# Implications of Transgenic Rice for Farm Households' Nutritional Vulnerability: Projections for Bangladesh[1]

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(Abstract)

This paper employs multivariate regression to forecast the calorie intake of Bangladeshi farm households in the hunger season based on the household income, production, and demographic composition in the current (post harvest) season. Nutritional vulnerability profiles are derived from the estimation of *ex ante* mean and variance of future consumption. The results show the income increase induced by introducing transgenic rice will reduce each individual household's probability of suffering a future consumption shortfall and its vulnerability. The overall vulnerability profile of farm households improves in Bangladesh.

Transgenic crops were first commercialized in 1996. By 2006, the global area of transgenic crops reached 102 million hectares. Despite the United States being the leading country in transgenic crop production, the proportion of global area of transgenic crops grown by developing countries increased every year from 1996 to 2006 (James, 2006). In 2006, developing countries accounted for about 40 percent of the global area, and had on average a higher growth rate of transgenics than did industrial countries. To date, there are approximately 10.3 million farmers in 22 countries that have adopted transgenic crops. Of the 10.3 million, 90 percent are small, resource poor farmers from developing countries whose increased income from transgenic crops contributes to their poverty alleviation (James, 2006). Compared with other major transgenic crops (e.g. soybean, maize, cotton, and canola), the production of transgenic rice is not yet on a large scale. Officially, *Bt* rice was grown on about four thousand hectares in Iran in 2005. It is reported, however, that China has already field tested transgenic rice in pre-production trials and may release it in a near future (James, 2005). Once commercialized on a large scale, due to its significance in providing food for the world's 1.3 billion poorest people and providing a livelihood for 250 million farmers, transgenic rice may have enormous implications for the alleviation of poverty, hunger, and malnutrition, particularly for countries in Asia that have been fighting poverty and under-nutrition for decades.

In Asia, rice provides more than 30 percent of total calorie supply and more than half of the calories consumed by the poor (Hareau, Norton, Mills and Peterson, 2005). Growth in rice yield and total production—an important part of the green revolution—played a significant role in reducing poverty and under-nutrition among the poor in Asia in the 1970s. Green Revolution varieties were developed through conventional breeding,

and no major breakthroughs have been made in the post-green revolution era. Consequently, the average annual growth rate of rice yield in Asian developing countries has declined from about 2.5% during 1961-1989 to 1.1% during 1990-2002 (Liang, Reaves, and Norton, 2005). The stagnation of yield growth and the existence of a production plateau have drawn attention to the promising potential of biotechnology in recent years. Many people hope that a gene revolution will have a similar effect on poverty alleviation as the green revolution once did. Therefore, whether transgenic rice will play such a role in ultimately addressing under-nutrition in Asian developing countries is relevant and warrants further investigation.

Recent research exploring the potential impacts of transgenic crops focuses primarily on distributional and welfare effects (FAO, 2004). For instance, Mamaril (2002) used a partial equilibrium model with data from the Philippines and Vietnam to analyze cross-country distributional effects of transgenic rice. Hareau, Norton, Mills and Peterson (2005) used a general equilibrium model to examine the total and distributional effects of transgenic rice in favorable and less favorable ecosystems. At the household level we recently used a farm household model to examine the effects of transgenic rice on farmers' income and nutritional status (Liang, Reaves, and Norton, 2006). Our farm household model captured the fact that being both consumer and producer, farmers usually make production and consumption decisions within a household unit. Changes in product price, households' relative income, and profits due to the adoption of transgenic rice can all potentially affect households' ability to acquire food and improve their nutritional status. Our result shows that transgenic rice is likely to improve farm households' nutritional status through increased income. Nutritional status at one point in

time, however, only illustrates the nutritional wellbeing of a household from a static perspective. As various risks affect households' food consumption over time, it is likely that farm households' nutritional wellbeing will vary over time. Therefore, to draw a full picture of the nutritional effects of transgenic rice, both the static and dynamic aspects of nutritional wellbeing need to be considered. This paper examines farm households' nutritional vulnerability in the context of Bangladesh.

**Definition of vulnerability**

As a forward-looking measurement of changes in the welfare of an individual or a household, vulnerability can either be broadly regarded as the welfare declines over time, or be defined and estimated by econometric methods. In recent years, there have been a number of empirical studies on vulnerability. For instance, the measurement of vulnerability includes measuring the ability to smooth consumption (Glewwe and Hall, 1998), variations in expected utility (Dercon and Krishnan, 2000), and the probability of future consumption shortfalls (Christiaensen and Boisvert, 2000). In this paper, nutritional vulnerability is defined as the possibility now that individuals' nutritional consumption in the future will fall below a socially accepted standard.

By definition, vulnerability is a probabilistic concept which considers the failure to attain a certain threshold of well-being in the future. It involves several key factors: a) a time horizon over which the potential of future shortfalls is assessed. In most cases, it is specified as one period ahead; b) an indicator of well-being ( $z$ ). In this paper, we focus on a farm household's nutrient intake; c) an *ex ante* probability distribution ( $f(\cdot)$) of ex post outcomes regarding the well-being indicator; d) the threshold for the well-being

indicator and for the probability level, respectively. When consumption is used as the well-being indicator, the consumption poverty line is commonly used as the threshold. The probability threshold $\theta$ refers to the situation, while a person or household will be considered vulnerable if its probability of shortfall exceeds $\theta$. $\theta$ is usually set at the 0.5 level (Christiaensen and Subbarao, 2001).

Mathematically, vulnerability of a person or household i now (at $t$) with respect to its future consumption ($c_{t+1}$) can then be expressed as

$$V_{i,t,\gamma} = F(z)\int_{\underline{c}_{t+1}}^{z} (z - c_{t+1})^{\gamma} \frac{f(c_{i,t+1})}{F(z)} dc_{t+1} \qquad (1)$$

where $\underline{c}_{t+1}$ is the lower bound of future consumption $c_{t+1}$, $f(\cdot)$ is the *ex ante* probability distribution of ex post outcomes regarding the well-being indicator. $F(\cdot)$ is the cumulative distribution function associated with $f(\cdot)$. A household's vulnerability is thus measured as the current probability of becoming poor (F(z)), multiplied by a conditional probability weighted function of shortfall below the poverty line. Depending on the value of $\gamma$, different aspects of shortfall can be measured. When $\gamma = 0$, vulnerability is measured as the probability of consumption shortfall. When $\gamma = 1$, vulnerability is measured as the product of the probability of consumption shortfall and the conditional expected gap. It accounts for the average depth of shortfall. When $\gamma>1$, given the same conditional probability of shortfall occurrence, larger shortfall is given more weight and means greater vulnerability. It accounts for the spread of the distribution of shortfalls (Christiaensen and Boisvert, 2000). In this paper the case $\gamma = 0$ is examined (Equation 2).

$$V_{i,t,0} = F(z) = \int_{\underline{c}_{t+1}}^{z} f(c_{i,t+1}) dc_{t+1} \tag{2}$$

A variety of risk factors can cause an individual or a household to be vulnerable. To reduce the risk exposure, farm households usually employ *ex ante* or ex post coping strategies. For instance, households can smooth consumption through asset depletion (Fafchamps, Udry and Czukas, 1998), borrowing (Udry, 1995), participation in government supported public work programs (Ravallion, 1991), activation of informal insurance networks (Grimard, 1997), reallocation of the labor supply to the labor market (Kochar,1995), temporal geographical reallocation of the household's labor supply, reconfiguration of spending patterns away from investment in human capital (Jacoby and Skoufias, 1997), or a combination of two or more of the above. The degree of risk exposure and its ability to cope with risk varies among households. The income and consumption smoothing strategies a household can actually employ depend on factors such as environment, endowments and the functioning of credit and insurance markets. The interaction between risk factors and a household's behavior determines the *ex ante* distribution of its future consumption. At the household level, vulnerability reflects not only a household's risk exposure, but also the lack of capacity to cope with it. It concerns the *ex ante* potential of a decline in well-being in the future, and is a function of the risk factors of a household's environment—the nature, frequency and severity of the shocks it is exposed to, its exposure to risks, as well as its ability to cope with it when the shock occurs. Farmer households' coping abilities are often determined by their asset endowment and demographic characters.

When transgenic rice is introduced, previous research shows that farm households expect higher profit (Liang, Reaves, and Norton, 2006). With this expected shock, farm

households are assumed in this paper to adjust their consumption behavior in the future. The effect of transgenic rice on households' nutritional vulnerability is therefore investigated through how the induced increase in income will affect households' future nutritional consumption. According to equation 2, the crucial issue in vulnerability measurement is to estimate the *ex ante* probability distribution of future consumption. In empirical studies, a number of consumption forecasting models have been constructed (Chaudhuri, Jalan and Suryahadi, 2001; Christiaensen and Boisvert, 2000). Once the future consumption and its probability distribution are known, in principle, the number of people, whose probability of future consumption falling below the poverty line is higher than a predetermined level, can be computed. Vulnerability profiles at different consumption levels can be established accordingly.

**Theoretic Model**

Vulnerability measures the consumption changes in a farm household over time. Changes in future consumption are usually caused by a variety of risk factors in agricultural production or social economic environments. Natural disasters like drought, widespread pests, or flood, as well as price fluctuation or job losses at the individual level, can all cause a group of farmers to become destitute. The effects of risk factors are particularly serious in developing countries. In some studies risks are modeled explicitly. For instance, Amin, Rai and Topa (1999), and Dercon and Krishnan (2000) modeled shocks and households' ability to cope in the context of Bangladesh and Ethiopia. In other studies, risks are modeled implicitly (Christiaensen and Boisvert, 2000; Chaudhuri, Jalan and Suryahadi, 2001). When risks are modeled implicitly, it is assumed that households

adjust their consumption behavior to cope with the effects of risk factors, and the adjustments are reflected in the observed consumption. Modeling risk implicitly is particularly useful when risk information is not available, or the need to identify risk sources is not on top priority. In this paper, we focus on how farm household nutrient consumption—per household resident calorie intake being used as a proxy—responds to the introduction of transgenic rice. No specific risk factor is modeled.

To derive the *ex ante* probability distribution, this paper specifies a stochastic multivariate linear regression model to estimate a household's future nutrient consumption. The model assumes that the *ex ante* mean and variance of household future consumption are both functions of the household's *ex ante* characteristics and its environment. The model also allows the conditional variance of consumption to be heteroskedastic. The heteroskedasticity implies that household characteristics can affect both the *ex ante* mean and variance of future consumption in different directions. This paper further assumes that household future nutrient consumption (daily per household resident calorie intake) is log-normally distributed. Since lognormal distribution is determined by its mean and variance, it is sufficient to estimate the conditional mean and variance of a household's future consumption to obtain an estimate of its *ex ante* distribution. A household's nutrient consumption function is thus specified as follows:

$$\ln c_{it+1} = f(X_{it};\alpha) + \mu_{it+1} = f(X_{it};\alpha) + h^{1/2}(X_{it};\beta) * e_{it+1} \qquad (3)$$

where $X_{it}$ is the *ex ante* household characteristics. $\alpha$, $\beta$ are the regression parameters of the mean and variance equations, respectively. It is assumed that

$$E(e_{it+1}) = 0, E(e_{it+1}, e_{kt+1}) = 0 \qquad \text{with } i \neq k$$

$$V\left(e_{i,t+1}\right)=\sigma_e^2$$

The conditional mean and variance are:

$$E\left(\ln c_{it+1}\middle|X_{it}\right)=f\left(X_{it};\alpha\right)$$

$$V\left(\ln c_{it+1}\middle|X_{it}\right)=h\left(X_{it};\beta\right)*\sigma_e^2$$

The first derivatives with respect to a particular characteristic $X_{itc}$ (c=1…k, where k is the number of household characteristics) can then be expressed as:

$$\partial E\left(\ln c_{it+1}\middle|X_{it}\right)/\partial X_{itc}=\partial f\left(X_{it};\alpha\right)/\partial X_{itc}$$

$$\partial V\left(\ln c_{it+1}\middle|X_{it}\right)/\partial X_{itc}=\left(\partial h\left(X_{it};\beta\right)/\partial X_{itc}\right)*\sigma_e^2$$

In contrast with the traditional demand specifications where the error term is specified in an additive or multiplicative manner, the multiplicative heteroskedastic specification in this paper (as shown by the first derivatives above) allows the marginal effects of the regressors on the *ex ante* mean and variance of future consumption to differ in sign.

Similar to other studies (Mullahy and Sindelar, 1995. Christiaensen and Subbarao, 2001), $f\left(X_{i,t,};\alpha\right)$ in equation 3 is specified in this paper as a linear function, and $h\left(X_{i,t,};\beta\right)$ is specified as an exponential function (equation 4).

$$\ln c_{it+1}=X'_{it}\alpha_X+\mu_{it+1}=X'_{it}\alpha_X+\left[\exp\left(X'_{it}\beta_X\right)\right]^{1/2}e_{it+1} \qquad (4)$$

Where

$$E\left(\mu_{it+1}\middle|X_{it}\right)=0\,,\,E\left(\mu_{it+1,}\mu_{kt+1}\middle|X_{it}\right)=0 \qquad i\neq k$$

$$V\left(\mu_{it+1}\middle|X_{it}\right)=\sigma_{it+1}^2=\sigma_e^2*\exp\left(X'_{it}\beta_X\right)$$

$\alpha$ and $\beta$ can be estimated by a three-step heteroskedastic correction procedure (Judge *et al.*, 1988). With the estimates of $\alpha$ and $\beta$, each household's *ex ante* mean and variance of future (logarithmic) nutrient consumption can be predicted by substituting individual household characteristics into the regression function. Given the log-normality assumption and the determination of a poverty line, each household's vulnerability $V_{ijt}$ can be determined and vulnerability profiles constructed.

**Data and results**

This paper examined the nutritional consumption of 388 rice farm households in Bangladesh during the hunger season (t+1) in April 1999 and the preceding post harvest season in December 1998 (t). The original household survey data were collected by the International Food Policy Research Institute (Del Ninno, 2001). The selection of two periods—hunger season and the preceding post harvest season—were justified by the fact that farm households are usually more vulnerable in hunger season than in post harvest season. Daily calorie intake per resident household member during the hunger season was obtained by converting total reported household food consumption over the 30 days prior to the interview into kilo calories. The list of total food includes 232 regularly consumed local food items (Del Ninno, 2001).

This paper assumes that each farm household's calorie intake in the future (hunger season) is affected by household income, production condition, assets, and demographic characteristics. Table 1 summarizes the independent variables for the regression function. On average, the daily calorie intake per resident household member in the hunger season is 2419 kcal among the 388 households. There exists large variation

in calorie intake among households. For the lowest 5 percentile households, daily calorie intake per resident household member is equal to or less than 1425 kcal. For the lowest 25 percentile, the calorie consumption is less than 1876 kcal. This 25% of the total population may represent the "ultra poor" households. Other studies in Bangladesh show that out of a total population of over 135 million people, about 20% —28 million people in more than six million households—suffer from chronic food insecurity and severe under-nutrition. On average, ultra poor households can only afford to consume about 1800 kcal calories per person per day, which is far below the World Bank recommended daily average of 2300 kcal calories (WFP, 2006).

Table 1 Descriptive statistics of the dependent and independent variables

| Variable | Mean | Standard Deviation | 5 Percentile | 25 Percentile | 75 Percentile |
|---|---|---|---|---|---|
| | | | | | |
| Daily calorie intake (kcal) per resident household member at hunger season (t+1) | 2419.138 | 751.8167 | 1425.089 | 1876.44 | 2843.535 |
| Agricultural income (taka) at t | 7481.736 | 10021.06 | 53 | 1796.6 | 9162.55 |
| Other income (taka) at t | 941.7537 | 6642.853 | 0 | 0 | 433.25 |
| Usual flood depth (Ft.) | 3.322971 | 3.624889 | 0 | 1 | 4 |
| Value (taka) of agricultural equipment, large trees, fishing tools at t | 6178.242 | 17483.99 | 0 | 225 | 5145 |
| Value (taka) of consumer durables at t | 5975.425 | 12366.89 | 120 | 690 | 5845 |
| Grain stock (kg, rice, paddy, wheat) at t | 73.52577 | 174.8354 | 0 | 0 | 62.5 |
| # of cattle (calves, dairy cow, bullock) at t | 1.57732 | 1.743708 | 0 | 0 | 2 |
| # of goat/sheep at t | 0.56701 | 1.307163 | 0 | 0 | 1 |
| # of chicken at t | 8.036082 | 8.734602 | 0 | 2 | 11 |
| At least one household member completed primary school at t (yes=1) | 0.546392 | 0.498486 | 0 | 0 | 1 |
| # of adult male at t | 1.762887 | 1.104589 | 1 | 1 | 2 |
| # of adult female at t | 1.53866 | 0.797963 | 1 | 1 | 2 |
| # of children at t | 2.657216 | 1.52279 | 0 | 2 | 4 |
| # of elderly at t | 0.219072 | 0.483257 | 0 | 0 | 0 |
| Household head age at t | 46.57732 | 12.51735 | 29 | 37 | 55 |

Similar to calorie consumption, households vary in income, assets, and household characteristics. For instance, on average, the household agricultural income at time t is

approximately 7482 taka with a standard deviation of 10021 taka. Among the surveyed households, approximately 55% of households have at least one member who completed primary education. On average, there are more adult male members than female members, and more children than elderly people in a household. The average age of the household head is 47 years.

The conditional mean and variance of log calorie intake per household resident during the hunger season was estimated by a 3-step OLS procedure (table 2). The results show that agricultural income positively affects both *ex ante* mean and *ex ante* variance of calorie intake. Increases in agricultural income increase the calorie consumption of a household. The variance of consumption increases as well. That is, a household's calorie intake becomes more dispersed. This increase in dispersion is probably due to various risk factors—drought, flood, insect and disease—which affect agricultural production. Exposure to these risks can cause agricultural output to fluctuate. Consequently, income from agricultural production varies over time. Therefore, if a household's calorie intake depends only on agricultural income, as income varies, consumption will spread over a larger range. In this research, the effect of transgenic rice on households' calorie intake is assumed to be the same as the increased agricultural income. Making this assumption enables this research to illustrate the potential income effect of the adoption of transgenic rice, and therefore, how transgenic rice will affect a household's calorie intake. It is worth noting that in addition to increased farm income upon adoption, most new transgenic rice varieties are factor biased. That is, technological characteristics of drought or insect resistance will reduce fluctuation of agricultural production and will stabilize

agricultural outcome. Therefore, theoretically, transgenic rice's impact on improving calorie intake status is likely to be higher than indicated in table 2.

Table 2 Three-step OLS estimates of conditional mean and conditional variance of logarithmic daily calorie intake per resident household member in the hunger season

| | $E(\ln c_{t+1}/X_t) = X_t'\alpha$ | | $\ln Var(\ln c_{t+1}/X_t) = X_t'\beta$ | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| Agricultural income at t | 4.09E-06 | 2.07 | 5.55E-06 | 0.39 |
| Other income at t | 2.97E-06 | 3.65 | -0.00003 | -1.49 |
| Usual flood depth | -0.006901 | -1.47 | 0.0330267 | 1 |
| Value of agricultural equipment, large trees, fishing tools at t | -2.88E-06 | -5.79 | -9.27E-06 | -1.06 |
| Value of consumer durables at t | 4.70E-06 | 4.03 | 2.61E-06 | 0.24 |
| Kg of grain stock (rice, paddy, wheat) at t | -3.74E-06 | -0.04 | 0.0002332 | 0.3 |
| # of cattle (calves, dairy cow, bullock) at t | 0.0315271 | 3.16 | 0.046247 | 0.6 |
| # of goat/sheep at t | 0.0114402 | 1.25 | -0.1131562 | -1.25 |
| # of chicken at t | 0.0023879 | 1.29 | 0.0115368 | 0.85 |
| At least one household member completed primary school at t (yes=1) | 0.0016397 | 0.05 | 0.05643 | 0.22 |
| # of adult male at t | 0.0177795 | 1.21 | -0.1479233 | -1.15 |
| # of adult female at t | -0.0082647 | -0.38 | 0.1193309 | 0.67 |
| # of children at t | -0.0616453 | -6.62 | 0.0433057 | 0.56 |
| # of elderly at t | -0.0136909 | -0.41 | 0.300408 | 1.23 |
| Household head age at t | 0.0000651 | 0.06 | 0.0089536 | 0.96 |
| intercept | 7.903972 | 121.63 | -4.622166 | -8.39 |
| $R^2$, F | 0.35 | 13.51 | 0.33 | 1.13 |
| Observations | 388 | | 388 | |

Compared with agricultural income, other income has a positive effect on *ex ante* mean and a negative effect on *ex ante* variance. Other income thus can increase the calorie intake and reduce the dispersion of the calorie intake at the same time. Among the surveyed households, other income resources include remittances, rental income of properties and equipment, and income from social assistance programs. There are a number of social assistance programs operated by the Bangladesh government, international organizations, and non-governmental organizations. For instance, the United Nations' World Food Programme (WFP) has worked in Bangladesh since 1974. Most of

its activities focus on development and disaster preparedness. To date, about 4 million people in Bangladesh annually benefit from the WFP, of which 2 million people (95% women) participate directly in its food-assisted programs. Approximately 500,000 people receive food and skills training through the Vulnerable Group Development (VGD) program. Participants in the Integrated Food Security (IFS) program receive food, cash and a 'development package' similar to those in the VGD program. In return, they build up physical assets - homestead raising, fishponds - through Food For Work activities (WFP, 2006).

Flooding occurs almost every year in Bangladesh. It has become a major factor affecting agricultural production. The result in table 2 illustrates how usual flooding will affect households' calorie consumption. The higher the flood level, the fewer calories households consume. Consumption also becomes more dispersed.

The results show that demographic composition affects household *ex ante* consumption. More adult male members increase the *ex ante* mean of calorie consumption and reduce the variance. More females, children, and elderly, on the other hand, reduce the *ex ante* mean of calorie consumption and increase its variance.

To obtain the *ex ante* probability distribution of each household's future nutrient consumption from the estimated results, daily calorie intake per resident household member is assumed to be log-normally distributed. The skewness/kurtosis test for normality fails to reject the assumption (table 3). Therefore, assuming log-normality, predications of each household's *ex ante* mean and variance of logarithmic calorie intake per resident member in the hunger season are sufficient to characterize a household's *ex ante* probability distribution of future consumption. Each household's *ex ante* probability

of future calorie consumption is obtained by substituting the values of regressors for the household into the equations whose estimated coefficients are presented in table 2.

Table 3 Skewness/kurtosis test for normality

| Variable | Pr(Skewness) | Pr(Kurtosis) | adjusted chi2(2) | Prob>chi2 |
|---|---|---|---|---|
| Logarithm of daily calorie intake per resident household member at hunger season | 0.879 | 0.59 | 0.31 | 0.8551 |

To establish the nutritional vulnerability profile, the probability threshold is set at 0.5 and daily per resident member calorie intake threshold is at four levels of 1800 kcal, 2105 kcal, 2300 kcal, and 2828 kcal. The 1800 kcal level is the minimum standard set by the World Bank in the World Food Program. The 2105 kcal level is the average calorie consumption level in Bangladesh. The 2300 kcal level is the recommended standard by the World Bank in the World Food Program. The 2828 kcal level is the average calorie consumption level in developing countries. Thus, a farm household being nutritional vulnerable means that the probability of per resident member's daily calorie consumption falling below the predetermined level (i.e. 1800 kcal or 2105 kcal) is equal to or higher than 0.5 (V>=0.5). Table 4 presents the predicted household vulnerability.

Table 4 Predicted household vulnerability at different calorie consumption levels

| | Per resident member daily calorie intake level | | | |
|---|---|---|---|---|
| Vulnerable V>=0.5 | <1800 kcal | <2105 kcal | <2300 kcal | <2828 kcal |
| Yes | 0 (0%) | 21 (5.4%) | 76 (19.6%) | 301 (77.6%) |
| No | 388 (100%) | 367 (94.6%) | 312 (80.4%) | 87 (22.4%) |
| Total households (%) | 388 (100%) | 388 (100%) | 388 (100%) | 388 (100%) |

The results clearly indicate that vulnerability exists among surveyed rice farm households. Although at the 1800 kcal level no household is vulnerable, at the 2105 kcal level, of 388 households, 21 are vulnerable by definition. That is, at the post harvest time 21 households have a probability higher than 0.5 of consuming less than 2105 kcal per person per day at the hunger time. As the consumption threshold increases, households on average become more vulnerable. For instance, 76 households are vulnerable at the World Bank recommended 2300 kcal level. In comparison, approximately 78% (301 households) of all households will not achieve the average consumption level of 2828 kcal in developing countries.

The results from previous farm household modeling indicate that the adoption of transgenic rice will increase farm household agricultural income (Liang, Reaves, and Norton, 2006). When agricultural income increases, the prediction on each household's future consumption shows that the probability of falling below the predetermined nutrient consumption level declines. That is, each household is less likely to become vulnerable. The impact of the agricultural income increase on the overall household vulnerability profile is illustrated by setting calorie intake at 2105 kcal (table 5). When agricultural income increases by 10%, 20% and 30%, one household, one household, and two households, respectively, out of the 21 vulnerable households in the sample, are no longer vulnerable. A similar trend is observed when calorie consumption is set at other levels.

Table 5 The impact of agricultural income increase on household vulnerability at 2105 kcal consumption level

| Vulnerable | At current income level | Income increase by | | |
|---|---|---|---|---|
| | | 10% | 20% | 30% |
| Yes | 21(5.4%) | 20(5.2%) | 20(5.2%) | 19(4.6%) |
| No | 367(94.6%) | 368(94.8%) | 368(94.8%) | 369(95.4%) |
| Total households (%) | 388(100%) | 388(100%) | 388(100%) | 388(100%) |

## Conclusion

Farm households face various risks in agricultural production and their social economic environment. Factors like drought, insects, commodity price changes, or job losses can all make farmers more destitute at the individual level. Among the approaches used to address the decline in social well-being of a farm household, the development and commercialization of transgenic crops exhibit a promising future. Rice being the single most important crop for providing nutrients, a study of the nutritional impact of transgenic varieties on farm households is of particular interest in Asian developing countries where millions of people still suffer from poverty and malnutrition.

Nutritional vulnerability, defined as the possibility now that individuals' nutritional consumption in the future will fall below a socially accepted standard, describes the dynamic changes in the nutritional wellbeing of a household over a time period. It complements the static aspects of poverty in empirical studies.

In this paper, multivariate regression is employed to forecast the caloric intake of 388 Bangladeshi farm households in the hunger season based on household income, production, and demographic composition in the current (post harvest) season. Nutritional vulnerability profiles are derived from the estimation of *ex ante* mean and variance of future consumption. The results indicate the existence of nutritional vulnerability among the farm households studied. They also indicate that the income increase induced by introducing transgenic rice will reduce each individual household's probability of suffering a future consumption shortfall and its vulnerability. The overall vulnerability profile of farm households improves in Bangladesh.

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