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Shijun Ding, Laura Meriluoto, Robert Reed, Dayun Tao, and Haitao Wu

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Department of Economics and Finance
College of Business and Economics
University of Canterbury
Private Bag 4800, Christchurch
New Zealand

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

by

Shijun Ding**, Laura Meriluoto***, W. Robert Reed***,
Dayun Tao****, and Haitao Wu**

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** Professor and Assistant Professor, respectively, at Zhongnan University of Economics and Law, Wuhan, China.
Email: dingshijun2006@yahoo.com.cn; wuhan_haitao@yahoo.com.cn

*** Senior Lecturer and Professor, respectively, at the University of Canterbury, Christchurch, New Zealand.
Email address: laura.meriluoto@canterbury.ac.nz ; bob.reed@canterbury.ac.nz

**** Professor, Yunnan Academy of Agricultural Sciences, Kunming, China.
Email address: taody12@public.km.yn.cn

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Abstract

This study analyzes the impact on income inequality of government efforts to increase agricultural incomes 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 15 percent higher than non-adopters. Despite this relatively large increase, we estimate that the impact on income inequality was relatively slight. This is primarily due to the fact that lower-income farmers adopted the improved rice technology at rates that were roughly equivalent to those of higher-income farmers. .

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.[2] 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).[3]

One key component of the government's agricultural policy has been the encouragement of productivity improvements in "marginal" agricultural land in rural areas via local extension services.[4] These areas are of particular importance because a

[1] For example, see http://english.people.com.cn/90001/90776/90882/6911854.html .
[2] For example, CPAD [1994] initiated China's 8-7 National Poverty Reduction Program; CPG [2001] launched the West Areas Development Strategy.
[3] Expenditures are in 1990 constant Yuan.
[4] 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

large portion of low income households are congregated there. Improving their incomes is key to reducing urban-rural income inequality in China.

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). Numerous studies have investigated 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 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 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 incomes increase. The latter mitigated the income inequality effects of the former.

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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) report that 40% of new agricultural technologies adopted by farmers during 1996 and 2002 were generated from public agricultural extension services.

An important difference between our study and Lin's is that his study focused on hybrid, paddy rice adoption in lowland areas. In contrast, our study focuses on hybrid rice adoption in upland areas. It is the latter which is now receiving much attention in the development literature (Conway, 1999; Fan and Hazell, 2000; Pender, 2008). Pender (2008, page 7) writes:

> During the past several decades, dramatic improvements in agricultural productivity and the reduction of poverty have been achieved in many countries of South and East Asia. …Despite this progress, hundreds of millions of rural people in less-favoured environments – areas where rainfed agriculture dominates and where there are critical biophysical constraints such as low and uncertain rainfall, steep slopes and poor soil, or socio-economic constraints such as poor access to markets, infrastructure and services – have obtained much less benefit from this progress.

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 reviews Lin's (1999) theoretical analysis of the impact of improved rice technology on household incomes. Section III presents some background concerning the agricultural 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. Lin's (1999) model of the effects of improved rice technology provides a useful framework for understanding the issues associated with our empirical analysis. The starting point is a two-good, two-household general equilibrium model where comparative advantage is driven by 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, 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:

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

It is assumed that Household 1 is land-abundant and has an endowment vector E_1 that gives it a comparative advantage in rice. It is also assumed that there are 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

$$I_i = y_{Ni} + \frac{p_R}{p_N} y_{Ri}\,.$$

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

$$x_{Ni} + \frac{p_R}{p_N} x_{Ri} = I_i = y_{Ni} + \frac{p_R}{p_N} y_{Ri}$$

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 technology adoption. For expositional purposes it is assumed that the two households have identical preferences, but that their PPFs differ due to 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 ($y_{R1} > y_{R2}$ and $y_{N1} < y_{N2}$).[5] Therefore, Household 1 sells rice to Household 2 in exchange for non-rice.

FIGURE 2 illustrates the main result of Lin's (1999) theoretical analysis. Lin assumes that the household that has a comparative advantage in rice will also have a comparative advantage in rice technology adoption. Hence it becomes the technology adopter. If the relative price of rice remains unchanged, adopters find it in their best interest to produce more rice and less non-rice. This implies that the total output of rice goes up, creating an excess supply of rice, and causing the relative price of rice to fall.

This reduction in the relative price of rice will induce both the technology adopter and non-adopter to produce more non-rice output and less rice. Overall, adopters will produce more rice ($y_{R1}' > y_{R1}$), but the change in non-rice will be ambiguous. Non-adopters will produce less rice ($y_{R2}' < y_{R2}$) and unambiguously more non-rice ($y_{N2}' > y_{N2}$). The incomes of both households increase unambiguously. Comparing the outputs of the two households, as long as both $y_{R1} > y_{R2}$ and $y_{N1} < y_{N2}$ prior to the technology adoption, it must be that technology adopters produce more rice and less non-rice than non-adopters ($y_{R1}' > y_{R2}'$ and $y_{N1}' < y_{N2}'$).

[5] 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 a superior endowment vector than Household 2.

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

While Lin's (1999) analysis is a useful starting point, it makes a number of simplifying assumptions that potentially limit its applicability.

1. It assumes that all products can be traded. If, for example, rice cannot be traded, then the household cannot move off of its production possibilities frontier, and the production of rice and non-rice will be determined by the tangency of the PPF and the relevant indifference curve. As a result, price changes will not mitigate the income distribution effects from technology adoption.

2. It assumes that the adoption of rice technology does not affect the production technology of other goods. However, if there are productivity spillovers to other agricultural outputs, then income distribution effects from adopting improved rice technology could be intensified by increased production of other agricultural outputs.

3. It ignores the role of income distribution in technology adoption. For example, if the benefits of improved rice technology are disproportionately distributed to wealthy (poor) farmers, then technology adoption will exacerbate (mitigate) income inequality.

4. It assumes away the role of factor markets. If, for example, technology adoption requires greater (lesser) labor inputs, then labor could be taken from (released for) the production of other outputs (including leisure).[6]

5. It ignores the interaction of credit rationing with the wealth effect from technology adoption. Higher incomes can allow households to purchase other inputs that can be used in livestock production and other activities that may be more profitable than rice farming (Heerink et al, 2006).

6. It does not account for complex interactions between production, consumption, and income distribution. Concerning these interactions, Taylor and Adelman (1996, page 248) write: "In a world where some goods and factors are tradable and others are not, and where some households interact with outside markets and others do not, analytical models lose their usefulness for policy analysis; they are generally incapable of reliably predicting the magnitude or even the direction of policy and market impacts on local economies."

[6] David and Otsuka (1996, page 415) conclude that the adoption of hybrid rice generally increases the demand for labor. However, they report that this does not appear to be the case for China, where the use of hybrid rice "reduces labor demand by about 4%" (pages 382f.).

All of the above reasons provide motivation to follow up Lin's analysis with further empirical investigation.

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 estimate the effect of technology adoption on the different components of farmers' incomes. We then simulate what farmers' incomes would be in the absence of technology adoption. These are then used to calculate Gini coefficients for the two scenarios of (i) technology adoption and (ii) no technology adoption.

III. BACKGROUND

This study analyzes recent government efforts to improve upland rice productivity in southern 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 comprises less than 4 percent of the total population. A relatively large share of the population (about a third) consists of ethnic minorities. Agriculture is a major source of income, but only about 5 percent of the land is cultivated. Approximately 94 percent of the land area is categorized as mountainous. Almost all cultivated land lies in elevated areas. 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. Because of the relative isolation of villages, income security in the remote, mountainous areas of Yunnan is a concern for both the national and provincial governments.

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 been complemented by local agricultural extension services, which promote the adoption of 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.

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. In 2005, teams from ZUEL and IRRI visited the area again and trained local staff from the county/township Agricultural Technology Extension Stations 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.

Southern Yunnan Province consists of five cities/prefectures. A modified, stratified random sampling procedure was designed to ensure adequate representation by (i) city/prefecture, and (ii) area devoted to upland rice production. Five strata were

[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.

employed. In decreasing order of aggregation, these were cities/prefectures, counties, townships, villages, and households.

Within each city/prefecture, 1-2 counties were randomly chosen, depending on whether the city/prefecture had less or more than 100,000 mu (6.669 hectares) of upland rice. A total of 7 counties were chosen.

Within each county, 1-5 townships were randomly chosen, depending on whether the respective county had an upland rice area (i) less than 30,000 mu; (ii) between 30,000-60,000 mu; (iii) between 60,000-90,000 mu; (iv) between 90,000-120,000 m;, and (v) greater than 120,000 mu. A total of 15 townships were chosen.

One village was randomly chosen from each township, and approximately 30 households were randomly chosen from each village. A total of 473 usable household observations were produced in this fashion.

TABLE 1 reports characteristics of the sample, categorized by whether the household was an adopter or non-adopter of improved upland rice technology in 2004.[8] Technology adopters are defined as using a combination of improved upland rice varieties with terracing and/or chemical fertilizers.

A little over half of the households are technology adopters. Adopters have annual incomes that are approximately 15 percent larger than non-adopters, where income includes both cash and imputed income. A larger percentage of adopters' incomes is derived from planting, and a smaller percentage from livestock and non-farm production.

Average household size for the overall sample is 4.7 persons, and a little over half of all household members participate in the labor force. Household heads for both non-adopting and adopting households average about 42 years of age, and the

[8] The survey obtained retrospective information about income and technology adoption for the years 2000, 2002, and 2004. Our analysis focuses on the 2004 data.

maximum educational attainment of households is approximately 8 years of formal education. Over 80 percent of adopting and non-adopting households are ethnic minorities.

Altitude is important in upland rice production. According to experiments from YAAS, upland rice has greatest adaptability at altitudes below 1400. Adopters are much more likely to locate in low altitude areas (less than 1400 meters). They are also likely to have more land, live in a village with an extension program, and be located closer to market. Rates of adoption differ widely across counties.

Much of the agricultural output produced in rural Yunnan farms is for self-consumption. Per unit market values were imputed in these cases. The income values reported in TABLE 1 – and the income values studied in the subsequent analysis – comprise the sum of cash and imputed income. TABLE 2 reports the extent of this income imputation for different samples of households. Column headings refer to specific samples. For example, total income data is available for 452 households, where "total" refers to the sum of income from food crops, cash crops, etc. Data on income for food crops is available for 449 households.

Focusing on Column (1), we observe that most households in the "Total Income" sample had a combination of cash and imputed income, though approximately 2 percent of households had no cash income (i.e., agricultural production for these households was entirely for self-consumption and there was no non-farm income). Even so, the average household in this sample received approximately 46 percent of its total income from production for self-consumption. The primary sources of self-consumption production were the producing of food crops (primarily upland rice, lowland rice, and maize) and livestock (pigs, cattle, sheep, chickens, and ducks). We emphasize that our subsequent income inequality analysis refers to the sum of households' cash and imputed incomes.

V. RESULTS

OLS estimation of the income equations. The first step in our two-step procedure consists of estimating the effect of upland rice technology adoption on farmers' incomes. If the decision to adopt technology is independent of factors that contribute to a farmer's income, then standard OLS regression, in the absence of misspecification, will provide an unbiased estimate of the "average treatment effect" associated with technology adoption. However, the assumption of independence is questionable. Therefore, we follow our OLS analysis with alternative methods designed to address endogeneity. A comparison of the two sets of estimates will be informative.

Our OLS regression is designed to estimate the effect of technology adoption while controlling for important other variables. Accordingly, we estimate the following specification relating farmers' incomes to household characteristics:

$$\begin{aligned} ln\left(Income\right)_i = {} & \alpha_0 + \alpha_1 Adoption_i + \alpha_2 Household\ size_i + \alpha_3 Labor\ proportion_i \\ & + \alpha_4 Age_i + \alpha_5 Age\text{-}squared_i + \alpha_6 Education_i + \alpha_7 Ethnic\ minority_i \\ & + \alpha_8 Low\ altitude_i + \alpha_9 Total\ land_i + \alpha_{10} Extension_i + \alpha_{11} Market\ distance_i \\ & + \sum_{c=1}^{6} \alpha_{12+c} D_i^c + \varepsilon_i . \end{aligned}$$

The main variable of interest is *Adoption*, which is a dummy variable that takes the value 1 if the household is an adopter of improved upland rice technology.

The subsequent variables are included as controls. *Household Size* is the number of persons in the household; *Labor proportion* is the share of total household members participating in the labor force; *Age* is the age of the household head; *Education* is years of schooling for the person with the highest educational attainment in the household; *Ethnic minority* is a dummy variable indicating that the household is an ethnic minority; *Low altitude* is a dummy variable taking the value 1 if the farm is situated at an altitude of 1400 meters or lower; *Total land* measures the area of the farmer's total land holdings; *Extension* is a dummy variable indicating that an extension service is located in the village; *Market distance* is the distance of the household to the nearest market, and D^c is a county dummy variable that takes the value 1 for the c^{th} county.

Adoption is expected to increase planting income from upland rice, and possibly other outputs depending on the extent of technology spillovers. *Household size* (holding constant *Labor proportion*), *Age, Education,* and *Total land* can be thought of as inputs into the farm production function, so that their increase is expected to result in greater output (though *Age* may manifest diminishing returns). With *Total land* held constant, *Low altitude* proxies for better quality of the land input. *Market distance* measures the cost of transporting tradable goods to and from the nearest local market, with greater distance expected to lower income. The county dummies pick up unmeasured characteristics of the quality of agricultural inputs, the effects of which are *a priori* ambiguous. The effects of *Ethnic minority* and *Extension* are also a priori ambiguous.

TABLE 3 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. Note that the headings of Columns (2) and (3) of TABLE 3 differ from those of TABLE 2. In other words, planting income is divided into the categories "Upland Rice" and "Other" in TABLE 3, compared to "Food crops" and "Cash crops" in TABLE 2.[9]

[9] This is due to the fact that information about cash income was queried in a separate module of the household questionnaire, using different income categories, than the module that obtained price and quantity information about household production.

Column (1) reports the effect of technology adoption on total income. All of the coefficients have the expected signs, and most are statistically significant at the 5 percent level (two-tailed test). The coefficient on *Adoption* is highly significant and large in size. Technology adopters are estimated to enjoy approximately 28 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). We expect the coefficient for *Adoption* to be positive and significant for income generated from Upland Rice production (cf. Column 2). The associated coefficient implies that households that adopt technology have "upland rice" incomes that are approximately 33 percent larger than non-adopters, ceteris paribus.

But the *Adoption* coefficient on planting income from other crops is also positive and marginally significant. This is the opposite of what Lin (1999) predicts and finds, and is consistent with the fact that upland rice technology may have spillover effects. Unlike Lin's study, technology adoption in our study includes not just the use of the improved upland rice hybrid, but also the employment of other bundled services provided by the Agricultural Technology Extension Stations. 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 3 can be interpreted as 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. In fact, the coefficient on the *Adoption* variable is positive and significant (at the 10% level) for Livestock Income. Recall that Lin (1999) predicted a negative effect on non-rice income as the relative rice price fell. The lack of a negative rice price effect may reflect factors not considered by Lin. For example, if the upland rice hybrid was labor saving, this could release labor for non-planting activities, such as livestock and non-farm production.[10,11,12] The associated increased income by adopters could balance any price-induced increase in non-rice income by non-adopters. This is unlikely, however, as the hybrid upland rice requires more labor inputs than traditional varieties, which do not use fertilizer and pesticides. An alternative explanation is that the positive association with technology adoption reflects endogeneity.

Addressing endogeneity. The previous analysis ignores the possibility that technology adoption may be correlated with other productive characteristics. For example, farmers who are sufficiently enterprising in adopting new technology may also be enterprising in other ways that improve productivity. Observed differences between adopters and non-adopters could reflect these inherent productivity differences rather than any productivity increases due to the new technology.

There are many ways to address endogeneity. This section reports the results of our use of matching methods (MMs). Matching methods compare the outcomes of two groups, one of which receives a "treatment" (in our case, "adopters"), while the other does not ("non-adopters"). MMs can be used to address endogeneity when the factors related to the adoption of the treatment are all observable.

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

[11] In the context of FIGURE 2, this would be reflected as a shift out of the PPF on *both* the rice and non-rice axes.

[12] An alternative explanation, also outside the Lin (1999) model, is that most of the increased production of upland rice from technology adoption goes towards self-consumption, so that there is very little effect on the relative rice price. As a result, the non-adopting farmer does not change his production of non-rice. In contrast, the lower shadow value of upland rice causes the adopting farmer to shift resources into non-rice production, so that, at the end, the adopting and non-adopting farmers receive similar incomes from non-rice production.

While there are many variations, MMs have the common characteristic that they match members of the treatment group with one or more members of the non-treatment group. We employ five different MMs: (i) Nearest Neighbor Matching (NNM) without replacement; (ii) NNM with replacement; (iii and iv) NNM with replacement subject to satisfying calipers of 0.01 and 0.1; and (v) kernel matching. A good review of these methods is provided by Todd (2008).

All of these methods require estimation of a "propensity score," which measures the probability that a given member will receive the "treatment." A commonly used propensity score is the predicted probability from a probit regression. TABLE 4 reports the results of estimating probit equations for the same set of subsamples analyzed in TABLE 3.

While the column headings indicate income categories (e.g., "Total Income," "Planting Income (Upland Rice)", etc.), the dependent variable is *Adoption*, not a measure of income. Thus, while Column (1) of TABLE 4 has the heading "Total Income," it means that it is estimating the determinants of technology adoption for the same 452 observations used in the OLS regression of Column (1) of TABLE 3. Note that Column (3) ("Planting Income-Other") analyzes the same observations as Column (1) ("Total Income"), hence the corresponding estimation results are identical.

Looking across the columns, the following factors are found to be significantly and positively associated with the adoption of upland rice technology: age of household head, amount of total land holdings, high altitude farm location, the presence of an extension service in the village, and distance from market. Number of working household members is negatively and significantly related to adoption. This latter result suggests that adoption of upland rice technology may serve as a substitute for household labor. County location of the household is also a significant determinant of technology adoption. The inclusion of county dummies is important, as both the low altitude dummy and distance from market variable change signs when the county dummies are omitted. Most of the other estimated coefficient signs have a straightforward interpretation.

The probit results of TABLE 4 are used to produce predicted probabilities of adoption for both adopters and non-adopters. The respective MMs then compare the predicted incomes of adopters with those of closely matched non-adopters. We do this for each of the five income categories of TABLES 3 and 4, obtaining predicted "average treatment effects" for each subsample. These treatment effects can then be compared with the OLS results from TABLE 3.

Three features of a good matched sample are that (i) the covariates are good predictors of the treatment variable, (ii) a large percentage of the treated observations are included in the analysis, and (iii) the individual variables used to match adopters and non-adopters are "balanced" across the treatment and control groups.

With respect to (i), a common goodness-of-fitness measure for probit analysis is the pseudo R-squared. These are reported at the bottom of TABLE 4 for the respective samples. The probit equations display a significant degree of explanatory power, with pseudo R-squared values ranging from 0.32 and 0.37. These are sufficiently high to justify the matching exercise and compare well with other studies.[13]

With respect to (ii), Panel A of TABLE 5 reports the percent of adopting observations included in the respective matching analyses. For example, there were 239 adopting observations in the sample of 452 observations analyzed in Column (1).

[13] See, for example, the studies published in the "Symposium on the Econometrics of Matching," in the *Review of Economics and Statistics*, Vol. LXXXVI, No. 1, February 2004.

The NNM without replacement procedure uses 89.1% of these in the subsequent matching analysis. With the exception of the Non-Farm Income sample (Column 5), the respective matching methods use a large percent of the total number of adopting observations. For the Total Income sample (Column 1), all of the matching methods use 89% or more of the 239 adopting observations in the sample.

With respect to (iii), we use two approaches for measuring the "balance" of variables across adopter and non-adopter groups. The Stata procedure "pscore" tests the balancing property using the algorithm described in Becker and Ichino (2002).[14] This procedure stratifies the sample based on propensity scores and then tests for significant differences between the covariates within strata. If the data are "balanced," there should be no significant differences between covariates within strata. All of the matching procedures for all of the subsamples report that the balancing property is supported by the data.

The second approach calculates pseudo R-squared for the same probit specification used in TABLE 4, albeit this time restricting the observations to the respective matched sample. If the covariates are well-matched/balanced, the decision to adopt technology should be random across the two groups, and the pseudo R-squared should be close to zero.

Panel B of TABLE 5 reports the respective pseudo R-squared values for each of the MMs and subsamples. Four of the five MMs show a substantial drop in the explanatory power of the respective probit equations when the sample is restricted to matched observations. The exception is NNM without replacement. In light of the above balancing results, the subsequent analysis restricts itself to matching estimates from the latter four matching procedures (NNM with replacement, NNM with

[14] The "pscore" procedure is described in Becker and Ichino (2002).

replacement and caliper = 0.01, NNM with replacement and caliper = 0.1, and kernel matching).

We now proceed to estimating the effect of technology adoption on farmers' incomes. TABLE 6 reports the estimated "average treatment effect" for each of the respective methods and samples. The last three rows report minimum and maximum estimated effects from the matching methods (omitting the NNM with replacement estimates as discussed above), and reproduce the OLS estimated effects from TABLE 3.

The comparison of the OLS results with the minimum and maximum estimates from the MMs is illuminating. First, the estimated effect of technology adoption is cut in half by the MMs; from approximately 29 percent (OLS) to between 14 and 16 percent (MMs). Second, the estimated adoption effect on upland rice income using matching methods is roughly in line with those obtained from OLS. The MM estimates range from 29 to 47 percent, while OLS produces an estimate of 33 percent. Third, we still see some evidence of technology spillovers, though smaller than estimated by OLS. The MM estimates for Planting Income other than upland rice range from 5 to 13 percent, and are significant at the 10 percent level. This compares with an OLS estimate of 19 percent.

One puzzling result from the OLS analysis is not confirmed using matching methods. The OLS procedure produces an estimated effect of technology adoption on livestock income of 17 percent, significant at the 10 percent level. In contrast, the MM estimates are much smaller, ranging from 0 to 6 percent, and are statistically insignificant. This suggests that the OLS estimate reflects endogeneity bias, rather than a real technology effect. Finally, both OLS and MM procedures estimate an insignificant effect of technology adoption on Non-Farm income.

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. To do that, we compare two sets of estimated income distributions: the distribution of farmers' incomes with and without technology adoptions. The difference in the respective distributions is our estimate of the effect of technology adoption on income inequality within the sample.

We use the observed, 2004 incomes of farmers as our estimate of farmers' incomes with technology adoption.[15] To calculate farmers' incomes without technology adoption, we start with farmers' incomes as observed in 2004. For farmers who are technology adopters, we subtract the estimated effect of technology adoption from their observed income to get an estimate of what their income would be without technology adoption. For non-adopting farmers, we use their observed 2004 incomes.

As noted in the discussion of TABLE 6, there is a range of estimated effects across MM procedures and income samples. Accordingly, we use three different sets of estimated technology effects on income. We use the minimum, average, and maximum values in adjusting adopting farmers' 2004 incomes to estimate what their income would have been in the absence of technology adoption.[16]

The corresponding Gini coefficients are reported in TABLE 7. Column (1) ("With Technology Adoption") reports Gini coefficients by income category for the full sample using the observed income distribution in 2004. The next three columns (2a through 2c) simulate what the income distribution would look like by subtracting the respective average treatment effects from observed incomes for adopters. As it

[15] The assumption here is that future adoption of technology by current non-adopters will not affect income inequality results based on 2004 adopters.
[16] Minimum, average, and maximum values were calculated over the latter four MM procedures, omitting NNM with replacement, as the latter was judged to not satisfy the balancing requirement.

turns out, Gini coefficients for the simulated income distributions without technology adoption are largely indifferent to the size of the estimated treatment effect.

A comparison of the Gini coefficients in Columns (2a) through (2c) with those in Column (1) reveals that the adoption of improved upland rice technology is estimated to have had only a negligible impact on income inquality. In each of the five income categories, the Gini coefficients associated with income distributions “With Technology Adoption” are virtually identical to those “Without Technology Adoption.” Despite the relatively large estimated impacts of technology income, as given by the MM estimates of TABLE 6, there is little evidence that this contributed to greater income inequality for the farmers of Yunnan Province.

The apparent contradiction of relatively large estimates of the impact of technology adoption in TABLE 6, and the negligibly small estimated income inequality effects in TABLE 7, is resolved by FIGURE 3. This figure graphs the rate of technology adoption by income deciles. The top panel estimates “pre-adoption” incomes in the same manner as described above for TABLE 6: Pre-adoption incomes are equal to observed incomes for non-adopters and, for adopters, equals their observed income minus the estimated treatment effect (calculated as the average of the MM estimates). We then calculate rates of adoption within each of the corresponding income deciles. While the relationship between technology adoption and income is non-monotonic, it is clear that lower-income farmers adopted technology at rates that were roughly equivalent to those of higher-income farmers.

To confirm this finding, we exploit the retrospective nature of our household survey. In 2000, 336 of the farmers had not adopted the improved upland rice technology. By 2004, 116 of these had become technology adopters. We use the 2000 incomes of the 336 farmers and divide these into income deciles. We then calculate the percent of farmers within each income decile who had adopted the technology by 2004. The results are plotted in the lower panel of FIGURE 3. We reach the same conclusion using this alternative approach. Lower-income farmers adopt technology at rates that are roughly equivalent to those of higher-income farmers. This is consistent with our estimates that show that technology has had little effect on income inequality amongst the farmers in Yunnan Province.

VI. CONCLUSION

This study uses household income data from farmers in rural China to evaluate the effect of improved upland rice 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 Technology Extension Stations. These have been widely used to promote new technologies among rural farmers. A concern is that these government efforts may themselves induce greater local income inequalities if the benefits of government support are disproportionately distributed.

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 programs 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 total incomes were approximately 14-16 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 lower-income farmers adopted technology at rates that were roughly equivalent to those of higher-income farmers. 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.

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TABLE 1
Mean Values of Household Variables for Adopting and Non-Adopting Farmers

Variable	*Non-Adopters*	*Adopters*
Number of households	220	253
Annual income (RMB)	12,087	13,700
Natural log of annual income	9.04	9.27
Percent of income derived from planting[a]	47.10	57.22
Percent of income derived from livestock[b]	44.91	37.33
Percent of income derived from non-farm production[c]	7.99	5.45
Household size (persons)	4.66	4.70
Proportion of household in labor force	0.57	0.53
Age of household head	42.23	41.64
Maximum educational attainment of household (years)	7.96	7.97
Ethnic minority[d] (dummy variable)	0.827	0.877
Low altitude (dummy variable)	0.359	0.597
Amount of irrigated land (mu)[e]	1.15	1.33
Amount of terraced land (mu)	2.64	4.43
Amount of sloped land (mu)	13.21	16.66
Amount of fruit garden land (mu)	0.13	0.09
Amount of forest land (mu)	4.82	5.66
Amount of waste land (mu)	0.37	0.52
Total amount of land (mu)	22.32	28.69
Village with extension program (dummy variable)	0.727	0.893
Distance from market (kilometers)	13.03	10.19

Variable	***Non-Adopters***	***Adopters***
Cangyuan county (dummy variable)	0.118	0.016
Jinghong county (dummy variable)	0.014	0.119
Lancang county (dummy variable)	0.350	0.166
Menghai county (dummy variable)	0.236	0.059
Menglian county (dummy variable)	0.132	0.518
Pinbian county (dummy variable)	0.082	0.047
Wenshan county (dummy variable)	0.068	0.075

[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.

[d] There are a large number of minority ethnic groups represented in our sample, including Yi, Bai, Hani, and others.

[e] 1 mu = 0.06667 hectares.

TABLE 2
Extent of Income Imputation

Variable	*Income (Total) (1)*	*Income (Food crops) (2)*	*Income (Cash crops) (3)*	*Income (Livestock) (4)*	*Income (Non-farm) (5)*
Number of households (Total income)	452	449	453	445	157
Number of households (Cash Income)	444	174	301	341	157
Percent of households with no cash income	1.8	61.2	33.6	23.4	0
Average household total income (RMB)	12951	3364	3508	5135	944
Average household cash income (RMB)	7050	1030	3507	1569	944
Percent of average household total income that is imputed	45.6	69.4	2.9	69.4	0

NOTE: The full sample consists of 473 households. The observations in the table record observations used in the subsequent empirical analysis. Not all households could be used because (i) the dependent variable is the log of income, and some of the households had nonpositive income values; and (ii) some of explanatory variables had missing values. The reason there are more observations for Cash Crop Income than Total Income is because one household had positive Cash Crop Income but negative Total Income.

TABLE 3
OLS Estimates of the Effect of Upland Rice Technology Adoption on Farmers' Household Incomes

Variable	*Total Income (1)*	*Planting Income (Upland Rice) (2)*	*Planting Income (Other) (3)*	*Livestock Income (4)*	*Non-Farm Income (5)*
Adoption	0.2505 (2.85)***	0.2835 (2.63)***	0.1698 (1.88)*	0.1557 (1.81)*	0.0448 (0.18)
Household size	0.1253 (4.20)***	0.0785 (2.89)***	0.0613 (1.09)	0.1510 (4.00)***	0.0871 (1.03)
Labor Proportion	0.3054 (1.55)	0.1321 (0.75)	-0.4118 (-1.11)	0.3542 (1.42)	0.4741 (0.89)
Age	0.0321 (1.58)	0.0324 (1.69)*	0.0725 (1.90)*	-0.0191 (-0.74)	-0.0204 (-0.30)
Age-squared	-0.0004 (-1.56)	-0.0004 (-1.81)*	-0.0008 (-1.90)*	0.0003 (0.95)	0.0002 (0.23)
Education	0.1968 (3.57)***	0.0117 (0.23)	0.1710 (1.65)*	0.3106 (4.42)***	0.4497 (2.95)***
Ethnic minority	-0.0537 (-0.22)	-0.0734 (-0.31)	0.7775 (1.69)*	0.0366 (0.12)	-0.7507 (-1.37)
Low altitude	0.4972 (4.43)***	0.7528 (7.30)***	0.1472 (0.70)	0.4676 (3.30)***	0.8919 (2.15)**
Total land	0.0145 (5.54)***	0.0139 (5.88)***	0.0284 (5.78)***	0.0064 (1.92)*	0.0110 (1.54)
Extension	0.0431 (0.42)	0.3404 (3.50)***	-0.0580 (-0.30)	-0.0919 (-0.72)	0.1964 (0.47)

Variable	*Total Income (1)*	*Planting Income (Upland Rice) (2)*	*Planting Income (Other) (3)*	*Livestock Income (4)*	*Non-Farm Income (5)*
Market distance	-0.0128 (-1.45)	-0.0136 (-1.61)	-0.0374 (-2.24)**	0.0028 (0.25)	0.0019 (0.06)
Lancang county	0.1780 (1.62)	0.2184 (2.14)**	0.2209 (1.07)	0.4403 (3.17)***	0.9151 (2.84)***
Cangyuan county	-0.1187 (-0.75)	-0.9641 (-6.74)***	0.6508 (2.18)**	-1.3037 (-6.43)***	-0.2373 (-0.25)
Menghai county	0.0796 (0.42)	-0.2929 (-1.63)	0.2526 (0.70)	0.2201 (0.91)	0.7869 (1.13)
Jinghong county	0.7517 (2.64)***	0.3329 (1.26)	0.8401 (1.56)	0.8925 (2.47)**	1.1894 (1.28)
Wenshang county	0.2175 (0.79)	-0.1643 (-0.62)	0.8654 (1.66)*	-0.2484 (-0.71)	1.1459 (1.65)
Pinbian county	0.2740 (0.91)	0.0660 (0.23)	0.4206 (0.74)	0.7576 (2.00)**	0.3316 (0.47)
R-squared	0.3449	0.4985	0.2407	0.2969	0.2874
Observations	452	405	452	445	157

NOTE: The dependent variable is the natural log of income. The omitted county is Menglian county. Estimated standard errors are robust to heteroscedasticity. *t*-statistics are reported in parentheses below coefficient estimates.

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

TABLE 4
Probit Estimates of the Probability of Upland Rice Technology Adoption

Variable	*Total Income (1)*	*Planting Income (Upland Rice) (2)*	*Planting Income (Other) (3)*	*Livestock Income (4)*	*Non-Farm Income (5)*
Household size	-0.0834 (-1.42)	-0.1059 (-1.64)*	*same as Column (1)*	-0.0917 (-1.53)	-0.0838 (-0.85)
Labor Proportion	-0.8317 (-2.13)**	-0.9701 (-2.32)**	---	-0.9065 (-2.27)**	-1.5151 (-2.34)**
Age	0.0790 (1.88)*	0.0831 (1.71)*	---	0.0889 (2.08)**	0.1690 (1.90)*
Age-squared	-0.0009 (-1.95)*	-0.0010 (-1.83)*	---	-0.0010 (-2.13)**	-0.0018 (-1.84)**
Education	-0.0321 (-0.30)	0.0658 (0.57)	---	-0.0583 (-0.53)	0.0249 (0.14)
Ethnic minority	0.7381 (1.44)	0.4493 (0.75)	---	0.7773 (1.50)	-0.2113 (-0.26)
Low altitude	-0.6138 (-2.77)***	-1.0610 (-3.72)***	---	-0.5853 (-2.61)***	-0.6747 (-1.16)
Total land	0.0193 (3.49)***	0.0171 (2.74)***	---	0.0203 (3.56)***	0.0114 (1.33)
Extension	1.0450 (4.68)***	1.3102 (5.60)***	---	1.0782 (4.75)***	1.9679 (3.47)***
Market distance	0.0776 (3.81)***	0.0676 (3.06)***	---	0.0806 (3.86)***	0.0160 (0.33)

Variable	*Total Income (1)*	*Planting Income (Upland Rice) (2)*	*Planting Income (Other) (3)*	*Livestock Income (4)*	*Non-Farm Income (5)*
Lancang county	-1.4734 (-7.26)***	-1.8064 (-7.30)***	*same as Column (1)*	-1.4838 (-7.22)***	-1.3667 (-3.30)***
Cangyuan county	-0.0186 (-0.05)***	0.2866 (0.59)	---	0.2210 (0.55)	-1.8689 (-1.88)*
Menghai county	-2.3732 (-6.32)***	-3.0525 (-6.65)***	---	-2.3680 (-6.29)***	-2.4653 (-6.65)***
Jinghong county	-4.2379 (-6.19)***	-3.8997 (-5.99)***	---	-4.3234 (-6.17)***	-2.6528 (-1.78)*
Wenshang county	-0.5767 (-1.04)	-1.6161 (-2.41)**	---	-0.6067 (-1.09)	-1.5292 (-1.60)
Pinbian county	-1.2440 (-2.10)**	-2.1163 (-2.96)***	---	-1.1645 (-1.95)*	-2.2261 (-2.21)**
Pseudo R-squared	0.324	0.374	---	0.338	0.323
Observations	452	405	---	445	157

NOTE: The dependent variable is the natural log of income. The omitted county is Menglian county. Estimated standard errors are robust to heteroscedasticity. *t*-statistics are reported in parentheses below coefficient estimates. Column (3) is identical to Column (1) because they use the same observations.

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

TABLE 5

A. Percent of Adopting Observations Included in the Matching Analysis by Procedure and Sample

Procedure	***Total Income (1)***	***Planting Income (Upland Rice) (2)***	***Planting Income (Other) (3)***	***Livestock Income (4)***	***Non-Farm Income (5)***
NNM without replacement	89.1%	69.9%	89.1%	88.1%	83.3%
NNM with replacement	97.5%	87.0%	97.5%	92.4%	83.3%
NNM with replacement and caliper = 0.1	97.5%	87.0%	97.5%	92.4%	83.3%
NNM with replacement and caliper = 0.01	91.6%	74.9%	91.6%	86.9%	48.6%
Kernel	91.6%	74.9%	91.6%	86.9%	48.6%
Total Number of Adopters	239	239	239	236	72

B. Indicators of Covariate Balancing: Pseudo R-Squared

Procedure	***Total Income (1)***	***Planting Income (Upland Rice) (2)***	***Planting Income (Other) (3)***	***Livestock Income (4)***	***Non-Farm Income (5)***
BEFORE	0.325	0.374	0.325	0.338	0.324
AFTER					
NNM without replacement	0.290	0.273	0.290	0.300	0.175
NNM with replacement	0.048	0.162	0.048	0.069	0.140
NNM with replacement and caliper = 0.01	0.051	0.142	0.051	0.068	0.100
NNM with replacement and caliper = 0.1	0.048	0.162	0.048	0.069	0.140
Kernel	0.045	0.111	0.045	0.042	0.095

TABLE 6
Matching Estimates of the Effect of Technology Adoption on Farmers' Incomes

Procedure	*Total Income (1)*	*Planting Income (Upland Rice) (2)*	*Planting Income (Other) (3)*	*Livestock Income (4)*	*Non-Farm Income (5)*
NNM without replacement	0.180 (2.47)**	0.311 (3.50)***	0.276 (2.27)**	-0.037 (-0.85)	-0.149 (-0.33)
NNM with replacement	0.129 (2.71)***	0.387 (3.98)***	0.051 (2.40)**	-0.004 (-0.79)	-0.217 (-0.36)
NNM with replacement and caliper = 0.01	0.141 (2.33)**	0.300 (2.75)***	0.048 (2.08)**	0.026 (-0.91)	0.025 (-0.35)
NNM with replacement and caliper = 0.1	0.129 (2.43)**	0.387 (2.94)***	0.051 (2.05)**	-0.004 (-0.92)	-0.217 (-0.40)
Kernel	0.147 (2.41)**	0.252 (2.67)***	0.120 (2.49)**	0.059 (-0.97)	0.000 (-0.33)
Minimum estimated effect[a]	0.129	0.252	0.048	-0.004	-0.217
Maximum estimated effect[a]	0.147	0.387	0.120	0.059	0.025
OLS estimated effect (from TABLE 3)	0.251***	0.284***	0.170*	0.156*	0.045

NOTE: The dependent variable is the natural log of income. *Z*-statistics are reported in parentheses below coefficient estimates. The procedure for estimation of standard errors is described in Becker and Ichino (2002).

[a] Minimum and maximum estimated effects do not include estimates from the "NNM without replacement" procedure because of its poor balancing properties.

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

TABLE 7
The Effect of Upland Rice Technology on Income Inequality

INCOME SOURCE	*WITH TECHNOLOGY ADOPTION (Observed) (1)*	*WITHOUT TECHNOLOGY ADOPTION (Simulated)*		
		Using Smallest Estimate (2a)	*Using Average Estimate (2b)*	*Using Largest Estimate (2c)*
Total Income	0.382	0.382	0.382	0.382
Planting Income (Upland Rice)	0.508	0.506	0.508	0.507
Planting Income (Other)	0.543	0.541	0.538	0.533
Livestock Income	0.479	0.478	0.479	0.481
Non-Farm Income	0.880	0.879	0.879	0.880

NOTE: Numbers in table are Gini Coefficents. "With Technology Adoption (Observed)" represents the observed degree of income inequality; i.e., it uses observed household income for both adopters and non-adopters. "Without Technology Adoption (Simulated)" calculates Gini coefficients as follows: For non-adopters, it uses observed incomes. For adopters, it subtracts the MM estimates from TABLE 6, using the (i) smallest, (ii) average, and (iii) largest estimated treatment effects from the respective samples in TABLE 6.

FIGURE 1
Equilibrium Before the Technology Adoption

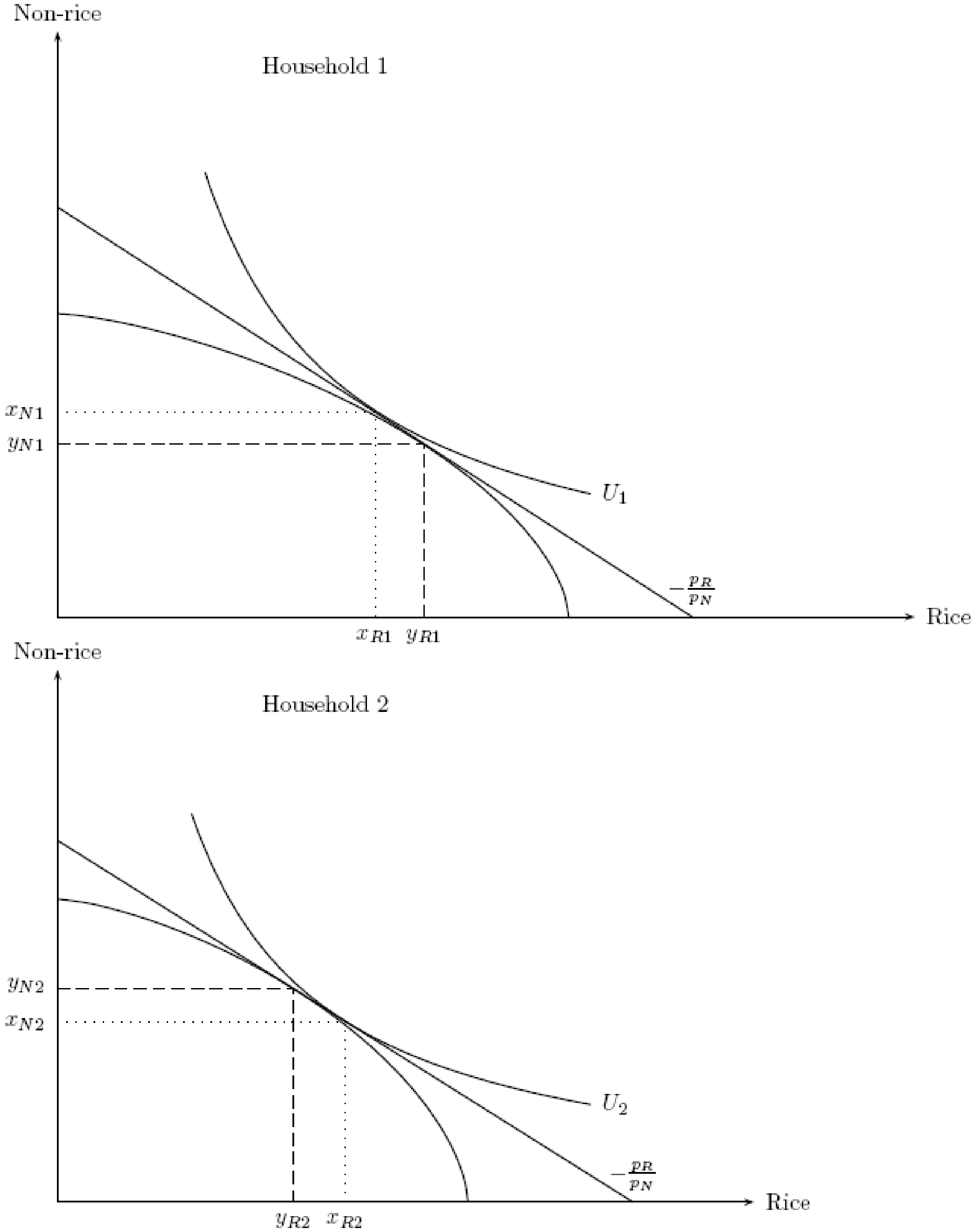


FIGURE 2
Equilibrium After Technology Adoption Without Spill-Over Effect

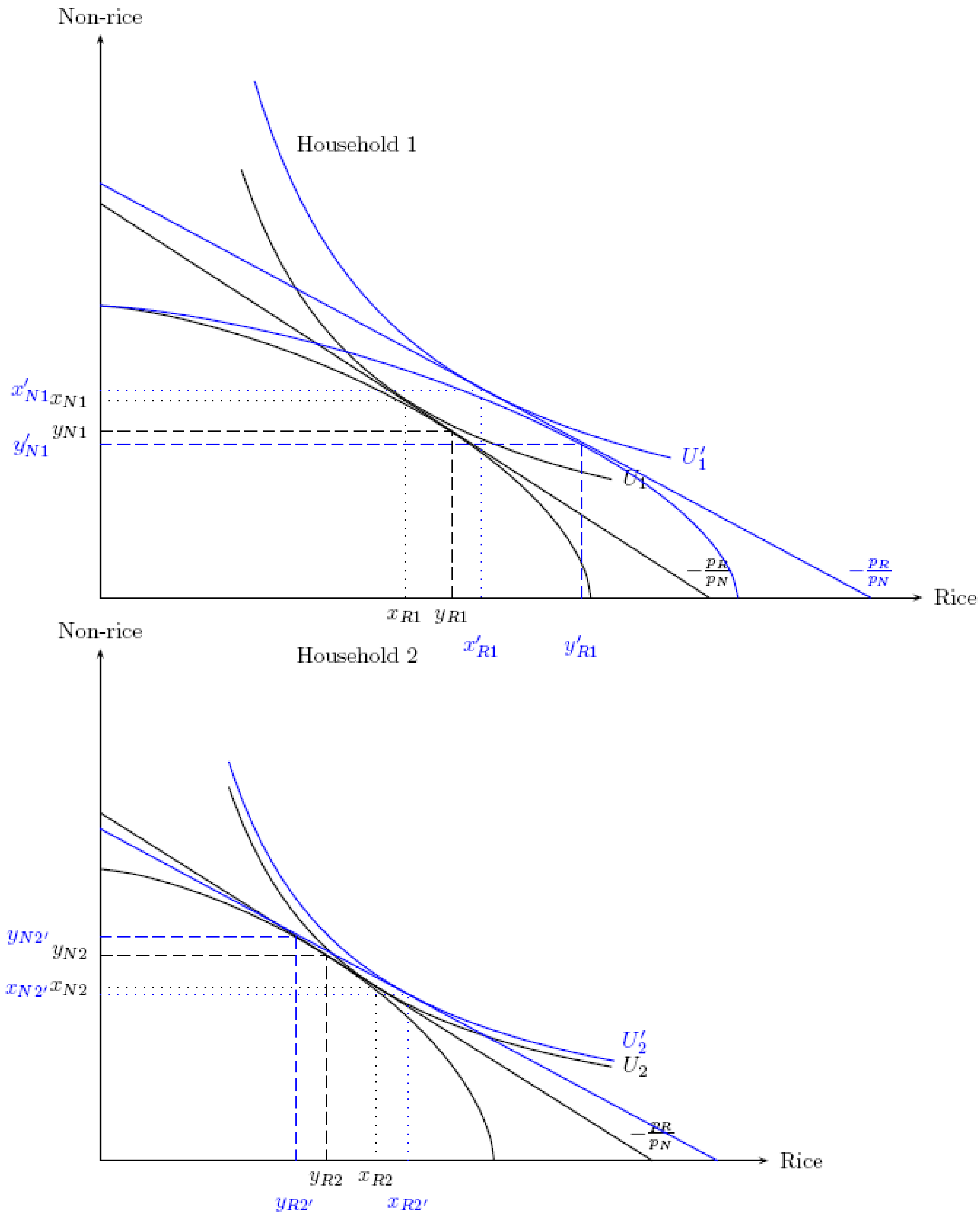
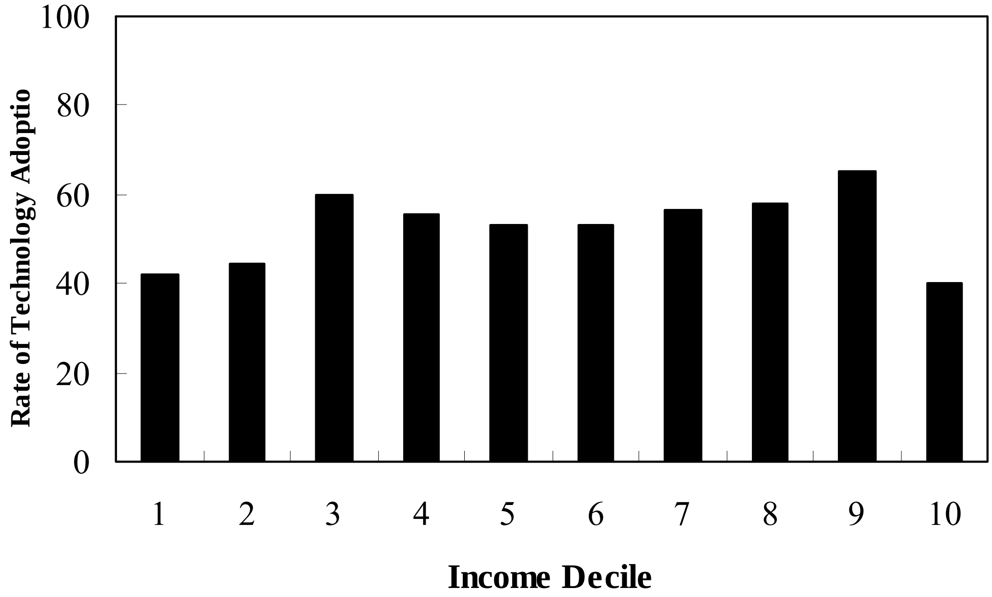


FIGURE 3
Technology Adoption as a Function of Farmer's Income

A. Pre-Adoption Incomes Calculated as Post-Adoption Incomes Minus Estimated Treatment Effect for Adopters (Full Sample)



B. Pre-Adoption Incomes Calculated as Incomes of Non-Adopters in 2000 (336 Non-adopters in 2000)