Evaluating poverty outreach of small business lending: a study of BRAC Bank, Bangladesh

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Relatively little is known about the profile of employees in small businesses in developing economies or how to track a lending programme's poverty outreach. Poverty outreach is considered one useful indicator of social performance. To shed more light on this issue, this study surveyed over 1,000 small business customers of BRAC Bank in Bangladesh and their over 7,000 employees. These businesses received average loans of just under $7,000 with a loan term of 21 months. Using a poverty scorecard, the study found that 17 per cent of the small business employees were poor according to the $1.08 per day purchasing power parity standard. Using standard regression techniques, the study derived a firm-level scorecard that can estimate the poverty rate of these firms' employees based on five indicators: the firm's economic sector, its rural or urban location, the portion of unskilled workers, whether the firm employs any women, and the total number of workers. Standardized reporting of these indicators contributes to the global discussion on poverty outreach of small business employment. More research is needed to reveal whether lending to small businesses benefits poor employees and to refine best practices on how to serve businesses with higher rates of employee poverty.

Keywords: poverty outreach, poverty indicators, poverty scorecards, social investors, small business lending

Little is known about job formation and poverty outreach associated with small business lending

WHILE SMALL BUSINESS LENDING in developing economies is attracting the interest of lenders and investors, relatively little is known about job formation and poverty outreach associated with such lending. The lack of data is due to the relatively recent interest in small business finance and to the often complex organizational structure of a small firm. Producing reliable data on their clients' employment patterns would position lending organizations to attract capital from social investors and, more

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importantly, to make informed decisions about growing their lines of business. This knowledge gap ultimately prevents small business lenders from reaching their full business potential.

The study's objective was to design and test a replicable, cost-effective data collection system to track the poverty of employees of small business borrowers. To do this, the study simultaneously evaluated what data to collect and how to collect it. The study:

- presents a comprehensive picture of employment and wages in the small businesses that borrow from one large-volume lender, BRAC Bank in Bangladesh;
- finds that five objective indicators – (1) percentage of unskilled workers, (2) whether the firm employs any women, (3) the firm's economic sector, (4) whether the firm is in a rural or urban location, and (5) the number of employees – are correlated with higher poverty rates;
- uses a basic logistic regression model to convert the data into a simple firm-level scorecard to estimate poverty rates among small business employees.

Using the firm-level scorecard, BRAC Bank can estimate employee poverty rates among small business borrowers

BRAC Bank can cost-effectively track these five indicators in its loan application and report the data in its existing recordkeeping systems. Using the firm-level scorecard, BRAC Bank can then estimate employee poverty rates among small businesses in different regions or over time.

This is a practical and cost-effective alternative to the more extensive poverty scorecards and poverty assessment tools that estimate poverty based on 10–15 indicators and must be collected from each employee. The search for easy-to-track indicators of employee poverty is a new one. This is an early attempt and much more could be done to develop the field.

The study does not address the question of whether lending to small businesses benefits poor employees

The small business industry is just beginning to join the global discussion about poverty outreach. There is an ambitious research agenda to be addressed, and this study offers a modest contribution by suggesting what indicators a small business lender could use to track its poverty outreach. The study does not address the relevant question of whether lending to small businesses benefits poor employees or helps them become less poor over time.

Little is documented about the profile of small business employment. Compared to the many studies in the field of microfinance, there is virtually no academic literature on the relationship between small business employment and poverty. The literature gap is even more pronounced for small growing businesses as opposed to small and medium-sized enterprises (SMEs). This study is not an impact assessment nor does the study method track changes in individuals' poverty status over time. Instead, it provides one of the first statistical profiles of the small business workforce in a developing economy and how to monitor the poverty outreach of a small business lending programme. In short, the study shows how relatively simple data collection can confirm whether poor people are reached and how to monitor whether that outreach varies over time or across different regions.

A key difficulty is the distance that separates the lender from the subject being studied

A key difficulty in designing a tracking system for assessing the poverty outreach of small business lending is the distance that separates the lender from the subject being studied (see Figure 1).

Contrast a small business lender with a microfinance lender: in a microfinance poverty outreach tracking system, researchers are interested in studying the client herself. In small business poverty outreach tracking systems, the target is the labour force of the client.

Additionally, a key part of most microfinance programmes is a visit to clients' homes; thus it is less difficult for field officers to speak to clients about personal family finances. The poverty level of a microfinance client can also be estimated by talking to this client or even by simply examining the external conditions of this client's house.

In the small business context, a cost-effective method for estimating poverty of the employee would not involve interviewing the employee or visiting the employee's household.

The challenge lies in persuading bank CEOs that it is worth reporting these data

The challenge lies in persuading bank CEOs that it is worth reporting these data. As a matter of more general good business management, lending institutions should collect data on their customers' profile. Better customer data would serve bank's commercial goals as well as social goals. Knowing one's customers is the best basis for improving operating efficiencies and maximizing the opportunity to serve more of their financial needs. A lender that regularly profiled and analysed its customer base would incur virtually no incremental cost in collecting these indicators of poverty outreach. If banks do not see such data reporting as being in their self-interest, then investors would need to require it as a precondition of their investment or pay for the customer survey themselves.

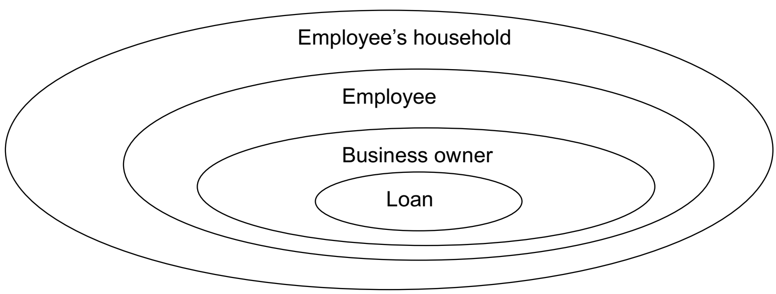


Figure 1. Distance from loan to employee household in small business lending

Small business lenders that seek to attract social investment capital must take the time to build these systems

Historically, the small business lending industry devotes much less time to these issues than the field of microfinance. Small business lenders that seek to attract social investment capital must take the time to build these systems. The most important point is that lenders should embed some consistent tracking process in the operations and business planning of the organization. This information should feed back into the lender's business planning and allocation of resources. Regular reporting of these data would mitigate the current scarcity of data on small business lending poverty outreach.

Potential payoff of integrating employment and loan repayment data

The most comprehensive way to track employment and wages would be to build a database that integrates small business loan application information with workforce data. Such a database could centralize a lending institution's data storage and would allow it to compare borrowers' financial characteristics with their employment figures and wages. This would also create a continuous longitudinal tracking system. In addition to measuring poverty outreach, a centralized system could be used to:

- manage each loan officer's pipeline of loan applications;
- streamline the loan approval process by triaging which loan applications deserve more in-depth or customized underwriting;
- compare business characteristics with loan repayment data, which would lead to more informed loan loss provisioning and risk-based pricing;
- track borrowers' evolving financial characteristics as employment in the firm changes;
- evaluate the lender's cost of underwriting the application.

The tracking system could compare business characteristics with loan repayment data

At the launch of this study in 2007, BRAC Bank (the 'Bank') was preparing to implement just such a comprehensive system. This strongly attracted the study team to try to integrate the collection of employment data into this system.

By late 2007, it was clear that intermittent electricity supply and inadequate internet bandwidth in Bangladesh would prevent the Bank from fully implementing the system. Also, the Bank did not have sufficient time to train the loan officers in how to gather the employment data.

Ultimately, the study team reverted to gathering loan application data manually in a field audit. This change does not affect the results of the study, though it does not create a continuous data collection system that relates employment and loan repayment data.

Profile of BRAC Bank as a small business lender

BRAC Bank has a high loan volume and is committed to economic development that benefits the poor

BRAC Bank is a commercial bank founded in 2001 in Bangladesh by the BRAC NGO with the goal of serving the small business market. ShoreCap selected BRAC Bank as the testing site for this study because of its high loan volume and the commitment of its owners to economic development that benefits the poor of Bangladesh.

The study collected data from small business clients of the Bank and their clients' employees through questions that were added to the small business loan application. A sample of 1,447 loan applications was initially selected for the study from 36 Bank offices out of 412 offices in operation as of April 2008. The sample was drawn from all applications submitted in April, May and June 2008. This constituted 25 per cent of all applications in these 36 offices. The 36 unit offices were randomly selected from the 99 unit offices that introduced the new BRAC Bank computer system. The 99 offices were divided evenly between urban and rural areas, and then the 18 urban and 18 rural offices were randomly selected.

Interviews were conducted to understand wages, employment and household poverty conditions

The final sample excluded applications with incomplete data, leaving a sample of 1,047 small businesses. Interviews were conducted with the 1,047 small business owners and their 7,068 employees to understand wages, employment and household poverty conditions. The average loan size was $6,582, equal to 4.7 times the Bangladesh GDP per capita of $1,400 (CIA World Factbook, no date). Of the loan disbursements, 78 per cent were new customers and 22 per cent were repeat customers (see Table 1). The Bank's clients are divided into four sectors: retail/wholesale trading, agriculture, service and manufacturing. The field auditors conducting the study were directed to sample all of the loan applications from the non-trading sectors, since those firms typically employ more people. The team also conducted

Table 1. BRAC bank volume of small business lending

Particulars	*April 2008*	*May 2008*	*June 2008*
Number of unit offices	412	415	424
Monthly disbursement (#)	5,230	9,164	7,693
Monthly disbursement ($)	$35.2 million	$59.6 million	$50.3 million
Average loan size	$6,714	$6,497	$6,536
Outstanding loans (Number)	87,370	93,938	98,158
Outstanding loans ($)	$336.6 million	$371.1 million	$394.4 million
Average term of a loan			21 months
Monthly average number loan made last 12 months			6,645
New loans (%)	71	79	79
Repeat loans (%)	29	21	21

14 in-depth case studies in order to obtain more qualitative insights into employment practices in addition to the statistical results of the study.

What is the profile of employment and wages in small businesses?

Manufacturing firms employ roughly three times as many employees per firm as trading or agriculture

Number of employees by skill level. The number of employees per firm varies significantly across sectors. Firms in the trading and agriculture sectors show the fewest average number of employees, and service and manufacturing firms the highest. Manufacturing firms employ roughly three times as many employees per firm as trading or agriculture firms (see Figure 2).

Employees were categorized as skilled, semi-skilled or unskilled. Skill level was determined primarily by the number of months needed to attain the skills for their position and the amount of supervisory responsibility.

Monthly cash wages are not the only compensation employees receive

Distribution of monthly wages. Establishing compensation levels in small firms can be difficult because monthly cash wages are not the only compensation employees receive. In the case studies carried out, owners reported that compensation may also include holiday bonuses (which may equal one or two months' salary), food, lodging, clothing, transportation allowance, commission and tips. The field researchers found it challenging to collect complete and comparable data from all owners. It also proved too difficult to monetize the value of non-cash compensation. For these reasons, the study found that only regular monthly cash wages could be used in practice to predict employees' poverty status.

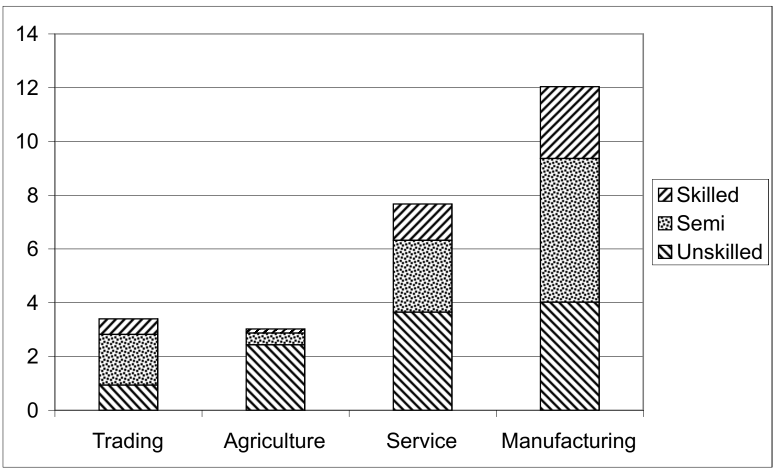
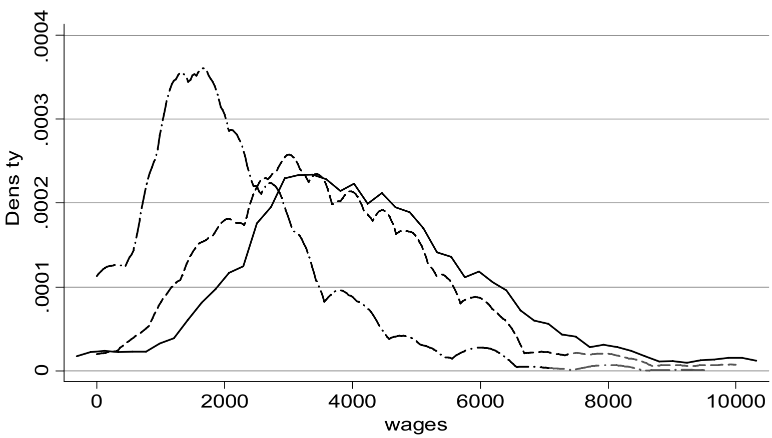


Figure 2. Average number of employees by sector

Employees reported their regular monthly wages in cash, excluding overtime pay, holiday bonuses and in-kind compensation. The wages of unskilled employees clustered around taka 2,000–3,000 ($29–$42) per month. The wages of semi-skilled and skilled employees show more dispersion than unskilled workers. Figure 3 shows that almost no employees in the sample reported wages over taka 8,000 ($114) per month.

Gender breakout by sector and area. The sample reveals a significant difference in employment of women by sector. The study found that most female employees in the surveyed businesses work in the manufacturing sector. In discussions with firm owners, a number of trading firms expressed strong reluctance to hire women. Owners mentioned repeatedly that it was not in keeping with the customs of the market to employ women. One trader said the market lacked toilet facilities for women and that long hours posed a danger to women. This sentiment against hiring women was expressed in both rural and urban trading firms. A furniture manufacturer in a rural area noted that he did not like to hire women because women and men working together had led to problems in the workplace and lessened the productivity of both employees. One rural manufacturing firm noted that since his factory is in a bazaar, it is not 'culturally suitable' for women to work at his factory. The trading sector shows the lowest incidence of employing women, followed by agriculture, service and manufacturing sectors (see Figure 4).

The trading sector shows the lowest incidence of employing women



Note: unskilled = dot-and-dashed line; semi-skilled = dashed line; skilled = solid line.
Figure 3. Distribution of wages

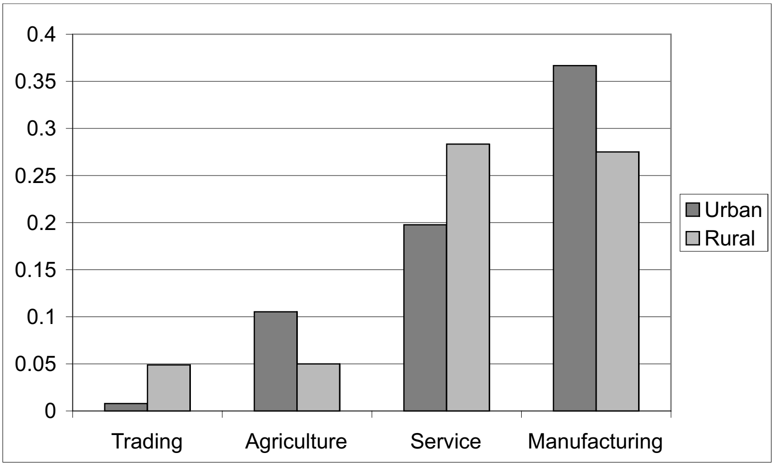


Figure 4. Percentage of firms that employ women

Are small business borrowers adding new employees?

Growth in number of employees. The survey asked employers how many employees worked in the firm 12 months ago compared to today. The trading, service and manufacturing sectors all added workers in the last year, from 5 per cent to 62 per cent over last year's employment. Data from the agriculture sector were inconclusive (see Table 2).

Between rural and urban firms, the increase in new employees is more pronounced in rural trading and rural manufacturing. The results for the service sector are mixed.

Does experience as a small business employee improve one's economic condition?

Determining who is a salaried versus casual employee can be complicated in a small firm in Bangladesh. Some firms employ workers on a piece-rate basis. Piece-rate workers often expect to complete a certain

Table 2. Percentage increase in number of employees over the last 12 months

	Trading	*Agriculture*	*Service*	*Manufacturing*
Urban				
Repeat loans	15	n/a	71	5
New loans	39	–13	43	25
Rural				
Repeat loans	24	n/a	50	27
New loans	28	n/a	58	62

set amount per month, thus mimicking features of a typical salaried employee. Other firms use a large amount of casual labour, but that casual labour is employed on a regular basis, thus mimicking features of a typical salaried employee.

Employees with longer tenures at the firm and more years of education earned higher wages

Overall, employees with longer tenures at the firm and more years of education earned higher wages. This is consistent with the possibility of (1) 'job ladders' or career paths in small firms and (2) lower skilled workers moving more rapidly from one firm to another than higher skilled workers. If career paths exist in small firms, then an employee might join the firm with low skills and, through on-the-job experience, rise to higher job classifications and compensation. This is not to say that all low-skilled workers can or will rise to higher skills or higher wages. The data do not conflict with the hypothesis that some workers can gradually improve their wage with more experience (see Figure 5).

Higher skilled positions are held by employees with more education and more tenure. Skilled workers average 5.7 years of education, with 3.4 years tenure at the firm and a wage of 4,365 taka ($62.36). Semi-skilled workers average 2.8 years tenure at the firm and a wage of 3,640 taka ($52.00). Unskilled workers average 1.9 years experience with the firm and a monthly wage of 2,123 taka ($30.33).

Do small businesses employ people in poverty?

To identify employees who might be in poverty, the study used a poverty scorecard tool already developed

To identify employees who might be in poverty, the study used a poverty scorecard tool developed by Mark Schreiner (full documentation of the scorecard is available at http://www.microfinance.com/English/Papers/Scoring_Poverty_Bangladesh_2006.pdf. The scorecard is

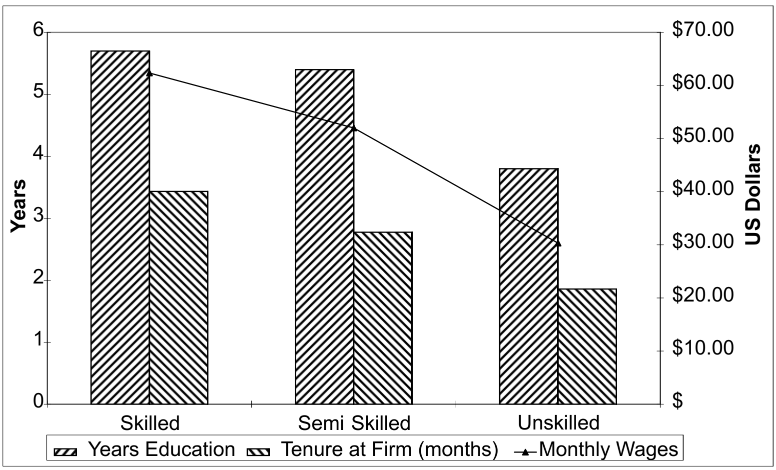


Figure 5. Education, tenure and wages of employees by skill level

based on the Bangladesh Household Income and Expenditure Survey conducted in 2005. The scorecard is designed for organizations to report overall poverty rates, to target services to the poor, and to track changes in poverty over time. The scorecard consists of 12 questions with objective answers that correlate with a poverty rate of $1.08/day at 1993 PPP. Poverty scores were assigned based on responses to each of the 12 questions and an aggregate score for the household was calculated. These scores were then converted to poverty likelihoods based on the conversion table provided by Schreiner. An average of these poverty likelihoods constitutes the overall poverty rate or percentage of people below the poverty line.

The survey found a poverty rate of 16.6 per cent in the entire sample of small business employees

The survey found a poverty rate of 16.6 per cent in the entire sample of small business employees. By comparison, BRAC NGO administered the same scorecard to their microfinance clients in 2008 and found an average poverty rate of 36 per cent. Since microfinance borrowers are typically one-person enterprises, it would be necessary to adjust the small business poverty rate by the number of total number employees to compare poverty outreach between the two lending programmes (see Figure 6).

The results of the poverty survey among small business employees indicate that:

Poverty rates are higher in firms in the non-trading sectors

- Poverty among small business employees is measurable in all sectors.
- Rural poverty rates are generally higher than urban rates; and
- Poverty rates are higher in firms in the non-trading sectors.
- Poverty rates among female and unskilled employees were significantly higher than the poverty likelihoods of all employees (see Table 3).

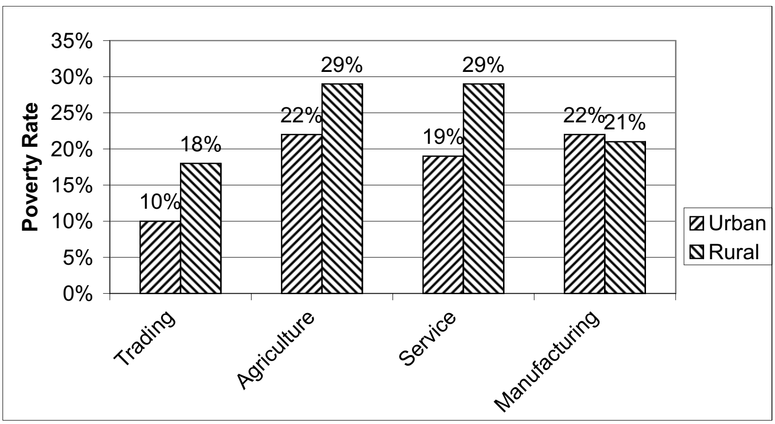


Figure 6. Percentage poverty rate among employees by economic sector and area

Table 3. Education, tenure and wages of unskilled and female employees.

	Total	*Unskilled*	*Female*
Number in sample	7,068	2,475	498
Tenure (years)	2.6	1.9	1.7
Education (years)	4.9	3.8	3.4
Monthly Wages	$46.46	$30.33	$27.00

These observations led the study to examine these indicators more closely for possible correlation with the poverty rate of each firm's pool of employees.

Generating a firm-level scorecard of employees' poverty status

The study team relied on experienced scoring expert Mark Schreiner to devise a scorecard at the firm level, and this section draws heavily on his technical memo (2009). To design the scorecard, the team used standard logistic regression techniques to determine which variables correlated with the average poverty likelihood among a firm's employees.

The study calculated the regression coefficients associated with the number of unskilled workers, female workers, the sector and location

Indicator	Value	Points	Score
1. Does the SME operate in a rural area?	A. No	0	
	B. Yes	10	
2. What sector does the SME work in?	A. Trade	0	
	B. Service	4	
	C. Manufacturing	10	
	D. Agriculture	29	
3. Does the SME employ any women?	A. No	0	
	B. Yes	20	
4. What share of the SME's employees are Unskilled?	A. None	0	
	B. Some, but less than half	14	
	C. Half or more	24	
5. How many employees does the SME have?	A. Two to five	0	
	B. Six to ten	6	
	C. One	7	
	D. Eleven or more	17	

Total score:

Figure 7. Firm-level scorecard of employees' poverty status

The variables were then converted into a firm-level scorecard

of the firm, and total workers at the small business employers. Many other firm-specific variables were not significant in explaining the average poverty likelihood of a firm's employees. The variables were then converted into a scorecard by normalizing the coefficients to a scale in which the lowest possible score is 0 and the highest is 100. The scorecard in shown in Figure 7.

The scores range from 0 (least likely poor) to 100 (most likely poor). To get from scores to the estimated average poverty likelihood for the employees of a given SME, one first divides the total score by 320.2, and then adds 0.0779, so that:

$$\text{Estimated average poverty likelihood} = \frac{\text{Total score}}{320{,}0} + 0.779.$$

In order to compute the number of poor people employed by a small business, multiply this estimated average poverty likelihood for the business by the number of employees. Or, to compute the poverty rate of employees of a group of businesses, take the average of the firms' individual average poverty likelihoods weighted by the number of employees in each firm.

Agriculture firms have the highest incidence of poverty

The regression shows that, controlling for other indicators in the regression, agriculture firms have the highest incidence of poverty, followed by manufacturing firms, service firms and then trading. The ordering of the effects of number of employees does not follow an intuitive pattern. The relatively low score for firms with two to five employees may be due to the concentration of trading firms in this size, since trading firms have the lowest observed poverty rate.

The bias and confidence intervals of the scorecard are confirmed by running 10 ordinary-least-squares regressions, setting aside a different 10 per cent of the observations each time. The remaining 90 per cent generated a scorecard via regression that was applied to the 10 per cent of observations that had been set aside. This means that each of the 10 scorecards was applied to observations that were not used in the scorecard construction to estimate the average poverty likelihood of the employees in the set-aside firms; that is, the scorecard was applied out-of-sample and its accuracy was measured via cross-validation.

To analyse for any bias in the regression, the estimated 'average (weighted by number of employees) average' poverty likelihood across firms was computed and compared to the true 'average average' poverty likelihood across firms. This difference is the bias of the scorecard estimator in a specific sample. These biases were then averaged across the 10 cross-validation samples and the 10 regressions. This gave an average difference between the estimated average average poverty likelihood and the true average average poverty likelihood of –0.0004, or –0.04 percentage points. This result indicated that the scorecard had essentially no bias.

The standard error of these differences was 3.9 percentage points. Thus, the 90 per cent confidence interval c for a sample of n = 938 is about 1.64 × 0.039 = 6.4 percentage points. (This is the sample size for the 10 regressions that were used to check for bias: 1,042 – (0.1 × x 1,402) = 938.)

For the textbook case with direct measurement, a population poverty rate of 16.6 per cent (0.166), a sample size of n = 1,042, and a 90 per cent desired confidence level, the confidence interval +/–*c* would be derived from:

$$1{,}042 = \left(\frac{1.64}{c}\right)^2 \cdot 0.166 \cdot (1 - 0.166)$$

This implies that c = 0.019, or 1.9 percentage points.

Thus, the confidence interval with indirect measurement via scoring is about 6.4/1.9 = 3.4 times larger than the confidence interval with direct measurement. To get the same precision as with direct measurement, the sample used with scoring must be 3.4 × 3.4 = 11.6 times as large. Thus, the sample-size formula for scoring is:

$$n = 11.6 \cdot \left(\frac{z}{c}\right)^2 \cdot \hat{p} \cdot (1 - \hat{p})$$

where:

$$z \text{ is } \begin{cases} 1.64 \text{ for confidence levels of 90 per cent} \\ 1.96 \text{ for confidence levels of 95 per cent} \\ 2.58 \text{ for confidence levels of 99 per cent} \end{cases}$$

c is the confidence interval as a proportion (for example, 0.02 for an interval of +/–2 percentage points), and

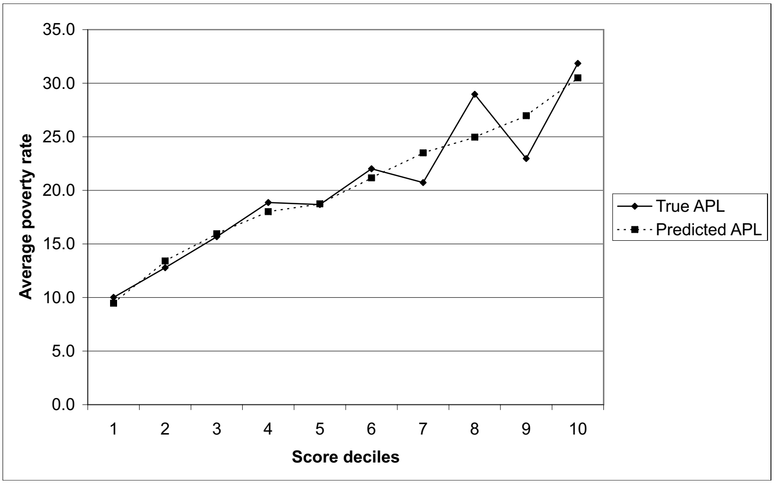
$\hat{p}$ is the expected (before measurement) proportion of households below the poverty line.

This formula can also be used to figure confidence intervals, if n is known.

The 11.6 factor is much larger than the factor for many of the household-level poverty scorecards developed by Schreiner, which are usually less than 1.0. This reflects the significant loss in accuracy when going from direct indirect measurement at the household level versus indirect measurement at the firm level.

> The scorecard's predicted average poverty rate was compared with the true poverty rate from the employee surveys

Another way to observe the accuracy of the scorecard is to compare the predicted average poverty rate with the true poverty rate from the employee surveys. The entire 1,047 firms were scored and then grouped into deciles. Figure 8 shows the predicted average poverty rate among employees using the scorecard with the true poverty rate from the employee scorecards.



Note: APL = average poverty level.
Figure 9. Predicted average poverty level versus true average poverty level by score deciles

Table 4. Additional data collection of small business loan applications

Male	*Female*	*Total*	
Total number of non-family employees (Current)			
Number of unskilled employees (<3 months training)			

The scorecard appears very close to the true poverty rate for the first six deciles. In the top four deciles, the predicted poverty rate is evenly positioned between the higher and lower actual rate.

For BRAC Bank to collect these data in the future, the additional question on the loan application would look like Table 4. Table 4 captures unskilled ratio, female workers and total workers – the indicators that correlate most closely with poverty outreach. Regular reporting of these data would show relative changes in poverty outreach and could be converted to the estimated poverty rates.

The study demonstrates that loan officers can be trained to collect employment and wage data, but training and managerial oversight is essential. Generally, employment data are not critical to making loans, and so this is not typically a duty of a loan officer or his or her supervisor. Loan officers have competing duties, and the lenders characteristically lack existing control systems to double-check accuracy of this kind of data.

Recommendations on collecting small business employment data

Small business lenders can report their poverty outreach based on simple, objective indicators that are correlated with employees' poverty rate

The study shows that small business lenders can report their poverty outreach based on simple, objective indicators that are correlated with employees' poverty rate. Therefore, it is not necessary to repeat individual employee interviews at each firm because the employer-level information correlates with employees' poverty.

A strong tracking system is built on (1) a baseline survey and (2) ongoing reporting of key indicators. This study recommends:

1. A baseline sample survey of small business owners and employees with sufficient representativeness from the types of loans that are likely to differ in employment and wage patterns (for example, pools of loans grouped by sector, urban/rural location, size of loan, size of firm). The loan pools and the size of the sample will be context-specific.
2. Regular tracking of the indicators that are correlated with poverty outreach. These indicators can be tracked on loan applications and reported periodically. Comparisons of this portfolio data to the baseline data by sector and by area continuously measures poverty outreach.

These indicators can be tracked on loan applications and reported periodically

Poverty scorecards and poverty assessment tools are available in more than 30 countries. Where poverty scorecards are not available, other cost-efficient proxies can be used, provided the lender is clear about their accuracy. For example, usable proxies could include a question about poverty self-perception, an absolute wage cut-off, or national economic data that identify high-poverty groups. Even without a baseline survey, lenders can draw inferences about relative increases or decreases in poverty outreach by consistently tracking firm-level indicators.

Why is this important to lenders? Small business lenders motivated either by commercial goals or poverty-alleviation goals should understand their clients' employment profile. This promotes a culture of analysis and strategy in the lending programme. Collecting employment data is a minor add-on to the collection other customer data. It sounds simple to recommend that lenders occasionally survey their customers, but few lending programmes take this on board. Systematically surveying and using the scorecard techniques in this study require more effort, but are useful for three reasons:

1. Improved operating efficiency – with these data, a manager can compare the poverty outreach of different branches and different branch managers. This allows a lender to determine best practices among the loan officers and to calculate the extra cost of reaching businesses with high-poverty workforces.

This technique gives investors evidence that loan programmes do reach poor employees

2. Improved social performance measures – poverty outreach is a primary goal of many development lenders and investors. This technique gives investors evidence that loan programmes do reach poor employees. To get the most from baseline survey and scorecard techniques, lenders should periodically report these data. Changes over time can be observed that would merit deeper qualitative investigation through field visits or focus groups of borrowers.
3. Improved financial performance – if the employment and loan repayment data are integrated, lenders can make more accurate decisions about loan reserves, risk rating and risk-based pricing. Ultimately, this is the basis for better business decisions.

Well-managed lenders should figure out how to measure achievement, how they will collect and report performance data, and how these will feed back into their strategy. The system for collecting even the most basic data on loan customers (for example, the firm's sector or type of loan) can also accommodate basic employment data. For small business lenders seeking to attract social investment capital, information about their clients' employment patterns can be crucial to investors' decision-making.

Future directions for research

The literature on the potential benefits of small business employment is almost nonexistent. Future studies could add significantly in the following ways:

- by adding to the commercial justification for collecting data on poverty outreach. Is there any correlation between poverty outreach and commercial success? Would effective poverty outreach attract more social investment?
- by demonstrating what computer operating systems can most efficiently track these data. Does this call for more expensive equipment and staff training? If so, investors and donors may need to absorb this expense;
- by testing whether these same firm-level indicators have predictive power in other developing countries. It is likely that female workers, unskilled workers, and workers in the non-trading sectors have higher poverty rates in most economies, but other baseline studies would be able to confirm this;
- by investigating the non-financial quality of jobs in small firms in terms of skill training and job mobility, as well as in alternative employment opportunities;

Future studies could investigate the non-financial quality of jobs in small firms

- by performing rigorous impact assessment studies that track employees in small firms over time compared to a control group of other workers. The same individuals would need to be evaluated over an extended period to observe the potential outcomes;
- by evaluating the impact of small business sector more broadly on poverty reduction, such as through addressing constraints on the growth of value chains in which the poor may benefit in other ways than as employees.

In short, what is known about the effects of small business lending is trivial compared to what is not known and has not been studied. Many critical questions remain unexamined, and the small business industry could benefit tremendously from a broad research agenda and industry discussion.

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