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Credit Access and Adoption of ICT by Small and Medium Sized Enterprises in Togo

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Abstract

The study aims to analyse the impact of credit access on the adoption of ICT by Small and Medium sized enterprises (SMEs) in Togo. To achieve the objective, the study uses the general enterprises census data collected by the National Institute of Statistics and Economic and Demographic Studies (INSEED) in 2018 and a propensity score matching method. The results globally show that credit access has a positive and significant impact on ICT adoption. Access to credit increases the probability of Togolese SMEs adopting ICT by about 0.032-0.234, 0.025-0.157 and 0.020-0.147 percentage point for computer, internet, and e-business adoption, respectively. Credit access has a positive and significant impact on ICT adoption for all types of enterprises except for medium enterprises. The study therefore suggests increasing access to credit to increase ICT adoption among Togolese SMEs.

Key-words: Credit constraint, computer, internet, e-commerce, ICT adoption, SMEs,

JEL classification: D25, G30, L25, 016

1. Introduction

The factors contributing to the growth and development of small and medium-sized enterprises (SMEs) have long been the subject of controversy among researchers. While some authors stress the importance of environmental and external factors (legal and regulatory framework, access to finance) for the growth and development of SMEs (Lumpkin & Dess, 1996; Berger & Udell, 1998; St-Jean et al., 2008), other authors have shown that internal factors such as entrepreneurial characteristics and technological capabilities are the main determinants of the growth and development of small and medium-sized enterprises (Wasserman, 2008). Despite this controversy, there seems to be a consensus among researchers that access to credit is a major factor that stimulates SME growth over time (Page & Söderbom, 2015; Fowowe, 2017). Access to credit promotes the expansion, sustainability, and development of SMEs through increased working capital, technology acquisition, and infrastructure investment (Aterido et al., 2013). However, while many studies have shown the positive effect of access to credit on the growth and development of SMEs in the literature (Aterido et al., 2013; Fowowe, 2017), few or no studies have analysed the effect of access to credit on the adoption of information and communication technologies (ICT) in the literature.

Described as a catalyst for development in the literature of both developed and developing countries, ICT is at the heart of the new knowledge-based economy. They are a driver of innovation for enterprises, enabling them to create new products and services and to improve the design of their products (Tarutė & Gatautis, 2014). ICTs are also an important factor for progress, enabling enterprises to become more competitive and efficient in a market where competition is fierce (Paré & Sicotte, 2004). The effects of ICT on SMEs have been demonstrated in several studies in developing countries (Machikita & Tsuji, 2010; Charlo, 2011; Nour, 2011). For example, Nour (2011) in his research on the Arab Gulf countries finds positive correlations between total ICT expenditure, output, and turnover of firms. These positive effects of ICT are justified by, among other things, improved product quality, reduced production costs, and increased exports (Machikita & Tsuji, 2010). In the same vein, Gbandi et al. (2025), evaluating the effect of internet adoption and use on the performance of Togolese micro-enterprises in the service sector using a sample of 23,542 observations from the general business census (2017-2018), found that Togolese micro-enterprises that use ICT are more productive than those that do not. In Togo, the recent data from the general census of enterprises demonstrate the importance of ICT adoption for Togolese SMEs. Indeed, Togolese SMEs that use ICT have higher turnover than their counterparts that do not. While the turnover of SMEs with computer, internet, and e-business adoption is, respectively, 21.87, 22.82, and 19.24 million CFA Francs, the turnover of those without computer, internet, and e-business adoption is, respectively, 2.03, 2.36, and 2.73 million CFA Francs. The Togolese government also supports the development of ICT in Togo by updating laws and improving the budget in the ICT sector. Despite the importance of ICTs for enterprises and the Togolese government's role in enhancing the ICT sector, we still observe a weak adoption of ICTs by SMEs in Togo. In Togo, only 7.55%, 5.70%, and 4.83% of SMEs use a computer, have an internet connection, and conduct business operations online, respectively (INSEED, 2019). Moreover, ICT adoption rates among Togolese SMEs remain low compared to other SMEs in Sub-Saharan African countries such as Senegal (12.3% and 7.1% of SMEs use a computer and an internet connection, respectively¹), and Nigeria (20.8% of SMEs conduct business operations with an internet connection²).

SMEs in Togo are struggling to adopt ICTs due to their high cost relative to the purchasing power of SMEs. According to the International Telecommunication Union, the price of a fixed broadband internet package accounted for 41.5% of average monthly income in Togo in 2018, compared to 19.8% and 25.2% in Senegal

¹ Source : Agence Nationale de la Statistique et de la Démographie (ANSD, 2017)

² Source: National Bureau of Statistics (Nigeria) (NBS, 2017).

and Nigeria, respectively. The same is true for mobile broadband data packages, which require Togolese to spend 16.6% of their average monthly income, compared to other countries such as Senegal and Nigeria, where the share of the price of this package is relatively lower. In view of these stylized facts, easy access to credit would help mitigate the high cost of ICT adoption by Togolese SMEs, but we notice that only 19.6% of SMEs in Togo have access to credit (INSEED, 2019) compared to 18.3% in Senegal (ANSD, 2017) and 49.5% in Nigeria (NBS, 2017). From this observation, we ask ourselves whether there is a cause-and-effect relationship between the low access to credit of Togolese SMEs and their low adoption of ICTs; in other words, does access to credit have an impact on the adoption of ICTs by Togolese SMEs?

Previous studies have consistently demonstrated that access to credit positively influences the investment behaviour of small and medium-sized enterprises (SMEs), particularly in developing economies (Regis, 2018; Aivazian & Santor, 2008). However, to our knowledge, no study in the literature has attempted to assess the impact of credit access on SMEs' ICT investments (SMEs' ICT adoption). Most existing research has focused on the inverse relationship, examining how ICT adoption affects SMEs' ability to secure credit (Pellegrina et al., 2017; Mushtaq et al., 2022). This study addresses this gap by shifting the analytical focus to the direct effect of credit access on ICT adoption, thereby contributing new insights into the financial determinants of technological uptake among SMEs. To achieve this objective, the study uses data from 59,043 SMEs obtained from the general enterprises census conducted by the National Institute of Statistics and Economic and Demographic Studies (INSEED) between 2017 and 2018. The results, which are obtained using both propensity score matching (PSM) and the recursive bivariate probit model, show that access to credit has a positive and significant impact on the adoption of ICT by Togolese SMEs. Specifically, access to credit increases the probability of Togolese SMEs to adopt ICT by about 0.032-0.234, 0.025-0.157, and 0.020-0.147 percentage points for computer, internet, and e-business adoption, respectively.

The remainder of the study is organized as follows: Section 2 presents the literature review; Section 3 presents the methodology; Section 4 presents the results and discussion; and Section 5 concludes.

2. Review of the literature

Access to credit is an essential factor for the growth and development of SMEs (Page & Söderbom, 2015; Fowowe, 2017) and one important channel through which access to credit impacts the growth of SMEs is the adoption of innovations such as ICT (Wellalage & Fernandez, 2019; Qi & Ongena, 2020; Bakhouché, 2021). Access to credit may influence the adoption of ICT by SMEs through the increase of the investment capacity of firms. Indeed, SMEs often suffer from cash flow constraints that jeopardize their investment capacity. To invest in innovative technologies, SMEs can access credit, thereby increasing their investment capacity and enabling them to purchase ICT.

Numerous theories in economic literature have highlighted the factors influencing corporate investment. First, the neoclassical theory states that the main determinant of corporate investment is sales. For this theory, an increase in a company's sales leads to an increase in its investments. According to the free cash flow theory (Jorgenson, 1971), endogenous factors, such as cash flow, determine SME investment. In addition to these determinants, other theories examine years of firm existence, firm growth potential, interest rates, and gross national product as determinants of SME investment (Deakins et al., 1998). In the early 2000s, Manikowski and Tarapata (2001) also identified two fundamental approaches to SME investment. These two approaches are: the material approach, which concerns the movement of goods, and the financial approach, which concerns the movement of money. Subsequently, the following aspects of financial investments were distinguished: tangible assets (fixed assets, machinery and equipment), financial assets (acquisition of securities or shares), and

intangible assets (Ostrowska, 2002; Michalak, 2007). We note that all these theories revolve around financing as a key determinant of SME investment.

It is admitted in the literature that access to credit promotes the growth and development of SMEs through the financing of investments, research and development activities, innovations such as ICT, etc. (Adegboye & Iweriebor, 2018; Wellalage & Fernandez, 2019; Qi & Ongena, 2020; Bakhouché, 2021). This is particularly true in developing countries, where SMEs often have limited access to credit because financial markets are poorly developed, segmented, or subject to arbitrary credit allocation mechanisms (Aivazian & Santor, 2008). Several authors have reported that this limited access to credit has a negative effect on SME's decision to invest (Eskandar & Hadadi, 2022; Gerlach-Kristen et al., 2015; Aivazian & Santor, 2008). For example, Eskandar and Hadadi (2022) have shown using a sample of companies listed on the Tehran Stock Exchange from 2011 to 2018 that credit constraints have a negative effect on investment in the short term. Using both bivariate probit and instrumental variable least squares models, Gerlach-Kristen et al. (2015) also found that credit constraint had a negative effect on investment decisions of credit-rationed SMEs in Ireland. They also found that credit-rationed SMEs were significantly less likely to undertake investments and that the probability of investing was almost 50% lower for these SMEs compared to non-rationed SMEs. Similarly, using data on 304 SMEs to evaluate the impact of the World Bank's credit program in Sri Lanka, Aivazian & Santor (2008) found that the World Bank's loan subsidy program led to higher levels of investment for financially constrained firms. Similar results were also obtained in China by Regis (2018), who showed, using data on 2700 SMEs, that access to credit was among the firm characteristics with the most significant impact on the likelihood of investing.

Although past studies have shown that access to credit has a positive impact on the likelihood of an SME to invest in the literature (Regis, 2018; Aivazian & Santor, 2008), no study to our knowledge has attempted to assess the impact of access to credit on SMEs' ICT investments (SMEs' ICT adoption). Almost all studies that have specifically examined the relationship between access to credit and ICT adoption have instead focused on the effect of ICT adoption on SMEs' access to credit (Pellegrina et al., 2017; Mushtaq et al., 2022). This study, therefore, fills this gap in the literature by focusing solely on the impact of access to credit on ICT adoption. We know that access to credit could increase SMEs' ICT adoption by defraying the cost of ICT, which is one of the barriers to ICT adoption by SMEs (Walczuch et al., 2000; Love et al., 2005; Harindranath et al., 2008; Chimucheka, 2013). Alternatively, access to credit can permit SMEs to acquire key productive equipment, thereby slackening the firm's budget constraint and increasing investment in other equipment, such as ICT. That is why we formulate the following hypothesis: *H: Access to credit has a positive impact on ICT adoption by SMEs in Togo.*

3. Methodology

3.1. Source of data

We use the general enterprises census data collected by the National Institute of Statistics and Economic and Demographic Studies (INSEED) in 2018. Data were collected to fulfil five main objectives: providing data on enterprises that will serve to elaborate national accounts, assessing the economic structure and the position of economic institutions, building a unique system of identification, and updating the list of economic institutions (INSEED, 2019). Data collection was organised in two great stages: The preparatory stage and the collection stage. The preparatory stage concerns all activities that precede the collection stage, such as the constitution of personnel, the cartography of the census area, the preparation of technical documents, the awareness activities, etc. The cartography stage permitted the INSEED to subdivide the whole territory into 626 census areas and to have the spatial distribution of economic institutions present in each census area. In the collection stage, each census agent was sent to one census area with the list of economic institutions to survey. All geographically localised economic institutions were surveyed by the census agent. A geographically localised economic institution is an economic institution that has a professional hall or place³ where it runs its business activities (INSEED, 2019). The population census also included special economic institutions without a professional hall, such as woodwork, extraction activities, car wash, car repair, etc. It also included public hospitals and an artisanal bakery. The census agents were trained before the beginning of the survey, and a pilot survey was also done before the principal survey. The full details of the data collection method and the questionnaire can be found in INSEED (2019).

Overall, the data are made up of 119,318 diverse economic institutions, including shareholder companies, sole proprietorships, non-governmental organisations, associations, cooperatives, trade unions, etc. Although 75,126 economic institutions are SMEs⁴, only 59,043 SMEs are retained in this study because of missing data on some important key variables and the presence of outliers. Outliers for continuous variables only were removed from the sample with trimming performed at 0.5 and 99.5 percentiles. These SMEs are spatially distributed across the national territory as presented in Table 1.

Table 1: Spatial distribution of SMEs

Statistic region	Economic institutions	
	Number	Frequency (%)
Grand Lomé	33,421	56.60
Maritime	5,297	8.97
Plateaux	7,202	12.20
Centrale	5,159	8.74
Kara	4,115	6.97
Savanes	3,849	6.52
Total	59,043	100

Source: Author's construction based on INSEED data

3.2. Empirical strategy to measuring the impact of credit access on ICT adoption

Modelling of the impact of credit access on the adoption of ICT can be represented by the equation below:

$$ICT_i = Z_i'\lambda + \alpha CA_i + v_i \quad (1)$$

³ A professional hall or place is a hall which is built with durable material and that has a front-door (INSEED, 2019).

⁴ SMEs are enterprises with turnover less than 1 billion CFA

Where ICT_i , Z_i , CA_i and v_i are respectively the adoption of ICT, the vector of control variables, the credit access, and the error term. The credit access variable here is a dummy variable that takes the value 1 if SME i has received credit and 0 otherwise. The adoption of ICT is also measured by a dummy variable that takes the value 1 if SME i uses at least one type of ICT (computer, internet, e-business) and 0 otherwise. Definitions and measurement units of variables are synthesized in Table 2.

To estimate the impact of credit access on ICT adoption, we could use a probit model. However, such an approach would yield an unbiased result if credit access is exogenous and randomly distributed across credit recipients and non-credit recipients⁵. This is not the case because access to credit is endogenous to the adoption of ICT. Access to credit is endogenous either because there exist some observable and unobservable variables explaining access to credit, which are also correlated with the adoption of ICT (self-selection), or because the adoption of ICT by SMEs may influence access to credit (Pellegrina et al., 2017; Mushtaq et al., 2022) (simultaneity or reverse causality). Thus, failure to account for the endogeneity of access to credit will lead to a biased estimator of the impact of credit access on the adoption of ICT.

Following Takam-Fongang et al. (2019), we used the propensity score matching method to correct for selection bias resulting from observable differences between credit recipients and non-credit recipients. The propensity scores matching method proceeds in four steps as follows:

- *Step 1 consists of estimating the determinants of SMEs' access to credit.* Here, the following equation is estimated by a probit model since the dependent variable (access to credit) takes values 1 or 0:

$$CA_i = X_i' \beta + u_i \quad \text{with} \quad CA_i = \begin{cases} 1 & CA_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Where CA_i^* is a latent variable linked to the credit access CA_i . X_i is a set of matching variables which include legal status of the enterprise, firm formality, sex and age of the manager of the enterprise, land tenure security, involvement in export activities and size of the enterprise. The choice of these variables is guided by the literature review and the availability of data (Aga & Reilly, 2011; Rand & Torm, 2012; Kira & He, 2012; Wellalage & Locke, 2017; Wellalage et al., 2020; Mouhamed, 2021). For example, Wellalage & Locke (2017) show that SMEs with a female top manager are less likely to face credit constraints than SMEs with a male top manager in South Asian countries. A similar result has also been obtained by Wellalage et al. (2020) for India. The later authors also show that managers' experience has a positive effect on credit access, while belonging to the sole proprietorship group has a negative effect on credit access in India. In our study, a manager's experience is proxied by the age of the manager because of the absence of a manager's experience variable in the data set. Other studies also show that access to credit is associated with enterprise export activities of the enterprise (Wellalage et al., 2020; Mouhamed, 2021) and the size of the enterprise (Kira & He, 2012). According to these authors, access to credit increases with the size of the enterprise but also with the involvement of the enterprise in export activities. The variable formality is also included as an independent variable as several studies have shown that formality increases a firm's access to credit (Aga & Reilly, 2011; Rand & Torm, 2012).

- *Step 2 deals with the determination of common support and the balancing test.* To select the matching variables, we ensure that the assumptions of common support and conditional independence (balancing test) are verified. The kernel density test, the covariance equilibrium test, and the common support test are used to check the plausibility of these assumptions. A sensitivity analysis based on the "bounding approach" (the Mantel & Haenszel (1959) test) is performed to check for hidden bias.

- *Step 3 is the matching of credit recipients with non-credit recipients.* Four matching methods (nearest neighbour, stratification, radius, and kernel) are used to match credit recipients with non-credit recipient enterprises in order to ensure the robustness of our results. The advantages and disadvantages of matching methods are discussed in Appendix 1.

⁵ A credit recipient stands for a SME that has received a credit ($CA=1$) while a non-credit recipient is a SME that has not received a credit ($CA=0$).

- *Step 4 is the estimation of standard error.* This is done by the bootstrap method. This method consists of drawing a repeated sample from the original sample and rerun the entire estimation procedure with each sample. Thus, standard errors are obtained by computing the standard error of the distribution of estimators obtained from each bootstrap. Although there is little formal justification for the bootstrap method, it permits, however to obtain valid standard errors and confidence intervals for propensity score and regression methods (Imbens, 2004).

However, given that the endogeneity of access to credit might also result from reverse causality or simultaneity between access to credit and adoption of ICT, we also use the recursive bivariate probit model. The recursive bivariate probit model is used because both access to credit and adoption of ICT are dummy variables. Thus, the impact of credit access on the adoption of ICT is modelled as follows:

$$\begin{cases} ICT_i^* = Z_i'\lambda + \alpha CA_i + v_i \\ CA_i^* = X_i'\beta + u_i \end{cases} \quad (3)$$

Where ICT_i^* and CA_i^* are latent variables linked to the adoption of ICT_i and the access to credit CA_i by the following relationships:

$$ICT_i = \begin{cases} 1 & ICT_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \text{ and } CA_i = \begin{cases} 1 & CA_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

X_i and Z_i are vectors of variables as previously defined. u_i and v_i are error terms are assumed to follow a bivariate normal distribution whose mean, variance and correlation coefficient are respectively zero, one and ρ . The model is estimated by the maximum likelihood method using the `rbiprobit` command in Stata. Following Coban (2021), we compute the ATT as follows :

$$ATT = \frac{1}{n_2} \sum_{i=1}^{n_2} \Phi \left(\frac{Z_i'\lambda + \alpha - \rho X_i'\beta}{\sqrt{1-\rho^2}} \right) - \Phi \left(\frac{Z_i'\lambda - \rho X_i'\beta}{\sqrt{1-\rho^2}} \right) \quad \forall CA_i = 1 \quad (5)$$

$$n_1 = n_2 = n$$

Table 2: Variables

Types of variables	Variables	Definition	Unit of account
Outcome variables	ICT	Adoption of ICT	1 if the enterprise uses at least one type of ICT (computer, internet and e-business) and 0 otherwise
	Computer	Adoption of computer	1 if the enterprise uses a computer and 0 otherwise
	Internet	Adoption of internet	1 if the enterprise uses an internet and 0 otherwise
	E-business	Adoption of e-commerce	1 if the enterprise does e-business and 0 otherwise
Key explanatory variable	CA	Access to credit	1 if the enterprise has received a credit and 0 otherwise
	Sex	sex of the top manager of the enterprise	1 if the manager is a man and 0 otherwise
Matching variables	Land	Land tenure security	1 if the place where the enterprise is localised belongs to the owner of the enterprise and 0 otherwise
	Stat	Legal status of the enterprise	1 if the enterprise is a sole proprietorship and 0 otherwise
	Formal	Firm formality	1 if the enterprise has an identification number at the enterprise registering office and 0 otherwise

Export	Involvement in exportation activities	1 if the enterprise exports goods or services and 0 otherwise
SE	Size of the enterprises	1 if the enterprise is a small enterprise and 0 if it is a medium one
Mage	Age of the top manager	1 if the age of the top manager is less than 25 years and 0 otherwise

Source: Authors' construction

4. Results and discussion

4.1. Descriptive statistics

Table 3 presents the descriptive statistics for the key variables. The last column shows the p-value for the proportion comparison test between credit recipient and non-credit recipient enterprises. Although Togolese SMEs are involved in diverse activities (commerce, manufacturing, accommodation, and fast food), the majority operate in the informal sector (93.44%). Most SMEs are sole proprietorships (98.46%). 5.56% of top managers are under 25 years of age, and 59.37% of top managers are male. The adoption of ICT is relatively low among the Togolese SMEs. Indeed, the statistics show that only 7.55 %, 5.70 % and 4.83 % of Togolese SMEs use a computer, have an internet connection, and conduct business operations with an internet connection, respectively. Only 19.60 % of SMEs have received a credit. Indeed, the statistics show that the proportions of male top managers, formal enterprises, landowner enterprises, sole proprietorships, medium enterprises, and enterprises involved in exports activities are respectively 52.12 %, 9.62 %, 25.61 %, 98.56 %, 1.31 % and 3.48 % for credit recipient SMEs against 61.13 %, 5.31 %, 27.30 %, 98.43 %, 0.80 % and 3.33 % for non-credit recipient SMEs. The statistics also show that the proportion of SME top managers under 25 years of age is 3.27% for credit recipient enterprises, compared with 6.11% for non-credit recipient enterprises. More importantly, the data show that ICT adoption tends to be higher among credit recipient enterprises than among non-credit recipient enterprises.

Table 3: Descriptive statistics

Variables	Modalities	Full sample (59,043)		Credit recipients (11,575)		Non-credit recipients (47,468)		p-value
		Absolute freq	Relative freq	Absolute freq	Relative freq	Absolute freq	Relative freq	
ICT	No	52000	88.07	9,692	83.73	42,308	89.13	0.000***
	Yes	7043	11.93	1,883	16.27	5,160	10.87	
Computer	No	54588	92.45	10,358	89.49	44,230	93.18	0.000***
	Yes	4455	7.55	1,217	10.51	3,238	6.82	
Internet	No	55677	94.30	10,657	92.07	45,020	94.84	0.000***
	Yes	3366	5.70	918	7.93	2,448	5.16	
E-business	No	56189	95.17	10,799	93.30	45,390	95.62	0.000***
	Yes	2854	4.83	776	6.70	2,078	4.38	
Sex	Female top manager	23991	40.63	5,542	47.88	18,449	38.87	0.000***
	Male top manager	35052	59.37	6,033	52.12	29,019	61.13	
Land	Do not own land	43118	73.03	8,611	74.39	34,507	72.70	0.000***
	Own land	15925	26.97	2,964	25.61	12,961	27.30	

Stat	Company	910	1.54	167	1.44	743	1.57	0.337
	Sole proprietorship	58133	98.46	11,408	98.56	46,725	98.43	
SE	Medium enterprise	533	0.90	152	1.31	381	0.80	0.000***
	Small enterprise	58510	99.10	11,423	98.69	47,087	99.20	
Formal	Informal enterprise	55170	93.44	10,461	90.38	44,709	94.19	0.000***
	Formal enterprise	3873	6.56	1,114	9.62	2,759	5.81	
Export	Do not do export activities	57061	96.64	11,172	96.52	45,889	96.67	0.406
	Do export activities	1982	3.36	403	3.48	1,579	3.33	
Mage	Top manager above 25 years old	55762	94.44	11,196	96.73	44,566	93.89	0.000***
	Top manager below 25 years old	3281	5.56	379	3.27	2,902	6.11	

Source: Author's construction based on INSEED data

*Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively; P-value for equal mean of covariates between credit recipients and non-credit recipient SMEs* **Description of variables:** *ICT = adoption of ICT, Computer = adoption of computer, Internet = adoption of internet, E-business = adoption of e-commerce, CA = access to credit, Sex = sex of the top manager of the enterprise, Land = land tenure security, Stat = Legal status of the enterprise, SE = Size of the enterprises, Formal = firm formality, Export = involvement in exportation activities, Mage = Age of the top manager.*

The statistics show that 10.51 %, 7.93 %, and 6.70 % of small and medium credit recipient enterprises use a computer, have an internet connection, and conduct business operations with an internet connection,, respectively, while these statistics are respectively 6.82 %, 5.16 % and 4.38 % for small and medium non-recipient enterprises. This is a sign of the potential impact of credit access on the ICT adoption, which is further investigated using the propensity score matching method.

4.2. The results of the propensity scores matching and discussion

4.2.1. Probit estimation

The first step of PSM estimation is the probit estimation. Table 4 reports the probit estimation results that is used to compute the propensity scores. These results show that the model is globally significant at 1 percent. The results further show that six variables out of the 7 included in our model are significant at 1 percent. Gender plays an important role in the determination of credit access by SMEs in Togo. SMEs managed by a woman have more chance to have access to credit than SMEs managed by a man. Similar results were also obtained by Quartey et al. (2017), Wellalage & Locke (2017) and Wellalage et al. (2020) respectively in South Asian countries, India and Mali. Two likely reasons may explain these unexpected results. This might suggest that female top managers have preferential treatment in Togo. It could also be explained by the fact that female-owned SMEs have less demand for credit than their male counterparts (Wellalage & Locke, 2017). The results also show that access to credit increases with the top manager's age. Before interpreting the result, it is important to recall that top manager's age is used here as a proxy for the top manager's experience. This positive effect of managers' experience on credit access was also obtained in previous studies and can be explained bearing in

mind that previous experience helps managers to avoid costly mistakes that can limit their ability to obtain credit (Kungu, 2011). Alternatively, this positive effect could also suggest that credit suppliers see older top managers as more responsible than younger top managers. Although previous studies have reported a positive effect of land tenure security in facilitating access to credit (Joel & Bergaly, 2020), our results show a negative effect. This unexpected result could be explained by the non-validity of the variable used as a proxy for land tenure security. Indeed, the land tenure security is measured in this study by a dummy variable taking the value 1 if the firm declares to be the owner of the place where it is set and 0 otherwise. Thus, many people own land but do not have land title that is often used as collateral to get credit. Further study is needed to assess the effect of land tenure security on SMEs credit access in Togo.

Table 4: Probit results

VARIABLES	Probit estimation	Marginal effect
Sex	-0.233*** (0.012)	-0.065*** (0.003)
Land	-0.079*** (0.014)	-0.021*** (0.004)
Stat	0.212*** (0.052)	0.053*** (0.012)
Formal	0.351*** (0.023)	0.108*** (0.008)
Export	0.021 (0.033)	0.006 (0.009)
SE	-0.252*** (0.061)	-0.076*** (0.020)
Mage	-0.336*** (0.029)	-0.080*** (0.006)
_cons	-0.672*** (0.07)	
Observations	59043	
Pseudo R ²	0.013	

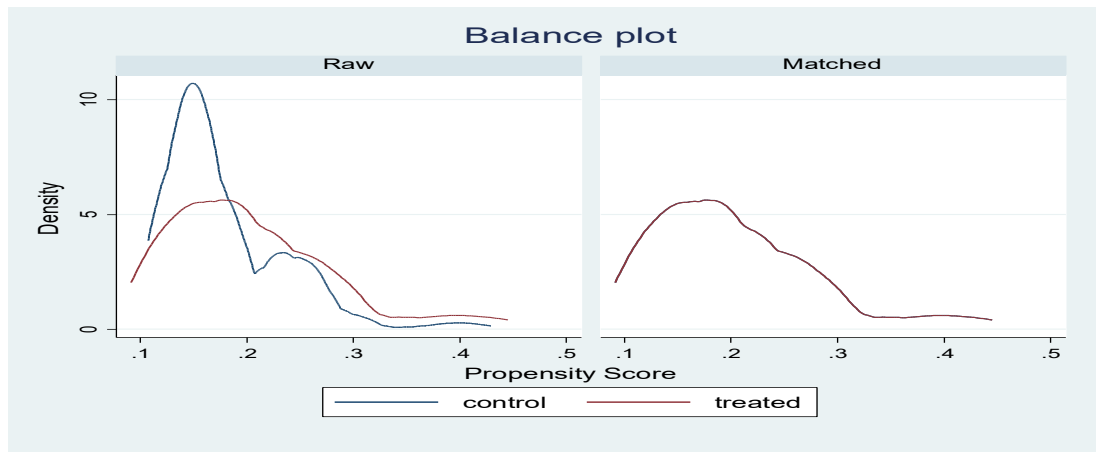
Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively ; Standard errors in parenthesis **Description of variables:** Sex = sex of the top manager of the enterprise, Land = land tenure security, Stat = Legal status of the enterprise, SE = Size of the enterprises, Formal = firm formality, Export = involvement in exportation activities, Mage = Age of the top manager

4.2.1. Checking for the plausibility of CIA and common support assumptions

- *Testing for the CIA hypothesis:*

Figure 1 shows the kernel density estimates of the propensity scores of SMEs that receive a credit (treatment group) and SMEs that do not receive a credit (control group) before and after matching. Considering Figure 1, the post-match propensity score distributions for the treatment and control groups fit perfectly. This perfect fit shows that the two groups have the same characteristics at baseline. We can conclude that the only factor that distinguishes the two groups is the fact that an SME has received credit.

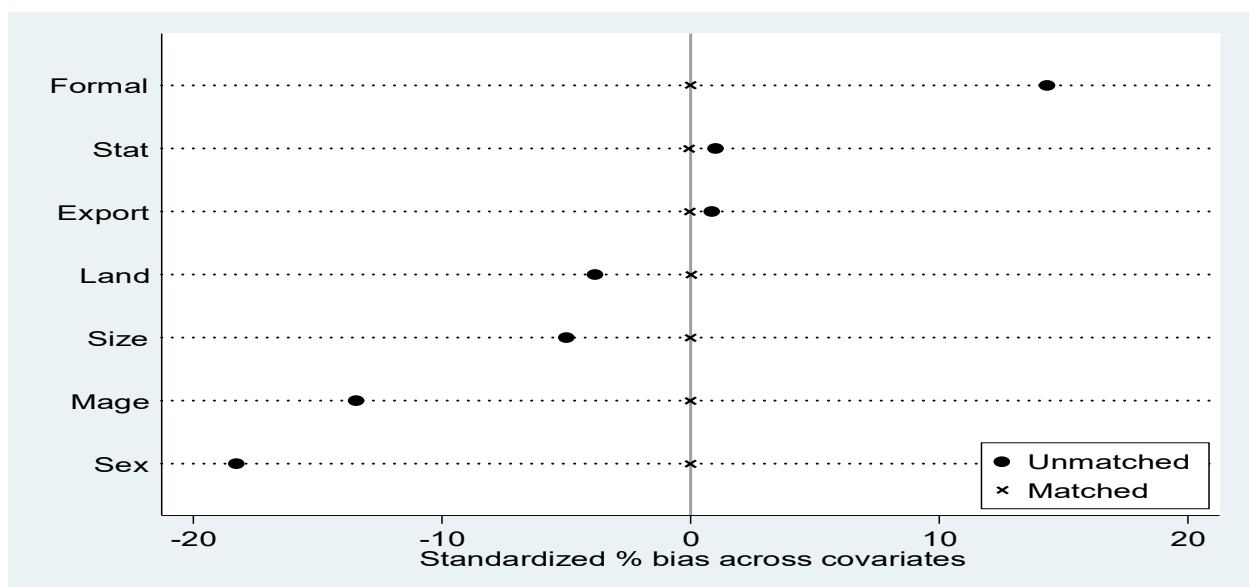
Figure 1: Distribution of propensity score density in the treatment (credit recipient SMEs) and control (non-credit recipient SMEs) groups before and after matching



Note: The left-hand side of the figure shows the distribution of propensity scores before matching for both groups (treatment and control), while the right-hand side shows the distribution of propensity scores after matching in both groups.

We also check at baseline whether there is no significant difference between SMEs that have a credit and SMEs that do not have a credit for each of the selected variables. Figure 2 presents a comparison of the standardised mean differences between SMEs with a credit and those without a credit for each variable, before and after matching. Since the standardised mean differences for all variables are close to zero after matching, we can conclude that, at baseline, there is no significant difference between SMEs with a credit and those without for any of the variables used.

Figure 2: Standardised mean differences between credit recipient SMEs and non-credit recipient SMEs for each of the variables before and after matching



Note: Figure showing the accuracy of propensity score matching for the mean of the variables used. The black circles represent the mean differences between the treatment (credit recipient SMEs) and control (non-credit recipient SMEs) groups at the baseline before matching. The crosses represent the mean differences between the two matched groups at the baseline.

- Verifying common support hypothesis:

The hypothesis that the propensity score values are similar between SMEs that have a credit and SMEs that do not have a credit is tested. The results of this test are presented in Table 5. These results show that the common support hypothesis is verified based on the same covariates. The results also show that the final number of blocks is ten, which ensures that the average propensity score does not differ between SMEs that have a credit and SMEs that do not have a credit in each block. The distribution of the control and treatment groups among the final blocks is, therefore, tabulated with the lower bound of each block.

Table 5: Description of propensity scores and the test of common support

The region of common support is [0.06769842, 0.46504866]				
Description of the estimated propensity score in the region of common support				
Estimated propensity score				
	Percentiles	Smallest		
1%	0.1000586	0.0676984		
5%	0.1473182	0.0676984		
10%	0.1530709	0.0676984	Obs	59,041
25%	0.1723691	0.0676984	Sum of Wgt.	59,041
50%	0.1723691		Mean	0.1960509
		Largest	Std. Dev.	0.0452128
75%	0.2383465	0.4650487		
90%	0.2383465	0.4650487	Variance	0.0020442
95%	0.2762785	0.4650487	Skewness	0.6573037
99%	0.3591545	0.4650487	Kurtosis	4.632228
Step 1: Identification of the optimal number of blocks				
The final number of blocks is 10				
The number of blocks ensures that the mean propensity score is not different for treated and controls in each block				
Step 2: Test of balancing property of the propensity score				
The balancing property is satisfied				
This table shows the inferior bound, the number of treated, and the number of controls for each block				
Inferior block of pscore	The firm has received credit		Total	
	No	Yes		
0.068	387	36	423	
0.1	2,722	367	3,089	
0.15	5,764	1,035	6,799	
0.163	18,180	3,765	21,945	
0.175	822	192	1,014	
0.2	6,114	1,659	7,773	
0.225	10,957	3,446	14,403	
0.25	1,877	705	2,582	
0.3	625	359	984	
0.4	18	11	29	
Total	47,466	11,575	59,041	

4.2.2. Checking for a hidden bias

It cannot be excluded that unobserved variables may simultaneously affect the assignment into the treatment group (the probability that a SME receives a credit) and the outcome variables (ICT, Computer, Internet, and E-business), leading to a hidden bias. According to Becker & Caliendo (2007), the matching technique eliminates biases due to the selection on observable characteristics, but biases can still result from unobservable heterogeneity, leading to non-robust matching estimates. To check for the presence of a hidden bias, the Mantel & Haenszel (1959) sensitivity test is carried out for different values of gamma (the differential of the probability of assignment to the treatment group due to unobservable factors) between 2 and 3 and for intervals of 0.1, using *mhbounds* command in *Stata*. The results in Table 6 show that for values of gamma lower than 2.3, the hypothesis of overestimation of the impact of credit access on the ICT adoption by SMEs in Togo due to an unobserved variable cannot be rejected at 5% level of significance, while the hypothesis of underestimation due to an unobservable variable can be rejected at the 1% level of significance. For a value of gamma equal to 2.3 and for values of gamma above 2.3, the two hypotheses of overestimation and underestimation due to an unobservable variable can be rejected at the 1% level of significance. We can conclude that the results of this study are not significantly influenced by the presence of an unobservable variable influencing both the treatment group assignment and the outcome variables.

Table 6: Mantel-Haenszel bounds to check for the presence of hidden bias

Gamma	Q mh+	Q mh-	p mh+	p mh-
2	1.20	36.39	0.11	0.00
2.1	0.037	37.78	0.48	0.00
2.2	1.03	39.11	0.15	0.00
2.3	2.09	40.41	0.01	0.00
2.4	3.11	41.66	0.00	0.00
2.5	4.09	42.88	0.00	0.00
2.6	5.03	44.05	0.00	0.00
2.7	5.94	45.20	0.00	0.00
2.8	6.81	46.32	0.00	0.00
2.9	7.65	47.40	0.00	0.00
3	8.47	48.46	0.00	0.00

Note: *Gamma* = odds of differential assignment due to unobserved factors, *Q_mh+* = Mantel-Haenszel statistic (assumption: overestimation of treatment effect), *Q_mh-* = Mantel-Haenszel statistic (assumption: underestimation of treatment effect), *p_mh+* = significance level (assumption: overestimation of treatment effect), *p_mh-* = significance level (assumption: underestimation of treatment effect)

4.2.3. Treatment effect of credit access on the adoption of ICT by SMEs in Togo

The average treatment effect on treated of credit access on the ICT adoption (ATT) is computed and presented in Table 7

Table 7: Impact of credit access on the ICT adoption

Outcome variables	Matching methods											
	Nearest Neighbour			Stratification			Radius			Kernel		
	Treated	Control	ATT	Treated	Control	ATT	Treated	Control	ATT	Treated	Control	ATT
ICT adoption	11,575	47,431	0.049*** (0.004)	11,575	47,466	0.048*** (0.003)	11,575	47,466	0.070*** (0.004)	11,575	47,466	0.058*** (0.004)
Computer adoption	11,575	47,431	0.032*** (0.003)	11,575	47,466	0.032*** (0.003)	11,575	47,466	0.054*** (0.003)	11,575	47,466	0.041*** (0.003)
Internet adoption	11,575	47,431	0.026*** (0.003)	11,575	47,466	0.025*** (0.003)	11,575	47,466	0.037*** (0.003)	11,575	47,466	0.030*** (0.003)
E-business adoption	11,575	47,431	0.020*** (0.003)	11,575	47,466	0.020*** (0.003)	11,575	47,466	0.031*** (0.003)	11,575	47,466	0.025*** (0.002)

*Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Standard errors are in parenthesis. Treated = credit recipient SMEs, Control = non-credit recipient SMEs, ATT = Average treatment effect on the treated*

All the matching methods show a positive and significant impact of credit access on the adoption of ICT by Togolese SMEs. Access to credit increases the probability of ICT adoption by about 0.048 to 0.070 percentage points according to matching methods. This result is consistent across the types of ICT (computer, internet, and e-business). Access to credit has a positive and significant impact on the computer, internet, and E-business adoption. It increases the probability of Togolese SMEs adopting ICT by about 0.032-0.054, 0.025-0.037, and 0.020-0.031 percentage points for computer, internet, and e-business adoption, respectively. These results therefore confirm our hypothesis that access to credit has a positive impact on the adoption of ICT by SMEs. Access to credit helps SMEs to overcome the financial constraints that may prevent firms from investing in ICT (Beck & Demirguc-Kunt, 2006). Given that ICT costs remain one of the main barriers to the adoption of ICT by SMEs (Walczuch et al., 2000; Love et al., 2005; Harindranath et al., 2008; Chimucheka, 2013), SMEs may use credit to purchase ICT. In Togo, for example, a gigabyte of mobile data costs approximately 8.4 dollars, making Togo the first Economic Community of West African States (ECOWAS) country where a gigabyte costs the most⁶. Several studies have also stressed the positive impact of access to credit on the likelihood of SMEs to invest (Regis, 2018; Aivazian & Santor, 2008). Access to credit also helps firms to acquire innovations. For example, Adegbeye & Iweriebor (2018) showed that external finance permitted SMEs to increase the use of foreign-licensed technologies in Nigeria. Similarly, using the PSM approach and a sample of 13430 SMEs from Eastern Europe and Central Asia, Wellalage & Fernandez (2019) also found a positive relationship between external financing and product and process innovation by SMEs.

Although the results show a positive impact of access to credit on the adoption of ICT by Togolese SMEs, it is important to note that the magnitude of the impact is relatively weak. This may suggest that the ICT adoption might not be amongst the immediate concerns that SMEs in Togo would like to address when they get access to credit.

⁶ Source : Jeune Afrique, [Internet mobile : Congo, RDC, Côte d'Ivoire... Dans quels pays la data est-elle la plus chère ? – Jeune Afrique](#)

We also performed heterogeneity analysis to check whether the impact of access to credit on the adoption of ICT is consistent across the types of enterprises (small enterprises vs medium enterprises and exporting enterprises vs non-exporting enterprises). The heterogeneity analysis is performed for the above types of enterprises for two main reasons. Firstly, the ICT adoption level is greatly different between small and medium enterprises. Indeed, the proportion of medium enterprises adopting ICT is greater and estimated at 60.23 %, 48.03 %, and 33.96 % respectively for computer, internet, and e-business, compared to small enterprises, where 7.07 %, 5.32 %, and 4.57 % are adopters of computer, internet, and e-business, respectively. Secondly, we also examined the impact of access to credit on the adoption of ICT between exporting and non-exporting enterprises because ICT adoption is a necessary condition for involving export activities. The results are presented in Table 8.

Table 8: Impact of credit access on the ICT adoption according to the types of enterprises

Outcome variables	Types of Enterprises	Matching methods											
		Nearest Neighbour			Stratification			Radius			Kernel		
		Treated	Control	ATT	Treated	Control	ATT	Treated	Control	ATT	Treated	Control	ATT
ICT adoption	Small enterprise	11,423	47,062	0.050** * (0.004)	11,423	47,085	0.049** * (0.004)	11,423	47,085	0.065** * (0.004)	11,423	47,085	0.056** * (0.004)
	Medium enterprise	152	369	-0.004 (0.049)	152	381	-0.022 (0.052)	152	381	0.053 (0.049)	152	381	-0.018 (0.053)
	Do not do export activities	11,172	45,876	0.048** * (0.004)	11,172	45,887	0.047** * (0.004)	11,172	45,887	0.068** * (0.004)	11,172	45,887	0.057** * (0.003)
	Do export activities	403	1555	0.079** * (0.026)	403	1579	0.063** * (0.025)	403	1570	0.110** * (0.026)	403	1579	0.068** * (0.024)
Computer adoption	Small enterprise	11,423	47,062	0.033** * (0.003)	11,423	47,085	0.032** * (0.003)	11,423	47,085	0.049** * (0.003)	11,423	47,085	0.038** * (0.003)
	Medium enterprise	152	369	-0.000 (0.049)	152	381	-0.021 (0.057)	152	381	0.053 (0.050)	152	381	-0.019 (0.049)
	Do not do export activities	11,172	45,876	0.032** * (0.003)	11,172	45,887	0.031** * (0.003)	11,172	45,887	0.053** * (0.003)	11,172	45,887	0.041** * (0.004)
	Do export activities	403	1555	0.046** (0.021) 0.025**	403	1579	0.026 (0.020) 0.025**	403	1570	* (0.021) 0.032**	403	1579	0.035 (0.025) 0.027**
Internet adoption	Small enterprise	11,423	47,062	* (0.003)	11,423	47,085	* (0.002)	11,423	47,085	* (0.003)	11,423	47,085	* (0.003)
	Medium enterprise	152	369	0.045 (0.050)	152	381	0.011 (0.053)	152	381	0.103** (0.051)	152	381	0.025 (0.049)
	Do not do export activities	11,172	45,876	0.025** * (0.003)	11,172	45,887	0.024** * (0.003)	11,172	45,887	0.035** * (0.003)	11,172	45,887	0.029** * (0.003)
	Do export activities	403	1555	0.041* (0.021)	403	1579	0.029 (0.023)	403	1570	* (0.021)	403	1579	0.031 (0.023)
E-business adoption	Small enterprise	11,423	47,062	0.020** * (0.002)	11,423	47,085	0.020** * (0.003)	11,423	47,085	0.027** * (0.002)	11,423	47,085	0.023** * (0.002)
	Medium enterprise	152	369	0.029 (0.048)	152	381	0.021 (0.050)	152	381	0.062 (0.048)	152	381	0.026 (0.044)
	Do not do export activities	11,172	45,876	0.018** * (0.002)	11,172	45,887	0.017** * (0.002)	11,172	45,887	0.027** * (0.002)	11,172	45,887	0.023** * (0.003)
	Do export activities	403	1555	0.088** * (0.023)	403	1579	0.083** * (0.025)	403	1570	0.109** * (0.023)	403	1579	0.086** * (0.021)

*Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Standard errors are in parenthesis. All companies in the database are formal enterprises. Treated = credit recipient SMEs, Control = non-credit recipient SMEs, ATT = Average treatment effect on the treated*

While most matching methods show that access to credit has a positive and significant impact on the adoption of ICT for almost all types of enterprises, that impact is not significant for medium enterprises. These results are consistent across the types of ICT adoption (computer, internet, and E-business). These results then suggest that increasing access to credit will help small enterprises (and not medium enterprises) to adopt ICT. ICT seems to be a priority for small enterprises, which need them to expand their activities. On the other hand, the purchase of ICT does not seem to be the primary use of credit for medium-sized enterprises. Medium enterprises could use credit to purchase different production equipment. The statistics also show that medium enterprises already have a higher level of ICT adoption as compared to small enterprises. While 60.23 %, 48.03 %, and 33.96 % of medium enterprises use a computer, have an internet connection, and conduct business operations with an internet connection, respectively, only 7.55 %, 5.70 %, and 4.83 % of small enterprises use a computer, have an internet connection, and conduct business operations with an internet connection, respectively. This may therefore justify why the purchase of ICT is not the main use of credits obtained by medium enterprises.

In relation to the export activities, the results show that access to credit increases the probability of ICT adoption for both exporting and non-exporting enterprises. This result is consistent for all types of ICT (computer, internet connection, and e-commerce). Although the impact of access to credit is positive for both exporting and non-exporting enterprises, it is important to note that the impact remains greater for exporting enterprises across all types of ICT. This greater impact could be explained by the greater desirability of exporting enterprises for the use of ICT than non-exporting enterprises. This greater desirability of exporting enterprises is justified by the kind of firm's activities that require ICT for monitoring export operations (Giunta & Trivieri, 2007; Lucchetti & Sterlacchini, 2004).

4.3. Robustness analysis

To ensure the robustness of the results, we also analyze the impact of access to credit on the ICT adoption by using the recursive bivariate probit model that controls for endogeneity of access to credit. Full details of regressions are presented in Appendices 2, 3, 4, 6, and 7, but we only concentrate our discussion on the impact of access to credit on the adoption of ICT. In all the regressions except in model 3c, the correlation coefficients are negative and statistically different from zero, thus justifying the use of the RBVP method to control for endogeneity of access to credit. The estimates of the impact of credit access on ICT adoption are reported in Table 9. The results show a positive and significant impact of access to credit on the adoption of ICT. Here, access to credit globally increases the probability of adopting ICT by 0.234, 0.241, 0.147, and 0.350 percentage points, respectively, for computer, internet, e-business, and all three ICTs together. This positive impact of access to credit is consistent across the four categories of enterprises, thus justifying the need to increase SMEs' access to credit to boost ICT adoption among SMEs. The present results corroborate those obtained from the PSM method, except for medium enterprises, where PSM results show no significant impact of credit access on their ICT adoption. The divergence between PSM and RBVP results for medium enterprises may be due to reverse causality bias, which the PSM method cannot control. Despite the divergence between PSM results and RBVP results for medium enterprises, the two methods (PSM and RBVP) globally show that access to credit increases the probability of SMEs adopting ICT. However, it is essential to note that the RBVP method estimates of impact are greater than those from the PSM method. The absence of certain observable factors in the PSM analysis may explain the higher impact estimates from the RBVP method. Thus, regardless of the impact evaluation methods used in the estimation, access to credit increases the probability of SMEs adopting ICT.

Table 9: ATT obtained from the RBVP model

Outcome variables	Types of enterprises	Observation (treated)	ATT	Standard error
ICT adoption	Full sample	11575	0.350***	0.018
	Small enterprise	11423	0.363***	0.019
	Medium enterprise	152	0.638***	0.102
	Do not do export activities	11172	0.352***	0.020
	Do export activities	403	0.515***	0.067
Computer adoption	Full sample	11575	0.234***	0.016
	Small enterprise	11423	0.245***	0.018
	Medium enterprise	152	0.754***	0.071
	Do not do export activities	11172	0.236***	0.017
	Do export activities	403	0.241***	0.081
Internet adoption	Full sample	11575	0.157***	0.019
	Small enterprise	11423	0.166***	0.023
	Medium enterprise	152	0.853***	0.129
	Do not do export activities	11172	0.157***	0.021
	Do export activities	403	0.258***	0.084
E-business adoption	Full sample	11575	0.147***	0.018
	Small enterprise	11423	0.157***	0.022
	Medium enterprise	152	0.601***	0.142
	Do not do export activities	11172	0.138***	0.021
	Do export activities	403	0.437***	0.093

***, ** and * indicate significance at 1%, 5% and 10% respectively

Conclusion

ICT plays an important role in the development of SMEs worldwide, but its adoption remains low among Togolese SMEs. Past studies have identified several factors of ICT adoption, such as firm formality, firm age, export orientation, and so on, but have failed to assess the impact of credit access on ICT adoption by SMEs. This study fills this gap by analysing the impact of credit access on the adoption of ICT by Togolese SMEs. The study uses general enterprises census data collected by the National Institute of Statistics and Economic and Demographic Studies in 2018 and both the propensity score matching method and the recursive bivariate probit model to assess the impact of credit access on the adoption of ICT by SMEs. The results show that credit access has a positive and significant impact on the adoption of ICT by Togolese SMEs. Specifically, we found that access to credit increases the probability of ICT adoption by about 0.048 to 0.350 percentage points. The results also show that access to credit has a positive and significant impact on computer, internet, and E-business adoption: access to credit increases the probability of Togolese SMEs adopting ICT by about 0.032-0.234, 0.025-0.157, and 0.020-0.147 percentage points for computer, internet, and e-business, respectively. The results further show that credit access has a positive and significant impact on ICT adoption for all types of enterprises except for medium enterprises. Although the impact of credit access is not significant for medium enterprises, the overall results suggest that access to credit has increased the adoption of ICT among Togolese SMEs. The probability of SMEs access to credit is currently 19.6%; and if this probability is to increase to 100% or if all the non-credit recipient SMEs were to receive a credit, the adoption rates of ICT will move from 7.55 %, 5.70% and 4.83% to about 10.12%-26.35%, 7.71-18.33% and 6.44-16.65%, respectively for computer, internet and e-business. Therefore, policies that facilitate SMEs' access to credit will definitely help to boost the adoption of ICT among SMEs. Different policies may be set to increase SMEs' access to credit. The facilitation of the process for registering a firm and a reduction of cost for registering a firm are examples of measures that can help to increase the number of formal enterprises and hence increase SMEs' access to credit. The government may serve as a warrantor to SMEs that want credit but do not have collateral. The study has shown that access to credit increases with enterprise size, so integration between enterprises must be encouraged.

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Appendix

Appendix 1: Advantages and disadvantages of the four matching methods used in this paper

We use four matching algorithms including the nearest neighbour matching, the radius matching, the stratification matching and the kernel matching. The four matching algorithms are used simultaneously to ensure the robustness of results as each matching algorithm has its own advantages and disadvantages. The nearest neighbour matching compares each treated individual with the untreated individual with the closest propensity score. The main critics of the nearest neighbour matching is that it can discard a large number of observations and by doing so it apparently lead to reduced power (Stuart, 2010). The quality of matches maybe lower if the closest control individual is numerically distant from the treated individual (Baser, 2006). Moreover, in nearest neighbour matching, some control individuals maybe ignored although having fairly similar propensity scores with the treated individual (Chintrakarn, 2008). To take into account of this latter situation, radius matching where each treated individual is matched only with control individuals that fall under a predefined neighbourhood of the treated individual has been suggested in the literature. By doing so, the radius matching permits to uses extra individuals when good matches are possible and fewer individuals when there are not (Dehejia & Wahba, 2002). However, a main critic of this matching technique is related to the choice of the reasonable radius (Baser, 2006).

Subclassification and kernel matching techniques are two other alternatives often used in the literature. While Subclassification build groups of individuals who are similar and compare the individual's outcomes within each group, the kernel matching technique matches each treated individual with weighted average of all control individuals with weights corresponding to the inverse of the distance between their propensity scores and that of the treated individual (Getnet & Anullo, 2012). One advantage of kernel matching is that it uses more information and then lower variance is achieved but its drawback is that some observations used for matching maybe poor matches of the treated individuals (Heinrich et al., 2010). Although the stratification matching technique has been shown to reduce approximately 90 percent of bias due to measured covariates (Rosenbaum & Rubin, 1984) with only 5 strata (Rosenbaum and Rubin, 1984), individuals may not be adequately distributed among strata because individuals at the margin of a strata might be classified in another strata (Lecocq et al., 2014). Thereby, the stratification matching technique may result to a higher number of unmatched individuals (as compared to the nearest neighbour matching) even with lesser distance just because they are found in another strata (Lecocq et al., 2014). The direct consequences are the reduction of sample size and statistical power.

Appendix 2: Recursive bivariate probit results for the full sample

Variables	Model 1a		Model 2a				Model 3a				Model 4a					
	ICT		CA		Computer		CA		Internet		CA		E-business		CA	
	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev
CA	1.962***	0.041			2.042***	0.046			1.715***	0.084			1.830***	0.082		
Sex	0.449***	0.014	-0.225***	0.012	0.616***	0.018	-0.226***	0.012	0.360***	0.017	-0.228***	0.012	0.317***	0.018	-0.231***	0.012
Size	-0.670***	0.059	-0.151**	0.064	-0.793***	0.060	-0.144**	0.064	-0.739***	0.061	-0.203**	0.062	-0.434***	0.061	-0.197**	0.062
Stat	-1.441***	0.045	0.295***	0.053	-1.515***	0.044	0.307***	0.054	-1.282	0.045	0.250***	0.052	-1.106***	0.045	0.279***	0.053
Export	0.305***	0.031	-0.023***	0.032	0.091**	0.036	-0.012	0.032	0.319***	0.036	0.002	0.033	0.461***	0.035	0.009	0.032
Mage	-0.011	0.030	-0.288***	0.028	-0.077**	0.036	-0.298***	0.028	0.056	0.037	-0.316***	0.029	-0.044	0.042	-0.325***	0.029
Land			-0.068***	0.012			-0.051***	0.013			-0.080***	0.013			-0.085***	0.013
Formal			0.574***	0.021			0.576***	0.021			0.445***	0.022			0.452***	0.022
_cons	0.387***		-0.872***	0.071	0.196**	0.069	-0.895***	0.072	-0.043	0.072	-0.765***	0.071	-0.558***	0.068	-0.797***	0.071
Rho	-0.856	0.015			-0.852	0.015			-0.724	0.032			-0.769	0.029		
Wald test of rho=0: chi2(1)	486.993				512.138				180.565				205.336			
Prob > chi2	0.000				0.000				0.000				0.000			
Obs	59043				59043				59043				59043			

*Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively*

Appendix 3: Recursive bivariate probit results for small enterprises

Variables	Model 1b				Model 2b				Model 3b				Model 4b			
	ICT		CA		Computer		CA		Internet		CA		E-business		CA	
	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev
CA	2.018***	0.040			2.133***	0.044			1.865***	0.086			1.983***	0.078		
Sex	0.445***	0.014	-0.227**	0.012	0.607***	0.018	-0.228***	0.012	0.362***	0.017	0.086***	0.012	0.317***	0.018	-0.231***	0.012
Size	-1.431***				-				-				-	0.049	0.304***	0.058
		0.047	0.310*	0.059	1.531***	0.047	0.321***	0.060	1.243***	0.048	0.017***	0.058	1.119***			
Stat	0.316***	0.031	-0.018**	0.033	0.105**	0.036	-0.006	0.033	0.314***	0.037	0.048	0.033	0.471***	0.036	0.011	0.033
Export	-0.000	0.030	-0.284**	0.028	-0.059	0.036	-0.294***	0.028	0.068*	0.037	0.037***	0.029	-0.026	0.041	-0.322***	0.029
Mage	-0.294***	0.048	-0.070**	0.012	-0.581***	0.048	-0.051***	0.012	-0.824***	0.049	0.037***	0.013	-0.985***	0.050	-0.087***	0.013
Land			0.568**	0.022			0.566***	0.022			0.049***	0.022			0.453***	0.022
Formal			-1.037*	0.060			-1.052***	0.061			0.086***	0.059			-1.019***	0.059
_cons	2.018***	0.040	-0.227**	0.012	2.133***	0.044	-0.228***	0.012	1.865***	0.086	0.017***	0.012	1.983***	0.078	-0.231***	0.012
Rho	-0.875	0.015			-0.879	0.014			-0.777	0.031			-0.818	0.025		
Wald test	470				527.854				178.313				228.338			
of rho=0:																
chi2(1)																
Prob >	0.000				0.000				0.000				0.000			
chi2																
Obs	58,510				58,510				58,510				58,510			

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively

Appendix 4: Recursive bivariate probit results for medium enterprises

Variables	Model 1c		Model 2c				Model 3c				Model 4c					
	ICT		CA		Computer		CA		Internet		CA		E-business		CA	
	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev
CA	1.444***	0.137			1.456***	0.097			1.644***	0.167			1.507***	0.29		
Sex	0.417**	0.133	-0.165	0.138	0.428**	0.129	-0.186	0.138	0.218*	0.127	-0.106	0.149	0.212	0.137	-0.180	0.142
Size	-1.215***	0.213	0.235*	0.130	-1.075***	0.139	0.290*	0.128	-1.142***	0.140	0.219*	0.130	-0.852***	0.152	0.192	0.125
Stat	-0.172	0.166	-0.185	0.163	-0.151	0.152	-0.166	0.160	0.205	0.149	-0.206	0.170	0.029	0.152	-0.166	0.164
Export	-0.509	0.403	0.059	0.386	-0.444	0.392	0.066	0.382	-0.131	0.379	0.062	0.382	-6.077	65399.180	0.007	0.424
Mage	0.303**	0.132	0.255**	0.103	0.228	0.162	0.159	0.104	0.057	0.160	0.102	0.136	-0.394**	0.178	0.158	0.110
Formal	0.327	0.224	-0.757***	0.119	1.456***	0.097	0.448***	0.092	1.644***	0.167	0.273**	0.137	1.507***	0.298	0.233*	0.123
Land			0.249**	0.178			-0.839***	0.174			-0.758***	0.180			-0.683***	0.177
_cons	1.444***	0.137	-0.165**	0.138	0.428	0.129**	-0.186	0.526	0.218*	0.127	-0.106	0.149	0.212	0.137	-0.180	0.142
Rho	-0.946	0.079			-0.962	0.039			-0.974	0.106			-0.863	0.185		
Wald test of rho=0:	5.75318				13.9884				1.07183				3.24446			
chi2(1)																
Prob > chi2	0.0165				0.0002				0.3005				0.0717			
Obs	533				533				533				533			

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively

Appendix 5: Recursive bivariate probit results for exporting enterprises

Variables	Model 1d		Model 2d				Model 3d				Model 4d					
	ICT		CA		Computer		CA		Internet		CA		E-business		CA	
	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev
CA	1.735***	0.161			1.521***	0.319			1.454***	0.313			1.953***	0.211		
Sex	0.558***	0.073	-0.304***	0.069	0.778***	0.107	-0.288***	0.071	0.492***	0.091	-0.320***	0.071	0.475***	0.081	-0.297***	0.070
Size	-0.206	0.167	-0.058	0.176	-0.520**	0.179	-0.097	0.175	-0.687***	0.173	-0.083	0.175	0.066	0.163	-0.069	0.175
Stat	-1.576***	0.163	0.272*	0.161	-1.721***	0.164	0.257	0.161	-1.318***	0.145	0.204	0.156	-1.218***	0.137	0.287*	0.161
Mage	-0.013	0.143	-0.304*	0.156	-0.153	0.200	-0.332**	0.163	-0.044	0.179	-0.309**	0.161	-0.021	0.167	-0.274*	0.155
Land			-0.104	0.071			-0.104	0.078			-0.156	0.076			-0.184**	0.071
Formal			0.449***	0.078			0.373***	0.084			0.344***	0.083			0.391***	0.077
_cons	0.345	0.204	-0.847***	0.195	0.145	0.232	-0.795***	0.197	0.208	0.214	-0.723***	0.196	-0.580**	0.172	-0.832***	0.197
Rho	-0.824	0.081			-0.682	0.148			-0.869	-0.280			-0.844	0.094		
Wald test of rho=0:	21.3786				9.05809				9.26093				14.4246			
chi2(1)																
Prob > chi2	0.0000				0.0000				0.0023				0.0001			
Obs	1,982								1,982				1,982			

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively

Appendix 6: Recursive bivariate probit results for non-exporting enterprises

Variables	Model 1e		Model 2e				Model 3e				Model 4e					
	ICT		CA		Computer		CA		Internet		CA		E-business		CA	
	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev	Coef	Std dev
CA	2.000***	0.042			2.078***	0.045			1.776***	0.088			1.827***	0.091		
Sex	0.443***	0.014	-0.223***	0.012	0.607***	0.018	-0.225***	0.012	0.354***	0.018	-0.225***	0.012	0.308***	0.018	-0.229***	0.012
Size	-0.729***	0.063	-0.174**	0.069	-0.834***	0.064	-0.163**	0.069	-0.737***	0.066	-0.223**	0.067	-0.516***	0.066	-0.221**	0.067
Stat	-1.426***	0.047	0.292***	0.057	-1.499***	0.047	0.304***	0.057	-1.270***	0.047	0.252***	0.056	-1.093***	0.048	0.273***	0.056
Mage	-0.007	0.030	-0.285***	0.028	-0.070*	0.037	-0.296***	0.029	0.065*	0.038	-0.316***	0.029	-0.044	0.043	-0.326***	0.029
Land			-0.066***	0.012			-0.049***	0.013			-0.078***	0.013			-0.081***	0.013
Formal			0.578***	0.022			0.588***	0.022			0.451***	0.023			0.456***	0.023
_cons	0.432***	0.075	-0.849***	0.077	0.224**	0.074	-0.876***	0.078	-0.055	0.077	-0.751***	0.077	-0.485***	0.091	-0.771***	0.077
Rho	-0.868	0.015			-0.863	0.015			-0.745	0.033			-0.767	0.032		
Wald test of rho=0: chi2(1)	454.336				513.778				170.896				171.157			
Prob > chi2	0.0000				0.0000				0.000				0.000			
Obs	57,061								57,061				57,061			

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively



Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.