How Do Health and Social Insurance Programs Affect the Land and Labor Allocations of Farm Households? Evidence from Taiwan

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Selected paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011

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Abstract

Using a unique dataset of 703,287 farm operators from the Taiwanese Census of Agriculture merged to administrative records from the National Farmers' Health Insurance (FHI) program, we examine the effects of the enrollment in the FHI program on farmers' on- and off-farm labor supply and the amount of land they allocate to Taiwan's land retirement program. In order to account for non-random self-selection into the FHI we use a matching procedure to estimate the impact of the program on land and labor allocations. Our results indicate that participation in the FHI increases (decrease) on (off) farm labor supply, and decreases the amount of land enrolled in the land retirement program. Our findings have implication for health care reforms that have been initiated in other countries, and the United States in particular.

Keyword: National Farmer's Health Insurance Program, labor supply, land retirement

program, Taiwan.

Introduction

Health care and social policy reforms are being initiated in many countries throughout the world, including the United States. For example, the Obama Administration has enacted reforms to provide access to health care for all Americans. Recent studies have explored the possible impacts of a national health insurance programs on population health (e.g., Holtz-Eakin 2011; Kenneth and Theodore 2011), but little is known about the impact on farmers.

Compared to other socio-demographic groups, universal health insurance and social insurance are more important to farm households in the U.S. for several reasons. Many farmers are self-employed, and as a result, must purchase health, life, and disability insurance in the individual market where premiums are significantly higher, and insurance companies are able to deny coverage to individuals considered “bad risks”. These access problems are reinforced by that fact that farm production is relatively risky (both in terms of income and health) compared to other job categories, further reinforcing the tendency of insurers to raise premiums and limit insurance offers. This is one reason why access to health insurance has been used in past studies as an indicator of the overall economic well-being of farm households (Jones et al, 2009).

In order to improve health care access some farmers have entered into cooperative agreements with others in order to purchase insurance on the group market where premiums are significantly lower due to better risk pooling and the lower administrative costs associated with underwriting policies for larger groups of insures. Some states have also facilitated the purchase of insurance through state Farm Bureaus. Although these efforts have helped to reduce rates of uninsurance among U.S. farmers below other self-employed individuals, they are still higher than for the general population (Zheng and Zimmer, 2008).

Furthermore, many farmers in the U.S. work off the farm to gain fringe benefits that include health and other forms of insurance at reasonable costs. In particular, Jensen and Salant (1985) found that the availability of fringe benefits from off-farm employment was positively associated with off-farm labor hours. Gripp and Ford (1997) examined the association between farm characteristics and the health insurance coverage and found that 20% of farm managers did not have health insurance. Of those that did have coverage, only 67% acquired it through their farm business.

It is also common for the spouses of farmers to seek off-farm employment, in part to gain access to health insurance for themselves and their family members. Using the 1996-2001 waves of the Medical Expenditure Panel Survey, Zheng and Zimmer (2008) found that 45% of farmers covered by employment-based health insurance were not the actual policy holders, and that 90% of these non-policy holders had a spouse with employer-sponsored coverage. They also found, after controlling for selection into health insurance coverage, that uninsurance in farm household significantly reduced the utilization of medical services. Using a household survey from Taiwan, Liao and Taylor (2010) found that the de-coupling of health insurance from employment brought about by the introduction of a National Health Insurance program in 1995 reduced the likelihood that wives in farm households worked off-farm by between 9.6 and 13.6 percentage points.

We use data from Taiwan in our empirical investigation of the impact of health and social insurance programs on the labor supply and land allocation decisions of farm households. This issue is of particular policy interest in Taiwan. Although the FHI successfully alleviates financial barriers farmers face accessing medical services and provides other social security benefits for a modest level of cost-sharing, a budget deficit occurred after implementation of the program that grew to NT$120 million in 2008 (COA, 2009). Balancing the FHI budget has therefore become a priority for the Health Department of Taiwan.

Despite the need to contain the costs of the FHI, policy makers must consider it effects on the welfare of older farmers and its impact of the agricultural industry before moving forward with reforms. The average age of Taiwanese farmers reached 61.2 in 2005, which means that many are eligible for FHI pensions are likely to increase their rate of medical care utilization as they age. In addition, the amount of land enrolled in the set-aside program increased to 239,747 hectares in 2004, which is approximate equal to the total cultivate land area in 2004 (237,351 hectares). To formulate broad based agricultural policy reforms the government needs to know whether land set asides are sensitive to farmers' participation in the FHI.

We are also motivated by the desire to provide empirical estimates that can be used to predict the impact of PPACA on U.S. farmers. Because PPACA will fundamentally change the structure of health insurance markets in the U.S. over the next several years, historical data are of limited use in predicting PPACA's wide reaching effects.[1] An alternative approach is to consider programs in other countries that are similar to the future reforms written into PPACA.

The Farmers Health Insurance (FHI) program in Taiwan contains several features that are similar to these reforms. In particular, the coupling of FHI premium and cost-sharing subsidies with universal coverage administered through Taiwan's National Health Insurance (NHI) program, are the very similar to PPACA's premium and cost-sharing subsidies for low-to-middle income families that are tied to health insurance plans made universally available to the plans individuals without employer sponsored coverage will be able to purchase through Health Insurance Exchanges.

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[1] Many of PPACA's provisions are either phased-in gradually, or do not take effect until 2014.

Given that median family income of farmers in the U.S. was $54,000 in 2007 ($58,320 in 2011 dollars), we estimate that well over half of U.S. farmers will qualify for these subsidies (USDA, 2010; Kaiser Family Foundation, 2010). Farmers will also qualify for additional insurance subsidies in the form of small business tax credits.

To analyze the impact of enrollment in the FHI we make use of a unique dataset of 703,287 farm operators from Taiwan's Agricultural Census merged to administrative data from the FHI program. This large scale population-based survey provides us sufficient power to precisely estimate the impact of FHI enrollment on labor supply and land allocation decision. Another distinct advantage of these data is that health insurance status of each farmer is validated using the administrative data rather than self-reported. This is important because past research has shown that health insurance status is often measured with significant error in survey data, and that such measurement error can have a large impact on econometric estimates (Kreider and Hill, 2009).

While the variable we construct to indicate enrollment in the FHI program is measured without error, it is still possibly endogenous in any labor supply or land allocation model. This is because there are unobservable factors, such as unmeasured health status or risk aversion, that are correlated both with FHI enrollment and these outcome variables. To overcome the endogeneity problem we use a coarse matching method to effectively generate a control group of farmers that is similar along observable dimensions to the treatment group that enrolls in the FHI. In so doing, we significantly reduce the potential for endogeneity bias in our treatment effect estimates.

Taiwan’s Farmer's Health Insurance Program

The Farmers’ Health Insurance Program (FHI) is a supplementary health insurance program for farmers, which has been administered by the government of Taiwan since 1989. The FHI was the first government sponsored health insurance in Taiwan, and was designed to both increase the health and welfare of farmers and to promote stability in rural areas. FHI coverage is mandatory for members of farmers’ associations, and other farmers above 15 year of age can electively enroll in the program.

Upon enrolling in the FHI farmers receive a favorable premium-benefit ratio and a premium subsidy. In particular, FHI enrolless pay only 30% of health insurance premiums levied at 2.55% of total benefits, whereas public sector and private sector employees have pay 40% of premiums levied at 7.15% of total benefits, and 30% of premiums levied at 5.5% of total benefits (Chiang, 1997). In addition to the subsidies in medical services, FHI enrollees receive lump sum payments for maternity, disability, and death as well as a pension upon turning 65 years old. When the FHI reaches 65, they are eligible to receive a lump sum monthly payment of NT$ 6,000.

Since the inauguration of the National Health Insurance (NHI) program in 1995, all of the medical care services provided to FHI enrollees have been administered through the NHI.[2] The cost of per doctor visit is same for each resident regardless of the type of the FHI health insurance status. However, the lump-sum cash payments in the form of maternity subsidies, disability compensation, and funeral allowance continued to be administered through the FHI. Program enrollees also continued to benefit from premium subsidies. In 2007, according to the official report by the Council of Agriculture, there were 1.6 million individuals enrolled in the FHI.

Taiwan's Land Retirement Program

In response to the requirements imposed by World Trade Organization (WTO) to decrease domestic rice subsidies, the Taiwanese government in 2002 launched a land set-aside program called the "Rice Paddy Utilization Adjustment Program" (RPUAP). The RPUAP is similar to the land set-aside program in the European Union and the Conservation Reserve Program in the United State. In particular, farmers have an option of voluntarily setting their land aside in return for compensation in the form of

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[2] A considerable number of studies have examined the effects of the implementation of the NHI on general population (e.g., Chou and Staiger 2001; Chou, Liu, and Hammitt 2003), and on the farm households in Taiwan (Liao and Taylor 2010). All of these used the Survey of Family Income and Expenditure (SFIE). Because the SFIE is designed for general population, it does not contain much information on the farm characteristics, and as a result, is not suitable for our analysis.

an annual direct payment of NT$ 45,000 per hectare. In 2006, the total fallow land in the RPUAP had reached 215,668 hectares.

Theoretical Framework

To guide our empirical specification, we construct a simple theoretical framework that combines the agricultural household model (e.g., Ahearn *et al.*, 2006; Huffman 1991; Lass *et al.*, 1991; Singh *et al.*, 1986) and health care demand model (Cameron et al. 1988; Zheng and Zimmer, 2008). We assume a standard farm household with an operator with fixed time endowment $\bar{T}$. He/she has to decide how to allocate the total available time between leisure ℓ, farm production, L^F, and off-farm work, L^{OF}. In addition to the time constraint, a constraint for land area is imposed. The farm operator also must decide how to allocate the total available land $\bar{A}$ between farm production, A, and land enrolled in the land set-aside program, A_s with per hectare payment p_A. Household income is earned from off-farm work at the wage rates, w, and from sales of the agricultural product at price p_f, produced with on-farm labor and operated land in accordance with a well-behaved (concave) production function, $f(L^F, A)$.

Further, denote the fixed wealth endowment of the farm household as $\bar{E}$. Following the specification in Cameron et al. (1988), the health status of the farm operator, H, is determined by the health production function (Becker 1965, Grossman

1972) defined over medical care utilization, M, and uncertain health state (or event) s. Each farmer does know their future health status but has a prior probability distribution over future states, defined as $\pi(s \mid K)$, where K are demographic characteristics. We also assume j indicates the insurance status j, where (j = 1 indicates FHI enrollment and j = 0 denotes non-enrollment; P_j represents the insurance premium paid by the farmer, so if the farmer does not enroll in the FHI, P_j = 0, otherwise P_j is greater than 0. P_M is the price per unit of health care service, and B_j is the supplement benefit of the FHI program.

If there is a single composite commodity of consumption goods, x, with unitary price, the farm household is assumed to maximize utility by choosing the levels of labor used for off-farm (L^{OF}) and on-farm production (L^{F}), medical care utilization (M), and the amount of land allocated to the land retirement program (A^S). The farm operator maximizes utility subject to constraints defined over land area, time, and earnings:

$$\underset{A^s, L^F, L^{OF}, M}{Max} \; EU_j = \int U_j \{x, \ell, H[M(s), s] \mid K\} d\pi(s \mid K)$$

$$\text{subject to:} \quad x = p_f \, f(L^F, A^F) + w\, L^{OF} + p_A A^S - p_M M(s) - P_j + B_j(s) + \overline{E}$$

$$\overline{T} = L^F + L^{OF} + \ell$$

$$\overline{A} = A^F + A^S \tag{1}$$

Finding an analytical solution to the maximization problem in Eq. (1) is complicated because of the health state s is unknown. Following Cameron et al. (1988) and Zheng and Zimmer (2008), this maximization problem can be solved as a two-stage process.

In the first stage, before the farmer's future health status is known, the farmer decides whether to enroll in the FHI and then in the second stage, after his health status has been revealed, he chooses an optimal level of health care consumption, on- and off-farm labor supply, and land allocation. If we solve the second stage-problem first, the optimal solutions for the endogenous variables, given the FHI program status *j*, can be represented as:

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(2)\quad
\begin{aligned}
L_j^{F*} &= L(z, \bar{E}, \bar{A}; K) \\
L_j^{OF*} &= L(z, \bar{E}, \bar{A}; K) \\
A_j^{S*} &= L(z, \bar{E}, \bar{A}; K) \\
M_j^{\ *} &= L(z, \bar{E}, \bar{A}; K)
\end{aligned}
$$

where the vector *z* indicate all of the exogenous price variables.

In the first stage, the farmer decides whether to enroll in the FHI. If we substitute the optimal solutions of the second stage (Eq. (2)) and integrate over *s*, we can derive the indirect expected utility associated with FHI enrollment. Therefore, the first stage optimization problem is solved by comparing the expected utility of enrolling and not enrolling in the FHI (*j=1* or *j=0*).

$$(3)\quad EU_j = \int U_j\{x^*, \ell^*, H[M^*(s), s] \mid K\} d\pi(s \mid K)$$

If $EU_{j=1} > EU_{j=0}$, the farmer chooses to enroll in the FHI.

This theoretical framework motivates our econometric analysis in two distinct ways. First, the first stage analysis is consistent with the random utility model proposed by McFadden (1989), and as a result, a binary discrete choice model is appropriate to model the FHI enrollment decision. Second, the theory suggests that the optimal land allocation and level of on- and off farm labor supply depends on the FHI participation decision. Therefore, the empirical model should be in accordance with the econometric literature of program evaluation.

Data

The primary dataset for our analysis is the Agricultural Census Survey in Taiwan in 2005, conducted by the Directorate-general of Budget, Accounting and Statistics, Executive Yuan, Republic of China, Taiwan. Since 1970, all farm households in Taiwan were interviewed every 5 years. The survey is designed to collect information on farm production practices and farm household activities. Each farm is asked to report on specific aspects of farm production , and on participation in the government programs during a face-to-face interview with officers of the local agricultural station (DGBAS 2005).[3] Data on socio-demographic characteristics of the farm operator and on-farm and off-farm activities are also collected.

We use the most recent wave of these data, collected in 2005. The survey consists of 889,055 total households, of which, 771,579 are identified as agricultural farms; 68,398 are forest farms; and 49,078 are fishery farms. Since our primary

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[3] The detailed information of this survey can be also found at: http://www.dgbas.gov.tw/np.asp?ctNode=2835

interest is in the land and labor allocation of the farm households that are eligible to participate in the land retirement program, we limit our sample to only crop farms, thereby and excluding livestock farms, fishery and forest farms.

In order to obtain information on each person's health insurance status, we merged the Agricultural Census to the administrative health claim profiles of all farmers enrolled in the FHI program in 2005. These data are maintained by the Bureau of Labor Insurance (BLI) of the Council of Labor Affairs in Taiwan and the data were merged using each participant's personal identification number under the supervision of the Council of Labor Affairs and the Council of Agriculture. After deleting observations with missing values on certain important socio-demographic characteristics we arrive at a final sample of 703,287 farm operators.[4]

Information of the on-farm hours of the farm operator are recorded in the Agricultural Census using an ordinal variable if the operator worked on-farm for 1-29, 30-59, 60-89, 90-149, 150-179, 180-249, and ≧250 days in 2005. We code these as discrete values 1-7 and model them using an ordered probit model. Four types of the off-farm jobs are documented our data. We assign the value 0 to those who did not

[4] Since only the personal identification number of the farm operator is documented in the Agricultural Census survey, we can only merge the farm operator data here.

work off the farm; 1 to those working off-farm for self-own other agricultural work[5]; 2 for self-own non agricultural job; 3 for hired agricultural work; 4 for hired non-agricultural work, respectively. In addition, the data contain the total number of hectares of land enrolled in the land retirement program, which is 0 for non-participants. Finally, we create a dummy variable whose value is 1 if the farm operator enrolled in the FHI program in 2005, and is 0 otherwise.

In accordance with previous studies on off-farm employment (e.g., Huffman and Lange, 1989; Lim-Applegate *et al*., 2002; Ahearn *et al*., 2006; Phimister and Roberts, 2006), and health insurance coverage of the farm households (e.g., Gripp and Ford 1997; Liao and Taylor 2010), we create several variables to measure the human capital of the farm operators and capture household and farm characteristics. We defined to indicate if the farm operator is less than 40, 40-49, 50-59, 60-69, and ≧70 years old, four dummy variables to indicate educational attainment at the primary, junior high school, senior high school, or college level, and a dummy variable to identify gender. We also create a variable to measure household size. Finally, we create variables to control for farm characteristics, including dummy variables to indicate whether the farm size is are less than 0.25, 0.25-0.49, 0.5-0.74, and ≧0.75

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[5] Self-own other agricultural work is defined if the farms provide agricultural services with paid income for other farms. These activities could be providing pest prevention technology to others, seed breeding etc.

hectares, a variable for total land area of the farm, and dummy variables to indicate whether the primary crop is rice, vegetable, fruit, and some other crop.

Econometric Analysis

We draw on the program evaluation literature to econometrically estimate the impact of FHI enrollment on the on-farm and off-farm employment of farm operators, and land enrolled in the land retirement program (Woodridge 2010). We use a matching technique to pair FHI enrollees with comparable non-enrollees. Using this matched sample, we then estimate several discrete choice models to analyze the effect of health insurance coverage through the FHI on labor supply and land enrolled in the land retirement program while controlling for nonrandom selection into the program. <u>Matching Process</u>

Consistent with the theoretical framework, if the variable y_i representing the outcome variable (i.e. on-farm, off-farm labor supply, and land enrollment), the equation of interests can be specified as:

(9) $y_i = \beta X_i + \gamma H_i + \varepsilon_i$

where H_i is a binary indicator of the health insurance coverage through the FHI, and X_i is the vector of other exogenous variables. β, γ are estimated parameters, and ε_i is the random error. We are primarily interested in the parameter γ, which measures the impact of FHI enrollment on the outcome variable. However, a direct estimation of Eq. (9) using the conventional ordinary least square method (if y_i is continuous) will yield biased estimation if the FHI enrollment and the outcome are correlated due to some unobserved common factors. To correct for the endogeneity problem, several methodologies have been proposed, including control function approach, instrumental variables, and matching (Wooldridge 2010).

Matching is a nonparametric method used to correct for endogeneity bias in observational studies where individuals have not been randomly assigned to treatment and control groups. The key goal of matching is to prune observations from the data so that the remaining data have better balance between the treated and control groups, meaning that the empirical distributions of the covariates (X_i) in the groups are more similar. Several algorithms had been proposed for matching. The *Exact Matching* method simply matches a treated unit to all of the control units with the same covariate values. Although the idea of this method is straightforward, this method often produces very few matches.

As an alternative, several other approximate matching methods specify a metric to find control units that are close to the treated unit. This metric is often the Mahalanobis distance or the propensity score, which is simply the probability of being treated, conditional on the covariates. A problem with this approach is that it requires the user to set the size of the matching solution *ex ante*, then check for balance *ex post*

(Guo and Fraser 2011; Wooldridge 2010).

We employ a matching method called “Coarsened Exact Matching” (CEM), which was recently suggested by Iacus *et al*. (2008). The advantage of CEM is that it is straightforward and easy to implement. Also, it belongs to the monotonic imbalance method. Implementing CEM requires several steps. First, variables are recoded into coarsened categories so that similar values are grouped together. In what follows, an "exact matching" algorithm is applied to the coarsened data (see Iacus *et al*. 2008 for the detailed procedure).

With the matched sample, the effects of self-selection into the FHI are greatly reduced. Therefore, for the case of a continuous outcome variable y_i, the average treatment effect is simply the differences in mean values between the enrollees and non-enrollees in the *matched sample*. In our case, we apply several discrete choice models to estimate the treatment effect due to the nature of the outcome variables. Since the off-farm employment is recorded as an ordinal variable, we sue the ordered probit model, and estimate a multimonial logit model for the off-farm job category. Finally, we estimate a tobit model using land enrolled in the land retirement program. All of these three models are specified without any covariates (but a constant) and a dummy indicator for health insurance coverage (H_i) in the matched sample.

Statistical Tests for the Matching Quality

To assess the quality of matches in the matches sample one can compare the descriptive statistics of the matching variables in both the treatment and the control group, before and after matching. A more formal method of comparison is based on the measure of imbalance suggested by Iacus *et al*. (2008):

(10) $$L(f,g)=\frac{1}{2}\sum_{l_1\ldots l_k}\left|f_{l_1\ldots l_k}-g_{l_1\ldots l_k}\right|,$$

which is the sum of absolute differences over all cells of a multivariate histogram. In Eq. (10), $f_{l_1\ldots l_k}$ denote the relative frequencies of the categorical variables for the treated farms, and $g_{l_1\ldots l_k}$ for the control farms. These frequencies are obtained in three steps. First, the number of categories for each (continuous) variable is chosen. Then, the discrete variables are cross-tabulated separately for the treated and the control group. Finally, the *k*-dimensional relative frequency is computed. Perfect balance across all variables is achieved if $L(f,g)=0$, whereas $L(f,g)=1$ indicates perfect separation. Letting the relative frequencies of the matched dataset be denoted by *f** and *g**, one hopes to find $\Delta L=L(f,g)-L(f^*,g^*)>0$. This difference can be interpreted as the increase in balance achieved as a result of matching. The measure defined in Eq. (10) can also be quantified for each variable *j* separately, allowing an assessment of the variable-specific imbalance.

Results

Table 1 contains information on the sample distribution of the on-farm and off-farm employment. Overall,, 61% of the farm operators participated in the FHI. Among the insured farm operators, 20% of them work on-farm between 1-29 days, 23% of them between 30-59 days, and only 10% of them work for more than 250 days. In addition, 71% of them did not work off-farm in 2005. For those who worked off the farm, the largest proportion worked for hire in a non-agricultural job (13%). A different pattern is revealed for the non-FHI enrolled farmers. Compared to their counterparts of enrollees they spent less time on their farm; only 7% of them work on farm for more than 250 days. A different pattern is also found for off-farm employment. Among the non-enrollees, 44% did not work off the farm. For those who had off-farm jobs, a large proportion worked for hire in the non-agricultural sector (35%).

Table 2 presents the sample distribution of the land allocated to the land retirement program by FHI status. FHI participation seems to be negatively correlated with the land enrolled in the land retirement program. As exhibited, the percentages of the enrollees and non-enrollees participating in the land retirement program are 19% and 23%, respectively. However, conditional on participating in the land retirement program FHI farmer enrolled more land than non-FHI farmers (59.38 vs. 55.09 hectares).

Table 3 contains sample statistics for farms and farm operator characteristics in the matched and unmatched samples. In the unmatched sample, significant differences in the socio-demographic characteristics, farm practices and family structure are found between the enrollees and non-enrollees. Farm operators in the FHI tend to be older and less educated. For instance, the proportions of the farm operators who are older than 70 years old are 0.34 and 0.20 for the enrollees and non-enrollees, respectively. In addition, 58% of FHI farm operators finished elementary school, but only 44% of non-enrollees had this same level of educational attainment. Enrollees also have larger farms than their counterparts; 33% of enrollees had farms greater than 0.75 acre, but only 29% of non-enrollees had farms this large. However, we find few differences by farm types.

<u>Investigation of Match Quality</u>

After applying the CEM matching procedure on the unmatched sample, we constructed a matched sample based on selected categories of the exogenous variables. The sample statistics of the matched sample are shown in the Table 3. In the matched sample, we retain 427,702 enrollees and 273,488 non-enrollees. As expected, the sample statistics of the exogenous variables are very similar between the enrollee and non-enrollee subgroups in the matched sample. To provide more formal statistical evidence of the quality of the matched sample, we present the differences in sample statistics between the unmatched and matched sample in Table 4.

In the unmatched sample, we find noticeable differences across age and education, with the *L* statics of 0.238, and 0.158 respectively. However, the *L* statics of all of the selected coared groups of the exogenous variables are less than 0.001. Consistent with the sample statistics presented in Table 3, the differences in these selected variables between enrollees and non-enrollees are much lower in the matched sample.

<u>Determinants of FHI enrollment</u>

We first investigated the association between socio-demographic characteristics of the farm operators, farm practices and family structure and participation in the FHI program using a Probit model. The estimated reported in Table 5 show that operator age is positively associated with the likelihood of participation in the FHI program. Compared to the farm operators who are <=40 years old, those farm operators whose age are >=70, 60-69 have higher probabilities of participating in FHI by 24.2% and 20.5%, respectively. The positive effect of operator age on health insurance coverage is consistent with the findings from the U.S (Gripp and Ford 1997). In addition, compared to female farm operators, male farmers have a higher likelihood of FHI participation by 6%. The education level of the farm operator also matters for FHI coverage. For instance, compared to those who have only primal education, farmers who finished college have a 7.4% lower probability of FHI enrollment.

Farm and family characteristics also play an important role in FHI participation.

An additional member in the household decreased the probability of FHI participation by 1.6%. Compared to the small farms, farms with land area greater than 0.75, 0.5-0.74, and 0.25-0.5 acres have higher probabilities of the FHI participation by 6.2%, 4.6%, and 4.1%, respectively. Finally, farm type is also related to FHI participation. Compared to other crop farms, rice, vegetable, and fruit farms have higher likelihood of FHI participation.

Impact of FHI enrollment on labor and land allocation

Table 6 presents the estimation results for our models of on-farm work days by farm operators. Since on-farm work days is coded as an ordinal dependent variable (see Table 1), we estimate the impact of FHI enrollment on this variable using an ordered probit model containing only a constant term and the binary indicator of the FHI program participation. This is because differences in the exogenous variables are eliminated in the matched sample..

The marginal effect estimates suggest that FHI enrollment is positively associated with on-farm days of the farm operator. Compared to the non-enrollees, the likelihood of working on the farm more than 250 days, 180-249 days, and 150-179 days is higher by 2.4%, 1.6%, and 1.8% for the insured farmers, respectively. For the sake of comparison, the estimation results on the unmatched sample are also presented. It is evident that the results are upwardly biased without controlling for the differences in exogenous variables (i.e. in the unmatched sample).

In Table 7 we report the coefficients and the marginal effects of the multinomial logit model for off-farm job type. In general, the results indicate that FHI enrollment is negatively associated with the likelihood that farm operators work off the farm. Compared to non-enrollees, the probability that FHI farm operators work off-farm for hired non-agricultural work, and self-own non-agricultural work, are lower by 12% and 2.7%, respectively. Comparing the results across the unmatched and matched sample suggests the impact of FHI participation on off-farm employment is over-estimated using the unmatched sample. This is similar to the case of on-farm employment (Table 6). In the case of farm operators that work off the farm in self-own non-agricultural work for instance, the estimated marginal effects is -0.046, which is 70% higher than the effect estimated in the matched sample (-0.027).

A positive (negative) effect of the FHI on the on(off) farm labor supply may reflect the life time choice of the farm operators. As indicated earlier, FHI covers several fridge benefits. One of the benefits is the old farm pension for the enrollees who are older than 65. For the older farm operators, a lump-sum payment of NT$ 6,000 will be paid in each month. These subsidies are likely to be used to support their living and used for retirement. Therefore, the enrollees are less likely to work off the farm.

In Table 8 we report Tobit estimates of the impact of FHI enrollment on the amount of land allocated to the land retirement program. FHI enrollment is negatively correlated with both the likelihood that land is put into retirement as well as the level of land enrolled in the program. Compared to the non-enrollees, the enrollees have a lower probability of participating in the land retirement program by 2.7%. The unconditional marginal effects show that the enrollment in the land retirement program by FHI enrollees is 2.121 acre less than non-FHI enrollees.

In contrast to the previous findings, these effects are under-estimated in the unmatched sample. There are several explanations for the negative association between enrolled land and the FHI participation. To be eligible for the FHI program, one of the requirements is that farmers must have at least 0.1 hectares of farm land, as so small farmers in particular are constrained in the amount of land they can retire if they wish to maintain eligibility for the FHI.

Conclusions and Policy Implications

Using a unique dataset we examine the impact of participation in Farmers' Health Insurance program on the on-farm and off-farm employment and land allocation to the land retirement program of farmers in Taiwan. Despite the fact that all farmers are eligible for the FHI only 61% choose to enroll in it. Enrollees and non-enrollees appear to vary in their socio-demographic profiles. In particular, farmers who are older, male, and less educated are more likely to enroll in the FHI program. The results we obtained using a matching procedure to account for non-random enrollment in the program suggest that FHI enrollees are more(less) likely to work on(off) the farm. Moreover, FHI-insured farmers tend to enroll less land in the land retirement program.

Based on our findings, it may be possibly conclude that although the FHI alleviates barriers of the farmers to access medical services and to provide social security under a modest cost-sharing mechanism, it has undesired effects on land and labor allocation of the farmers. In particular, the supplement old pension benefits of the program provides an incentive for older farmers to stay in the program, which could be beneficial if doing so increases their welfare and makes them less reliant on social services, but could be undesirable if they are less productive than the younger farms who would replace them.

Given some of the similarities between the FHI program in Taiwan and certain aspects of PPACA, such as the ability for self-employed farms to purchase health insurance at subsidized rates, we can use the results of our analysis to predict how PPACA might affect U.S. farmers. Currently, many U.S. farmers, or their spouses, work off- farm to obtain fringe benefits that include health insurance. Our results suggest that universal access to health insurance, coupled with the premium and cost-sharing subsidies that will be available to the majority of farmers may reduce off-farm labor hours and increase on-farm hours. In addition, PPACA may reduce the amount of land allocated to the Conservation Reserve Program. This may be particularly true for older farmers who are still too young to qualify for Medicare benefits. In addition, PPACA may reduce the amount of land allocated to the Conservation Reserve Program.

However, several limitations of our study must be kept in mind that may affect the generalizability of our results. While the FHI also contains maternity, disability, and life insurance benefits, and a pension for those over-65, PPACA is focused on the provision of health insurance. As a result, the effects we observe of FHI enrollment in Taiwan may be larger than should be expected to occur as a result of PPACA in the U.S. Finally, it should be noted that our dataset is cross section, and does not allow us to consider dynamic aspects of labor supply and land allocation decisions. This issue can be better addressed if a panel data is available.

Reference

Council of Agriculture. 2009. Agricultural Statistical Year Book. Published by Council of Agriculture in Taiwan, Executive Yuan, Taiwan.

Cheng, T-L. 1997. Taiwan's 1996 Health Care Reform, *Health Policy* 39:225-239.

Chou, Y., and D. Staiger. 2001. Health Insurance and Female Labor Supply in Taiwan. *Journal of Health Economics* 20: 187-211.

Currie, J., and B. Madrian. 1999. Health, Health Insurance and the Labor Market. In *Handbook of labor Economics,* vol. 3C, edited by Orley Ashenfelter and David Card, pp. 3309–406. Amsterdam: Elsevier.

Dehejia, R., and S. Wahba. 2002. Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics* 84(1): 151–61.

Directorate-General of Budget, Accounting and Statistics, Executive Yuan, Republic of China, Taiwan 2007. The 2005 Agricultural, Forest, Fishery and Husbandry Census.

Fleming, L., O. Gomez-Marin, D. Zheng, F. Ma, and D. Lee. 2003. National Health Interview Survey Mortality Among U.S. Farmers and Pesticide Applicators. *American Journal of Industrial Medicine* 43: 227–33.

Gripp, S., and S. Ford. 1997.: Health Insurance Coverage for Pennsylvania Dairy

Farm Managers. *Agricultural and Resource Economic Review* 26(2):174–83.

Gruber, J., and J. Poterba. 1994. Tax Incentives and the Decision to Purchase Health Insurance: Evidence from the Self-employed. *Quarterly Journal of Economics* 109(3): 701–33.

Guo, S., and M. Fraser. 2011. *Propensity Score Analysis: Statistical Method and Applications*. Sage Publications, Inc.

Heckman, J., H. Ichimura, and P. Todd. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies* 64(4): 605–54.

Holtz-Eakin, D. 2011. Does Massachusetts's Health Care Reform Point to Success with National Reform? *Journal of Policy Analysis and Management* 30(1): 178–84.

Iacus, S., G. King, and G. Porro. 2011. Multivariate Matching Methods That are Monotonic Imbalance Bounding. *Journal of American Statistical Association* (forthcoming).

Iacus, S., and Porro, G. 2009. Random Recursive Partitioning: A Matching Method for the Estimation of the Average Treatment Effect. *Journal of Applied Econometrics* 24:163–85.

Jensen, H., and P. Salant. 1985. The Role of Fringe Benefits in Operator Off-farm

Labor Supply. *American Journal of Agricultural Economics* 67(5): 1095–9.

Jensen H, and W. Saupe. 1987. Determinants of Health Insurance Coverage for Farm Family Households: A Mid–western Study. *Northern Central Journal of Agricultural Economics* 9:145–55.

Jones, A., T. Parker, M. Ahearn, A. Mishra, and J. Variyam. 2009. Health Status and Health Care Access of Farm and Rural Populations. Economic Information Bulletin No. 57, Economic Research Service, US Department of Agriculture, Washington DC.

Kaiser Family Foundation. 2010. Summary of New Health Reform Law. http://www.kff.org/healthreform/upload/8061.pdf. Accessed April 29, 2011.

Kandilov, A., and I. Kandilov. 2010. The Effect of Legalization on Wages and Health Insurance: Evidence from the National Agricultural Workers Survey. *Applied Economic Perspectives and Policy* 32(4): 604–23.

Klemick, H., K. Leonard, and M. Masatu. 2009. Defining Access to Health Care: Evidence on the Importance of Quality and Distance in Rural Tanzania. *American Journal of Agricultural Economics* 91(2): 347–58.

Kreider, B. and S. Hill. 2009. Partially Identifying Treatment Effects with an Application to Covering the Uninsured. Journal of Human Resources 44(2): 409-449.

Kuruvilla, S., and M. Liu. 2007. Health Security for the Rural Poor? A Case Study of A Health Insurance Scheme for Rural Farmers and Peasants in India. *International Social Security Review* 60(4): 3-21.

Liao, P. and J. Taylor. 2010. Health Care Reform and Farm Women's Off-Farm Labor Force Participation: Evidence from Taiwan. *Journal of Agricultural and Resource Economics* 35(2): 281–98.

Lottero W, Seifert R, and N. Kohn. 2006. Losing Ground: Eroding Health Insurance Coverage Leaves Kansas Farmers with Medical Debt. Boston: The Access Project.

McNamara, P. and C. Ranney. 2002. Hired Farm Labour and Health Insurance Coverage. in Findeis, J.L., A.M. Vandeman, J.M.Larson, and J.L. Runyan, eds. *The Dynamics of Hired Farm Labor*, Wallingford, UK: CAB International.

Phimister, E. and D. Roberts. 2006. The Effect of Off-farm Work on the Intensity of Agricultural Production. *Environmental and Resource Economics* 34(4): 493–515.

USDA. 2010. Structure and Finances of U.S. Farms: Family Farm Report, 2010 Edition. ERS Economic Information Bulletin #66, Washington, D.C.

Wooldridge, J. 2010. Econometric Analysis of Cross Section and Panel Data. MIT press.

Zheng, X. and D. Zimmer. 2008. Farmers' Health Insurance and Access to Health Care. *American Journal of Agricultural Economics* 90(1): 267–79.

Table 1: Sample distribution of the on and off farm days by health insurance status

FHI enrollee		Yes	No
Sample (%)		428,677 (61%)	274,610 (39%)
Code	Category of on-farm days		
1	If 1-29 days	86,863 (20%)	77,871 (28%)
2	If 30-59 days	100,407 (23%)	70,732 (26%)
3	If 60-89 days	64,444 (15%)	41,741 (15%)
4	If 90-149 days	54,653 (13%)	29,207 (11%)
5	If 150-179 days	47,049 (11%)	22,028 (8%)
6	If 180-249 days	33,092 (8%)	14,494 (5%)
7	If >=250 days	42,169 (10%)	18,537 (7%)
Code	Category of off-farm work		
0	If don't work off the farm	303,162 (71%)	119,803 (44%)
1	If works off-farm for self own agricultural work	32,398 (8%)	22,931 (8%)
2	If works off-farm for self own non-agricultural work	24,499 (6%)	27,196 (10%)
3	If works off-farm for hired agricultural work	11,476 (3%)	7,562 (3%)
4	If works off-farm for hired non-agricultural work	57,142 (13%)	97,118 (35%)

(.) is the percentage.

Table 2: Sample distribution of land enrolled in the land retirement program

FHI enrollee	Yes	No
If participated in the land set-aside program (=1)	0.19	0.23
	(0.39)	(0.42)
Land enrolled in the set-aside program (are)	8.67	9.59
	(30.36)	(32.99)
Enrolled land for program participants only (are)	59.38	55.09
	(57.48)	(61.20)

(.) are standard deviations. 1 hectare=100 are.

Table 3: Sample statistics of the exogenous variables

		Full sample		Unmatched sample				Matched sample			
FHI enrollee		--		Yes		No		Yes		No	
Sample		703,287		428,677		274,610		427,702		273,488	
Variable	Definition	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age											
Age40	If operator age <40 (=1)	0.04	0.19	0.03	0.16	0.06	0.23	0.03	0.16	0.03	0.16
Age4049	If operator age >=40 and <50 (=1)	0.15	0.36	0.11	0.32	0.20	0.40	0.11	0.32	0.11	0.32
Age5059	If operator age >=50 and <60 (=1)	0.25	0.43	0.20	0.40	0.32	0.47	0.20	0.40	0.20	0.40
Age6069	If operator age >=60 and <70 (=1)	0.28	0.45	0.32	0.47	0.22	0.42	0.32	0.47	0.32	0.47
Age70	If operator age >=70 (=1)	0.29	0.45	0.34	0.47	0.20	0.40	0.34	0.47	0.34	0.47
Education											
Primal	If operator had no education (=1)	0.11	0.32	0.12	0.33	0.10	0.30	0.12	0.33	0.12	0.33
Elementary	If operator finished elementary school (=1)	0.53	0.50	0.58	0.49	0.44	0.50	0.58	0.49	0.58	0.49
Junior	If operator finished junior high school (=1)	0.17	0.37	0.15	0.35	0.20	0.40	0.15	0.35	0.15	0.35
Senior	If operator finished senior high school (=1)	0.15	0.36	0.12	0.32	0.20	0.40	0.12	0.32	0.12	0.32
College	If operator had college degree or higher (=1)	0.05	0.21	0.03	0.18	0.07	0.25	0.03	0.18	0.03	0.18
Farm land											
Land1	If operated land <0.25 hectare (=1)	0.24	0.43	0.22	0.42	0.27	0.45	0.22	0.42	0.22	0.42
Land2	If operated land >=0.25 and <0.50 hectare (=1)	0.27	0.44	0.27	0.44	0.27	0.45	0.27	0.44	0.27	0.44
Land3	If operated land >=0.50 and <0.75 hectare (=1)	0.17	0.38	0.18	0.38	0.17	0.37	0.18	0.38	0.18	0.38
Land4	If operated land >=0.75 hectare (=1)	0.31	0.46	0.33	0.47	0.29	0.45	0.33	0.47	0.33	0.47
Farm type											
Rice	If rice farms (=1)	0.47	0.50	0.46	0.50	0.47	0.50	0.46	0.50	0.46	0.50
Vegetable	If vegetable farms (=1)	0.16	0.37	0.15	0.36	0.17	0.37	0.15	0.36	0.15	0.36
Fruit	If fruit farms (=1)	0.25	0.44	0.27	0.44	0.23	0.42	0.27	0.44	0.27	0.44
Other crop	If other crop farms (=1)	0.12	0.32	0.11	0.32	0.12	0.33	0.11	0.32	0.11	0.32
HH size	Persons living in the household	4.34	2.27	4.22	2.26	4.52	2.27	4.21	2.25	4.21	2.25
Male	If operator is male (=1)	0.83	0.38	0.83	0.37	0.82	0.38	0.84	0.37	0.84	0.37

Table 4: Statistics of the differences in the unmatched vs. matched sample

	Unmatched sample						
Category	L	Mean	Min	25^{th}	50^{th}	90^{th}	Max
Age	0.238	0.525	0	1	1	1	0
Male	0.013	0.013	0	0	0	0	0
Education	0.158	-0.324	0	0	0	-1	0
Farm size	0.052	0.147	0	1	1	0	0
HH. size	0.087	-0.304	0	-1	0	0	0
Farm type	0.033	0.026	0	0	0	0	0
Multivariate L1	**0.270**						
	Matched sample						
	L	Mean	Min	25^{th}	50^{th}	90^{th}	Max
Age	1.50E-13	-7.90E-13	0	0	0	0	0
Male	3.80E-14	-2.10E-14	0	0	0	0	0
Education	1.50E-13	-2.90E-13	0	0	0	0	0
Farm size	1.50E-13	-7.90E-13	0	0	0	0	0
HH. size	1.70E-13	-4.80E-13	0	0	0	0	0
Farm type	1.60E-13	-3.90E-13	0	0	0	0	0
Multivariate L1	**1.65E-13**						

The Coarsed Matching Method (CEM) is used for matching procedure.

Table 5: Probit model of FHI enrollment

	Coefficient	SE	Marginal Effect	SE
Age4049	0.096 ***	0.014	0.022 ***	0.003
Age5059	0.134 ***	0.014	0.031 ***	0.003
Age6069	0.930 ***	0.014	0.205 ***	0.003
Age70	1.119 ***	0.015	0.242 ***	0.003
Male	0.249 ***	0.007	0.060 ***	0.002
Elementary	0.298 ***	0.009	0.070 ***	0.002
Junior	0.148 ***	0.012	0.035 ***	0.003
Senior	-0.015	0.012	-0.004	0.003
College	-0.303 ***	0.015	-0.074 ***	0.004
Land2	0.174 ***	0.007	0.041 ***	0.002
Land3	0.200 ***	0.008	0.046 ***	0.002
Land4	0.267 ***	0.007	0.062 ***	0.002
HH size	-0.069 ***	0.001	-0.016 ***	0.000
Rice	0.026 ***	0.008	0.006 ***	0.002
Vegetable	0.024 **	0.010	0.006 **	0.002
Fruit	0.256 ***	0.009	0.060 ***	0.002
Constant	-0.469 ***	0.019		
Log-likelihood		-444,924		

***,**,* indicate the significance at the 1%, 5%, 10% level.

Table 6: Marginal effects from the on-farm days equation

Code	On-farm days	Unmatched Sample		Matched sample	
		Marginal Effect	SE	Marginal Effect	SE
1	If 1-29 days	-0.080***	0.001	-0.055***	0.001
2	If 30-59 days	-0.029***	0.000	-0.022***	0.000
3	If 60-89 days	0.009***	0.000	0.005***	0.000
4	If 90-149 days	0.021***	0.000	0.014***	0.000
5	If 150-179 days	0.026***	0.000	0.018***	0.000
6	If 180-249 days	0.022***	0.000	0.016***	0.000
7	If >=250 days	0.033***	0.000	0.024***	0.000
Log-likelihood		-1,292,047		-1,298,775	

Estimated using an ordered probit model.

The definition of each value code can be also found in Table 1.

The estimated equation is on-farm days= f (FHI)

*** indicate the significance at the 1% level.

Table 7: Estimation of the off-farm work equations

			Use unmatched sample			
Code	Type of off-farm work	Variable	Coefficient	SE	Marginal effect	SE
0	If do not work off-farm		--		0.271	0.001
1	If self-own other agricultural work	FHI	-0.535 ***	0.010	-0.004 ***	0.001
		Constant	-1.773 ***	0.008		
2	If self own non-agricultural work	FHI	-1.036 ***	0.009	-0.046 ***	0.001
		Constant	-1.392 ***	0.006		
3	If for hired agricultural work	FHI	-0.511 ***	0.015	-0.001 **	0.000
		Constant	-2.763 ***	0.012		
4	If for hired non-agricultural work	FHI	-1.459 ***	0.006	-0.220 ***	0.001
		Constant	-0.210 ***	0.004		
Log-likelihood		-762,559				
			Use matched sample			
Code	Type of off-farm work	Variable	Coefficient	SE	Marginal effect	SE
0	If do not work off-farm		--		0.151 ***	0.001
1	If self-own other agricultural work	FHI	-0.300 ***	0.011	-0.004 ***	0.001
		Constant	-2.009 ***	0.009		
2	If self own non-agricultural work	FHI	-0.602 ***	0.010	-0.027 ***	0.001
		Constant	-1.826 ***	0.008		
3	If for hired agricultural work	FHI	-0.224 ***	0.017	0.000	0.000
		Constant	-3.050 ***	0.014		
4	If for hired non-agricultural work	FHI	-0.883 ***	0.007	-0.120 ***	0.001
		Constant	-0.786 ***	0.005		
Log-likelihood		-737,671				

Estimated by the multinomial logit model

FHI is the binary indicator of the health insurance program.

The value code 0 is used for the reference group in estimation

***, ** indicate the significance at the 1%, 5% level.

Table 8: Estimation of the retired land equations

	Unmatched sample								
	Coefficients			Marginal Effect					
				Unconditional			Probability		
	Est.		SE	Est.		SE	Est.		SE
FHI	-10.989	***	0.416	-1.721	***	0.066	-0.023	***	0.001
Constant	-112.305		0.461						
sigma	116.785		2.953						
log-likelihood	-866,009								
	Matched sample								
	Coefficients			Marginal Effect					
				Unconditional			Probability		
	Est.		SE	Est.		SE	Est.		SE
FHI	-13.425	***	0.519	-2.121	***	0.084	-0.027	***	0.001
Constant	-113.523		1.138						
sigma	119.845		9.927						
Log-likelihood	-868,656								

Estimated by the tobit model. The dependent variable is the land enrolled in the set-aside program.
FHI is a binary indicator of the health insurance program.
*** indicate the significance at the 1% level.