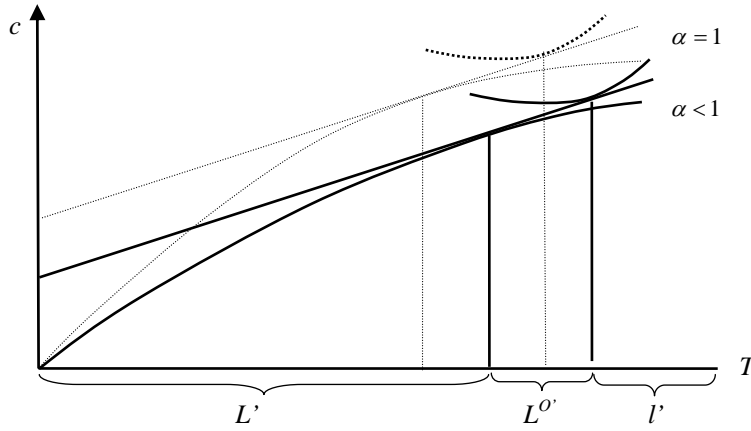
The first term on the right-hand side denotes the marginal product of effective on-plot labor on output, which is positive given our assumptions on technology and profit maximization. The second term is the effective labor on-plot input, which is non-negative according to our assumption. The third term is the second derivative of the production function with regard to effective labor input, which is negative given our concavity assumption $Y_{11} < 0$. Hence, a negative number is added to a positive one, so that the sign of the composite is theoretically undetermined. A numeric simulation demonstrating this point is available from the authors upon request.

Figure 1 Land fragmentation in the separable agricultural household model

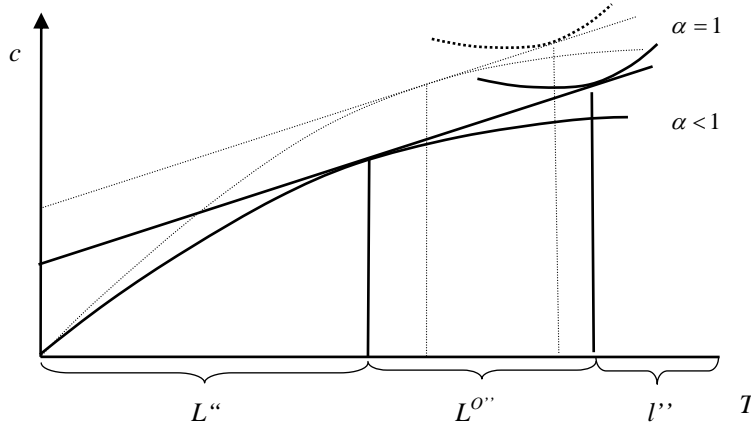
(a) separable household model



(b) land consolidation has positive effects on off-farm labor supply: $\partial L^O / \partial \alpha > 0$



(c) land consolidation has negative effects on off-farm labor supply: $\partial L^O / \partial \alpha < 0$



Source: Author's depiction.

2.2 The effect of land fragmentation on off-farm labor supply

Now, we turn to the consequences of land fragmentation on off-farm labor supply. The reduced form off-farm labor supply equation derived from the above model is as follows:

$$(7) \quad L^o = L^o(w, a, A, \alpha)$$

The level of L^o is given by $L^o = T - l - L$, so that:

$$(8) \quad \frac{\partial L^o}{\partial \alpha} = -\frac{\partial l}{\partial \alpha} - \frac{\partial L}{\partial \alpha}.$$

The effects of land fragmentation on off-farm labor supply depend on the effects of land fragmentation on leisure time and on-farm time, since the household is subject to a total time endowment constraint. When the effect of α on the MPL is undetermined, we do not know *a-priori* whether the household will employ more or less labor on-farm as a result of varying land fragmentation. *The effect of land fragmentation on off-farm labor supply is hence undetermined, too.*

In equation (8), the plausible hypothesis will be that $\frac{\partial l}{\partial \alpha} > 0$, implying that richer households consume more leisure (as depicted in Figure 1 (b) and (c)). When land consolidation decreases on-farm employment, and an increase of leisure time does not exceed the decrease of agricultural work, land consolidation will promote the off-farm labor supply (Figure 1 (b)). Conversely, when land consolidation results in an increase of on-farm employment without hiring laborers, off-farm labor supply will be reduced, as depicted in Figure 1 (c).

2.3 Potential sources of labor market imperfections

Numerous authors have pointed out that the assumption of a perfect labor market is a strong one in many empirical settings, including China (Benjamin, 1992; Bowlus and Sicular, 2003; Wang et al., 2007). For example, there may be an exogenously imposed upper bound to the number of hours a household can find employment at the going market rate, and this bound may be lower than actual labor supply. There are several plausible reasons for such constraints in the Chinese context. In addition to a simple lack of jobs in rural areas, rural inhabitants may not possess the necessary education for off-farm employment (Yang, 2004), the allocation of jobs by village leaders may be based on non-market, political and social criteria such as family connections or household income (Bowlus and Sicular, 2003), or farm households working off-farm may fear the loss of their rights to land use (Kung, 2002; Wang et al., 2011). In such cases of off-farm labor rationing, the wage line in Figure 1 will be truncated to the right and the separability property of the model breaks down. If in the extreme there is no off-farm employment opportunity at all, land consolidation will fail to affect observed off-farm employment. It is rather likely to increase the amount of leisure time and/or somewhat reduce hidden unemployment, depending on the household's preferences for leisure (or home time) consumption (Brooks and Tao, 2003; Ho et al., 2004). If off-farm work is possible at some wage, this wage may nevertheless be endogenous and dependent on

household characteristics (Sumner, 1982; Skoufias, 1994). Estimations of empirical labor effects should take this potential endogeneity into account.

3 Data

The database used in this study comes from the three Chinese provinces of Zhejiang, Hubei and Yunnan. The survey was conducted by the Rural Survey Team of the Research Centre for Rural Economy in the Ministry of Agriculture in China (RCRE). The empirical study is based on a panel data set covering 9 villages in Zhejiang, 15 villages in Hubei, and 5 villages in Yunnan and contains annual data from 1995 to 2002. Zhejiang is one of the most developed provinces, where land, labor, insurance and credit markets are more developed compared to its counterparts; Hubei is one of the most important agricultural provinces; and Yunnan is a less developed province in the west of China.

The dataset is described in Table 1. The average farm size is 4.85 mu with 6.66 plots on average. The overall average labor input is 238 person days. The off-farm labor input is 326 person days on average. Each household has 4 persons on average, and among them one person graduated from elementary school, one person graduated from secondary school, while there is only one graduated from high school in 6 households.

Table 1 Data description

Variable	Mean	Std. Dev.
For production function		
Value of Output (1995 yuan)	1026.87	872.15
Labor (person days)	237.61	158.34
Capital (yuan)	576.82	417.67
Land (mu)	4.85	3.80
Number of plots	6.66	4.92
Number of observations	12,104	
For off-farm labor supply function		
Off-farm labor input (per person days)	325.95	244.18
Off-farm wage (yuan/day)	30.05	47.02
Pesticide price (yuan/kilogram)	15.31	9.48
Number of out-migrants in the village level	191.79	162.07
Distance of village to main concrete road (km)	1.61	3.31
Percentage of total arable land participating in village land market	0.08	0.14
Number of plots	5.91	4.26
Number of members in the household	4.19	1.38
Average land per capita in the village (mu)	1.08	0.80
Number of members having elementary education level in the household	1.09	0.90
Number of members having secondary school level in the household	1.03	0.94
Number of members having high school level in the household	0.17	0.45
Average net income per capita in the village (yuan)	2781.23	2090.97
Number of unemployed people in village	82.53	143.79
Number of observations	7302	

4 Empirical study of land fragmentation effects

4.1 The effect of land fragmentation on agricultural labor productivity

A first aim of the econometric analysis in this paper is to provide an unbiased estimate of the effect of land fragmentation on labor productivity, hence an estimate of equation (6). The strategy used here is to estimate a flexible production function that takes into account the number of plots per farm N as a measure of land fragmentation¹. As summarised by Deaton (1995, 1824-1827), estimating production functions from micro data involves a number of econometric challenges that are discussed in the following, together with their potential remedies.

Previous studies have used CD production functions to estimate the impact of land fragmentation (Fleisher and Liu, 1992; Nguyen et al., 1996). In order to estimate a partial effect of land fragmentation on MPL, a more flexible approach is needed that allows interactions among factors. Similar to Wan and Cheng (2001), we therefore employ a translog function, which extends the CD by both interaction and square terms of the factors.

Given the three conventional inputs plus the number of plots as arguments, the translog function with land fragmentation can be expressed as follows:

$$(9) \quad \begin{aligned} \ln Y_{it} = & \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 \ln A_{it} + \beta_4 \ln N_{it} + \beta_5 \ln N_{it} \ln L_{it} \\ & + \beta_6 \ln N_{it} \ln A_{it} + \beta_7 \ln A_{it} \ln K_{it} + \beta_8 \ln L_{it} \ln K_{it} + \beta_9 \ln N_{it} \ln K_{it}, \\ & + \beta_{10} \ln L_{it} \ln A_{it} + \beta_{11} (\ln L_{it})^2 + \beta_{12} (\ln K_{it})^2 + \beta_{13} (\ln A_{it})^2 + \beta_{14} (\ln N)^2 + u_{it} \end{aligned}$$

where u_{it} is an identically and independently distributed (i.i.d.) error term, K indicates all capital input. Therefore, N is allowed to affect all marginal products of inputs.

The direct effect of land fragmentation on agricultural production is β_4 , which is supposed to be negative according to equation (9). Nguyen et al. (1996) and Wan and Cheng (2001) report regression estimates that support this assumption. If $\beta_4 = \beta_5 = \beta_6 = \beta_9 = 0$, land fragmentation has a zero impact on the marginal product of inputs, otherwise, the impact of land fragmentation is undetermined. The effect of land fragmentation on labor is β_5 which will be determined by the local shape of the production function. When β_5 is positive, it indicates that the MPL on fragmented land is higher than that on consolidated land at the same amount of every input. When β_5 is negative, it indicates that the MPL on fragmented land is lower. As this parameter is of prime interest in our analysis, we attempt to estimate equation (9) in the following.²

¹ There are also other approaches to measure land fragmentation degree, such as Simpson index measuring the average distance from plots to homestead (Tan et al., 2006), but we could not use this index due to lack of data.

² A commonly used approach in the literature is to estimate agricultural technology based on a dual specification. Sometimes, the production function is taken as a starting point, but more frequent is the use of profit or cost functions (Capalbo, 1988). Estimation is typically based on the derived set of input share equations, which will depend on input quantities in the case of a production function, and on input prices and output quantities or prices in the cases of cost and profit functions (see Capalbo, 1988 for a summary,

A common problem in estimating production functions from observational data is that individual farm output may be affected by unobserved characteristics of the farm. These characteristics may be due to “management bias” as introduced to the literature by Mundlak (1961) or reflect socio demographic or geographic characteristics of the farm that are constant over time. For example, soil fertility, management ability of farmers and technology are supposed to be correlated with inputs. If panel data is available as in our case, the typical way to eliminate the influence of these factors is to use a fixed-effects (FE) or “within groups” estimator. However, an ordinary FE model depends on the assumption of linear additivity and fails to eliminate the level effect in the presence of interaction terms (Angrist and Pischke, 2009, 222). To control time-invariant heterogeneity in our translog model, we therefore use time-demeaned Ordinary Least Square (OLS) regression (Wooldridge, 2009, 481) to estimate equation (9). Rather than simply adding household-specific dummy variables to the estimating equation as in the standard FE approach, all variables were first groupwise time demeaned and then interacted. In addition, year dummies for every year except 1995 were added.

An additional concern in primal estimations of production functions is the endogeneity of inputs (Deaton 1995, 1824). While variations in output may well be explained by variations in inputs on statistical grounds, the concern is that this correlation may be spurious and not due to an appropriately specified causal effect. Hence, the independency part of the i.i.d.-assumption is violated. In equation (9), the land and number of plots can be assumed to be exogenous due to the restrictions of the Chinese land market. Capital input is regarded as exogenous in our estimation for both simplification and concentration. Labor input is the most likely to be an endogenous variable for the various reasons mentioned above, as pointed out before. To the extent that the omitted factors are time invariant, our FE approach yields unbiased estimates of the causal effect. We also experimented with instrumenting the labor variables used in equation (9), however, due to a lack of suitable instruments, this did not yield useful results. Even so, we consider the likely direction of the endogeneity bias in the production function below.

To ease the interpretation of coefficients in the translog model, geometric sample means were subtracted from all variables after taking logs, so that the estimates of β_1 to β_4 are the production elasticities of the factors at geometric sample means.

A common problem in analysing microdata is that observations come from clustered samples, for example many households from the same village. This is also the case in our current sample, as described in the data section. Deaton (1997, 73-78) argues that standard errors are too small if the conventional formula is applied, because the “identical” part of the i.i.d.-assumption is violated. Some correction for this

and Berndt, 1991, chapter 9, for further technical detail and literature). As we are interested in recovering the parameter β_5 of the production function in (9), dual specifications of profit or cost functions that do not include this parameter are of little help. While a modified system of share equations dependent on input quantities may be used to provide an estimate of this parameter, it does not solve the endogeneity problems discussed below. Furthermore, it requires the calculation of cost shares for all inputs, which in our case is prohibited by lacking data, particularly for labor and land. It is unclear how fragmentation could be included in such an approach. We therefore resort to estimating (9) in a direct, primal way. See Mundlak (2001) for critical remarks on the dual approach to estimating production technology.

heteroscedasticity based on the cluster-specific regression residuals is suggested, following White (1984). We report related results in the following.

4.2 The effect of land fragmentation on off-farm labor supply

In a second step, we aim to estimate the off-farm labor supply equation in order to identify the fragmentation effect in equation (8). The off-farm labor supply is a projection of off-farm wage and other demographic variables that can be specified as follows:

$$(10) \quad L_{it}^o = \delta_0 + \delta_1 w_{it} + \delta_2 x_{it} + v_i + u_{it}, \quad t = 1, \dots, T, \quad i = 1, \dots, n,$$

where x_{it} includes all the other independent variables except for the off-farm wage w_{it} , such as the number of plots as a measure of land fragmentation degree and the demographic characteristics, δ_0 , δ_1 , δ_2 are unknown parameter vectors, v_i is an unobserved time-invariant effect, and u_{it} is an i.i.d. error.

Following our considerations on endogenous labor market access above and recent empirical literature (Sumner, 1982; Benjamin, 1992; Skoufias, 1994), we treat the wage as potentially endogenous in the following. A Fixed Effects-Two Stage Least Square (FE-2SLS) model can control endogeneity, but when some households do not provide off-farm labor in a specific year, the off-farm wage can not be observable and the FE-2SLS model suffers from sample selection bias due to the incidental truncation of the off-farm labor participation. Then a test for sample selection bias is indispensable (Sumner, 1982; Wooldridge, 2002, 551-552).

Considering sample selection and unobserved heterogeneity at the same time is methodologically challenging if households switch their selection status over time. In this case, the typical within estimators to sweep out fixed effects cannot be used, as the group of selected households changes its composition over time. There are two competing approaches in the literature how to circumvent this issue. The first is due to Wooldridge (1995), who proposes to estimate level equations in which the conditional expectations are parameterized by using Heckman-type corrections for each year in the panel, whereas fixed effects are controlled by including time averages of the exogenous variables in the equation (following Mundlak 1978). The second goes back to Kyriazidou (1997) and is based on matching selected households in first differences. While this second approach requires fewer distributional assumptions, it takes for granted that the selection effect is equal for different years in which the household is in the selected group (called conditional exchangeability assumption). The latter does not hold when the distribution changes over time (see Dustmann and Rochina-Barrachina, 2007, for discussion).

In the following, we adopt Wooldridge's (1995) methodology because it avoids the conditional exchangeability assumption and can be technically implemented in a straightforward way. The off-farm labor supply function we estimate is as follows:

$$(11) \quad L_{it1}^o = \delta_0 + \delta_1 w_{it1} + \psi_1 x_{it} + \psi_2 \bar{x}_i + \ell_t \lambda(H_{it2}) + u_{it1},$$

where \bar{x}_i is the means of independent variables except for off-farm wage, $\lambda(\cdot)$ are the inverse Mills ratios (IMR) calculated according to H_{it2} , which is a reduced index for the selection equation and determined by the probit model:

$$(12) \quad s_{it} = 1[\varphi_{i2}x_{it2} + v_{i2} + \varepsilon_{it2} > 0], \quad \varepsilon_{it2} | x_i \sim \text{Normal}(0,1),$$

δ_0 , δ_1 , ψ_1 , ψ_2 , φ_{i2} , η_2 and ℓ_i are unknown parameter vectors, and ε_{it2} is an idiosyncratic error. To conserve the degrees of freedom (Wooldridge, 2002, 582), we adopt Mundlak's (1978) approach to estimate H_{it2} and replace v_{i2} with $\eta_2 + \xi_2\bar{x}_{i2}$. Thus the probit model becomes:

$$(13) \quad s_{it} = 1[\eta_2 + \gamma_{i2}x_{it2} + \xi_2\bar{x}_{i2} + \varepsilon_{it2} > 0], \quad \varepsilon_{it2} | x_i \sim \text{Normal}(0,1),$$

where η_2 , γ_{i2} and ξ_2 are unknown parameter vectors, x_{it2} contains all the exogenous variables which are x_i and instrumental variables for w_{it1} , and \bar{x}_{i2} is the vector of means of all the exogenous variables.

The number of outmigrants in the village, the number of unemployed people in the village, log of pesticide price, distance of village to main concrete road (km), and average net income per capita in the village are chosen as external instrumental variables for the off-farm wage. The overidentification test could not reject the validity of our instruments. It is noticed that the off-farm labor supply could also be influenced by demographic characteristics of the households, the number of members in the household, the number of members having elementary education level in the household, the number of members having secondary school level in the household, and the number of members having high school level in the household. In addition to that, the percentage of total arable land participating in the village land market and log of average land per capita in the village are also controlled in the off-farm labor supply function. The probit model in equation (13) is projected on all the exogenous variables including the number of plots, the instrumental variables and the control variables in off-farm labor supply function we just mentioned and the means of all exogenous variables.

5 Results

5.1 The effect of land fragmentation on agricultural labor productivity

The regression results for the translog production function are shown in Table 2. All coefficients of the three inputs of labor, land and capital are positive. The inputs represent the production elasticities at geometric sample means and are generally in a plausible order of magnitude. Scale elasticity, given as the sum of the partial production elasticities of the three inputs in Model A, is 0.82, which is coherent with the finding by Wan and Cheng (2001). Hence, the mean farm operates at decreasing returns to scale, which is theoretically consistent. Labor elasticity is 0.26, and capital elasticity is 0.25 in Model A, both of which are similar to the results estimated by Lin (1992), while the land elasticity is 0.36, which is lower in our case.

Land fragmentation reduces total farm output, but the only channel through which this happens is via reducing labor productivity. Land fragmentation decreases the MPL ($\beta_5 < 0$). At sample means, a decrease in the number of plots by 10% raises agricultural labor productivity by approximately 1.5%. The output raised by an additional labor input can not compensate for the loss due to land fragmentation. Therefore, land fragmentation lowers labor productivity. The reduction of capital input that results from land

fragmentation is not significant, which may be due to less machinery usage in these three provinces.

We noted above the potential endogeneity problem in labor use. Farmers who participate more in off-farm work are also likely to be the ones who have a higher MPL, for example because they are younger or better educated (Huang et al. 2009). The omitted farmer's ability is likely to be positively correlated with the MPL, so that the estimated coefficient on labor use is biased upwards and represents an upper bound to the real coefficient. Another concern in our production function is the inability to include the application of organic manure. Qiao et al. (2011) found that the application of organic manure increased in poor areas due to more backyard livestock and declined in rich areas. The poor areas are often located in mountainous region with higher land fragmentation degree. In other words, highly fragmented farms appear more productive in the data because they apply more manure. This means the omitted manure application variable may falsely bias upwards the marginal product of the number of plots. Both of these omitted variables make the coefficient of land fragmentation on agricultural labor productivity β_5 to be an overestimation of the true effect. The negative effect found in our study will thus be even lower if other sources of endogeneity were controlled.

An important finding of this section is thus that consolidation of land will make on-farm work more productive. As a consequence, it will reduce off-farm labor supply of farm households, whereas further fragmentation will increase it. We turn to a direct examination of this issue in the next section.

Table 2 Translog production function with time-demeaned OLS

<i>Variable</i>	<i>Coef.</i>	<i>Std. Err.</i>
Labor	0.26***	0.08
Capital	0.25***	0.07
Land	0.36***	0.05
Plots	0.08	0.05
Plots*labor	-0.15**	0.07
Plots*land	0.13	0.14
Land*capital	0.03	0.05
Capital*labor	-0.1***	0.03
Plots*capital	-0.08	0.07
Labor*land	0.22**	0.11
Labor^2	-0.03	0.05
Capital^2	0.04**	0.02
Land^2	-0.05	0.08
Plots^2	0.07	0.06
Number of obs	12,104	
Year dummies	Yes	
Cluster robust standard errors	Yes	
Number of clusters	29	

Note: all metric variables demeaned and in logs. *** indicates a 1% significance level, ** indicates a 5% significance level, and * indicates a 10% significance level.

5.2 The effect of land fragmentation on off-farm labor supply

In order to directly analyse the effects of land fragmentation on off-farm labor supply, we first estimate equation (10) using the conventional FE-2SLS model (Table 3). An increase in the off-farm wage raises off-farm labor supply, whereas the land fragmentation effect is close to zero. Anyway, both coefficients are not significantly different from zero. The household size and all education levels give rise to the off-farm labor supply, while the land endowment dampens it. This result is robust to endogeneity, time-invariant heterogeneity and the clustering characteristics of samples, but is subject to sample selection bias.

To control the sample selection, we estimated equation (11) with pooled 2SLS following Wooldridge's (1995) model, and the results are reported in the last two columns of Table 3. The tests for the panel data sample selection bias and the fixed effects were obtained by employing joint Wald tests. The null hypothesis is ($H_0 : \ell_1 = \ell_2 \dots \dots = \ell_8 = 0$), i.e. there is no sample selection bias. The Wald test statistical results reveals that the null hypothesis is rejected at the 5% significance level ($\chi^2_8 = 17.15$). Therefore, the approach of controlling sample selection bias in panel data is required in estimating off-farm labor

supply. The null hypothesis for fixed effects test is ($H_o : \psi_1 = \psi_2 \dots = \psi_7 = 0$), i.e. a random effects model should be applied. This null hypothesis is also rejected by the Wald test at 1% significance level ($\chi^2_7 = 27.09$) suggesting a fixed effects model. In this way, the model is robust to sample selection bias and allows a correlation between the unobserved heterogeneity and the independent variables.

The estimated coefficients hence suggest that land fragmentation tends to have positive impacts on the off-farm labor supply, which is consistent with our findings in the previous section. However, the statistical significance of these coefficients could not be established. A natural explanation for this finding represent the potential imperfections in Chinese rural labor markets as listed in section 2.3. If there is non-price rationing on the labor market, reactions in labor allocation to changing patterns of land fragmentation will be muted and not visible in the data. However, it seems likely that rationing will be more severe the stronger a household is involved in off-farm work. To investigate this effect, we categorize the data into three subsamples based on the off-farm work participation rate ($= L^o / (L + L^o)$): Group 1 contains the households with a rate not higher than 0.3 but bigger than 0, Group 2 contains the households with a rate higher than 0.3 but not higher than 0.6, and Group 3 contains the households with a rate higher than 0.6 but lower than 1. We apply Wooldridge's (1995) method for each subsample separately and the estimation results are shown in Table 4. Land fragmentation increases off-farm labor supply significantly in Group 1, but not in Group 2 and 3.

For the rural laborers in Group 1, the labor market is less constrained due to the fact that these households still depend on agricultural income and have a higher incentive to increase agricultural output. In this manner, a land consolidation will reduce off-farm labor supply for these households. Whereas, land consolidation or not does not affect off-farm labor supply in Group 2 and Group 3 since these households have a stronger willingness to participate off-farm work.

The other results in Table 3 reveal that an increase of the off-farm wage significantly leads to an increase of the off-farm labor supply, which is consistent with previous studies that the off-farm wage has a positive relationship with off-farm labor supply (Sumner, 1982; Wang et al., 2007). The households with more land endowments are more involved in agricultural production leading to a reduction of off-farm work. However, the number of members in the household has no significant impact on the off-farm labor supply after controlling for sample selection bias. The households with better education have more opportunities to supply more off-farm labor than the other households, which supports findings by other authors that an increasing years of schooling contributes to the participation of off-farm work (de Brauw et al., 2002; Uchida et al., 2009).

The over-identification test shows that the instrumental variables are valid in both models reported in Table 3. The first stage results for the instrumented off-farm wage are reported in Table 5.

The findings of this section lend further support to the idea that land consolidation reduce off-farm labor supply in rural China. At the same time, it is empirically qualified, because a statistically significant effect could only be established for farm households which participate in off-farm work to a small extent (less than 30 percent of their total labor

time). A likely explanation for this finding is that households that are already more involved in off-farm labor markets are also the ones which are more heavily constrained in expanding their labor market participation further. If this is true, their labor market behaviour cannot react to changing fragmentation degrees, and an ultimate answer to the fragmentation effects on labor markets cannot be given.

Table 3: Estimation results of off-farm labor supply

	<i>FE-2SLS without sample selection</i>		<i>Wooldridge (1995) sample selection model</i>	
<i>Variables</i>	<i>Coef.</i>	<i>Std. Err.</i>	<i>Coef.</i>	<i>Std. Err.</i>
Log of off-farm wage	0.26	0.19	0.7**	0.29
Log of plots	0.03	0.07	0.14	0.11
Percentage of total arable land participating in the village land market	0.05	0.19	-0.03	0.28
Number of members in the household	0.04**	0.02	0.01	0.02
Log of average land per capita	-0.09*	0.05	-0.17**	0.09
Number of members having elementary education level in the household	0.09***	0.03	0.12***	0.04
Number of members having secondary school level in the household	0.24***	0.04	0.25***	0.04
Number of members having high school level in the household	0.25***	0.04	0.23***	0.05
F	F(8, 28) = 15.06		F(8, 28) = 11.25	
Over-identification test	0.87		0.40	
Number of observations	7,302		7,302	
Cluster robust standard errors	Yes		Yes	
Number of clusters	29		29	
Sample selection	No		Yes	
Fixed effects controlled by	Differencing out group average		Mundlak's approach	

Note: *** indicates a 1% significance level, ** indicates a 5% significance level, and * indicates a 10% significance level. The dependent variable is the log of the off-farm labor supply. Sample selection bias test for Wooldridge's method: $\chi^2_8 = 17.15(0.03)$. Fixed effects test for Wooldridge's method: $\chi^2_7 = 27.09(0.00)$.

Table 4: Estimation results of off-farm labor supply grouped by off-farm work participation ratio

	<i>Group1 (0<off-farm work participation ratio≤0.3)</i>		<i>Group2 (0.3<off-farm work participation ratio≤0.6)</i>		<i>Group3 (0.6<off-farm work participation ratio<1)</i>	
<i>Variables</i>	<i>Coef.</i>	<i>Std. Err.</i>	<i>Coef.</i>	<i>Std. Err.</i>	<i>Coef.</i>	<i>Std. Err.</i>
Log of off-farm wage	0.10	0.18	-0.09	0.15	0.28***	0.11
Log of plots	0.48***	0.12	0.04	0.05	0.06	0.04
Percentage of total arable land participating in the village land market	0.77	1.26	0.12	0.13	0.17	0.10
Number of members in the household	0.07	0.05	0.06***	0.02	0.01	0.01
Log of average land per capita	-0.15	0.18	0.08	0.06	0.07	0.04
Number of members having elementary education level in the household	0.01	0.06	0.07***	0.02	0.12***	0.02
Number of members having secondary school level in the household	0.13**	0.06	0.11***	0.02	0.17***	0.03
Number of members having high school level in the household	-0.002	0.12	0.21***	0.03	0.15***	0.05
F	F(8, 25) = 3.77		F(8, 27) = 27.38		F(8, 27) = 13.73	
Over-identification test	0.17		0.16		0.47	
Number of observations	1,420		2,453		3,429	
Cluster robust standard errors			Yes			
Number of clusters	26		28		28	
Sample selection			Yes			
Fixed effects controlled by			Mundlak's approach			

Note: *** indicates a 1% significance level, ** indicates a 5% significance level, and * indicates a 10% significance level. The dependent variable is the log of the amount of off-farm labor supply.

Table 5: First stage regression results for off-farm wage

<i>Variables</i>	<i>FE-2SLS without sample selection</i>		<i>Wooldridge (1995) sample selection model</i>	
	<i>Coef.</i>	<i>Std. Err.</i>	<i>Coef.</i>	<i>Std. Err.</i>
Log of plots	-0.07**	0.03	-0.04	0.04
Percentage of total arable land participating in the village land market	0.12	0.19	0.13	0.18
Number of members in the household	-1.3E-03	1.1E-02	0.03*	0.01
Log of average land per capita in the village	-0.02	0.04	0.01	0.04
Number of members having elementary education level in the household	0.01	0.02	-0.02	0.02
Number of members having secondary school level in the household	-0.01	0.03	-0.05	0.03
Number of members having high school level in the household	-0.02	0.03	-0.04	0.04
Number of outmigrants in the village	5.0E-04	3.5E-04	-2.7E-04	2.9E-04
Number of unemployed people in the village	-8.6E-05***	3.1E-05	-2.5E-04	2.1E-04
Log of pesticide price	-0.02	0.02	-0.10***	0.03
Distance of village to main concrete road (km)	-1.5E-02***	2.9E-03	-4.2E-03	7.7E-03
Average net income per capita in the village	8.9E-05***	2.6E-05	1.1E-04***	2.5E-05
F (P-value)	F(12,28) = 6.69 (0.00)		F(12,28) = 5.77 (0.00)	
Partial R ² of excluded instruments	0.02		0.06	
Number of observations	7,302		7,302	
Cluster robust standard errors	Yes		Yes	
Number of clusters	29		29	

Note: *** indicates a 1% significance level, ** indicates a 5% significance level, and * indicates a 10% significance level.

6 Conclusions

Taking the mixed and only indirect evidence from the literature as a starting point, the aim of this analysis was to clarify the relation between land fragmentation and off-farm labor supply among Chinese farm households. Building on household-level panel data from three structurally different provinces, our results support the conventional wisdom that, holding other inputs constant, more fragmented farms are less productive. However, by employing a flexible production function, we extend the literature by showing that this productivity loss occurs because land fragmentation reduces labor productivity. This finding establishes a direct link to the issue of off-farm labor supply, as it means that more consolidated land makes farm work more attractive and thus reduces off-farm labor supply. This result is in contrast to suggestions by Tan et al. (2008) who argue that farmers with more fragmented land use more labor, in order to compensate for the negative effects of fragmentation. According to our findings, land fragmentation makes labor less productive, so that a rational response will be to use less of it on-farm and rather switch to off-farm income generation activities. This result is supported by direct estimates of the effect of land fragmentation on off-farm labor supply. By using Wooldridge's (1995) panel data sample selection model, these estimates take into account that the group of households participating in off-farm labor markets may be a non-random subsample of all farms. However, the positive effect on off-farm labor was borne out only for the group of farms with the lowest degree of labor market involvement. Households with a high share of off-farm work in their total time allocation are likely to face binding constraints on a further expansion of their labor time, so that the potentially positive effect of land fragmentation is not reflected in observed labor time allocations.

The land market policy of the Chinese government has recently displayed a tendency towards a reduction of administrative land reallocations at the local level and the permission of local land rental markets. The land tenure contract has been expanded from 30 years in 2002 (Rural Land Contract Law) to an unspecified "long term" in 2008 (3rd plenary meeting of the 17th Party Congress) and land reallocation is only allowed when two thirds of Villagers' representatives approved (Wang et al., 2011). This policy is supposed to facilitate unproductive farmers to transfer their farmland to the other farmers and assist voluntary land consolidation through land markets, thereby increase agricultural productivity. Indeed, land fragmentation was slightly reduced recently in China (Tan et al. 2006). Against this policy background, our findings have clear implications. If more liberal land market policies and hardened property rights will allow more consolidated farmland in the future, this will not trigger a flood of former farmers leaving rural areas in search for alternative incomes. As it makes farm work more productive, it will rather provide an incentive to continue farming and raise agricultural productivity.

This conclusion comes with one important caveat. The analysis in this paper looked at a sample of continuously existing farms, operated either full-time or part-time. Farm exits were not considered. Improved opportunities to consolidate farmland due to better functioning land markets may at the same time convince some of the least productive farmers to give up farming altogether and earn their living fully from nonfarm sources.

This process may well increase the number of urban job searchers and may lead to an increasing specialization and differentiation within the pool of Chinese rural households.

References

- Angrist, J. D., Pischke, J. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton, NJ: Princeton Univ. Press.
- Benjamin, D. (1992). Household Composition, Labor Markets, and Labor Demand: Testing for Separation in Agricultural Household Models, *Econometrica* 60(2), 287-322.
- Berndt, E. R. (1991). *The Practice of Econometrics: Classic and Contemporary*. Reading: Addison-Wesley.
- Bowlus, A. J., Sicular, T. (2003). Moving toward markets? Labor allocation in rural China, *Journal of Development Economics* 71, 561-583.
- Brooks, R., Tao, R. (2003). *China's Labor Market Performance and Challenges*. IMF working paper.
- Brosig, S., Glauben, T., Herzfeld, T., Rozelle, S., Wang, X. (2007). The dynamics of Chinese rural households' participation in labor markets, *Agricultural Economics* 37, 167-178.
- Capalbo, S. M. (1988). A comparison of econometric models of U.S. agricultural productivity and aggregate technology. In: Capalbo, S. M., Antle, J.M. (Eds.): *Agricultural Productivity. Measurement and Explanation*. Washington D.C.: Resources for the Future, 159-188.
- Carter, M. R., Yao, Y. (2002). Local versus Global Separability in Agricultural Household Models: The Factor Price Equalization Effect of Land Transfer Rights. *American Journal of Agricultural Economics* 84, 702-715.
- Chen, Z., Huffman, W.E., Rozelle, S. (2009): Farm technology and technical efficiency: Evidence from four regions in China, *China Economic Review* 20, 153-161
- de Brauw, A., Huang, J., Rozelle, S., Zhang, L., Zhang, Y. (2002). The Evolution of China's Rural Labor Markets During the Reforms, *Journal of Comparative Economics* 30, 329-353.
- Deaton, A. (1995). Data and econometric tools for development analysis. In: Behrman, J., Srinivasan, T.N. (Eds.): *Handbook of Development Economics*. Volume III. Amsterdam: Elsevier, 1785-1882.
- Deaton, A. (1997): *The Analysis of Household Surveys. A Microeconomic Approach to Development Policy*. Baltimore: Johns Hopkins University Press (for The World Bank).
- Dustmann, C., Rochina-Barrachina, María Engracia (2007). Selection Correction in Panel Data Models: An Application to the estimation of females' wage equations, *Econometric Journal* 10, 263-293.
- Fleisher, B. M., Liu, Y. (1992). Economies of Scale, Plot Size, Human Capital, and Productivity in Chinese Agriculture, *Quarterly Review of Economics and Finance* 32(3), 113-123.

- Ho, P., Eyferth, J., Vermeer, E. B. (2004). *Rural development in transitional China: the new agriculture*. London: Frank Cass Publishers.
- Huang, J., Wu, Y., Rozelle, S. (2009): Moving off the farm and intensifying agricultural production in Shandong: a case study of rural labor market linkages in China, *Agricultural Economics* 40, 203-218.
- Kung, J. K.-s. (2002). Off-Farm Labor Markets and the Emergence of Land Rental Markets in Rural China, *Journal of Comparative Economics* 30, 395–414.
- Kyriazidou, E. (1997). Estimation of a panel data sample selection model, *Econometrica* 65(6), 1335-1364.
- Lin, J. Y. (1992). Rural reforms and Agricultural Growth in China, *American Economic Review* 82(1), 34-51.
- McPherson, M. F. (1982). *Land fragmentation: a selected literature review*. Development Discussion Paper No. 141. Harvard University: Harvard Institute for International Development.
- Mullan, K., Grosjean, P., Kontoleon, A. (2011). Land Tenure Arrangements and Rural–Urban Migration in China, *World Development* 39(1), 123-133.
- Mundlak, Y. (1961). Empirical Production Function Free of Management Bias. *Journal of Farm Economics* 43, 44–56.
- Mundlak, Y. (1978). On the pooling of time series and cross-sectional data, *Econometrica* 46, 69-85.
- Nguyen, T., Cheng, E., Findlay, C. (1996). Land Fragmentation and Farm Productivity in China in the 1990s, *China Economic Review* 7(2), 169-180.
- Qiao, F. Q., Chen, J., Carter, C., Huang, J., Rozelle, S. (2011). Market Development and the Rise and Fall of Backyard Hog Production in China, *The Developing Economies* 49(2), 203–222.
- Skoufias, E. (1994). Using Shadow Wages to Estimate Labor Supply of Agricultural Households, *American Journal of Agricultural Economics* 76(2), 215-227.
- Sumner, D. A. (1982). The Off-Farm Labor Supply of Farmers, *Amer. J. Agr. Econ.* 64(3), 499-509.
- Tan, S., Heerink, N., Qu, F. (2006). Land fragmentation and its driving forces in China, *Land use policy* 23, 272-285.
- Tan, S., Heerink, N., Kruseman, G., Qu, F. (2008). Do fragmented landholdings have higher production costs? Evidence from rice farmers in Northeastern Jiangxi province, P.R. China, *China Economic Review* 19, 347-358.
- Uchida, E., Rozelle, S., Xu, J. (2009). Conservation Payments, Liquidity Constraints, and Off-farm Labor: Impact of the Grain-for-Green Program on Rural Households in China, *Amer. J. Agr. Econ.* 91(1), 70–86.
- Wan, G. H., Cheng, E. (2001). Effects of land fragmentation and returns to scale in the Chinese farming sector. *Applied Economics* 33, 183-194.
- Wang, X., Herzfeld, T., Glauben, T. (2007). Labor allocation in transition: Evidence from Chinese rural households, *China Economic Review* 18, 287-308.

Wang, H., Tong, Juer , Su, Fubing , Wei, Guoxue, Tao, Ran (2011). To reallocate or not: Reconsidering the dilemma in China's agricultural land tenure policy, *Land use policy* 28, 805-814.

White, H. (1984): *Asymptotic theory for econometricians*. New York: Academic Press.

Wooldridge, J. M. (1995). Selection corrections for panel data models under conditional mean independence assumptions, *Journal of Econometrics* 68, 115-132.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. London: The MIT Press.

Wooldridge, J. M. (2009). *Introductory econometrics: a modern approach*, 4. ed., internat. student edition. Mason: Thomson South-Western.

Yang, D.T. (2004): Education and allocative efficiency: household income growth during rural reforms in China, *Journal of Development Economics* 74, 137– 162.

Yao, Y. (1999). Rural Industry and Labor Market Integration in Eastern China, *Journal of Development Economics* 59(2), 463-496.