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THE IMPACT OF AGRICULTURAL TECHNOLOGY ADOPTION ON INCOME INEQUALITY IN RURAL CHINA

by

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Abstract

This study analyzes the impact of government efforts to increase agricultural incomes on income inequality in rural China. It collects and analyzes survey data from 473 households in Yunnan, China in 2004. In particular, it investigates the effects of government efforts to promote improved upland rice technologies. Our analysis shows that farmers who adopted these technologies had incomes approximately 32 percent higher than non-adopters. While much of this came from increased incomes from the selling of upland rice, adopters also enjoyed higher incomes from other cash crops. We attribute this to technology spillovers. Despite substantial increases associated with the adoption of improved upland rice technologies, we estimate that the impact on income inequality was relatively slight. This is primarily due to the fact that low income farmers had relatively high rates of technology adoption.

JEL Categories: O13, O18, O53, Q12

Keywords: Rural economic development, Chinese economic development, upland rice, rural-urban income inequality, agricultural income policy.

I. INTRODUCTION

Over the last several decades, China has made unparalleled progress in increasing incomes and reducing poverty. Government policy, and changes in government policy, can rightly be credited with much of this progress. One undesirable consequence of this progress has been the widening income gap between rural and urban areas. The current rural-urban income gap is the result of a long-term trend that began in 1978 with the economic reforms of Deng Xiaoping. In 1978, rural incomes were approximately 39 percent of urban incomes. By 2010, they had fallen to 30 percent (NBS, 2009). This has occurred despite a massive reallocation of labor from rural to urban areas. Over the same period, the share of China's total population living in rural areas fell from 82 percent to approximately 50 percent (NBS, 2009).

Chinese policy-makers are keenly aware of the political ramifications associated with the widening gap between rich and poor (e.g., Jiang, 1997).[1] This has resulted in a proliferation of policy initiatives (e.g., CPAD [1994] initiated China's 8-7 National Poverty Reduction Program; CPG [2001] launched the West Areas Development Strategy). A major thrust of these initiatives has been the effort to increase rural incomes via state support of agriculture. This is evidenced by the large increases in the national government's agricultural budget that have occurred in recent years. For example, national budget spending on agriculture increased in real terms from 25 billion RMB Yuan in 1990, to 81 billion RMB Yuan in 2000, and to 533 billion RMB Yuan in 2009 (MOF, 2009).[2]

[1] For example, see http://english.people.com.cn/90001/90776/90882/6911854.html .
[2] Expenditures are in 1990 constant Yuan.

One key component of the government's agricultural policy has been the encouragement of productivity improvements via local extension services in rural areas.[3] A potential problem with these efforts is that they may increase local income inequality. Indeed, a large literature, stimulated by interest in the consequences of the "green revolution," reports that agricultural technology adoptions can sometimes worsen income inequality (Griffin, 1974; Pearse, 1980, Lipton and Longhurst, 1989; Freebairn, 1995). This occurs when the households that adopt new technologies are those that are better off to begin with.

A substantial literature exists on income inequality in rural China (Chen and Zhang, 2009). Benjamin, Brandt, and Giles (2005) report that most rural inequality is due to local (within village) differences rather than differences across villages or provinces. While studies reach different conclusions as to the source of local income disparities, Ravallion and Chen (1999) conclude that when it comes to farm income, grain production is a -- if not the -- major contributing factor.

Given this interest in rural income inequality, it is perhaps surprising that little is known about the distributional impacts of government-aided productivity improvements in Chinese farming communities. We are aware of only one study that directly addresses the impact of improved agricultural technology. Lin (1999) investigated the effects of F_1 hybrid rice adoption. He used data from a cross-sectional survey of 500 households in 5

[3] The Chinese government re-established its public agricultural extension service in the late 1970s. By the middle of the 1980s, China had established public agricultural extension service stations in every county and township, including remote regions. The system provided high-quality agricultural extension service. By the middle of the 1990s, it employed an extension staff of more than one million, approximately 70% of whom had graduated from technical high schools or colleges. More than 90% of these worked at public agricultural extension system stations at the county and township levels (Lu, 1999; Hu, et al, 2009). Based upon a survey of 28 counties in rural China, Hu et al (2004) reports that 40% of new agricultural technologies adopted by farmers during 1996 and 2002 were generated from public agricultural extension services.

counties of Hunan Province taken in December 1988 and January 1989. While he did not come to a definitive conclusion regarding income inequality, Lin found that adopters saw their rice incomes increase; and non-adopters saw their non-rice, agricultural incomes increase. The latter mitigated the income inequality effects of the former.

Gustafsson and Li's (2002) finding of substantial heterogeneity in income growth rates across counties in rural China is a reminder that one-size-fits-all generalizations should be viewed with caution. There is therefore a need for additional studies to confirm or disconfirm the findings of Lin's (1999) research. This study meets that need by analyzing the income effects of technology adoptions associated with the introduction of an improved upland rice variety. We draw on a cross-sectional survey of rural households in Yunnan province conducted in 2005. While our study differs from Lin in some important respects, it reaches a similar conclusion. We find no evidence that the adoption of improved upland rice contributes to increased income inequality.

Our study proceeds as follows. Section II presents a theoretical analysis that shows how the predictions of previous analyses require revision when there are technology spillovers. Section III presents some background concerning the technology adoption studied here. Section IV discusses the data used in our empirical analyses. Section V reports the results of our investigations. Section VI concludes.

II. THEORY AND METHODOLOGY

Theory. Our model generalizes Lin's (1999) theoretical framework. Like Lin, we work within a two-good, two-household general equilibrium model where comparative advantage is driven by access to different input endowments of the households as well as different input requirements of the two goods. The two goods produced are rice (R) and non-rice (N). Rice is assumed to be land-intensive and non-rice is labor-intensive. The two households are indexed by $i=\{1,2\}$, and possess endowments E_i. The production possibilities frontier of non-rice for household i is defined as:

$$y_{Ni} = F_i(y_{Ri}, E_i)\,.$$

We assume that household 1 is land-abundant, that is it has an endowment vector E_1 that gives it comparative advantage in rice. We maintain Lin's assumption of no factor markets but perfect product markets, so that all transactions take place through the product market. The income of household i is defined as

$$I_i = y_{iN} + \frac{p_R}{p_N} y_{iR}\,.$$

Household i consumes a bundle (x_{iR}, x_{iN}) that maximizes its utility given the budget constraint

$$x_{iN} + \frac{p_R}{p_N} x_{iR} = I_i = y_{iN} + \frac{p_R}{p_N} y_{iR}$$

The equilibrium relative price of rice p_R/p_N is such that the excess supply of rice of household 1 exactly equals the excess demand of rice of household 2, and, simultaneously, such that the excess demand of non-rice of household 1 exactly equals household 2's excess supply of non-rice.

FIGURE 1 illustrates the equilibrium before the technology shock. We have assumed for expositional purposes that the preferences of the two households are identical, but that their PPFs differ due to the differences in their factor endowments. Household 1's PPF is biased towards rice and household 2's PPF is biased towards non-rice. The market-clearing relative price of rice results in household 1 producing more rice and less non-rice than household 2 ($y_{1R} > y_{2R}$ and $y_{1N} < y_{2N}$). Therefore, household 1 sells rice to household 2 in exchange of non-rice.[4]

FIGURE 2 demonstrates the essence of Lin's (1999) hypothesis. The prediction of Lin is that a technology shock for rice production will bias the PPF of a technology adopter towards rice. In particular, he assumes that the household that has comparative advantage in rice will also have a comparative advantage in technology adoption and therefore becomes the technology adopter. If the relative price of rice remains unchanged, the adopters find it in their best interest to produce more rice and less non-rice than before the technology adoption change. This implies that the total output of rice goes up creating an excess supply of rice causing the relative price of rice to fall.

This reduction in the relative price of rice will induce both the technology adopter and the non-adopter to produce more non-rice output and less rice. Overall, therefore, adopters will produce more rice than before ($y_{1R}' > y_{1R}$), but the change in non-rice will be ambiguous. Non-adopters will produce less rice ($y_{2R}' < y_{2R}$) and unambiguously more non-rice ($y_{2N}' > y_{2N}$) than before. The incomes of both households increase unambiguously. Comparing the outputs of the two households, as long as both $y_{1R} > y_{2R}$ and $y_{1N} < y_{2N}$ prior to the technology adoption, it must be that technology adopters produce more rice and less non-rice than non-adopters ($y_{1R}' > y_{2R}'$ and $y_{1N}' < y_{2N}'$).

Lin (1999) confirms this prediction using a micro-dataset of rural Chinese farmers. He concludes that the output adjustment of non-adopters towards non-rice -- the

[4] Notice that for this result to be true, household 1 must not have access to more of both land and labor than household 2, as it could produce more of both goods simply by having superior endowment vector than household 2.

relative price of which has increased -- mitigates the local income inequality consequences of the new rice technology.

Our analysis generalizes Lin (1999) in that we allow the technology shock to have a spill-over effect in the production of non-rice.[5] As we discuss below, this possibility seems reasonable in the context of the particular technology shock that we analyze. As a result of this generalization, an adopter of the new technology will not only expand its production possibilities frontier in the direction of rice, but also in the direction of non-rice. FIGURE 3 demonstrates such a technology shock, adopted by household 1.

After the technology adoption, household 1 will not only produce more rice than before but also, given a sufficiently large spill-over effect, more non-rice than before ($y_{1R}' > y_{1R}$ and $y_{1N}' > y_{1N}$). If household 1 produces more of both goods, it is no longer necessary for the relative price of rice to fall to clear the market. Furthermore, if the relative price of rice falls, the drop is smaller than it would have been in the absence of the technology spill-over.

FIGURE 3 is constructed such that the technology adoption has a negligible effect on the relative price of rice because the increase in supply of the two goods is exactly proportional to the relative demand of the two goods. If the technology change does not result in a reduction in the relative price of rice, the non-adopter will not change its output mix and therefore will not experience an increase in income. The technology adopter will have an unambiguous increase in income. If the spill-over effect is large

[5] We give more detail below about the nature of the technology shock.

enough, we can get a result that the adopter will produce not only more rice but also more non-rice than the non-adopter ($y_{1R}' > y_{2R}'$ and $y_{1N}' > y_{2N}'$).[6]

If the output adjustment is as we describe and the relative price of rice does not change after technology adoption, the income of the non-adopter will not change while the income of the adopter will increase. We therefore conclude that the technology shock could have a worse outcome for income inequality than that predicted by Lin if the technology shock has a spill-over effect to non-rice.

Methodology. In light of the theory above, our study adopts a two-step procedure to estimate the effect of technology adoption on income inequality. First, we use conventional regression analysis to estimate the determinants of individual farmers' incomes, including the effect of technology adoption on the different components of farmers' incomes. We then use the estimated equation(s) to simulate what farmers' incomes would be in the absence of technology adoption. These are used to calculate Gini coefficients for the two scenarios of (i) technology adoption and (ii) no technology adoption. In this way we determine whether government efforts to increase rural incomes via support of upland rice production result in greater or lesser income inequality.

III. BACKGROUND

This study analyzes recent government efforts to improve upland rice productivity in Yunnan Province, China. Yunnan Province is located in southwestern China, bordering Vietnam, Laos, and Myanmar. It is one of the poorest provinces in China. 10.6 percent of those living in poverty in China reside in Yunnan, despite the fact that the province

[6] Notice that adopters produce more non-rice than non-adopters only if the productivity improvement of rice is large enough, the spill-over to non-rice productivity of adopters is large enough, and the non-adopter is not too much better than the adopter in producing non-rice prior to the technology adoption.

comprises less than 4 percent of the total population. A relatively large share of the population (about a third) consists of ethnic minorities. Approximately 94 percent of the land area is categorized as mountainous. Agriculture is a major source of income, but cultivatable land is scarce. Planting is restricted to upland plains and sloped hillsides. Slash and burn practices are quite common, and terracing is still relatively rare in remote areas. Level land is extremely scarce. Only about 5 percent of the land is cultivated.

Income security in the remote, mountainous areas of Yunnan is a concern for both the national and provincial governments. Because of the relative isolation of villages, it is imperative that local farmers have sufficient resources to support themselves. Even if sufficient food is available outside the region, it may be difficult to transport to these areas.

While some farmers raise maize as a staple food, rice is generally preferred.[7] Unfortunately, traditional varieties of rice are generally low-yielding on the upland slopes of Yunnan; and paddy rice is usually infeasible due to a lack of water. To address this problem, rice scientists/breeders at Yunnan Academy of Agricultural Sciences (YAAS) have developed alternative upland rice hybrids. This effort has recently been complemented by local agricultural extension services, which promote the hybrid upland rice. Because these hybrids have greater growing requirements than traditional varieties, they require farmers to use chemical fertilizers, and are best used in terraced planting environments. The local government provides subsidies for both the purchase of fertilizer and the building of terraces.

[7] Maize and traditional upland rice with very low yield served as staple foods in the study areas for hundreds of years. Improved upland rice technology introduction is seen by farmers as key for their staple food transfer from maize.

Most upland rice is grown for self-consumption. Increased productivity in the growing of upland rice is seen as key for establishing income security. By increasing the output associated with upland rice production, farmers can free up scarce cultivatable land resources for the production of cash crops. This translates directly into increased incomes.

IV. DATA

The data for this study comes from individual household surveys. Preliminary work began in 2004 when a team composed of a rice breeder from YAAS and rice economists from Zhongnan University of Economics and Law (ZUEL) and the International Rice Research Institute (IRRI) designed the survey, visited the area, and directed a pilot survey. A geographical cluster sampling procedure was used for the main survey, with selected households chosen from villages in seven counties in southeast, south, and southwest Yunnan. In 2005, teams from ZUEL and IRRI visited the area and trained local staff from the county/township Agricultural Technology Extension Stations (ATES) in how to administer the survey. These teams then travelled to the respective villages, surveying households door-to-door. Most surveys were conducted with the household head. A total of 473 usable surveys were produced.

As discussed above, Yunnan's terrain is generally mountainous, and most cultivated land takes place at elevated altitudes. The seven counties in this study range in altitude from 700 to 1900 meters. Altitude is important in upland rice production. According to experiments from YAAS, upland rice has greatest adaptability at altitudes below 1400 meters. As upland rice is a staple crop, this physiological fact is an important determinant of farming activity. TABLE 1 reports sample characteristics of the 473 households in our sample, categorized by low (1400 meters or less) and high (greater than 1400 meters) altitude.

Average household size for the overall sample is 4.7 persons. There are approximately 2.5 working members per household, with little difference between low and high altitude households. There exist, however, substantial differences in the amount of cultivated farmland. On average, high altitude farmers cultivate approximately a hectare and a quarter of land. Low altitude farmers cultivate a full hectare more. Low altitude farmers also earn considerably more than high altitude farmers. Average income for low altitude farmers is 16,763 RMB Yuan, approximately 80 percent higher than the annual income of high altitude farmers.[8] There are also substantial differences between the amount of income derived from planting and livestock. Low altitude farmers derive greater income from planting, whereas high altitude farmers derive the majority of their income from livestock.

While upland rice is grown primarily for self-consumption, both sets of farmers earn approximately a quarter of their planting income from the sale of upland rice. For both low and high altitude farmers, a much higher percent of income is earned from planting, and much smaller percentage of income is earned from non-farm activities, than is typical for rural Chinese farming households (Benjamin, Brandt, Giles, and Wang, 2007). High altitude farmers have slightly less terraced land, and slightly more irrigated land. Finally, the uptake of improved upland rice technology is approximately 50 percent greater amongst low altitude farmers (65.7 percent versus 42.0 percent). Technology

[8] As discussed in Chen and Zhang (2009), there are a number of difficult issues in calculating rural households' total incomes. Major issues include the valuation of production used for own consumption, and imputed rental income from own-housing. Our income values do not reflect these sources of income. While this is a deficiency of the current study, it does facilitate direct comparison with Lin (1999) who also omitted these sources of income.

adopters are defined as using a combination of improved upland rice varieties with terracing and/or chemical fertilizers.

TABLE 2 reports farmers' income inequality, as measured by the Gini coefficient, for the seven different counties in our sample. It is apparent that income inequality differs substantially across counties. This is a function of a number of factors, including different degrees of income inequality by income category, and different degrees of reliance upon the four categories of income.

V. RESULTS

Evidence of a price effect on land use. Government efforts to improve upland rice productivity can affect income inequality through a variety of channels, both direct and indirect. Ceteris paribus, increased rice productivity increases rice production, generating greater income from rice planting for those who adopt the technology. Whether this increases income inequality depends on whether the adopting farmers have relatively high or low incomes. In addition, Huang and Qian (2003), point out that there may also be a compensating price effect. The greater supply of rice will result in a lowered price. This serves to counter the income gains from adopters.

As discussed above, Lin (1999) notes that the lower price of rice also encourages shifting of cultivatable land to other cash crops. TABLE 3 presents evidence that a similar market response may be at work in Yunnan. Over the period 2000 to 2004, the percent of cultivatable land devoted to upland rice production fell for both adopting and non-adopting farmers.[9] The fact that the reduction is lower for adopting farmers is

[9] Data on land use in previous years was collected via questions on the 2005 survey that retrospectively queried households about past farming practices.

consistent with a higher marginal product of land in rice production mitigating the incentive to shift out of rice production.

OLS estimation of the income equations. The first step in our two-step procedure consists of estimating farmers' incomes. We want to identify the effect of technology adoption, while controlling for important other variables. Accordingly, we estimate the following specification relating farmers' incomes to household characteristics:

$$\begin{aligned} ln\ \ Income_{i} = & \alpha_0 + \alpha_1 Land_i + \alpha_2 Labor + \alpha_3 Age_i + \alpha_4 Education_i \\ & + \alpha_5 HHSize_i + \alpha_6 Terrace_i + \alpha_7 Low\ Altitude_i + \alpha_8 Market_i \\ & + \alpha_9 Adoption_i + \sum_{c=1}^{7} \alpha_{9+c} D_i^c + \varepsilon_i \end{aligned}$$

where *Land* measures farm size (in hectares), *Labor* the number of working household members, *Age* and *Education* are the age and maximum educational attainment of the household head, *HHSize* the number of persons in the household, *Terrace* the percentage of terraced land, *Low Altitude* is a dummy variable taking the value 1 if the farm is situated at an altitude of 1400 meters or lower, *Market* is the distance in kilometers of the household to the nearest market, *Adoption* is a dummy variable that takes the value 1 if the household is an adopter of improved upland rice technology, and D^c is a county dummy variable that takes the value 1 for the c^{th} county.

Land, *Labor*, *Age*, and *Education* can be thought of as inputs into the farm production function, so that their increase is expected to result in greater output. *HHSize*, holding constant *Labor*, is included to pick up opportunities for household production specialization that allows farm laborers to produce more agricultural output. With *Land* held constant, the variables *Terrace* and *Low Altitude* proxy for the quality of the land input. *Market* measures the cost of transporting goods to market, with greater distance expected to lower income. *Adoption* is expected to increase planting income from upland rice, and possibly other outputs depending on the degree of technology spillover. The county dummies pick up unmeasured characteristics of the quality of agricultural inputs, the effects of which are *a priori* ambiguous.

TABLE 4 summarizes the results of regressing farmers' incomes on the variables above -- first with respect to total income, then with respect to the individual components of farmers' incomes. Column (1) reports the effect on technology adoption on total income. All of the coefficients have the expected signs, though not all of them are statistically significant. The coefficient on the technology adoption is significant and large in size. Technology adopters are estimated to enjoy 32 percent higher incomes, ceteris paribus.

It is also useful to look at the effect of adoption on the different components of income (cf. Columns 2 through 5). Here again, most of the coefficients have the expected signs, though there are some interesting differences across the different income components. For example, education does not produce much of a return for planting income associated with upland rice, but is a positive and significant determinant of livestock, non-farm, and (marginally) planting income from other crops. Unlike upland rice production, these activities are primarily engaged in for the purpose of market exchange. Education may pay off here because of its value in determining (and learning) the most profitable market activities for the household.

Not surprisingly, land is an important determinant for planting and livestock income, but not for non-farm income. Interestingly, terracing, which was primarily promoted as a means of gaining greater yields from the improved upland rice varieties, appears to have its most significant effect in planting income from other crops.

Most interesting is the adoption variable. We expect the coefficient for *Adoption* to be positive and significant in Column (2), and it is. The associated coefficient implies that households that adopt improved upland rice technology have incomes from selling upland rice that are approximately 45 percent larger than non-adopters, ceteris paribus. But the *Adoption* coefficient on planting income from other crops is also positive and significant. This is the opposite of what Lin (1999) predicts.

Our explanation relates to the theory we presented above. Unlike Lin's study, technology adoption in our study includes not just the use of the improved upland rice hybrid, but also employment of the other bundled services provided by the Agricultural Technology Extension Stations (ATES). These include the use of fertilizer and support in terrace building. The latter two services are easily transferred to cash crops, where they are also expected to increase output. Thus the positive and significant (at the 10-percent, two-tailed level) of the *Adoption* coefficient in Column (3) of TABLE 4 is evidence of a technology spillover.

Not only do we not see evidence of a negative *Adoption* coefficient for the two components of planting income, but neither do we see it for livestock and non-farm income. Here the explanation of a direct technology spillover is less tenable. More likely, technology adoption allows some farmers to reduce their labor input into planting for self-consumption.[10] This frees up resources for non-planting income, such as

[10] Subramanian and Qaim (2009) find evidence of a similar labor-saving effect from the introduction of Bt cotton in India.

livestock and non-farm production. The effect is likely not large, but large enough to compensate for the negative price effect predicted by Lin (1999).

Addressing endogeneity. One concern with the previous analysis is that it ignores the possibility that technology adoption may be correlated with other productive characteristics. The associated positive *Adoption* coefficients may be proxying for these characteristics, rather than picking up a productivity effect from improved technology. Fortunately, we have a variable that is a good candidate for an instrumental variable.

An important determinant of whether a household is a technology adopter is that there exists an extension program supported by the Agricultural Technology Extension Station (ATES) in the village. Approximately 80 percent of the farmers in our sample live in villages with an ATES-supported extension program (cf. Appendix). The program supplies both advice through an extension agent, and direct inputs in the form of chemical fertilizers. Only farmers in the village can avail themselves of the program. Therefore, the presence of a program in a village is highly correlated with the decision to adopt the improved upland rice technology.

We also expect that the presence of a program in a village will be uncorrelated with farmers' incomes in that village. While the decision to start a program is no doubt partly a function of the size of a village[11], which is likely positively related to the productivity of farmers' lands, this is balanced by the desire to locate program in low-income areas where agricultural productivity is relatively low.

TABLE 5 reports the results of re-estimating the preceding regression equations using 2SLS. Column (1) reports the results of the first-stage regression, where the variable *Adoption* is now the dependent variable. The specification includes all the

[11] This is because more people can benefit from a program if a village is relatively large.

variables of TABLE 4, except that the endogenous variable *Adoption* is replaced with an *Extension* dummy variable, indicating the presence of an extension program in the village.

The coefficients are somewhat difficult to interpret. For example, we know from TABLE 1 that farmers in low altitude areas are approximately 50 percent more likely to adopt upland rice technology. Yet the coefficient for *Low Altitude* is negative and significant. This results from including county dummies in the specification. Nevertheless, it is clear that the presence of a program is a positive and significant determinant of *Adoption*, as indicated by the coefficient for the *Extension* variable. Further, the associated *t* statistic of 4.24 more than satisfies the Staiger-Stock (1997) rule-of-thumb for avoiding "weak instruments."[12]

The second column of TABLE 5 reports the 2SLS analog of the OLS coefficients in Column (1) of TABLE 4. While a Hausman endogeneity test rejects the null hypothesis of exogeneity (or equal coefficients) at the 5 percent level, the 2SLS coefficients are relatively close to their OLS counterparts. In particular, the estimated coefficient of the *Adoption* variable using 2SLS is 0.2987, compared to an OLS estimate of 0.2786. Both are significant at the 1 percent level.

The subsequent analysis uses both the OLS and 2SLS estimates to calculate the impact of technology adoption on income inequality. These will produce very similar results, though for a number of reasons, we prefer the OLS estimates.[13]

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[12] Staiger and Stock recommend a partial *F*-statistic of 10 or larger. See also Stock and Yogo (2005).

[13] One reason we prefer the OLS estimates is that the expected endogeneity bias is positive. Thus, correcting for endogeneity should produce coefficients that are less positive. In fact, the *Adoption* coefficients in Columns (2) through (4) of TABLE 5 are larger than their TABLE 4 analogs. A further reason to prefer the OLS estimates is that the size of the *Adoption* coefficients in Columns (3) and (4) strain incredulity. Nevertheless, these issues matter little for the conclusions of our study.

Estimating the effect of technology adoption on income inequality. We are now in a position to estimate the effect of technology adoption on farmers' income inequality in Yunnan Province. We start with the OLS regressions of TABLE 4. We use the estimated regression coefficients from Column (1) of TABLE 4 to predict income for each of the 452 farmers in that sample. The associated predicted incomes represent farmers' incomes in an environment where technology adoption is available to all, but only some choose to adopt.

We then assign a value of zero for *Adoption* to all the farmers in this sample and recalculate their predicted incomes, using the same coefficients from Column (1) of TABLE 4. These incomes represent farmers' incomes in an environment where technology adoption is not available to any farmers. The two sets of predicted incomes are then used to calculate Gini coefficients for the samples "with technology adoption" and "without technology adoption" respectively. We also use the 2SLS coefficients of Column (2) of TABLE 5 to obtain alternative predictions of farmers' incomes. This provides us an alternative set of predictions for calculating the Gini coefficient for the environment "with technology adoption."

These calculations are reported in TABLE 6. The top row reports the Gini coefficients using predictions for "Total Income." For an environment without technology adoption, we calculate a Gini coefficient of 0.285. This rises slightly to 0.288 and 0.291 when technology adoption is possible, depending on whether we are using the OLS or 2SLS estimates to predict farmers' incomes. In any case, the differences are negligible, at least compared to the cross-county Gini coefficients reported in TABLE 2.

When we redo the exercise for the income subcomponents (cf. Rows 2 though 5 of TABLE 6), we see some evidence of greater income inequality for the individual components of income, but not enough to change our overall conclusion. Despite the relatively large estimated impacts of technology income, as given by the regression equations of TABLES 4 and 5, there is little evidence that this contributes to greater income inequality for the farmers of Yunnan Province.

The apparent contradiction of large technology impacts in TABLES 4 and 5, and relatively small income inequality effects in TABLE 6, is resolved by FIGURE 4. This figure graphs the rate of technology adoption by (pre-technology adoption) income deciles.[14] Evident is the high rates of technology adoption among lower income deciles. While the relationship between technology adoption and income is non-monotonic, it is clear that lower-income farmers adopt technology at rates that are roughly equivalent to those of higher-income farmers. Thus, the benefits of technology adoption flow relatively evenly across the income distribution of rural farmers in our dataset.

VI. CONCLUSION

This study uses household income data from farmers in rural China to evaluate the effect of government promotion of improved agricultural technology on income inequality. Income inequality is a serious concern in China, where the rural-urban income gap has been growing wider in recent years. As a result, both national and provincial governments have taken numerous steps to increase agricultural incomes. A key component of these is government efforts to increase productivity via Agricultural

[14] As the data is cross-sectional, we do not have pre-technology adoption incomes for adopters. Instead, we use predicted incomes for all households assuming no technology adoption as our measure of pre-technology adoption income.

Technology Extension Stations (ATES). These have been widely used to promote new technologies among rural farmers. A concern is that government efforts may induce greater local income inequalities if the benefits of government support flow to those who are relatively well-off.

We look at one such effort in Yunnan Province. Here, rice breeders have developed a new upland rice hybrid. In combination with chemical fertilizers and terracing, these improved upland rice varieties offer substantial productivity gains over traditional upland rice varieties. Village-based technology extension program have been instrumental in encouraging the uptake of this improved technology. Our study compares adopters with non-adopters to estimate the income effects of technology adoption, along with the corresponding impact on income inequality.

Approximately half of the 473 households in our survey adopted the improved upland rice technology. We estimate that incomes were approximately 32 percent higher for adopters. Furthermore, we find that adopters experienced not only higher incomes from planting upland rice, but also from planting other cash crops. The latter result is contrary to the finding of Lin (1999). We attribute this difference to the fact that the adoption of improved upland rice technology, which includes the use of chemical fertilizer and terracing, had spillover effects on cash crops.

Despite the fact that the associated income effects of improved upland rice technology are relatively large, we find no evidence to indicate that these translate into substantial increases in local income inequality. This is due to the fact that a substantial proportion of households in the lower income deciles are technology adopters. We note that this conclusion is broadly consistent with the findings of Lin (1999), despite there being substantial differences in our studies. While additional research is called for, this provides some degree of encouragement that government efforts to raise rural, agricultural incomes are not being undermined by the exacerbation of local income disparities.

REFERENCES

Benjamin, D., Brandt, L., and Giles, J. "The Evolution of Income Inequality in Rural China." *Economic Development and Cultural Change* Vol. 53, No. 4 (2005): 769-824.

_____________, and Wang, Sangui. "Inequality and Poverty in China during Reform." PMMA Working Paper 2007-07, 2007.

Chen, Xi and Zhang, Xiaobo. "The Distribution of Income and Well-Being in Rural China: A Survey of Panel Data Sets, Studies, and New Directions." Working paper, Munich Personal RePEc Archive, Paper No. 20587, 25 October 2009.

CCCP and SC (The Central Committee of the Communist Party of China and the State Council), "Improving the Balance between Urban and Rural Development and Strengthening the Foundation for the Development of Agriculture and Rural Areas," 2010. http://news.xinhuanet.com/politics/2010-01/31/content_12907829.htm. Accessed 29 March 2010.

CPAD (State Council Leading Group Office of Poverty Alleviation and Development), "China's 8-7 National Poverty Reduction Program," 1994. http://www.cpad.gov.cn/data/zcfg/. Accessed 29 March 2010.

CPG (The Central People's Government of the People's Republic of China), "Tenth Five-year Plan on National Economic and Social Development Outline of China upon Development of the Western Area," 2010. http://www.gov.cn/gongbao/content/2001/content_60699.htm. Accessed 29 March 2010.

Freebairn, Donald K. "Did the Green Revolution Concentrate Incomes? A Quantitative Study of Research Reports." *World Development* Vol. 23, No. 2 (1995): 265-279.

Griffin, Keith. The Political Economy of Agrarian Change, London: The MacMillan Press, Ltd., 1974.

Gustaffson, Bjorn and Shi, Li. "Income Inequality Within and Across Counties in Rural China: 1988 and 1995." *Journal of Development Economics* Vol. 69, No. 1 (2002): 179-204.

Hu, R., Huang, J., and Li, L. "Agricultural Technology Extension: Current Status, Problems and Measurements." *Management World* Vol. 5 (2004): 50−57 (in Chinese).

Hu, Ruifa, Yang, Zhijian, Kelly, Peter, and Huang, Jikun. "Agricultural Extension System Reform and Agent Time Allocation in China." *China Economic Review* Vol. 20 (2009): 303–315;

Jiang, Z. M. "Hold High the Great Banner of Deng Xiaoping Theory for an All-round Advancement of the Cause of Building Socialism With Chinese Characteristics Into the 21st Century - Report Delivered at the 15th National Congress of the Communist Party of China", Presidential Address, September 12, 1997. http://news.xinhuanet.com/ziliao/2003-01/20/content_697189.htm. Accessed 29 March 2010.

Lin, J.Y. "Technological Change and Agricultural Household Income Distribution: Theory and Evidence from China." *The Australian Journal of Agricultural and Resource Economics* Vol. 43, No. 2 (1999):179-194.

Lu, M. *Fifty Years of Agricultural Science and Technology in China*. Beijing, China: China Agricultural Press, 2009 (in Chinese).

Lipton, Michael, Longhurst, Richard. New Seeds and Poor People. London: Unwin Hyman, Ltd., 1989.

MOF (Ministry of Finance), Finance Yearbook of China 2009, China Finance Magazine Press, 2009.

NBS (National Bureau of Statistics), *China Statistic Yearbook*, China Statistics Press, 2009.

Pearse, Andrew. Seeds of Plenty, Seeds of Want. New York: Oxford University Press, 1980.

Ravallion, Martin and Chen, Shaohua. "When Economic Reform is Faster Than Statistical Reform: Measuring and Explaining Income Inequality in Rural China." *Oxford Bulletin of Economics and Statistics* Vol. 61, No. 1 (1999): 33-56.

Staiger, D. and Stock, J. H. "Instrumental Variables Regression with Weak Instruments." *Econometrica* Vol. 65 (1997): 557-586.

Stock, J.H. and Yogo, M. "Testing for Weak Instruments in Linear IV Regression." In D.W.K. Andrews and J.H. Stock, eds., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. Cambridge: Cambridge University Press, 2005, pp. 80–108.

Subramanian, Arjunan and Qaim, Matin. "Village-wide Effects of Agricultural Biotechnology: The Case of Bt Cotton in India." *World Development*, Vol. 37, No. 1 (2009): 256-267.

TABLE 1
Summary of Household Characteristics for Low and High Altitude Farmers

Characteristic	*Low Altitude*	*High Altitude*
Number of households	230	243
Average persons per household	4.74 (1.34)	4.62 (1.51)
Average number of household members in labor force	2.57 (1.09)	2.41 (1.08)
Average annual income (RMB)	16,763 (12,399)	9,342 (7,638)
Percent of income derived from planting[a]	59.8 (23.8)	41.6 (25.0)
Percent of income derived from livestock[b]	32.8 (20.9)	51.2 (24.4)
Percent of income derived from non-farm production	7.4 (12.9)	7.1 (16.6)
Percent of planting income derived from upland rice production	30.2 (23.8	23.3 (18.8)
Average amount of cultivated land area (CLA) in hectares	2.24 (1.27)	1.23 (0.80)
Percent of CLA that is sloped	73.9 (26.2)	74.8 (22.8)
Percent of CLA that is terraced	21.1 (18.5)	15.5 (15.7)
Percent of CLA that is irrigated	5.0 (10.5)	10.2 (11.9)
Percent of households adopting improved upland rice technology	65.7	42.0

[a] In addition to upland rice, planting income is derived from: 1) maize and paddy rice (in upland areas, not all farm households plant paddy rice due to limited land resources and rainfall); 2) rapeseed and buckwheat; and 3) perennial plants such as tea, rubber, sugarcane, and coffee.

[b] Livestock income is primarily derived from 1) pigs (which are also raised for self-consumption), 2) draught animals (in some cases, farm households sell their cattle), and 3) chickens and ducks.

[c] Non-farm income sources primarily include: 1) transfer payments (e.g., government Slope Land Conversion Program), and 2) local casual labor work.

TABLE 2
Gini Coefficients of Total Household Income and Income Components

Income Source	*Income Share*	*Component Gini*	*Total Household Income Gini*
<u>COUNTY 1</u>			
Planting Income (Upland Rice)	0.161	0.446	
Planting Income (Other)	0.425	0.498	0.339
Livestock Income	0.367	0.396	
Non–Farm Income	0.046	0.886	
<u>COUNTY 2</u>			
Planting Income (Upland Rice)	0.151	0.397	
Planting Income (Other)	0.360	0.443	0.408
Livestock Income	0.410	0.459	
Non–Farm Income	0.078	0.877	
<u>COUNTY 3</u>			
Planting Income (Upland Rice)	0.083	0.422	
Planting Income (Other)	0.781	0.332	0.291
Livestock Income	0.133	0.613	
Non–Farm Income	0.003	0.942	
<u>COUNTY 4</u>			
Planting Income (Upland Rice)	0.083	0.302	
Planting Income (Other)	0.459	0.336	0.299
Livestock Income	0.420	0.432	
Non–Farm Income	0.038	0.877	
<u>COUNTY 5</u>			
Planting Income (Upland Rice)	0.066	0.635	
Planting Income (Other)	0.299	0.353	0.345
Livestock Income	0.597	0.463	
Non–Farm Income	0.038	0.818	

Income Source	***Income Share***	***Component Gini***	***Total Household Income Gini***
<u>COUNTY 6</u>			
Planting Income (Upland Rice)	0.130	0.381	
Planting Income (Other)	0.445	0.683	0.493
Livestock Income	0.291	0.325	
Non–Farm Income	0.133	0.835	
<u>COUNTY 7</u>			
Planting Income (Upland Rice)	0.075	0.403	
Planting Income (Other)	0.164	0.297	0.263
Livestock Income	0.572	0.305	
Non–Farm Income	0.189	0.657	
<u>AGGREGATE</u>			
Planting Income (Upland Rice)	0.142	0.508	
Planting Income (Other)	0.389	0.543	0.382
Livestock Income	0.397	0.479	
Non–Farm Income	0.073	0.880	

TABLE 3
Changes in the Percentage of Total Cultivated Land Area Devoted to Upland Rice Production over Time

		Year		*Change from*
	2000	*2002*	*2004*	*2000 to 2004*
Adopting farmers	37.8	36.1	32.1	-15.1%
Non-adopting farmers	33.8	32.0	25.8	-23.7%

TABLE 4
The Effect of Upland Rice Technology on Farmers' Household Incomes

Variable	***Total Income (1)***	***Planting Income (Upland Rice) (2)***	***Planting Income (Other) (3)***	***Livestock Income (4)***	***Non-Farm Income (5)***
Land	0.0150 (5.65)***	0.0130 (5.31)***	0.0295 (5.9)***	0.0084 (2.52)**	0.0109 (1.52)
Labor	0.0744 (1.88)*	0.0510 (1.40)	-0.0329 (-0.44)	0.0603 (1.21)	0.0718 (0.67)
Age	0.0011 (0.34)	-0.0022 (-0.73)	0.0009 (0.14)	0.0059 (1.45)	-0.0044 (-0.45)
Education	0.1918 (3.51)***	-0.0036 (-0.07)	0.1686 (1.63)	0.2886 (4.17)***	0.4365 (2.88)***
HHSize	0.0849 (2.70)***	0.0642 (2.21)**	0.0934 (1.57)	0.1016 (2.56)**	0.0497 (0.54)
Terrace	0.1586 (0.71)	0.0499 (0.23)	0.8993 (2.13)**	-0.0899 (-0.32)	0.2898 (0.42)
Low Altitude	0.5058 (4.59)***	0.8193 (7.98)***	0.1799 (0.86)	0.4514 (3.26)***	0.9078 (2.68)***
Market	-0.0103 (-1.15)	-0.0145 (-1.62)	-0.0305 (-1.8)*	0.0038 (0.33)	0.0091 (0.3)
Adoption	0.2786 (3.05)***	0.3704 (4.20)***	0.1836 (1.69)*	0.1020 (0.65)	0.0469 (0.19)
R-squared	0.32	0.46	0.21	0.27	0.20
Observations	452	405	452	445	157

NOTE: The dependent variable is the natural log of income. Estimated standard errors are robust to heteroscedasticity. All regression specifications include county dummies.

*, **, *** Indicates statistical significance at the 10 percent, 5 percent and 1 percent levels (two-tailed tests).

TABLE 5
The Effect of Upland Rice Technology on Farmers' Household Incomes: Correcting for Endogeneity

Variable	*First-Stage Regression*[a] *(1)*	*2SLS Total Income (2)*	*2SLS Planting Income (Upland Rice) (3)*	*Planting Income (Other) (4)*	*Livestock Income (5)*	*Non-Farm Income (6)*
Land	0.0051 (3.65)***	0.0144 (4.16)***	0.0057 (1.79)*	0.0329 (5.08)***	0.0099 (2.28)**	0.0067 (0.58)
Labor	-0.0447 (-2.09)**	0.0786 (1.85)*	0.1081 (2.73)***	-0.0568 (-0.71)	0.0505 (0.94)	0.1008 (0.80)
Age	-0.0005 (-0.30)	0.0012 (0.37)	-0.0012 (-0.40)	0.0003 (0.05)	0.0057 (1.38)	-0.0035 (-0.35)
Education	-0.0109 (-0.37)	0.1946 (3.48)***	0.0366 (0.72)	0.1529 (1.46)	0.2812 (3.99)***	0.4482 (2.93)***
HHSize	0.0047 (0.28)	0.0844 (2.67)***	0.0548 (1.89)*	0.0965 (1.62)	0.1028 (2.58)***	0.0471 (0.51)
Terrace	0.1794 (1.47)	0.1238 (0.48)	-0.3032 (-1.28)	1.0962 (2.26)**	-0.0117 (-0.04)	0.1010 (0.12)
Low Altitude	-0.1789 (-3.03)***	0.5238 (4.08)***	1.0138 (8.63)***	0.0784 (0.32)	0.4108 (2.55)**	0.9552 (2.73)***
Market	0.0212 (4.47)***	-0.0132 (-0.95)	-0.0447 (-3.56)***	-0.0137 (-0.52)	0.0108 (0.62)	-0.0148 (-0.25)
Adoption	----	0.2987 (2.60)***	1.3006 (4.12)***	0.5647 (1.82)*	-0.0993 (-0.18)	0.8542 (0.49)
Extension	0.230002 (4.24)***	----	----	----	----	----
R-squared	0.38	----	----	----	----	----
Observations	452	452	405	452	445	157

[a] The dependent variable in this OLS regression is *Adoption*.

*, **, *** Indicates statistical significance at the 10 percent, 5 percent and 1 percent levels (two-tailed tests).

NOTE: All regression specifications include county dummies.

TABLE 6
The Effect of Upland Rice Technology on Income Inequality

INCOME SOURCE	***OLS*** ***Without Technology Adoption (1)***	***OLS*** ***With Technology Adoption (2)***	***2SLS*** ***With Technology Adoption (3)***
Total Income	0.285	0.288	0.291
Planting Income (Upland Rice)	0.367	0.376	0.379
Planting Income (Other)	0.494	0.499	0.596
Livestock Income	0.298	0.301	0.300
Non-Farm Income	0.381	0.380	0.395

NOTE: Numbers in the table are Gini coefficients calculated for the full sample of households. The methodology is described in the text. Columns (1) and (2) use the OLS coefficients from TABLE 4 to calculate predicted incomes in the absence/presence of technology adoption. Column (3) uses the 2SLS coefficients from TABLE 5.

FIGURE 1
Equilibrium Before the Technology Adoption

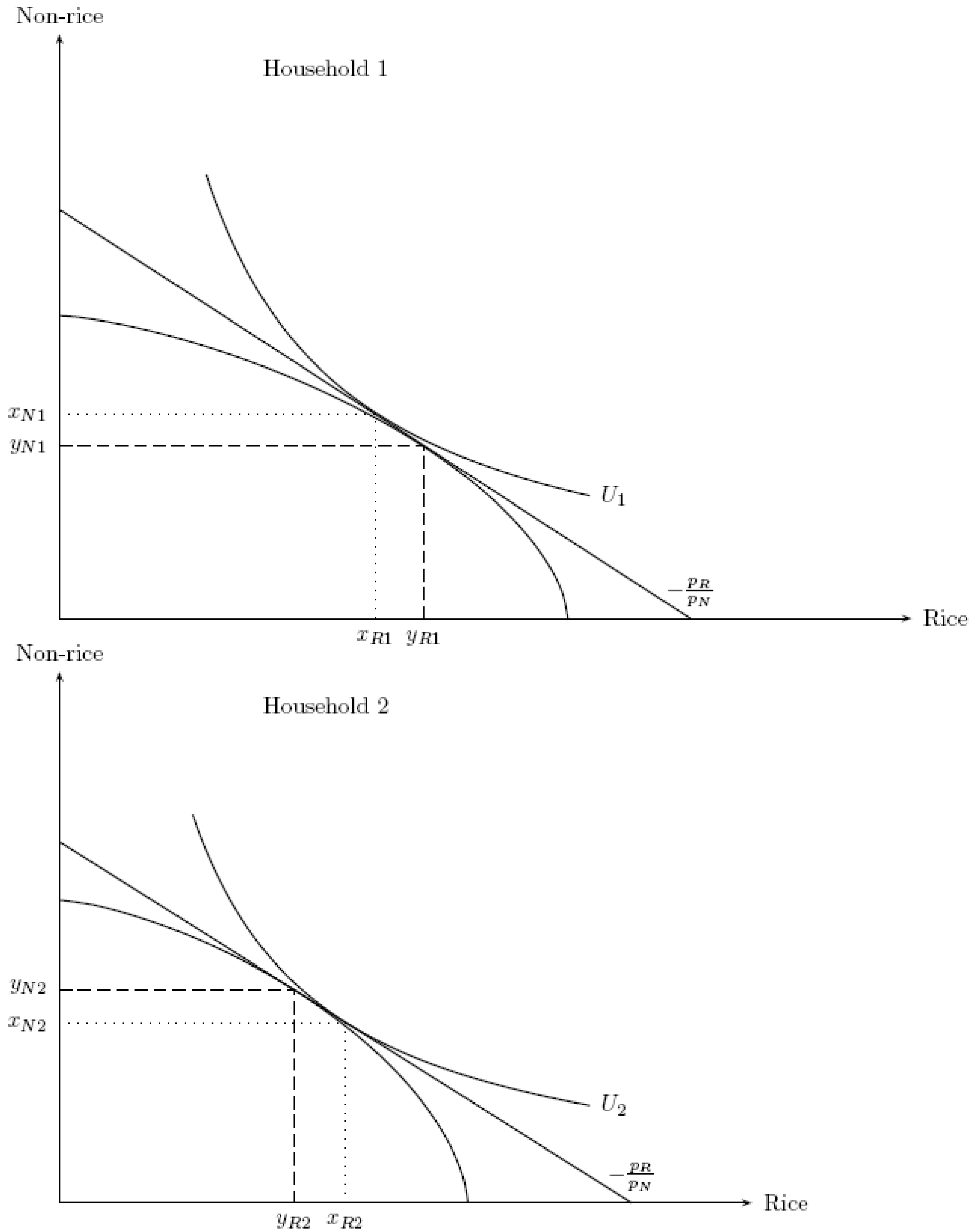


FIGURE 2
Equilibrium After Technology Adoption Without Spill-Over Effect

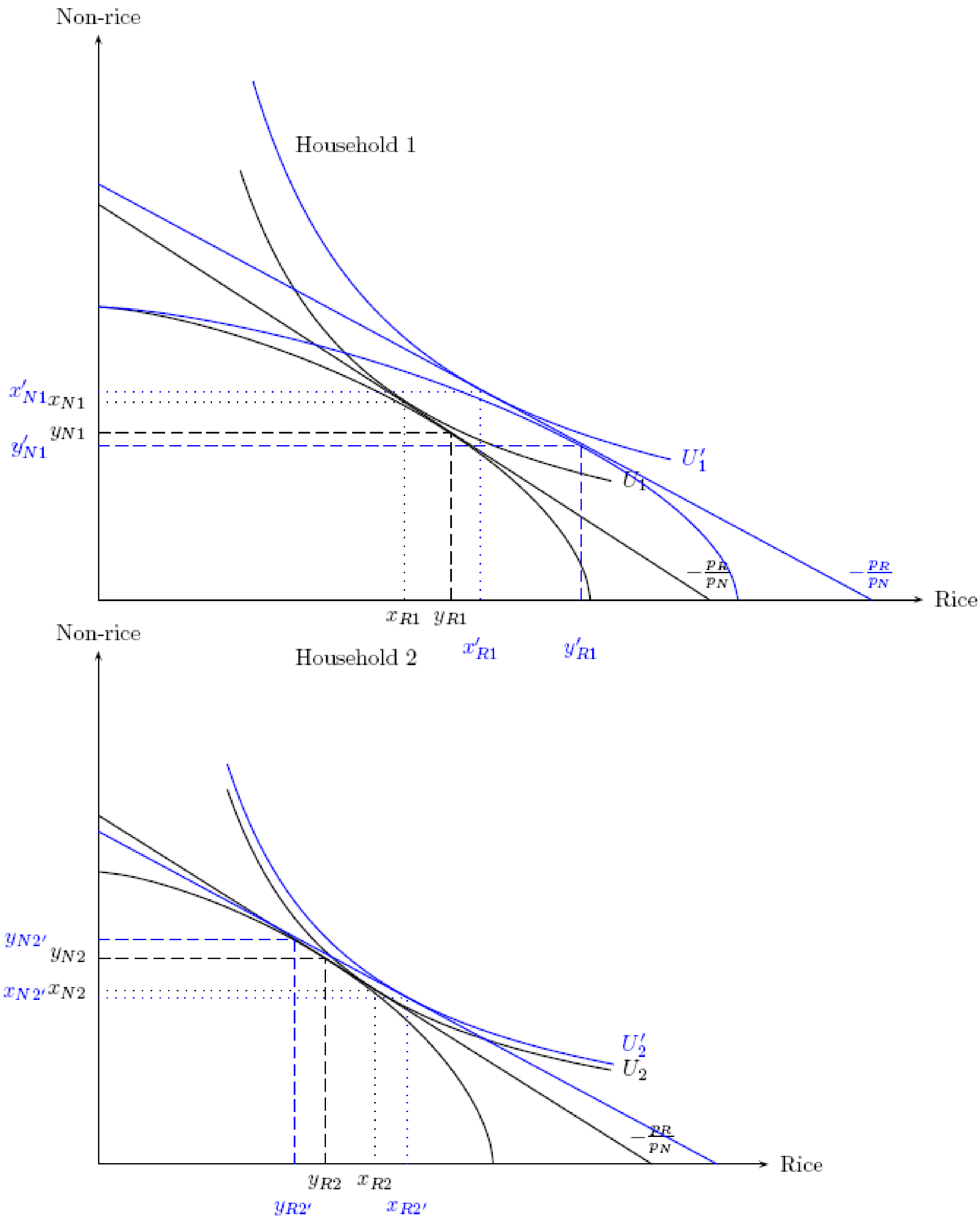


FIGURE 3
The Effect of Techology Adoption On Non-Rice Production

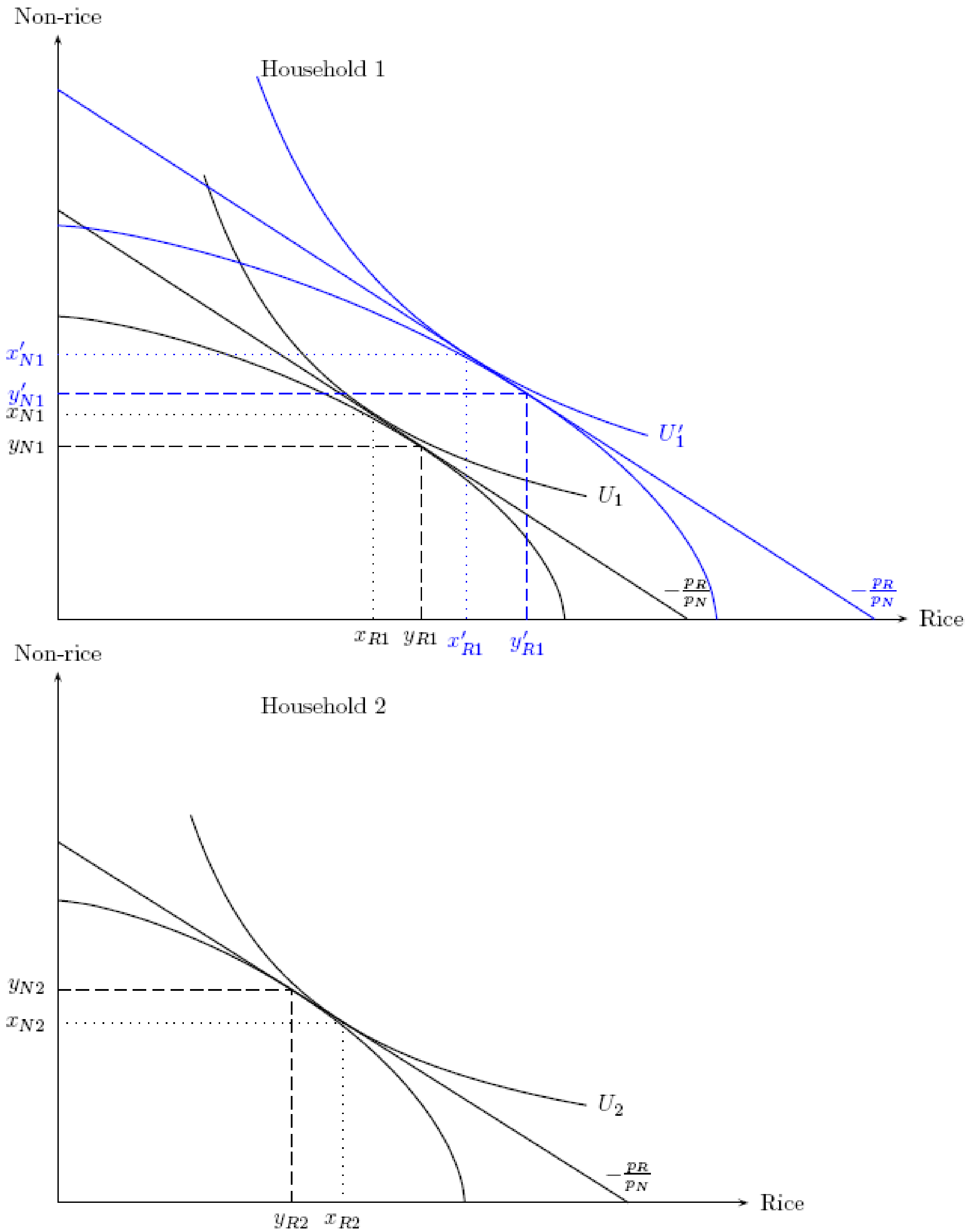
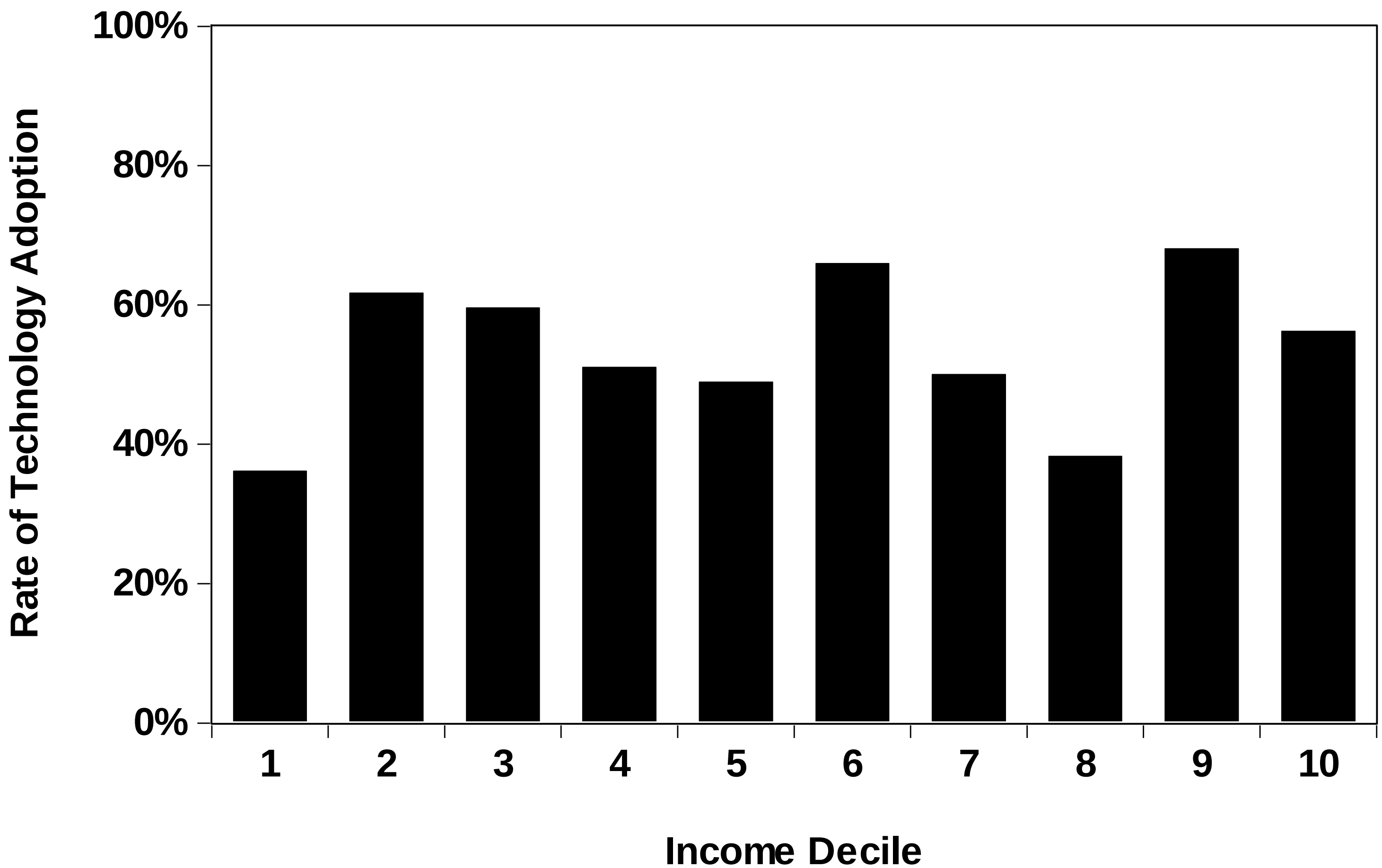


FIGURE 4
Technology Adoption as a Function of Farmer's Income



APPENDIX
Variable Definitions and Summary Statistics

Variable[a]	*Mean*	*Std. Deviation*	*Minimum*	*Maximum*
Adoption	0.535	0.499	0	1
Age	41.9	11.1	18	76
County1	0.338	0.474	0	1
County2	0.252	0.434	0	1
County3	0.070	0.255	0	1
County4	0.063	0.244	0	1
County5	0.142	0.349	0	1
County6	0.072	0.259	0	1
County7	0.063	0.244	0	1
Education	7.97	1.22	0	12
Extension	0.816	0.388	0	1
HHSize	4.68	1.43	1	10
Income	12,951	10,876	0.82	101,780
Labor	2.49	1.08	1	7
Land	25.7	17.5	0	124
Low Altitude	0.486	0.500	0	1
Market	11.51	9.95	3	40
Terrace	0.146	0.172	0	1

[a] *Adoption* is a dummy variable that takes the value 1 if the household is an adopter of improved upland rice technology; *Age* and *Education* are the age and maximum educational attainment of the household head (in years); the different *County* variables

are dummy variables identifying the county in which the household is located; *Extension* is a dummy variable that takes the value 1 if there is an agricultural extension program in the village; *HHSize* is the number of persons in the household; *Income* is the household's annual income in Chinese yuan; *Labor* is the number of working household members; *Land* measures farm size (in hectares); *Low Altitude* is a dummy variable taking the value 1 if the farm is situated at an altitude of 1400 meters or lower; *Market* is the household's traveling distance to the nearest market (in kilometers); and *Terrace* measures the percentage of terraced land.