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Sustainable Financing Strategies for the SMEs: Two Alternative Models

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Abstract: A sustainable financing strategy for SMEs should aim to enhance a low-cost collateral-free supply of loans to SMEs with good track records of repayments to banks. In this paper, we suggest two alternative financing models for SMEs that address certain borrowing constraints of SMEs. First, the model incorporates institutional mechanisms involving the government, banks, and SMEs. The strategy employs a two-pronged approach: (i) the government enhances the supply of loanable funds to banks, and (ii) identifies good SME borrowers through skills development programs and introduces them to banks. This model will reduce default risk and allow banks to offer lower-interest and collateral-free credit to SMEs, thereby improving their access to finance and performance. Second, the model could be extended to accommodate digital finance using a data-driven credit risk score of the borrowers to reduce banks' default risks and transaction costs with or without government funds. The proposed model could resolve the moral hazard and selection bias problems. Our proposed models are based on a public-private partnership approach and therefore could solve certain borrowing constraints of SMEs. Our empirical results support the model outcomes and therefore are consistent with the predictions of our theoretical models.

Keywords: SME financing models; credit wholesale program; default risk; digital finance; Bangladesh

JEL Classification: O16; L25

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1. Introduction

Access to formal finance has been a predominant problem for the development of SMEs in developing countries. A high interest rate, stringent collateral requirements, the opaqueness of SMEs, etc. affect SMEs access to finance. As a result, most SMEs depend on informal sources for financing that are costly, and on top of that, it does not meet all the financing needs [1,2]. Smaller firms could finance on average 13% points lower investments with bank finance compared to large firms [3]. A survey of manufacturing SMEs in Bangladesh shows that though small firms can finance 52% of their total investments with formal credit, they still blame high-interest rates as the main obstacle to having access to formal credit [4]. Default risk is the main concern for banks while processing a loan for SMEs [5]. A higher interest rate for SMEs is usually justified by the high default risk for SME loans, which ultimately increases the borrowing costs of SMEs [6].

To solve the financing bottlenecks of SMEs, various innovative financial approaches, such as credit guarantee schemes (CGS), business angels, factoring, etc. are applied in many countries [7–10]. None of the methods are fully flawless [5,11,12]. For example, for the credit guarantee scheme, moral hazard and political interferences, are two competing constraints that jeopardize the objective of the financing mechanism. Factoring and business angel models are less followed and have demerits as well. A new strand of research emphasizes for local-level financial development by expanding bank branches at the subnational level may largely solve SMEs financing bottlenecks, though the process is complex and costly [6,13]. Therefore, countries are still in search of a sustainable financing model for SMEs. In Bangladesh, a special credit program, known as the "Credit Wholesale Program" (CW program) was initiated by the government through its agency "SME Foundation" (SMEF) in 2009 to provide low-cost credit to SMEs [14]. The program provides subsidized loanable funds to selected banks to disburse loans at a government-determined lower interest rate among the beneficiary firms of the SMEF. (The Program sets the interest rate at 9%, which was lower than the market rate, 12% or more. SMEF provides various types of training on business processes, MIS, accounting procedures, etc. to the beneficiary firms. These firms' business situation is well known and is held with the database of the SMEF.) Interestingly, the repayment rate of the CW program is over 95%, making it a very successful one compared to banks' regular credit programs for SMEs. However, the program suffers from its limited coverage and shortage of funds.

Taking the CW program into perspective, in this paper, we have developed a theoretical model of SME financing incorporating the role of government, banks, and SMEs that delineate a sustainable financing strategy. The strategy employs a two-pronged approach: (i) the government enhances the supply of loanable funds to banks, and (ii) identifies good SME borrowers through skills development programs and introduces them to banks. The match-making role of a government agency helps reduce the "asymmetry of information" between banks and SMEs, leading to lower interest rates due to low default risks. The model resolves some borrowing constraints of SMEs, such as higher interest rates and the requirement of collateral as the identification of borrowers by the government agency works here as an implicit guarantee. The important aspect of the model is that it emphasizes the borrower selection criteria—if borrowers are selected by an agency through their skills development interventions, it could not only improve SMEs performances, it also improves SMEs loan repayment capacities and consequently reduces loan default risk of banks.

The model is extended further by introducing a digital financing mechanism and a data-driven credit risk score in order to generalize and scale up. In particular, our proposed model could resolve moral hazard problems, and in that context, it might perform better than some of the existing models, such as the Credit Guarantee model (There are various approaches to credit risk management in the financial sector [15–18]. The concern here is that SME financing is a primary concern of all the governments in developing countries despite their opaqueness. Traditional credit risk analysis of the banks may not help SMEs and therefore in our model, we combine a public-private partnership approach with a data-driven credit risk analysis method. Our model emphasizes on the selection of good SME borrowers by creating a network through interventions on their various capacity building. In this context, this model addresses the moral hazard problem of selection biases and makes some improvements over some of the existing models).

The theoretical underpinning is that a subsidized government fund (such as the Credit Guarantee Scheme) may usually lead to moral hazard and selection bias, and therefore it may not be a sustainable option in the long run. This paper predicts that a public agency's subsidized credit program may be useful for increasing access to finance for SMEs at a lower cost if certain conditions are met: the agency provides funds to banks at a lower cost and identifies good SME borrowers through their skills development programs and introduces them with banks. In this process, the agency provides certain implicit guarantees, though they will not bear the cost of default, if there is any. It could be termed a public-private partnership in SME financing. The paper further suggests that introducing a digital financing mechanism in the model for fund transfers and repayment with credit risk information of the borrowers through credit scoring for each borrower could improve SME financing even without subsidized funds from the government agency.

We use the data from a survey of both CW beneficiaries and non-beneficiaries for our empirical analysis in support of our theoretical model. The prediction of our theoretical model is consistent with the outcome of the CW program in Bangladesh. We consider the case of Bangladesh mainly because of the availability of an SME financing model close to our theoretical model. Alike other developing countries, SMEs are more prominent in Bangladesh in its industrial structure (over 95% are SMEs). Nonetheless, access to finance has been a perennial problem for SME development all over the world. The CW program runs well so far with improved SMEs' performance as well as the lending conditions of the program, which could be instrumental to support our theoretical framework of the financing strategies.

The paper is organized as follows. Section 2 provides theoretical model frameworks for two alternative financing strategies for SMEs. Section 3 discusses the CW program, data, and variables for empirical analysis. Section 4 develops empirical strategies and discusses the results. Section 5 concludes the paper.

2. Theoretical Model Framework for SME Financing Strategies

We develop a simple theoretical model following [10] to derive sustainable financing strategies for SMEs considering the borrowing constraints of SMEs. The model framework conceptualizes and identifies conditions for financing SMEs involving three sectors, such as banks, SMEs, and the government (See Figure 1).

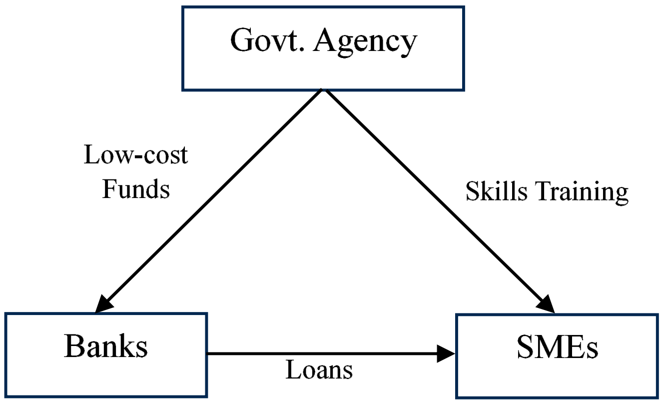

Figure 1. The Model Framework.

2.1. Government's Policy Objective Function

The equation below shows the policy objective function of the government:

$$\cup = \omega_1 (L - L^*)^2 + \omega_2 (\rho - \rho^*)^2 \tag{1}$$

where U is the government's objective function. Equation (1) shows that the government has two objectives while determining bank loans to SMEs. The first objective is to ensure the optimal quantity of loans to SMEs $(L - L^*)$ where L is actual SME loans and L^* is desired SME loans. The second objective of the government is to set the nonperforming loans ratio to the desired ratio $(\rho - \rho^*)$, here ρ is the current default loan ratio, and ρ^* is the desired default loan ratio. ω_1 and ω_2 in Equation (1) are the policy weights for the two objectives. ω_1 is the weight for optimal SME loans, and ω_2 is the weight for reducing the nonperforming loan ratio. If the two objectives have equal weight, then $\omega_1 = \omega_2 = 0.5$. In Equation (1), $L^* = (1 + a)L_{t-1}$, a is the desired growth rate of SME loans and is set by the government. And in Equation (1), $\rho^* = (1 + b)\rho_{t-1}$ b is the change in the desired nonperforming loan ratio compared with the previous year.

The loan demand function for Equation (1) is:

$$L = \alpha_0 - \alpha_1 r_l + \alpha_2 Y^e \tag{2}$$

where α_0 is the fixed demand for loans, r_l is the loan interest rate, and Y^e is the expected output of SMEs. α_1 is the coefficient of the interest rate on loans and is theoretically negative.

When the interest rate increases, the demand for loans decreases, which means the slope of the function is negative. In good economic conditions, demand for loans will increase, hence α_2 is expected to be positive.

2.2. SME Sector

In this section, we look at the firm's (SME) behavior in order to obtain the loan demand equation. In Equation (3) we assume a Cobb-Douglas production function for the SMEs:

$$Y = Y(N, K) = Y(N, K(\rho)) = N^{\alpha}[K(\rho)]^{1-\alpha} \tag{3}$$

where Y is the total output of the SMEs, N and K is the labor input and capital input of the SMEs, respectively. Labor input is equal to labor (N) and capital (loan) is a function of the default risk of the bank. Next, the firm's objective function is defined in Equation (4):

$$\pi = P \times Y(N, K(\rho)) - w \times N - r \times K \tag{4}$$

where π denotes the firm's (SME) profit with respect to L and L*, where P is the price of the firm's product, and w is the wage rate. We are assuming that the capital of the firm is only coming from a bank loan, ($L^d = K$).

The firm is maximizing its profit, hence we get the first order condition π with respect to K and write it in Equation (5):

$$\frac{\partial \pi}{\partial K} = (1-\alpha)\frac{P \times Y(\rho)}{K(\rho)} - r = 0 \tag{5}$$

Solving Equation (5), we get K in Equation (6):

$$K(\rho) = \frac{(1-\alpha)P \times Y(\rho)}{r} \tag{6}$$

Then replacing K by loan demand in Equation (6), we get

$$L^d = \frac{P \times (1-\alpha) \times Y(N, K(\rho))}{r} \tag{7}$$

The log-linear form of Equation (7) is thus

$$l^d = K(\rho) = -\beta r + \gamma(1-\alpha)P \times Y(N, K(\rho)) \tag{8}$$

If an agency provides training to the firm's employees, then human capital will be more productive. In that case, we assume $N = N^*$ and if the agency provides loanable funds (deposit) to the bank, it is assumed that the default risk ratio will decline. In that case, $\rho = \rho^*$

Now, the loan demand will increase from good firms with lower interest rates because banks are willing to provide loans to SMEs due to the lower default ratio. The log-linear loan demand function will thus be as follows:

$$l^{d*} = -\beta \times r^* + \gamma \times (1-\alpha) \times P \times Y\big(N, K(\rho^*)\big) \tag{9}$$

2.3. Banking Sector

Assuming that π denotes the bank's profit, r_l denotes a bank's lending interest rate, r_l^* denotes the bank's lending interest rate under the subsidized government credit program (desired interest rate), L^s is the amount of the bank loan, ρ is default risk of bank loans, which is dependent on the information about the borrower (g) and the marginal cost (or, transaction costs) of lending, MC. r_D denotes the deposit interest rate, D is the amount of deposits that banks receive, and C denotes the total costs of the bank, which is a function of loan supply, and the amount of deposits. For simplicity, we are assuming that the supply of loans is equal to deposits and the capital of the bank is zero (as banks' main source of funds is deposits due to low exposure to the capital market) and banks keep all of their assets in the form of loans and all of the banks' debts are in the form of deposits. The objective is to maximize the profit function of a bank:

$$\text{Max. } \pi^b = r_l \times L^s - \rho(g) \times L^s - r_D \times (L^s - A) - C(L^s, D) \tag{10}$$

$$S.t.\ balance\ sheet\ of\ a\ bank : L^s = D + \overline{A}$$

The cost function of a bank is:

$$C(L^s, D) = C_1(L^s)^2 + C_2(D)^2 + C_3(D \times L^s) \tag{11}$$

Now, the first order condition turns out to be:

$$\frac{\partial \pi}{\partial L^s} = r_l - \rho(g, MC) \times L^s - r_D - 2C_1 \times L^s - C_3 \times D = 0$$

Then,

$$L^s = \frac{1}{2C_1}[r_l - \rho(g, MC) - r_D - C_3 \times D] \tag{12}$$

where $\rho = \rho(g, MC)$, that is, the loan default ratio is a function of information about the borrower (g), and the marginal cost of the loan. Here g presents information about SMEs' performance including its credit worthiness, and the marginal cost of the loan, $MC = \frac{\partial C}{\partial L^s}$.

If an agency provides a certain amount of subsidized loanable funds to the bank (D_A) to increase its supply of loans with information about the creditworthiness of the borrower, (say, g), then the total deposit of a bank will stand out to be:

$$D^* = D + D_A$$

Then the new profit function of the bank with government support (agency intervention) will be

$$\pi^* = {r_l}^* \times L^* - \rho^*(g, MC) \times L^* - {r_D}^* \times (L^* - A) - C^*(L^*, D^*) \tag{13}$$

Then solving $\frac{\partial \pi^*}{\partial L^*} = 0$, the desired loan is L^* in Equation (14).

$$L^* = \frac{1}{2C_1}[{r_l}^* - \rho^*(g, MC) - {r_D}^* - C_3 \times D^*] \tag{14}$$

Equation (14) reveals that lending to SMEs will increase as the transaction costs of lending (C_1) go down because of lower default risk with better information about the borrowers. In Equation (14), the interest rate is expected to go down due to an improvement in the loan default ratio. Given that L converges to L^*, then $r_l \to r_l^*$ if $\rho \to \rho^*$. This satisfies the government's policy objective function.

Hence, in the government's agency-based lending program for SMEs, the bank's performance is expected to be better as the indicators are better than the usual situation as indicated below:

$$C^* < C, r^* < r, \rho^*(g) < \rho, D^* > D$$

2.4. A Blended Approach: Digital Finance with Agency Information

The previous section discusses an innovative agency-based approach that involves two distinct features: the government agency provides funds to banks and information about the borrowers who received training from the agency. Both the funds and information about the borrower reduce fund constraints and default risks of the banks and therefore increase access to low-cost formal finance for the SMEs. This model apparently works better with limited coverage and scopes. However, as the government's funds are limited, it is very unlikely to scale up the program. Moreover, this financing strategy might induce moral hazard problems in the selection of borrowers, which might jeopardize the model in the long run. Therefore, it is important to find a sustainable solution to the problems involved in the financing model.

Against the backdrop, we extend the model with two improvements: (i) to avoid borrower selection biases and widen the coverage of the program, instead of providing funds to the banks, in this model the government (a dedicated government agency) provides credit information of the SME borrowers to banks by making a credit scoring of the SME borrowers through credit risk analysis of the respective SMEs, and (ii) the banks use the scores to disburse loans under a digital financing method in order to reduce transaction costs and default risks that will facilitate faster loan disbursement and recovery process [19]. In this model, it is crucial for the government to set up a dedicated agency such as the Credit Risk Database (CRD) of Japan [20] (Japan's CRD is a successful database, which is created by the CRD Association. The members of the CRD Association maintain the database by offering SME financial statements. The Small and Medium Enterprise Agency of the Ministry of Economy, Trade and Industry provides funds to the CRD Association for the development of CRD. The public sector also offered human resources to establish the CRD.) to collect credit information of SMEs and provide big data analytics to come up with a credit score for each of the SMEs based on their previous credit history. The credit risk score may be fine-tuned with various types of methods, such as Artificial Neural Networks, Fuzzy logic, Vague data, psychometric algorithms, statistical regressions, etc. [21–25].

The model is expected to reduce banks' transaction costs for lending ($\mathrm{MC_{ICT}}$) and improve loan default ratio, ρ_{ICT}. Use of the digital platform, either the mobile financial service (MFS) or agent banking or any other form is possible as the credit size for SMEs is reasonably lower than the larger firms [19]. In this model, we assume that ρ_{ICT} is a function of information about the borrowers from the CRD and the marginal cost of lending through a digital platform. Then,

$$\rho_{ICT} = (g_{CRD}, MC_{ICT}) \tag{15}$$

Equation (14) will now take the form

$$L^*{}_{ICT} = \frac{1}{2C_{1(ICT)}}\left[r_I{}^* - \rho^*(g_{CRD}, MC_{ICT}) - r_D{}^* - C_{3(ICT)} \times D^*\right] \tag{16}$$

Thus, the digital microfinance $L^*{}_{ICT}$ will depend on the marginal cost of lending $\mathrm{C_{1ICT}}$ through digital finance, which is expected to be lower than $\mathrm{C_1}$ in Equation (14). Whether $L^*{}_{ICT}$ is greater than $\mathrm{L^*}$ in Equation (14) depends on the successful implementation of digital financing strategies of the banks and CRD. Presumably, Equation (16) provides better results with higher coverage and in that perspective, the blended approach in Equation (16) is likely to produce better results than the subsidized lending-based approach in Equation (14).

A comparative scenario of outcomes of the three financing strategies (Equation (12) (baseline), Equation (14) (subsidized fund), and Equation (16) (CRD and digital finance)) is shown in a simple Figure 2. Note that in the agency-based credit program, the interest rate is $r^* = r_A + \rho^* + MC^*$, that is, the interest rate will be determined by the agency's subsidized interest rate to banks ($\mathrm{r_A}$), new default risk (ρ^*) and marginal costs of the bank (MC^*). In Figure 2, the middle line represents the supply and demand for loans in a subsidized agency-based credit program, which is better than the usual SME credit programs of the banks (baseline). The third line represents the supply and demand for loans in a proposed blended approach of a CRD-based digital finance program, which is better than the agency-based subsidized credit program.

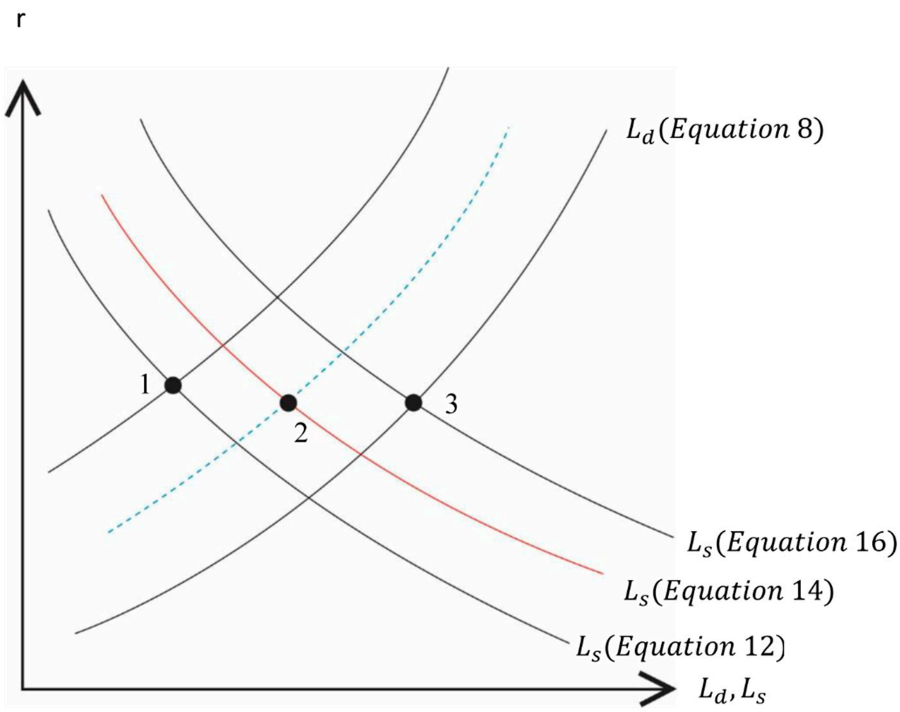

Figure 2. Impact of agency's subsidized fund on bank's loan performance.

Figure 2 shows that the bank's default rate will decrease and so does MC due to the government's subsidized loan fund and information about good borrowers. The equilibrium loan position will shift from (1) to (2), that is, the interest rate will decrease for the beneficiaries, and therefore the supply of loans will increase. With further innovations in model 2, the loan equilibrium position will further shift from point (2) to point (3) in the long run. This point determines the desirable amount of credit to SMEs with the possible lower interest rate because of the lower loan default ratio. These positive outcomes are expected to overcome financing bottlenecks for SMEs. Even credit guarantee schemes or other existing schemes may be accommodated in our proposed blended approach.

3. The CW Program, Data, and Variables

3.1. The CW Program

Our theoretical model predicts that a government agency-based program with a supply of loanable funds and information about borrowers could be beneficial for both the banks and borrowers as it reduces the default risk of the banks and thereby increase access to finance with lower interest rates for the borrowers. We evaluate a similar program, namely the Credit Wholesale Program of Bangladesh, which is run by a government agency, the SME Foundation (SMEF) of Bangladesh. Note that SMEs constitute over 95% of all industrial units and are considered as the engine of growth of a fast growing country, Bangladesh [26]. SMEF initiated the CW program in 2009 with the objective of ensuring the supply of loans to SMEs without collateral and at a single-digit rate of interest (say, 9%, which is lower than the market rate). Under the program, SMEF provides funds to partner financial institutions (PFIs) at a 4–5% interest rate (lower than the deposit rate of the banks) so that they can have an interest margin of about 4–5%. Furthermore, the borrower SMEs are selected from the pool of SMEF beneficiaries who had received training on business support services, and for the sake of better selection, the program is restricted to only the country's 177 SME clusters.

Furthermore, beneficiary banks in some cases adopt a group-based lending approach like the one adopted widely in micro-credit programs to reduce the default risk (Joint-liability mechanism works successfully as a safeguard against credit default in many micro-credit programs, particularly in Bangladesh [27,28]. Therefore, these two criteria of selecting borrowers—an SMEF beneficiary and being a part of group-based lending—reduce the asymmetry of information about the borrowers and increases the probability of loan repayment significantly. Therefore, these repayment criteria make banks willing to implement the program with lower interest rates and without any collateral or guarantor. Here the identification of a firm by the SMEF and introducing them to banks work as an implicit guarantee (without any collateral) about the credit repayment. In reality, over 95% of repayment confirms the working of this strategy. Furthermore, since the beneficiary firms receive various types of training on skills development and business improvement, they are in need of financing, which is met by the CW program. Therefore, receiving loans might have an incremental beneficial impact on the performances of the firms, which also facilitated repayment of loans under the CW program.

The CW program's coverage in terms of both loan amount and the number of beneficiaries is limited due to the fund constraints of the SME Foundation. The program has so far disbursed Tk. Tk 2271.5 million to 5000 micro and small enterprises with a substantial number being woman entrepreneurs. From 2009 to 2017, though the overall disbursement had an annual growth of 53.75%, the credit amount is still meager compared to SMEs' needs, ranging between Tk. 0.05 to 2 million with a maximum of 4 years of loan repayment period (Figure 3).

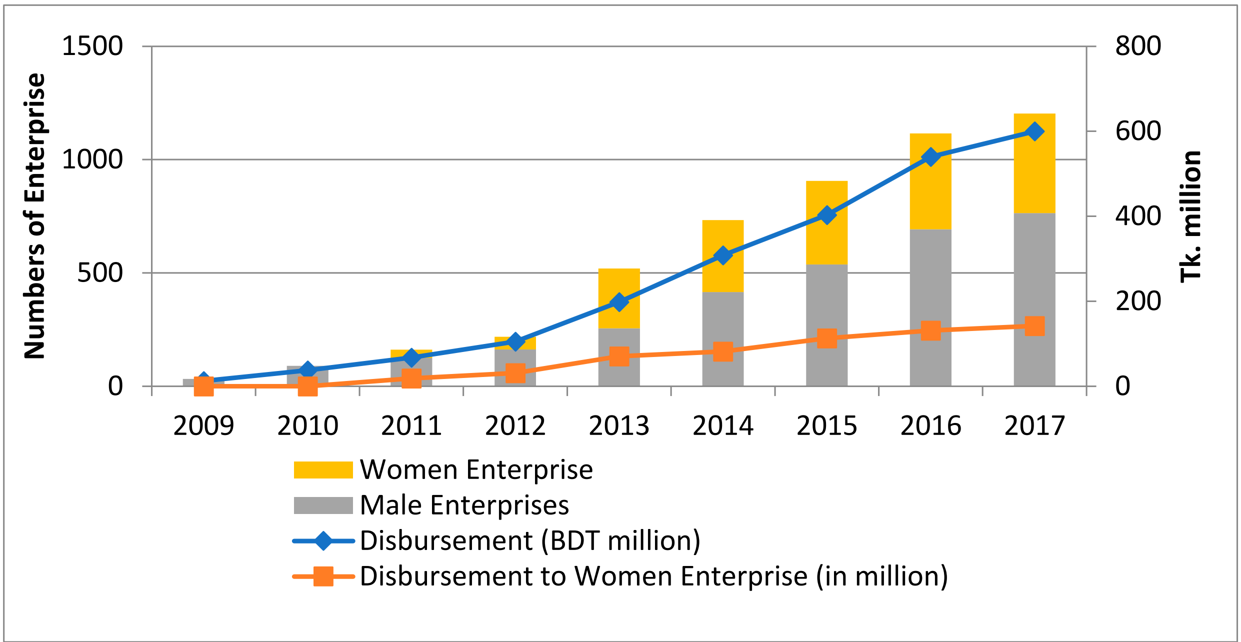

Figure 3. Growth of beneficiaries and amount of credit under CW program [14].

Survey [29] results show that credit from the CW program can meet up only 51 percent of financing needs of SMEs and it contributes to 26% of total loan portfolio and 36% of other loans of the firms in 2016 (Figure 4). The main source of credit is personal savings (49.5%) followed by commercial banks (32%). The rate of interest on credit is the lowest for the CW program (9 percent) compared to other sources. The interest rate on credit offered by other commercial banks was reported to be approximately 11 percent for SMEs and this rate jumps to around 15 percent when the loan is taken from NGOs or other private institutions. Figures 3 and 4 thus indicate the limited coverage of the CW program despite its popularity.

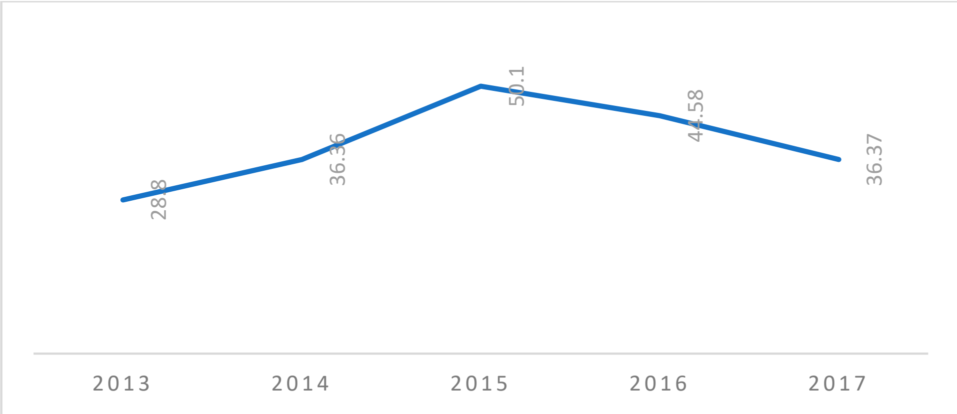

Figure 4. CW loan as a percentage of other loans, 2013–2017 [29].

The CW beneficiary firms appear to receive a higher amount of credit from banks compared to non-beneficiaries indicating a positive spill-over effect of the CW program (Table 1). The reason could be that firms who receive CW credit, they appear to be more trustworthy and creditworthy as they were identified by SMEF. Similarly, such recognition helps them to get commercial bank loans relatively at a lower rate.

Table 1. Loan volume, interest rate and finance gap.

A. Amount of Loan (Last 5 Years) across Sources				
	Treatment (CW beneficiary)	Control	Diff.	*p* value
Loan from banks	3,133,833	1,063,750	1,412,542	0.03
Loan from CW program	546,217.9	–	–	–
Loan from personal sources	600,000	204,285.7	−196,574.1	0.65
NGOs/microfinance institutions	4,850,000	664,815.4	−4,185,185	0.02
Others	40,000	186,111.1	146,111.1	-
B. Interest on loan (%)				
Commercial bank	10.81	10.92	0.11	0.85
CW program	9.00	–		
Personal sources	12	12	0	–
NGOs/ pvt. Institutions	15.25	15.20	0.05	0.97
Others *	10	12.40	-	-
B. Financing gap according to the sources of finance (%)				
Commercial bank	46	67.07	21.07	0.01
CW program	51	–		
Personal sources	50	69.22	19.22	0.34
NGOs/ pvt. Institutions	42.25	54.69	12.44	0.45
Others *	10	12.40	-	-

* small sample; Source: [29].

3.2. Data and Variables

We use the data of 526 SMEs taken from a survey conducted in January-February 2018 across 6 divisions and 10 districts of Bangladesh among both CW beneficiary and non-beneficiary firms including manufacturing and service enterprises [29]. In the analysis, the sample size varies based on missing information. (After 2018, this survey was not carried out further. Due to COVID-19, it was even not possible to do a similar survey. However, our main objective is to examine the impact of the CW program on firms' performances, which has nothing to do with the time period during which the data was collected.). Of the sample firms, 83% are manufacturing and 17% are service firms. Sample firms were selected from the list of beneficiaries of SMEF (who received training from the SMEF) across clusters in different locations using the PPS (probability proportional to size) method. Through this process, a total of 104 CW beneficiary enterprises (if a firm receives credit from the CW program in the last 4 years) are selected, and the rest 381 enterprises belong to non-CW beneficiary (control) enterprises. For the final analysis, we have used information from a total of 485 firms.

Access to the CW program is the key outcome variable. In addition to some common factors, such as age and gender of owner, size, and age of firm, manufacturing type, ownership type, etc., we include lagged values of some performance indicators to see whether firms were selected for CW loans based on their previous year's performances.

4. Estimation Strategy and Results

In our theoretical model, it is anticipated that access to a government agency-supported finance program with borrower identification criteria will increase the output of SME firms. Our empirical analysis in this section will therefore assess whether access to finance from the CW program enhances SMEs performances and allows them to access additional funds from banks. Since the reported default rate for this program is less than 5 percent, we do not estimate the default rate (ρ). As the loan amount is given, we, therefore, do not restrict our empirical analysis to estimating the model parameters, such as loan demand (L) and default ratio (ρ).

4.1. Determinants of Firm's Access to CW Program

Given the importance of the firm's selection process for the CW program, we examine here what determines a firm's access to the CW program. We estimate the reduced form equation as follows:

$$C_{it} = \alpha + \beta X_{it} + \varepsilon_{it} \tag{17}$$

where C_{it} is firm i's access to the CW program in year t, X_{it} is a set of firm-level characteristics and ε_{it} is an unobserved random error term. β are unknown parameters to be estimated.

We consider the access of firms to the CW program for the years 2014–2017 as the outcome variable. Since access to CW is a dummy variable, we apply the *probit* model to determine the factors. To assess the sensitivity over time, we run several regressions over the years 2014–2017. The results are reported in Table 2. The results suggest that 'women entrepreneurs', 'belong to a cluster', and 'received training from SME Foundation' are the key factors that determine firms' access to loans from the CW program. These findings are consistent with the basic criteria for eligibility of a firm to receive credit from the program. However, the previous year's performance of a firm was not found significant for receiving loans from the CW program, which allows us to assess the performance of the firms after its access to CW loans (In the survey, information on performance indicators of firms, such as sales, production, profit, etc. was collected for several years on a retrospective basis.).

4.2. Impact of CW on Firm Performances

Though the above analysis rules out the possibility of selection bias towards better firms for CW loans, still there might have some unobserved factors that might affect the firm selection process. Therefore, to overcome endogeneity biases or reverse causation, we adopt several estimation strategies.

Table 2. Determinants of Firm's Access to CW Program (Probit model).

	(1)	(2)	(3)	(4)	(5)
Variables	**CW in 2017 (T = 42; C = 348)**	**CW in 2016 (T = 37; C = 228)**	**CW in 2015 (T = 40; C = 308)**	**CW in 2014 (T = 12; C = 303)**	**All (T = 104; C = 333)**
Age of owner	−0.001	−0.008 ***	−0.001	−0.000	−0.006 ***
	(0.001)	(0.003)	(0.001)	(0.000)	(.002)
Gender of owner (1 = men, 0 = women)	−0.078 **	−0.131 **	−0.030	0.017 ***	−0.115 ***
	(0.035)	(0.055)	(0.033)	(0.006)	(0.052)
Enterprise size (1 = micro; 2 = small; 3 = medium)	−0.001	0.019	0.014	0.004	−0.023
	(0.014)	(0.028)	(0.016)	(0.005)	(0.022)
Manufacturing type (1–38 categories)	0.004	−0.009 *	−0.000	−0.004	−0.0034
	(0.002)	(0.005)	(0.003)	(0.002)	(0.0057)
Belong to a cluster	0.095 **	0.104 **	0.079 **	−0.009	0.162 ***
	(0.043)	(0.050)	(0.040)	(0.009)	(0.058)
Ownership type	−0.039	–	−0.089 *	0.011	−0.236 ***
	(0.029)		(0.051)	(0.012)	(0.078)
Member of a business association (1 = yes, 0 = no)	0.048 *	0.030	−0.023	0.013 **	−0.0088
	(0.024)	(0.039)	(0.031)	(0.007)	(0.045)
Age of firm	0.002	0.003	0.001	0.001	0.0111 ***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)
Have a bank account	0.050 **	–	0.069 **	0.007	0.189 ***
	(0.025)		(0.027)	(0.009)	(0.042)
Lagged Profit (%)	0.002	0.002	0.000	−0.001 **	–
	(0.001)	(0.002)	(0.001)	(0.001)	
Lagged log(sale)	−0.002	−0.016	0.022 **	0.002	–
	(0.008)	(0.015)	(0.011)	(0.002)	
Have taken training from SMEF	0.055 ***	0.022	0.103 ***	0.003	0.161 ***
	(0.021)	(0.042)	(0.026)	(0.007)	(0.037)
Lagged log (employee)	0.015	0.050 *	0.001	−0.007	–
	(0.013)	(0.029)	(0.016)	(0.005)	
Observations	390	265	348	315	437

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Lagged values for some performance indicators are used to examine whether a firm's performance did matter to get access to the CW program. Marginal effects are reported. T represents treatment (CW beneficiary) and C represents control (non CW-beneficiary). In Regression (5), all the CW beneficiaries during 2013–2017 are included in the model and dropped the performance variables from the regression as their access does not commensurate with yearly performances.

First, we adopt an estimation strategy involving firms that received CW loans in different years over the 2013–2017 period within the cluster. Out of 104 CW beneficiaries, 8 firms received credit in 2013, 11 firms in 2014, 37 firms in 2015, 31 firms in 2016, and 17 firms in 2017 (See Table 3). So, for 2013, 8 firms are considered as treatment, and the rest 477 firms are considered as control. Similarly, for 2014, 19 firms (8 in 2013 plus 11 in 2014) are treatment and the rest are control, and so on. And then we apply the difference-in-differences estimation techniques as described below in Equation (18) to obtain the impact of CW loans on different indicators of firm performances. This estimation strategy allows us to control for selection biases with a large number of control firms that have received similar skills development interventions from the SMEF.

Again, we wanted to see the impact of CW loans if all the SME beneficiary firms are considered. Our motivation here is that since all non-CW beneficiary 381 firms received training and consultancy support from the SMEF, comparing them with CW loan beneficiaries will provide a better understanding of the impact of access to formal finance on firms' performances.

Table 3. Impact of CW on firm performances.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Log (Sales Revenue) (Only Treated Firms)**	**Log (Sales Revenue) (All SMEF Beneficiaries)**	**Profit (Only Treated Firms)**	**Profit (All SMEF Beneficiaries)**	**Log (Productivity) (Only Treated Firms)**	**Log (Productivity) (All SMEF Beneficiaries)**
Time	−2.817 ***	−3.205 ***	−0.088 ***	−0.129 ***	−2.523 ***	−2.540 ***
	(0.238)	(0.101)	(0.007)	(0.012)	(0.291)	(0.209)
Treated	0.160	0.179 **	0.016 **	0.020	0.098	0.080
	(0.136)	(0.088)	(0.008)	(0.015)	(0.122)	(0.077)
Diff-in-diff	3.047 ***	3.422 ***	0.061 ***	0.101 ***	2.632 ***	2.616 ***
(Time*treated)	(0.268)	(0.134)	(0.012)	(0.020)	(0.306)	(0.224)
Small	−1.821 ***	0.624 ***	0.057 ***	−0.116 ***	−2.980 ***	0.284 **
	(0.553)	(0.154)	(0.009)	(0.020)	(0.396)	(0.126)
Micro	0.537 ***	0.723 ***	−0.002	−0.049 ***	0.206	0.289 ***
	(0.133)	(0.071)	(0.006)	(0.015)	(0.138)	(0.060)
Manufacturer	0.827 ***	0.729 ***	−0.086 ***	−0.079 ***	0.202	0.249 ***
	(0.213)	(0.093)	(0.010)	(0.018)	(0.207)	(0.073)
Firm’s age (years)	0.014 **	0.056 ***	0.000	−0.000	−0.000	0.016 ***
	(0.006)	(0.006)	(0.000)	(0.001)	(0.006)	(0.004)
Months of operation (in a year)	0.446 ***	0.407 ***	−0.010	0.027 ***	0.422 ***	0.318 ***
	(0.083)	(0.047)	(0.007)	(0.003)	(0.068)	(0.039)
Age of firm owner	0.016 **	0.002	−0.000	−0.000	0.005	0.005
	(0.008)	(0.005)	(0.000)	(0.001)	(0.007)	(0.004)
Gender of firm owner	−0.165	−0.700 ***	0.015 **	0.046 ***	0.038	−0.417 ***
	(0.147)	(0.084)	(0.007)	(0.010)	(0.146)	(0.068)
Education of owner	−0.036 *	0.075 ***	−0.010 ***	−0.008 ***	−0.047 ***	−0.011
	(0.020)	(0.015)	(0.001)	(0.002)	(0.017)	(0.012)
Constant	7.862 ***	8.175 ***	0.534 ***	0.084 *	7.605 ***	8.991 ***
	(1.102)	(0.595)	(0.086)	(0.049)	(0.958)	(0.495)
Observations	485	1618	485	1618	485	1616
R-squared	0.441	0.435	0.154	0.197	0.288	0.169

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We first run the following difference-in-difference regression.

$$Y_{it} = \beta_0 + \beta_1 Time_{it} + \beta_2 Treatment_{it} + \beta_3 Time_{it} \times Treatment_{it} + X_{it} + u_{it} \quad (18)$$

where Y_{it} is the outcome indicator for firm i in period t, t includes 2013–2017. The variable $Time_{it}$ is a dummy variable that takes the value of 1 if the year corresponds to the year(s) after the intervention (CW loan) is received and zero otherwise. This *time* variable captures the impact of the duration since the first CW loan is taken. The *Treatment* variable is also a dummy variable which is 1 if the firm received the CW loan anytime between 2013–2017 and 0 otherwise. β_1 captures the time trend common to treatment and control firms. β_2 accounts for the average permanent difference in outcome variables between the treatment and control firms. The coefficient β_3 captures the treatment effect (difference-in-differences)—the impact of CW on the outcome variables. We run OLS to estimate the impact of CW loans at the firm level. We use a wide range of control variables (X_{it}) that might have a bearing on the likelihood of being treated. These include firm size, location of the firms, whether the firm is a member of a business association, types of ownership, age of the factory, and so on.

The results are reported in Table 3. Columns 1, 3 and 5 report the results for the treated firms only while columns 2, 4 and 6 report the results for the combined sample for different time periods (years). The difference-in-differences variable is significant and positive for all the specifications implying that the CW program has a positive and significant impact on firms’ sales revenue, profit and productivity over time. Firm size, years of operation, gender of owners and education of owners are significant in most cases. While lower education matters, women owners are more productive. Age of firm owners does not have significant effect on firm performances.

4.3. Assessing Spillover Benefits of the CW Program

Further, we attempt to examine whether participation in the CW program has any spillover effect on firms' overall access to credit. For example, a firm's access to CW credit might facilitate its access to credit from other sources, such as banks and non-banks due to its good track record of loan repayment under the CW program as well as its relationship with banks. Therefore, we make an attempt to test further whether participation in the CW program has an impact on loan volume, loan interest rate, and reducing the financing gap. Thus, our regression model specification here is as follows:

$$F_{it} = \beta C_{it} + \gamma X_{it} + \varepsilon_{it} \tag{19}$$

where F_{it} represents financing indicators such as loan, interest rate, or finance gap, C_{it} represents a firm *i*'s access to the CW program at time *t* (1 if a firm gets credit under the CW program), and X_{it} is a set of firm-level characteristics. β and γ are unknown parameters to be estimated, and ε_{it} is a zero-mean disturbance term.

Following the specification Equation (19), we run several regressions in Table 4. First, in col. (1) we assess the impact of participation in the CW program on bank loans (other than CW loans) taken in 2017. We observe that CW participation has a negative but insignificant effect on firms' access to a bank loan. Next in col. (2) we assess whether CW participation has any impact on the total loan a firm received from various sources. We see that CW has a significant impact on a firm's access to loans implying that CW loan improves the firm's capacity to avail credit from other sources. Further, to substantiate the findings, we examine the impact of CW access on a ratio of bank loans over CW loans in col. (3). We find that participation in CW increases the amount of bank loan for the respective firm significantly indicating that a firm that receives a loan under the CW program has a higher probability of getting a loan from other sources. Next, from the regression results reported in col. (4) we observe that participation in the CW program reduces the financing gap of a firm significantly, which is about 59%. Finally, the results suggest that a CW beneficiary firm might enjoy some benefits from the bank because of its good reputation for loan repayment (lower default risk) with the bank. This analysis indirectly suggests that CW participation reduces the loan default risk of a bank. Moreover, relatively younger (as the age of the firm is negative and significant) but larger (as the total employee is positive and significant) firms can take advantage of their relationship with banks established through CW program participation.

This analysis motivates us that a subsidized loan program with information (training and other soft information) about the borrowers might increase the access to finance for SMEs and improves their performances. Due to the low default risk under this program, a bank became interested to provide loans to CW beneficiaries further from its regular program. The findings have interesting caveats. Information about the credit track record of a firm (SMEs) plays a crucial role for further opportunities for the firm's access to additional finance. Therefore, credit scoring based on a firm's previous credit history might be useful for credit disbursements to the firm. This is consistent with our theoretical proposition that credit risk analysis and a scoring method might play a crucial role in widening access to formal finance for SMEs. As digital finance methods could reduce transaction costs, adopting digital finance methods for SME finance could be a viable option for banks. Therefore, a credit-risk score might be instrumental in adopting digital finance for SMEs.

Table 4. OLS estimates on the impact of the CW program on firm's financial indicators.

	(1)	(2)	(3)	(4)	(5)
Variables	**Log (Bank Loan in 2017)**	**Log (Total Loan in 2017)**	**Ratio of Bank Loan over CW Loan**	**Log (Finance Gap)**	**Log (Interest Rate in 2017)**
CW (1 = beneficiary, 0 = non-beneficiary)	−0.332	2.840 ***	0.113 *	−0.594 ***	−0.022
	(−0.75)	(3.95)	(1.60)	(−3.74)	(−1.37)
Enterprise size	−0.209	−0.134	−0.009	−0.012	0.000
	(−0.97)	(−0.50)	(−0.58)	(−0.15)	(0.08)
Age of firm	−0.065 ***	−0.078 ***	−0.000	−0.023 ***	0.000
	(−3.62)	(−3.36)	(−0.22)	(−3.16)	(0.67)
Owner's education	0.215	−0.455 *	0.025	0.003	−0.005
	(1.18)	(−1.77)	(1.23)	(0.05)	(−1.46)
Log (total employee in 2017)	0.876 ***	1.246 ***	0.038 *	0.446 ***	−0.004
	(3.89)	(4.45)	(1.92)	(5.06)	(−1.12)
Training received from SMEF	−0.408	−0.456	0.008	−0.070	−0.006
	(−1.04)	(−0.92)	(0.38)	(−0.49)	(−0.86)
Participated in SME Fair	0.150	−0.602	0.012	0.488 ***	−0.012
	(0.40)	(−1.10)	(0.56)	(3.09)	(−1.38)
Constant	2.353 **	5.216 ***	−0.106	0.719	0.027
	(1.98)	(3.27)	(−1.08)	(1.55)	(1.18)
Observations	507	507	507	507	507
R-squared	0.074	0.134	0.044	0.133	0.986

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A sustainable financing strategy for SMEs should aim to enhance the supply of loanable funds to banks with a provision to identify good borrowers, reducing bank transaction costs and default risks. This purpose is being served by the CW program. However, the CW program works better because of its low coverage and low scalability. This also allows banks to apply a joint-liability approach. But the challenge lies with scaling up the program where joint liability may or may not work if firms are not located in a cluster or clientele. In that situation, the role of the institution that will be in charge of SME financing will be crucial, particularly in identifying the borrowers. Further, choosing beneficiaries by an agency like SME Foundation might involve certain risks of moral hazard and politicization of the program. To address the problem, this paper suggests a digital finance model with support from a government agency dedicated to collecting and analyzing the credit risk of SMEs and preparing the credit scores of SMEs. The data-driven credit score can be estimated through regression analysis, using artificial intelligence, or Fuzzy logic or Neural Networks along with some psychometric algorithms [16]. We could not substantiate the idea with empirical results as the CW program does not adopt a digital finance approach yet.

5. Conclusions

This paper proposes two alternative financing models for SMEs. One is based on subsidized funds from the government channeled through banks and other financial institutions with support in selecting good borrowers. Under this financing strategy, emphasis has been given to the selection of borrowers in order to reduce selection biases and default risks. Since the selection of firms is based on skills development interventions, it will improve firms' performances as well as credit repayment capacity. Introducing good borrowers to banks 'by the government agency from the pool of their beneficiary firms here works as an implicit guarantee for banks, and therefore no guarantee or collaterals is required. This model, based on public-private partnership, attempts to correct the moral hazard problem of the existing models, such as the Credit Guarantee Scheme. The model predicts that with the convergence of loan volume for SMEs to a desired level due to the government's subsidized fund, and as the loan default risk is reduced with the identification of good borrowers, the financing model finally reduces interest rates for SME loans. The prediction of the model is largely consistent with a similar small-scale program, the Credit

Wholesale Program in Bangladesh. Therefore, we perform some empirical analyses to examine the outcomes of the program. Since the program is largely free from borrower selection biases, and the results are in line with the prediction of our theoretical model, the Credit Wholesale Program may be extended following the suggested theoretical model and replicated elsewhere.

In the process of scaling up the program, it might suffer from selection biases because of moral hazard and political interferences as the subsidized government fund is involved. To this end, we extend our model by involving digital technologies in disbursing and repaying loans. In this extended version, a data-driven credit score for each potential borrower will be estimated using various methods and based on the score, banks will decide to disburse loans. This mechanism might reduce the default risks as well as transaction costs of the banks, which will allow banks to charge a lower interest rate. The credit-score-based digital finance mechanism will reduce default risks if the credit score offers good predictive power.

A sustainable financing approach for SMEs is a long-standing objective of the respective governments, particularly in developing countries. Since the developing countries' governments do not have enough funds to cater to the needs of the SMEs, the governments could rather invest in creating institutions for providing skills development interventions and unbiased credit risk scores for SMEs. At the same time, governments should invest in facilitating digital financing platforms to accelerate the financing process. All the efforts together could provide a basis for sustainable financing for SMEs. Since we could not empirically test the implications of digital microfinance and its associated risks from Bangladesh data, future empirical research on digital microfinance will shed more light on various aspects of the proposed model.

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