Banking on the Poor?

Branch Placement and Non-Farm Rural Development in Bangladesh

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We assess whether bank branch placement in Bangladesh responds to any unexploited potential for non-farm rural development. The location choices of the famous Grameen Bank are compared to those of more traditional banks. We allow for heterogeneity in household characteristics conducive to success in non-farm activities when measuring the potential gains from switching out of farming. Farmers are both poor, and poorly equipped for success at non-farm enterprises. Even so, seemingly feasible, but unrealized, gains from switching are evident. Grameen Bank is attracted to areas where those gains favor the poor. Other banks put higher weight on potential gains to the non-poor.

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1 Introduction

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Casual observations suggest that there may be large unrealized gains to poor people from the sectoral reallocation of economic activity in underdeveloped economies. For example, the family of a petty trader in rural Bangladesh has on average a 50% higher consumption per person than the family of a landless farm worker. Lack of access to credit for setting up new enterprises is often identified as the reason why these gains have not already been exploited. Credit market failures are thought to be pervasive, and may entail large aggregate gains from successful efforts at enhancing access to credit for starting rural non-farm enterprises. There are other reasons for unexploited gains from non-farm rural development, including uninsured risk and imperfect information. Traditional banks have not, however, had a good reputation for enhancing the access of poor rural people to credit, or in dealing with other constraints on small-scale enterprise development.[2] By this view, bank behavior is one cause of persistent poverty.

Micro-credit banks have emerged in a number of countries. Their espoused aims and methods often appear to be more favorable to realizing any potential gains to the poor from relaxing credit constraints, and providing supportive non-lending services, including better information. Group-based lending arrangements, such as used by a number of these banks, may also help pool risks. Many of the new micro-credit banks, such as Bangladesh's famous Grameen Bank, have said explicitly that their aim is to reduce poverty by mobilizing resources and

[2] Introductions to the issues and literature on these points can be found in Hoff and Stiglitz (1993), Besley (1995) and Lipton and Ravallion (1995, section 6.4).

targeting credit and non-lending services to poor rural households for setting up new enterprises.[3]

Are the traditional banks really failing to exploit the potential gains to the poor from non-farm rural development? Is this new class of banks doing any better? The answers are unclear on a priori grounds. It is not even clear that there will be any real gains from facilitating sector switches. The higher levels of living of rural non-farm households, compared to farming households, may be due entirely to heterogeneity in characteristics which are conducive to success in rural non-farm enterprises, such as education or access to urban markets. Poor farmers may well be the most credit constrained - but they may also lack the education or other attributes which allow a new entrant to the non-farm sector to succeed. Credit market failures do not necessarily imply that efforts to lend more for non-farm rural enterprises will be pro-poor. Controlling for heterogeneity, the supposed gains may well vanish. Or there may well still be large unrealized gains, but favoring the non-poor, leaving the new micro-credit banks with little scope for helping the poor.

This paper attempts to assess whether banks are responding to the potential gains to Bangladeshi farm households from switching to the non-farm sector. To test for such a response we study the placement of bank branches. In an underdeveloped rural economy, branch location is bound to be an important factor in determining access to credit. While other relevant indicators might be identified (such as a bank's attempts at targeting poor households within a given area), branch location also has the advantages of being well measured and of being consistent between banks. By combining information on branch location with independent household survey data, we

[3] See, for example, Yunus (1984), Hossain (1984), Getubig (1992), and Khandker (1996).

aim to better understand the(potentially diverse) motives behind bank behavior.

There appears to have been very little previous work on the location decisions of micro-credit banks. We know of only one previous empirical study, namely by Khandker et al. (1995), also using data for Bangladesh. Their regressors were measures of accessibility, flooding and the moisture content of the soil. However, these variables had negligible explanatory power. In their regression for Grameen Bank branches, none of the regressors were significant and the adjusted R^2 was 0.04. We suspect that the main reason for this poor explanatory power is the omission of measures for the expected welfare gains from bank activity in different locations, as determined by the relevant socio-economic characteristics of the customers living in each area.

We offer a method for estimating the unexploited gains from non-farm rural development. The method allows us to collapse a potentially large number of determinants of the gains from switching from farming to non-farm activities into a single measure, which can be tested as an explanatory variable for bank branch location. We find that this measure has considerable explanatory power in understanding bank locations in Bangladesh.

Section 2 presents the theoretical model of branch placement which motivates our empirical work. Section 3 discusses our methodology, while section 4 describes our data. The estimated gains from sector switching are presented in section 5, while section 6 looks at the their implications for explaining branch placement. Section 7 concludes.

2 Theoretical model of branch placement

To motivate our empirical work, we begin with a model of the optimal spatial allocation of bank branches. We are clearly dealing with banks which do not necessarily aim to maximize

profits. We assume that the bank maximizes a weighted sum of expected utilities, where the weights embody the bank's distributional goals. This characterization of a nonprofit bank's welfare objective would seem to encompass the objectives that one would expect to find in this setting. The stated objectives of the Grameen Bank (as in, for example, Yunus, 1984) suggest that the weights on expected utilities are highest for the poorest, but decline as utility increases. By contrast it is sometimes argued that the traditional banks are more concerned with the welfare of rich patrons, which one could interpret as having lowest weights for the poorest. As we will see, a profit maximizing bank can also be interpreted as a special case of our model.

The model assumes two sectors, interpretable as "farm" and "non-farm", and it assumes that the way in which access to a bank matters in this context is in fostering successful transitions from farming to the better off non-farm sector, rather than by increasing the welfare of people <u>within</u> a given sector. Also, while the bank has a number of instruments at its disposal, we focus on just one of them, namely the geographic allocation of its branch offices. More general models could be formulated. However, this simple model is adequate for motivating the empirical specifications we will use later.

The number of customers the bank has in the j'th area is denoted N_j. This is assumed to depend on the number of branches it has in that area, B_j, and on other geographic variables, Z_j, such as the density of economic activity, and of other banks. This can be written:

$$N_j = N(B_j, Z_j) \qquad (j=1,..,n) \qquad (1)$$

We assume that higher accessibility to bank branches raises the number of customers ($N_B > 0$), but that it does so at a declining rate ($N_{BB} < 0$).

The bank does not, however, care about more customers as such, but rather about aggregate welfare gains. In this simple model, the welfare gains arise solely from successful transition from farm to non-farm sector, whereby household i in area j reaches utility U_{ij}^{NF}, while utility as a farmer is U_{ij}^{F}. The bank allocates its efforts so as to maximize expected gain in social welfare. Utilities are weighted according to the bank's normative judgements on which households are more deserving. (For example, higher weight might be given to poorer farm households.) Expected weighted utility in the farm sector in area j is $E_j[w_{ij}U_{ij}^{F}]$, while it is $E_j[w_{ij}U_{ij}^{NF}]$ if transition to the non-farm sector is successful. The expected weighted gain per customer in area j is $E_j[w_{ij}G_{ij}]>0$ where the gain from successful switching is $G_{ij} = U_{ij}^{NF}-U_{ij}^{F}$. The weights can also be interpreted as probabilities of success in non-farm activities, or some combination of success probabilities and distributional weights.

The bank's problem is then to choose the allocation of its branches across geographic areas so as to maximize the expected gain in social welfare from its lending operations without exceeding a total cost of C. The bank then chooses B_j (j=1,..,n) to solve the problem:

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$$\text{Max} \quad E_j[w_{ij}G_{ij}]N(B_j, Z_j) \text{ s.t.}$$

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$$C(B_j, Z_j)$$

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$$\text{C} \qquad (2)$$

where $C(B_j, Z_j)$ is the cost of placing B_j branches in area j. We assume that marginal cost is positive (C_B >0) and non-decreasing (C_{BB}

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0).

A unique optimal placement of branches exists under these assumptions, such that

$$E_j[w_{ij}G_{ij}]N_B(B_j, Z_j) = lC_B(B_j, Z_j) \qquad (3)$$

for all j, where l is the (positive) multiplier on the bank's budget constraint. We can re-write (3) in explicit form:

$$B_j = B(E_j[w_{ij}G_{ij}]\, l^{-1}, Z_j) \qquad (4)$$

Differentiating (3), it is readily verified that the function B will be increasing in the first argument, and increasing (decreasing) in Z_j as long as N_B/C_B is also increasing (decreasing) in Z_j.

The above model can be generalized in a number of ways without altering the form of equation (3). For example, in the above formulation the expected gain from switching sector only enters the problem as a weight on the number of customers in each area. Instead, one could allow N_j to be also influenced directly by $E_j[w_{ij}G_{ij}]$. This would still deliver a solution of the form of (3), although whether B_j is strictly increasing in the expected gain will depend on the way in which it influences the number of customers (if N_B is non-decreasing in the expected gain then, keeping the other assumptions, B_j will be strictly increasing in the gain).

One can also reinterpret the model to allow a profit maximizing bank. $E_j[w_{ij}G_{ij}]$ is then the expected profit in area j, where G_{ij} is profit from lending to customer i in j if there is no default, and w_{ij} can be interpreted as a weight determined by both the bank's ex-ante subjective probability of default and default profit relative to non-default profit for each customer.[4] With this change of notation, expected profit is maximized by branch placements satisfying (3).

3 Measuring the potential gains from rural non-farm development by area

[4] Let d_{ij} denote the expected (ex-ante) probability of default, and let L_{ij} denote the profit (or loss) if default occurs. Expected profit is $(1- d_{ij})G_{ij}+ d_{ij}L_{ij}$. Then $w_{ij}=1-d_{ij}(1-L_{ij}/G_{ij})$.

Our first step in estimating an empirical model based on equation (3) is to measure the potential gains to a household from switching sector.

For expository purposes, let us begin with a simple case. Assume that the weights are equal, utility is given by log consumption, and that transition to the non-farm sector entails that a randomly chosen farm household becomes a randomly chosen non-farm household. Let the set of households in the non-farm sector be *NF* and let *F* denote the set of farm households, and let the real consumption of household *i* in area *j* be C_{ij}. Then the expected gain from switching would be $E[logC_{ij} \mid i \in NF]-E[logC_{ij} \mid i \in F]$, i.e., the mean proportionate gain in consumption.

However one clearly wants to relax these assumptions, so at to allow unequal weights, other determinants of utility, and to allow for heterogeneity in characteristics conducive to success in non-farm enterprises. We introduce these features below.

3.1 Consumption gains at the farm-household level

We assume that utility is a strictly increasing function of log consumption and of household characteristics X_{ij} (the same function for all households). We postulate that consumption of household *i* in area *j* is determined by:

$$logC_{ij} = b_{NF} X_{ij} + \eta_{NFij} \qquad (i \in NF) \qquad (4.1)$$

$$logC_{ij} = b_{F} X_{ij} + \eta_{Fij} \qquad (i \in F) \qquad (4.2)$$

where X_{ij} is a vector of household characteristics (including a complete set of dummy variables for geographic areas), b_{NF} and b_F are parameters, and η_{NF}, η_F are error processes. Some elements of *X* may be altered by the bank's lending; we allow this later, but ignore it for the purposes of

this exposition. Also, some elements in either of the parameter vectors b_{NF} and b_F may be set to zero, to permit sector-specific variables, such as occupations only found in one sector.

Our aim is then to estimate the gain to each farm household from an exogenous switch to the non-farm sector, controlling for the household's characteristics, given by the X vector.[5] Since we are controlling for X_{ij}, we can measure utility gain by the proportionate increase in consumption. The gain from a sector switch conditional on X_{ij} is then given by:

$$G_{ij} = (b_{NF} - b_F)X_{ij} + E[\eta_{NFij} - \eta_{Fij} \quad X_{ij}, i \in F] \qquad (5)$$

To estimate this we use the consumption model (equations 4.1 and 4.2) to predict what consumption level a farm household would have in the non-farm sector, given its value of X and unobserved attributes captured by the residual; all we change is the sector. A farm-household consuming C_{ij} will consume $exp(logC_{ij}+G_{ij})$ in the non-farm sector. Notice that if there is no sector-selection bias then $E[\eta_{NFij} - \eta_{Fij} \quad X_{ij}, i \in F]$ in (5) can be set to zero; if there is bias then that term can be estimated using sector bias-correction terms (Appendix).

3.2 Weights

[5] If there is sample selectivity then this vector will have to be augmented to include any variables which influence sector choice but not consumption given sector; see the Appendix.

With enough degrees of freedom one could let the data determine the appropriate weights. However, that will not be feasible here. One option is to set the weights equally. But this is clearly too restrictive. Another option is to use a poverty measure as the weight, as would be appropriate for a bank such as Grameen which claims to be aiming to reduce poverty. A simple, but defensible, option is to use poverty-gap weights, defined as $p_{ij}=(1-C_{ij})/PG$ for $C_{ij} < 1$ with $p_{ij}= 0$ otherwise, where PG is the aggregate poverty-gap index, $PG=E[max(1-C_{ij}, 0)]$.[6] Normalizing the gains by PG assures that if the gains are the same for everyone then the poverty-weighted mean gain will be the same as the ordinary (unweighted) mean gain.[7] For more traditional commercial banks, poverty weights are implausible. However, the mirror image of poverty weights may make more sense. This can be modeled simply by using $1-p_{ij}$ as the weight for household i in area j.

Combining these observations, we will test an encompassing model in which the unweighted expected gain, $E_j[G_{ij}]$, and the poverty-weighted gain, $E_j[p_{ij}G_{ij}]$, are included as separate explanatory variables. This allows the data to determine which weighting scheme is to be preferred. If equal weights are appropriate then the unweighted gain, $E_j[G_{ij}]$, will have a significant positive coefficient, but the coefficient on $E_j[p_{ij}G_{ij}]$ will not be significantly different from zero. If only poverty weights are needed then the opposite will hold, and only $E_j[p_{ij}G_{ij}]$ will matter. However, there are many combinations. A poverty-oriented bank may attach some value

[6] Poverty-gap weights arise naturally when the squared-poverty gap, $SPG=E[max\{(1-C_{ij})^2, 0\}]$, is used to assess overall poverty impacts since PG affects the marginal impacts on SPG of switching sector; unlike PG, SPG reflects the extent of inequality amongst the poor (Foster et al., 1984).

[7] To assure comparability across sub-groups, the PG used for normalization is the aggregate PG for all farm households, not the sub-group values by district.

to higher average gains (possibly a negative value, if it expects other banks will chase those gains), as well as putting positive value on how pro-poor the gains are. A traditional bank may put lower weight on poorer households amongst the poor, so that one would then find that the coefficients of $E_j[G_{ij}]$ and $E_j[p_{ij}G_{ij}]$ have opposite signs, with the former positive.

3.3 Remarks

(i) In calculating $E_j[w_{ij}G_{ij}]$ we assume that only a small randomly-chosen number of households within some target group (all farm households, or a sub-group, such as landless farm workers) switch sector. Since the number of switching households is small we are justified in treating the model parameters b_{NF}✐ and b_F✐ as fixed. (It is implausible that the parameters would be unchanged if a large number of farm households switched to the non-farm sector, or that there would be no impacts on existing non-farm households.)

(ii) Note also that the value of $E_j[w_{ij}G_{ij}]$ derived this way is a function of the X_{ij} vectors in (5) for all i🗀F in the given geographic area. One can thus interpret our estimation method as a means of collapsing the number of dimensions of potential explanatory variables into just one dimension. If there were no sector-selection terms then $E_j[G_{ij}]$ would be a weighted mean of the vector of means, $E_j[X_{ij}]$, with the weights determined by the b_{NF}✐- b_F✐ parameters. More generally, there will also be distributional weights and nonlinearities arising from the selection terms.

(iii) With sufficient degrees of freedom one might prefer instead to enter the vector of mean X_{ij}🖬s in the model of branch locations without any aggregation. (Although sector-selection effects and distributional weights could introduce considerable nonlinearity.) As we will see in the

next section, we do not have sufficient degrees of freedom (in either the survey sample of the geographic data) to go this route. The above approach does, however, offer a defensible method of aggregating the information on a potentially large number of explanatory variables.

(iv) We will treat $E_j[w_{ij}G_{ij}]$ as exogenous to branch placement. For the X_{ij}'s we will be using (described below), this would seem a defensible assumption. The alternative would presumably be that higher branch density in an area reduces the expected gains, in which case our results will underestimate the impact of the expected gains on branch placement.

4 Data

For estimating the potential gains, our data consist of 3817 randomly sampled rural households from the 1991/92 Household Expenditure Survey (HES) of the Bangladesh Bureau of Statistics. The consumption measure is comprehensive (including all market commodities, with market-based imputed values when they do not entail market transactions). Regional price differences were taken into account by deflating nominal consumption by regional poverty lines giving the estimated cost of basic consumption needs; for further details see Wodon (1996).

We use the primary occupation of the household head (whether male or female) to classify households into the two sectors. The HES provides data on occupations according to 31 categories. To obtain sufficient sample sizes, these categories have been aggregated into five farm groups and seven non-farm groups. The farm groups are: (1) landless agricultural workers, (2) agricultural workers with land, (3) workers in fisheries, live stock, and forestry, (4) tenant farmers, and (5) owner farmers. The non-farm groups are: (1) servants and day-laborers, (2) transport and communication workers, (3) salesmen, service workers, brokers, and middlemen,

(4) factory workers and artisans, (5) petty traders and other small businessmen, (6) executives, officials, professionals, and teachers, and (7) non-working heads (retired, unemployed, or students). Table 1 gives summary data by sectors of employment.

Using the head's primary occupation as the criterion for the farm/non-farm classification has its limitations. It does not take into account the secondary occupation of the head, or the occupations of the spouse and other household members, who may well be part of the non-farm sector when the head is in the farm sector, or of the farm sector when the head is in the non-farm sector. However, the extent of such secondary "cross-sectoral" effects is small; only 19% of farm households defined by the head's primary occupation had a secondary non-farm activity (as either a secondary activity of the head or an activity of the spouse), and only 7% of households classified as being in the non-farm sector by our criteria had a secondary farm activity.

Banks such as Grameen have relied heavily on female membership.[8] It was not feasible with these data to estimate a gender-specific measure of the gains from switching; there were only 180 female heads or spouses with occupations as recorded in the HES.

The survey data identify household location by 20 districts, and the data are representative at that level. One district (Chittagong Hill Tracts) did not have any observations in the sample, and two were aggregated to contiguous districts for sample size considerations. We thus have 17 areas in all. Data on bank branches are also available by district.

[8] This is not necessarily because of gender-specific gains from setting up new enterprises; more plausibly, it is because of the organization's desire to promote female empowerment and because women appear to be less likely to default. In any case, we would conjecture that the gains from women alone shifting to the non-farm sector will be highly correlated with the gains from the head shifting, as we have measured them.

5 Estimated gains from sector switching

Table 2 gives our estimates of the parameters of equations (4.1)-(4.2), and their Huber-White standard errors. We include variables describing primary occupation, location, education, land ownership and demographics. The Appendix gives our test results for sector-selection bias, which indicate we can safely omit correction terms from the consumption equations.

Some of our specification choices were difficult. Including occupation dummy variables raises a concern about possible endogeneity, although there is likely to be a trade off here with greater omitted-variable bias in the other parameters of interest if we deleted the occupation dummy variables for this reason. We were also reassured by our test results on sector-selection bias (Appendix). Some of our specification choices were determined by data limitations, both in terms of the variables collected by the HES and the survey's sample size (which limits how finely one can identify geographic effects, for example.) However, there were other variables that one might want to include. For example, we tested robustness to a specification which included secondary occupations (of the head, or spouse), though recognizing that this is likely to raise further concerns about endogeneity (while one might argue that the primary occupation of the head can be taken to be exogenous to consumption decisions, this is clearly more problematic for secondary activities.) However, only a few of the variables describing secondary activities were significant, and the main results (described below) on consumption gains from switching primary sector were very similar. We dropped the secondary activities from all specifications.

Table 2 suggests a number of similarities between the determinants of consumptions in the two sectors. For example, better education and more land increase per capita consumption, while larger households tend to have lower per capita consumption. The consumption returns to

owning land are not significantly different between households who farm land themselves and those who rent it out (recalling that there is little secondary farming activity amongst primarily non-farm households). Similarly, while there are gains to having a better educated spouse, they are no different between the two sectors. And the impacts of most household size variables are similar between sectors. So none of these variables have a significant impact on the gain to a farmer from switching to the non-farm sector.

However, there are a number of sectoral differences in the process determining consumption. The returns to the head's education are significantly higher in the non-farm sector. Having a better educated household head raises the marginal benefit to a farm household of switching to the non-farm sector. The hypothesis that all non-occupation coefficients are the same in both equations is rejected at the five percent level (Table 3). Also, different geographic factors are at work in the two sectors, since the area dummy coefficients differ significantly between the two equations (Table 3). We will discuss the geographic effects in more detail later.

We give our estimates of the average gain under various assumptions in Table 4. These are based on the regressions dropping the selection-bias term, and including occupation dummies, as in Table 2. In each case we give both the average differential in log consumption, as well as the gains controlling for all other characteristics of the specific sub-group (all farm households, or landless farm workers) as described above. The numbers under "unconditional" do not use any controls; they are simply the differences in the sample averages for the relevant groups. Comparing the conditional and unconditional numbers thus indicates the bias arising from failure to deal with heterogeneity in household characteristics. To the extent that current farm households tend to have characteristics which have lower (higher) returns in the non-farm sector,

the unconditional means will over (under) estimate the gains from switching.

The first row of Table 4 gives the estimated average gains for farm workers switching to the non-farm sector. Without controlling for heterogeneity, the effects are substantially over-estimated; the unconditional gain in consumption is 8.9%, as compared to the average gain controlling for heterogeneity of 6.2%. Table 4 also gives results for a landless agricultural worker shifting to the transport sub-sector or joining the petty traders.

The proportionate gains tend to be larger for poorer farm households. Figure 1 plots the gain against initial log consumption. (Since consumption is normalized by the poverty line to reflect spatial cost-of-living differences, those with negative log consumptions are poor.) The regression line (indicated in the figure) has slope -0.057 (standard error of 0.0051). The mean proportionate gain for the poor is 8.2% while for the non-poor it is 4.3%.

It is clear from Tables 2 and 3 that the geographic effects on living standards are not the same between sectors; there are a number of significant differences between sectors in the coefficients on the geographic dummy variables. To assess the gain from switching to the non-farm sector by area, we need to consider the characteristics of each farm household in that district, as well as the geographic characteristics of the district. As before, for each farm household we assigned a probability of working in any of the non-farm occupations equal to the observed probabilities for non-farm households. Thus we can interpret the result as the average expected gain from switching sector, by area.

The estimated gains by area are in Table 5. There are large geographic differences. The highest unweighted average gain is in Dhaka where we estimate that a representative farm household would have 24% higher consumption in the non-farm sector. The lowest unweighted

gain is in Noakhali where consumption would fall by 4% on average. Table 5 also gives the unconditional mean differences in log consumption, so as to assess how far off this might be as a guide to the (conditional) gains from switching sector. Figure 2 plots the mean gains against the unconditional ones by district. There is a positive relationship, though bias is still indicated, with a tendency for the simple (unconditional) averages to overestimate the gains at high levels but underestimate them at low levels.

We also give poverty-gap weighted gains in Table 5. There is a tendency for poorer districts to be the ones with higher estimated gains; the correlation coefficient between mean consumptions and the estimated gain is -0.44 which is significant at the 2% level. However, the district with the largest average gain, namely Dhaka, is one of the least poor areas. Possibly this reflects larger gains among some non-poor farm households. To check this we also examine the poverty-gap weighted average gains. The poverty-weighted gains are more strongly correlated with average consumptions by district than are the unweighted gains (Figure 3); the correlation coefficient between the weighted gains and initial log consumptions per person is -0.65 which is significant at the 0.5% level. The three districts with highest weighted gain are also the three districts with lowest mean consumption.

6 Implications for understanding the placement of bank branches

The above results suggest substantial geographic variation in the gains from exogenous switching from the farm to non-farm sector. So there may well be large welfare gains from geographic targeting of efforts to promote the non-farm sector. We can now return to the question we started with: To what extent does the existing geographic distribution of efforts to

promote the non-farm sector reflect the distribution of the potential gains? To address this question, we use our estimates of the geographic variation in the gains from switching to the non-farm sector to estimate a model of branch placement motivated by equation (4).

We have data on the distribution by district of the branches of the governmental banks and the largest non-governmental bank in Bangladesh, namely the Grameen Bank (GB), which provides credit for microenterprises targeted to poor rural households; Grameen accounts for 17% of all bank branches.[9] In addition to $E_j[p_{ij}G_{ij}]$ and $E_j[G_{ij}]$ (section 3.2), we include population density; more dense areas will presumably generate higher demand for GB loans per unit area, and may also entail a higher marginal cost to the bank.

Regressing GB density on these three variables we obtained the results in Table 6. The impact of the poverty-weighted marginal benefit on the spatial allocation of GB branches is highly significant (a t-ratio of 4.14, which is significant at the 0.1% level). The other two factors hypothesized to influence local demand for GB loans are also significant.

Are similar factors at work in determining the geographic distribution of other banks? The third column of Table 6 also gives the results obtained on regressing the density of other ✌non-Grameen✍ banks on the same three variables. While population density continues to have a positive impact on bank density, the other two variables have reversed their signs; as expected, higher values of the unweighted gain from sector switching attract other banks, consistently with our interpretation of the result for GB density in Table 6. However, the other banks are clearly

[9] For fuller discussions of how Grameen Bank works see Hossain (1984), Khandker, Khalily, and Khan (1995), and Khandker (1996).

attracted by gains to the non-poor, as indicated by the (significant) negative coefficient on poverty-weighted gain, controlling for the unweighted gain.

It is notable that, comparing the regressions in Table 6, the coefficients on poverty-weighted gains and unweighted gains are roughly equal, but with opposite signs, for the two types of banks. The restrictions that the coefficients on the weighted and unweighted mean gain sum to zero is accepted for both regressions (a t-test gives a value of 0.615 for GB branches and 0.789 for other banks). Columns 2 and 4 of Table 6 give the regressions when these restrictions are imposed. Figures 4 and 5 plot the densities of Grameen and other banks (respectively) against the difference between the unweighted and poverty weighted gains from sector switching. (In both cases, the restricted-form regressions in Table 6 have been used to control for population density; bank branch density is the predicted value if each area had the same population density.)

So our results indicate a marked difference in the branch location decisions of Grameen Bank versus the traditional governmental banks. The potential gains from promoting sector switching influence both types of banks, but they appear to evaluate the distribution of those gains very differently. The implicit Grameen weights are highest for the poorest but decline as consumption rises, becoming negative above some point and constant after the poverty line.[10] Our results for Grameen Bank are consistent with the bank's stated objectives of reaching the poorest rural households (as espoused by the Bank's founder; see Yunus, 1984).

By contrast, in the branch placements of "non-Grameen" banks, the relevant weights on individual gains are lowest for the poorest, then rise until the poverty line, and are equal after that.

[10] Recall that $w_{ij} = (1-C_{ij})/PG$ for $C_{ij} < 1$ and $w_{ij} = 0$ otherwise. Therefore, because GB switches away from districts with higher unweighted mean gain, the implicit weights become negative when consumption normalized by the poverty line exceeds $1-PG$, which is equal to 0.88 for our data.

The mirror reversal in behavior of the traditional banks is consistent with a view that these banks put low priority on reaching the poor. This suggests that the poor are perceived as bad risks by traditional banks; the implicit default risk in the ✌non-Grameen Bank✍ regression decreases as consumption rises until the poverty line is reached, above which it is constant.

Finally we note that our results cast considerable doubt on any assumption that bank placement is random. Thus, evaluations of the welfare impacts of credit programs which employ that assumption for identification purposes can be questioned.

7 Conclusions

We have assessed whether bank branch placement in Bangladesh is consistent with the pursuit of unrealized gains to the poor from non-farm rural development. The main explanatory variable we have tested is our own estimate of the gains to switching from the farm to non-farm sector, based on independent household survey data. Our estimation methods allowed for heterogeneity in the prospects of being successful in non-farm activities, and included tests for whether or not a process of endogenous self-selection was already at work.

We find that typical farm households in Bangladesh are both poor, and poorly endowed in characteristics conducive to success in more profitable non-farm activities. Thus, comparing average living standards overstates the potential gains to switching from the farm to non-farm sector. Nevertheless, we find that unexploited gains from switching exist, even after controlling for a wide range of household attributes, including education levels, landholding, demographics and location. Average consumption for a farm household would be about 6% higher in the non-farm sector, and the proportionate gains tend to be largest for the poorest farm households. There

are striking geographic differences in the gains. Across districts of Bangladesh, the average gain (controlling for heterogeneity) varies from -4% to 24% of consumption. The highest average gains from switching to the non-farm sector are not, however, in the poorest rural areas.

The geographic placement of bank branches is strongly influenced by the potential gains from switching to rural non-farm activities. But there is a marked difference in the way the (private, nonprofit) Grameen Bank responds to the potential gains versus the traditional, governmental, banks. While the traditional banks appear to be attracted by areas where the gains favor the non-poor, Grameen is attracted by areas where the gains favor the poor. This is consistent with a difference in the objectives of the two types of institutions, with Grameen Bank putting far higher weight on the potential for reducing poverty thought its lending operations.

Appendix: Tests for sample selectivity bias

Our data allow us to control for a reasonably comprehensive list of variables in X, including education, landholding, location, demographics, and occupation. Nonetheless, there could well be omitted variables in the error terms of equations (4.1) and (4.2) which also influence whether a household is in the farm or the non-farm sector. We used the standard test for such bias, by postulating that sector choice is determined by a latent variable (dropping the j subscript for area):

$$S_{ij}^* = \gamma \quad W_{ij} \quad + \nu_{ij} \tag{A1}$$

which gives the net gain (or loss) to living in the farm or non-farm sector for each household, as a function of a vector of variables W_{ij}. We do not observe S_{ij}^*, but we do observe whether the household is farm (S_{ij}=0) or non-farm (S_{ij}=1); S_{ij} = 1 if $S_{ij}^* > 0$ and S_{ij} = 0 if S_{ij}^* 0.

There will be selectivity bias in our estimates of the gains from sector switching if the error term ν in (A1) is correlated with the error terms of equations (4.1) and (4.2). Following common practice, we estimate the selection model as a probit, assuming that the error term ν is standard normal. The expected value of the residuals in (4.1) and (4.2) are then given by:

$$E[\quad_{NFij} | X_{ij}, W_{ij}, i \quad NF] = cov(\quad_{NF}, \nu)\phi(\gamma \quad W_{ij})/\Phi(\gamma \quad W_{ij}) \tag{A2}$$

$$E[\quad_{Fij} | X_{ij}, W_{ij}, i \quad F] = -cov(\quad_{F}, \nu)\phi(\gamma \quad W_{ij})/[1-\Phi(\gamma \quad W_{ij})] \tag{A3}$$

where ϕ and Φ are the density and cumulative density functions of the standard normal distribution. In shifting a farm household to the non-farm sector, we must compute:

$$E[\quad_{NFij} - \quad_{Fij} | X_{ij}, W_{ij}, i \quad F] = [cov(\quad_{F}, \nu) - cov(\quad_{NF}, \nu)]\phi(\gamma \quad W_{ij})/[1-\Phi(\gamma \quad W_{ij})] \tag{A4}$$

If the estimates of both cov($_{F}$,ν) and cov($_{NF}$,ν) are insignificant, then there is no sample correction term to be included in the gains from changing sector.

The probit estimates are available from the authors. The results were fairly intuitive. Households with better educated members have significantly higher probabilities of working in the non-farm sector, while a higher level of land ownership is associated with a higher probability of working in the farm sector. Households in the Dhaka district, with younger and older heads, and non-Muslim heads also have a higher probability of joining the non-farm sector. The probit was then used to construct estimates of the expected values of the error terms in (4.1)-(4.2) conditional on X and W, which are used to test for correlations between $_{NF}$ and ν, and between $_{F}$ and ν.

We derive identifying restrictions from a life-cycle model of consumption smoothing through participation in the rural non-farm sector.[11] We postulate that as a farm household ages, and the children reach adulthood, some of the children take over the farm (leaving the parents supported by transfers and some non-farm activity, which may have been there all along, but was secondary), while other children split away to take up non-farm activities (possibly new ones, or possibly pre-existing secondary activities). Thus, at any one time, we will see a U-shaped relationship between probability of being in the non-farm sector and age of the household head; the middle-aged heads (with children not yet at earning ages) will be more likely to still be in farming. By this process of shifting between farm and non farm sectors according to stage of the life cycle, combined with intra-family (inter-household) transfers, we assume that consumption within each sector can be smoothed over the life-cycle. Thus, while stage of the life cycle is an important determinant of mobility across sectors within the rural economy, consumption within sectors is successfully protected from life-cycle effects. We tried two versions of these life-cycle identifying restrictions. In the first, the vector W in the selection model included all variables in X plus the age and age squared of the spouse. In the second we deleted age and age squared of the head from X, but retained them in W.

Consistently with treating farm vs non-farm sector choice as endogenous, we also

[11] On life-cycle/demographic effects on participation in non-farm activities see Kimhi (1996). Strictly identification is possible without exclusion restrictions, given the nonlinearity in W.

estimated the consumption equations with and without the occupations dummies; since there are no obvious instrumental variables, dropping the occupation dummies is the only option if one wants to treat them as endogenous.

We conducted four tests of sample selection, corresponding to the two identifying restrictions and the two models with and without occupation dummies within the farm and non-farm sector. The data are consistent with the identifying assumptions on life-cycle effects. There was a significant life-cycle effects in the probit for sector choice, with a U-shaped relationship between probability of being in the non-farm sector and age of the head, in which the turning point is at a mean age of around 40 years. Yet, the coefficient estimates (not reported here) for age and age squared of the head and of the spouse were insignificant in the consumption regressions in both sectors in the models with sample correction terms.[12]

Turning to the sample selection test results, Table A1 gives our estimates of cov($_{F}$,ν) and cov($_{NF}$,ν) . These are not significantly different from zero in the consumption equations in all four cases considered. So there was no indication of sector-selection bias due to a significant correlation between omitted variables in the consumption model and omitted determinants of sector choice. We followed the recommendation of Davidson and MacKinnon (1993, Chapter 15) of dropping the sector-bias terms in this case.

[12] We kept the age of the head and its square in the model without sample selection reported in Table 2, and again, the coefficient estimates of these variables are not significant.

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Table 1: Poverty profile by sector of employment in rural Bangladesh, 1991-92

	Mean consumption (normalized by pov.line)	Poverty rate (% below pov.line)
Farm sector		
Landless farm worker	0.853	74.61
Farm worker with land	1.025	55.80
Fisheries/forestry/live stock worker	1.036	54.87
Tenant farmer	1.133	42.86
Owner farmer	1.345	30.30
Non-farm sector		
Servant, day-laborer	0.968	61.75
Transport or communication worker	1.150	46.56
Salesman, service, broker, or middleman	1.034	54.62
Factory worker or artisan	1.053	59.20
Petty trader or small businessman	1.339	39.22
Executive, official, profess., teacher	1.573	16.20
Retired person, student, not working	1.311	36.04

Source: Authors' computations from Household Expenditure Survey (HES).

Table 2: Determinants of consumption

	Farm sector		Non-farm sector		t-test of equality
	coeff-icient	stand. error	coeff-icient	stand. error	
Constant	15.97	8.56	28.85*	10.39	-1.01
Occupation of Head (Farm)					
Agricultural worker with land	11.11*	2.20	n.a.		
Fisheries/forestry/live stock worker	16.13*	3.14	n.a.		
Tenant farmer	19.92*	2.43	n.a.		
Owner farmer	20.23*	2.32	n.a.		
Occupation of Head (Non-Farm)					
Transportation, communication worker	n.a.		7.05	3.76	
Salesman, service, broker, middleman	n.a.		10.32*	3.99	
Factory worker, artisan	n.a.		4.61	4.28	
Petty trader, small businessman	n.a.		14.40*	3.50	
Executive, official, professor, teacher	n.a.		14.63*	4.32	
Retired person, student, not working	n.a.		-0.98	3.92	
District					
Mymensingh	-11.22*	3.63	-30.45*	5.39	3.39
Faridpur	-21.29*	4.24	-40.12*	4.31	3.21
Tangail/Jamalpur	-24.14*	3.86	-33.83*	4.73	1.67
Chittagong	24.33*	4.29	3.33	4.42	3.39
Comilla	7.29	3.82	-13.87*	4.23	3.94
Sylhet	33.55*	3.80	8.24	5.07	4.43
Noakhali	10.41*	4.61	-17.33*	4.71	4.37
Khulna	-4.89	4.44	-27.75*	5.35	3.56
Jessore	8.50*	4.15	-10.78*	5.44	3.04
Barisal/Patuakhali	-9.50*	3.85	-33.02*	4.51	4.28
Kushtia	-3.33	4.72	-11.37	9.51	0.86
Rajshahi	-14.79*	3.74	-33.27*	5.26	3.12
Rangpur	-22.68*	3.54	-38.52	5.43	2.75
Pabna	-13.78*	4.72	-27.34*	4.91	1.95
Dinajpur	-3.41	4.21	-28.85*	5.74	3.88
Bogra	-9.68*	4.89	-31.67*	5.54	3.24
Education of Head					
Below class 5 (some primary school)	4.20*	1.80	12.80*	2.64	-2.82
Class 5 (completed primary school)	5.91*	2.40	15.72*	3.19	-2.39

Class 6 to 9 (some secondary school)	10.54*	2.84	21.21*	3.86	-2.42
Higher level (completed secondary school)	18.77*	4.87	25.99*	4.27	-1.21
Education of Spouse					
Below class 5 (some primary school)	5.95*	2.06	2.23	2.96	1.02
Class 5 (completed primary school)	11.15*	3.47	11.80*	3.43	-0.14
Class 6 to 9 (some secondary school)	15.53*	4.30	17.82*	4.14	-0.39
Higher level (completed secondary school)	19.87	14.27	27.76*	9.04	-0.64
Household member with better education					
One level higher than max (head, spouse)	8.22*	1.91	11.26*	2.77	-0.94
Two levels higher than max (head, spouse)	11.78*	2.72	17.39*	3.58	-1.26
Three levels higher than max (head, spouse)	15.23*	3.06	18.84*	4.18	-0.67
Four/more levels higher than max (head, spouse)	4.40	4.13	24.16*	8.03	-1.96
Land Ownership					
0.05 to 0.49 acres	7.49*	1.93	7.36*	2.44	0.04
0.50 to 1.49 acres	13.33*	2.31	19.21*	2.97	-1.59
1.50 to 2.49 acres	22.82*	2.94	31.66*	3.98	-1.78
2.50 acres or more	38.13*	3.05	42.40*	4.16	-0.87
Demographics					
Number of babies	-20.56*	1.55	-19.50*	2.02	-0.41
Number of babies squared	2.93*	0.50	2.86*	0.59	0.08
Number of children	-15.39*	1.32	-19.44*	1.80	1.81
Number of children squared	1.91*	0.29	2.49*	0.39	-1.10
Number of adults	-14.07*	1.94	-9.85*	2.05	-1.72
Number of adults squared	1.32*	0.21	0.57*	0.20	2.99
Sex of the head	-14.83*	7.26	-2.43	6.23	-1.46
No spouse, married	20.43*	5.63	16.34*	6.31	0.59
No spouse, single	7.60*	3.42	14.83	7.77	-1.11
No spouse, divorced/widowed	10.56	6.13	-6.91	6.55	2.12
Age of the head	0.34	0.36	0.65	0.38	-0.63
Age of the head squared	0.00	0.00	0.00	0.00	0.47
Non Muslim	-3.48	2.27	-8.79*	2.71	1.51

Source: Authors' computations from HES.

Note: The dependent variable is 100 times log consumption normalized by the area-specific poverty line. Standard errors are corrected for heteroscedasticity. Observations: 2345 farm and 1472 non-farm. Adjusted R^2= 0.52 (farm) and 0.46 (non-farm). "n.a." denotes not applicable. (*) indicates significance at the 5% level. Excluded dummies: Dhaka district, married head with a spouse, male household head, Muslim religion, illiterate head, illiterate spouse, zero education differential, landless household, and landless agricultural worker (for farm) or servant/day-laborer (for non-farm).

Table 3: Test of structural differences between the farm and non-farm regressions

	RSS	Number of restrictions	F value	F test (5% level)
Unrestricted model	371.62	-	-	-
All non-occupational variables	381.49	46	2.15	Rejected
Constant	371.72	1	1.03	Accepted
Non-geographic variables	377.12	29	1.90	Rejected
Household size variables	373.96	6	3.90	Rejected
Other demographics/religion	372.48	7	1.23	Accepted
Education of head	372.81	4	2.97	Rejected
Other education variables	372.31	8	0.87	Accepted
Land variables	372.20	4	1.46	Accepted
Geographic variables	375.57	16	2.47	Rejected

Source: Authors' computations from HES.

Table 4: Estimated average gains to switching from farm to non-farm sector

	Initial mean consumption (proportion of the poverty line)	Unconditional: Average proportionate difference in consumption (%)	Conditional: Gain from switching controlling for initial household characteristics (%)
Farm to non-farm switch (given sector occupation distributions)	1.016	8.90	6.18
Agricultural labor without land to transport and communication worker	0.787	27.97	15.89
Agricultural labor without land to small businessman/petty trader	0.787	38.48	23.24

Source: Authors' computations from HES.
Note: A value of 1.0 for initial consumption indicates that on average, households in that sector or occupation are at the poverty line.

Table 5: Gains by area, with and without poverty weights

	Initial log farm consumption (normalized by pov.line)	Estimates of proportionate gains in consumption from switching to non-farm sector		
		Unconditional mean difference in consumption between sectors (%)	Average gain at given initial household characteristics (%)	Poverty-weighted gains at given initial characteristics (%)
Dhaka	1.095	19.06	24.15	18.94
Mymensingh	0.974	4.39	6.65	9.13
Faridpur	0.880	-0.06	4.47	7.96
Tangail/Jamalpur	0.844	12.16	12.95	22.98
Chittagong	1.216	12.59	2.01	0.64
Comilla	1.140	4.77	4.84	2.15
Sylhet	1.533	-7.85	-1.76	0.01
Noakhali	1.138	4.19	-3.98	-1.58
Khulna	1.039	5.59	5.31	2.46
Jessore	1.158	8.14	6.15	6.24
Barisal/Patuakhali	0.974	6.24	2.26	3.42
Kushtia	1.074	26.08	15.21	14.62
Rajshahi	0.919	9.43	8.39	11.53
Rangpur	0.820	12.34	13.24	23.04
Pabna	0.830	17.17	15.72	24.29
Dinajpur	1.018	-8.25	2.08	4.66
Bogra	0.981	1.40	4.08	7.01

Source: Authors' computations from HES.
Note: A value of 1.0 for initial consumption indicates that on average, farm households in that district are at the poverty line.

Table 6: Determinants of the branch placement

	Density of Grameen Bank branches		Density of governmental bank branches	
Intercept	-0.753 (0.769)	-0.492 (0.617)	-2.635 (3.141)	-4.001 (2.867)
Poverty-weighted gain from switching to the non-farm sector	0.202 (0.049)	n.a.	-0.903 (0.154)	n.a.
Unweighted gain from switching	-0.236 (0.101)	n.a.	1.083 (0.267)	n.a.
Unweighted gain minus poverty-weighted gain	n.a.	-0.186 (0.031)	n.a.	0.820 (0.201)
Population density	1.128 (0.273)	0.986 (0.131)	5.579 (1.461)	6.327 (1.028)
R^2	0.609	0.598	0.866	0.858

Sources: Authors' calculations from table 6 and BBS for branch density (1995a, b). Bank density measured as the number of branches per 100,000 acres, and population density measured as persons per 100 acres. Gains are multiplied by 100.
Notes: Standard errors in parentheses. 17 observations.

Table A1: Tests for sector-selection bias

	Cov($_{NF}$, ν)	Cov($_{F}$, ν)
First identifying restriction With occupation dummies	3.85 (10.92)	5.85 (10.36)
Second identifying restriction With occupation dummies	-3.50 (6.12)	-3.42 (6.15)
First identifying restriction Without occupation dummies	7.41 (11.02)	-2.13 (10.55)
Second identifying restriction Without occupation dummies	5.52 (5.59)	-8.18 (6.29)

Source: Author's computations from HES.
Note: Standard errors in parentheses. First identifying restriction is with age and age squared of the head (but not of the spouse) in the consumption regressions, and second identifying restriction is without age and age squared of the head in the consumption regressions.