Youth Entrepreneurship Performance in Benin: The Role of Family, Formal and Informal Credits

Djossou Gbetoton Nadege  
Department of Economics, University of Abomey Calavi, Benin

Novignon Jacob  
Department of Economics, Kwame Nkrumah University of Science and Technology, Kumasi-Ghana

Atchade Touwédé Bénédicte  
Department of Economics, University of Abomey Calavi, Benin

Abstract

Youth entrepreneurship becomes an important lever for economic growth and employment creation in developing countries. Access to credit, however, continues to pose significant limitations to the sustainability of these small-scale enterprises. In this paper, we estimate the impact of credit access (Formal, Informal and Family) on youth entrepreneurship performance in Benin. The 2014/16 panel data from a World Bank survey on enterprise formalisation was used for analysis. To address potential endogeneity and ensure robustness of results, we employed multiple models and estimation techniques (Difference-in-Difference, Fixed Effects, Endogenous Switching Regression and Lewbel approach). The results show that, while formal credit was most important for larger firms, smaller firms benefited mainly from informal or family credit. The impact of credit uptake was generally higher for female-owned firms. There were also variations across age of firm owner, and where older firm owners having higher impact. The findings highlight the importance of informal and family credit sources, especially for start-ups and small firms.

Key words: Youth Entrepreneurship, Microcredit, Small-scale Enterprises, Benin

JEL: D12, M53, M1
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1. Introduction

There is a growing consensus in the economic literature that suggests that Entrepreneurship is an important engine of economic growth and innovation (Naudé, 2008; Toma et al., 2014). Entrepreneurship leads to the creation of new businesses that turn to create new jobs and increase production (Acs, 2006). According to the Schumpeterian (1942) “creative destruction” theory, the entrepreneurial process constitutes a key economic development factor and entrepreneurs are considered to be coordinators of production and agents of change. In particular, in developing countries, Small and Medium-scale Enterprises (SMEs) have the potential to achieve both employment and income distribution objectives. SMEs are more labour-intensive production processes, and therefore provide productive employment opportunities. This leads to the generation of income and eventually poverty reduction.

Growing number of academics have focused on access to microcredits as a tool of business creation and expansion; and on micro-entrepreneur capacity building to improve their business probability of success. Indeed, credit constraints have been identified among others, as potential limitations to a firms’ ability to grow (Attanasio et al., 2015; Banerjee and Duflo, 2005). Therefore, a significant number of microcredit programs were implemented to encourage entrepreneurship start-up and the expansion of the small-scale enterprises, and this, with the ultimate aim of poverty reduction and well-being improvement. Even though there is no consensus among researchers on the impact of microcredit on firms’ performance, there was some evidence that microcredit positively affects entrepreneurship initiative and allow entrepreneurs to invest in their existing business (Angelucci et al., 2015; Banerjee et al., 2015b; Karaivanov and Yindok, 2015).

In recent years, there has been a growing interest among researchers and policy makers alike to understand how to encourage youth entrepreneurship and to improve their business profitability across developing countries. This is because the youth group constitutes a great share of unemployed or underemployed population in Africa. Moreover, their potential contribution to the economic performance of a country cannot be overemphasised. According to AfDB (2016), one third of youth aged 15-35 are unemployed and discouraged, another third are vulnerably employed, and only one in six is in wage employment. In Benin, even educational attainment does not guarantee employment. ILO (2015) statistics show that the youth unemployment rate for people with primary or less, secondary and tertiary educational attainment are 4.7 per cent; 22.7 per cent and 39.3 per cent, respectively. Due to the lack of public sector employment opportunities in the country, the youth are pushed into self-employment. 35 per cent of youth are in self-employment into SMEs, 26.1 per cent are in non-paid family work, 19.4 per cent are in wage employed, and only 5.4 are employers (INSAE, 2014). Furthermore, on average, 72.5 per cent of youth are in vulnerable work (ILO, 2015).

While the growing interest on youth in entrepreneurship is encouraging, several practical limitations hinder the success of youth entrepreneurs. INSAE (2014) survey on youth unemployment and transition from school to work in Benin has identified financial constraints as the important limit for youth entrepreneurship. To start their business, 40.2 per cent of youth surveyed have relied on their personal fund, 19.4 per cent on family/friend financial aids. None has received a loan from banks to start their business and 1.2 per cent were financed by informal financial markets.

It is therefore important to understand how the access to the different sources of credit (formal, informal and family) affect youth small-scale entrepreneurship initiative and
performance in Benin. Even though informal credits play an important role in financing start-ups in Benin there is to our knowledge, no evidence on their impact on small scale firms' performance. Indeed, in many developing countries like Benin, formal credit sources have complexities that limit their access to start-ups and small firms. For instance, the need to present collateral before accessing formal credit may prevent these firms from seeking such credit. On the contrary, credit from informal and family sources are more flexible in terms of access and repayments. They may be more suitable.

The current study proposes to: (i) estimate the impact of the different sources of credit uptake (formal, informal and family) on performance of youth entrepreneurship in Benin and (ii) analyse the gender and age group dynamics of this impact.

The rest of the paper is organised as follow. In section 2, we present conceptual and empirical literature on the objectives of the study. Sections 3 and 4 present data used and the methodology. Section 5 presents results of the study and Section 6 summarises and concludes.

2. Literature review

2.1 Conceptual framework

The conceptual framework that governs this study is the microeconomic theory of production under which we consider capital and labour as corporate into factors of production such as capital and labour to improve the firm outcome. Thus, the growth or performance of firms depends on the supply of capital, of labour and of the quality of management, as well as on the opportunities for the profitable investments. In particular, access to credit is an important instrument to improve SMEs performances in developing countries where SMEs are shut out from conventional financial services because of lack of collateral. Access to credit encourage entrepreneurship and favour business development and performance (Ekpe et al., 2010; Salman, 2009).

Watson and Everett (1999) stated that financial services are important tools for mobilising resources for productive use. Access to credit enables SMEs to overcome their liquidity constraints and undertake investments such as acquisition of new technologies to improve their performance (Heidhues, 1995). By offering financial services to individuals, it is also giving them opportunity to invest in capital to start or to expand business, for more competitiveness, increase of sales volume and having thereby more profits (Alhassan et al., 2016). Access to credit contributes to the growth of enterprises as it can increase or improve the number of employees, the asset base and the levels of stocks and services of the business (Njoora and Kyalo, 2014). When credit does not improve the business profitability, the adjustments in stocks and in services being used to sustain the business and avoid failure.

2.2 Formal credit and enterprise performance

In this study, we consider formal credits as the different types of microcredits that individuals can access through formal institutions such as Microfinance Institutions and banks. The empirical review from experimental and quasi-experimental analyses in different countries and contexts shows that access to formal credit has heterogeneous and mixed impact on SMEs. The impact of access to microcredit depend on different factors, such as the size of
the business, the age of the business’s owner (Banerjee et al., 2015a), the length of exposure to the microcredit (Banerjee et al., 2015b; Crépon et al., 1998), the type of credit (individual or group credit) (Attanasio et al., 2015), the motivation of business initiative (Karaivanov and Yindok, 2015), etc.

In urban Hyderabad (India), Banerjee et al. (2015a) distinguished two types of entrepreneurs: entrepreneurs with large business scale targets (the gung-ho entrepreneurs (GE) that had business before the microcredit) and entrepreneurs with small business scale target (the reluctant entrepreneurs, RE). The authors found evidence that microfinance only had positive and large impact on business scale and performance of GE. Moreover, microcredit access impact increased with the length of exposure and the effect even persists after exposure. While Crépon et al. (2015) found in rural Morocco, an overall positive impact of access to microcredit on firms’ profit, this impact is limited in the short run. Banerjee et al. (2015b) have gone into more detailed analysis and find that access to microcredit has positive impact only for old businesses that operate in the upper tail (95th percentiles and above). The impact of microcredit was positive in particular when the loans are used for investment and risk management of existing businesses (Angelucci et al., 2015).

Attanasio et al. (2015) investigated the impact of a joint-liability microcredit on women entrepreneurship and poverty through a randomised field experiment in rural Mongolia. They provided evidence that group loans allowed adult females to set up new small-scale enterprises and to improve business’ profitability and asset accumulation. In rural areas of Morocco, Crépon et al. (2015) found that household access to microcredit expands the self-employment activities and increases the profit. Credit relaxes the financial constraint and allows entrepreneurs to earn more and also to shift from involuntary to voluntary entrepreneurs (Karaivanov and Yindok, 2015). In Ivory Coast, from a quasi-experimental approach using Propensity Score Matching method, Becho (2017) makes evidence of a positive and significant impact of microfinance on informal enterprises performance. By opposite to the previous studies, Karlan and Zinman (2011) found no impact of access to microcredit on micro-entrepreneurs’ profits in Philippine. Atandi and Wabwoba (2013) also found no positive effect by examining the effect of credit on different performance indicators of micro and small enterprises in Kitale town in Kenya. Access to credit has not necessarily lead to addition of assets, guarantee of bigger market share and good performance.

2.3 Informal/family credits and enterprise performance

Hanedar et al. (2014) define informal finance as financial transactions that occur outside official financial institutions and that are not regulated by governmental authorities. This includes informal credit from family or friends, moneylenders, informal credit unions, etc. Individuals that are excluded from the formal credit market are those who rely mostly to the informal credit market. In this market, one finds poor households, SMEs who are unable to meet the collateral requirements or located in rural areas far from formal credit institutions. According to Lin and Sun (2006), informal lenders have an advantage over formal financial institutions in collecting “soft information” about SME borrowers that can allow higher rates of reimbursement.

Even though informal credits are not the best ones, they help SMEs in alleviating the impact of credit restraint on their operation and growth (Fanta, 2015). In a study on 27 countries from Europa and Asia, Hanedar et al. (2014) found that 12.5 percent of SMEs facing credit constraints use informal credit to finance part of their fixed asset investments and/or working capital purchases. They also found evidence of a negative association between female
ownership and informal credit use. The evidence of Mungiru and Njeru (2015) in Kiambu County in Kenya, suggests that informal finance has a positive impact on SMEs’ performance. However, Shylock (moneylenders) should be avoided as they charge high rates of interests and this affect negatively firms’ performance.

3. Data

To answer the research questions in this study, we relied on data from the World Bank study on formalising informal firms in Benin. The study sought to understand why several firms remain informal and how they could be formalised (Benhassine et al., 2017). Through a Randomised Control Trial (RCT), the authors test the effectiveness of offering supplementary services to enhance the take up of and returns to formalisation. The treatment consisted of the following packages: (A) information on enterprise status\(^1\) and assistance in registering; (B) provision of business services and trainings, and assistance in opening a bank account (the training was about basic accounting, initiation to tax obligations and financial education); (C) provision of tax preparation support and tax mediation services. 3,596 informal firms were sampled and included in the survey in the largest city of Benin, Cotonou. The survey consisted of a baseline survey conducted in March-April 2014, prior to program implementation and subsequent follow-up surveys in April-June 2015 and May-June 2016.

The data suits our study because it is one of the most recent and comprehensive data on enterprises in Benin. It collects information on a wide spectrum of firm characteristics that fits our objectives. For instance, the data contains comprehensive information on firm output sales, profitability, labour productivity, access to credit, training to build business management capacity, tax system, etc. The fact that the survey focused only on informal enterprises is not a limitation as most of the enterprises in Benin are in the informal sector. Indeed, according to the last Enterprises General Census (2008), about 98% of enterprises in Benin are individual enterprises in the informal sector. Also, the data from the household survey conducted by the National Institute of Statistical and Economic Analysis in 2011 showed that 90.4% of employment are from the informal sector and only 4.9% are from the formal private sector.

The panel nature of the data also makes it unique and gives us enough advantage in our analysis. For the purposes of our study, we will further reduce the sample to firms owned by youth entrepreneurs. Here we define youth enterprises as business owners between the ages of 18 and 35 years. Given the two-year period of the World Bank survey, 16-year-olds at the end of the survey would be 18 years old, which is the ideal age to look for work or likely to create a business. In this age group, young people have already completed their studies or training and are able to self-initiate.

While the data was originally generated from an experimental research design, we used the data as a regular panel of youth enterprises and employed non-experimental techniques to

\(^1\) _Entreprenant_ status is a simplified legal regime specifically designed for small entrepreneurs to facilitate their migration from informal sector into formal sector.
achieve the objectives of the study. This was necessary, as the treatments in the experiments did not include credit uptake by firms. Another challenge with the data was the need to deal with missing values in the variables. Given that the same observations were followed over time, missing values were treated using information from previous years. Fortunately, information was available for all observations in the baseline survey. In this case, for variables that did not change over time, we simply repeat information from the baseline for follow-up periods. For instance, the gender of an individual will remain the same from the baseline to the follow-up. This means that for individuals whose gender was missing in a particular wave, it was easy to treat this. For variables that change over time, we used some rational rules including sample medians to treat missing values of these variables.

4. Methodology

The panel specification in equation (1) presents the base model to estimate the impact of credit uptake on firm’s performance.

\[
\ln Y_{it} = \theta_i + \delta \text{credit}_{it} + \beta X_{it} + \mu_t + \varepsilon_{it}
\]  

(1)

Where \( Y_{it} \) denotes the outcome variable (sales) of enterprise \( i \) at time \( t \), \( \text{Credit}_{it} \) is a dummy variable, which takes the value 1 if the enterprise took microcredit at time \( t \) and 0 if not. The term \( X_{it} \) is the vector of covariates that captures enterprise specific characteristics, \( \theta_i \) represents an unmeasured determinant of enterprise’s performance that is time invariant, \( \mu_t \) represent the time factor, \( \varepsilon_{it} \) is the idiosyncratic errors with conditional mean equal to zero, \( \delta \) and \( \beta \) are unknown parameters to be estimated.

However, the estimation of this model may involve biases in the measurement of the treatment (microcredit uptake) effect. There is potential selection bias in the credit uptake that may also create endogeneity bias in estimating the treatment effect. For instance, the decision to take up microcredit may depend on both observable and unobservable factors, which are correlated with the outcome variable. Firm owners who are better motivated are more likely to take up credit for expansion even though motivation levels are mostly unobservable. While the observable factors can be accounted for in a regression, the unobservable factors remain uncounted for. Such factors may be correlated with the enterprise’s performance and hence create some bias. That is, errors in the treatment assignment equation will be correlated with errors in the outcome equation.

Thus, we require an instrumental variable that meets all the basic requirements. That is, it must be correlated with microcredit uptake but not with sales. To surmount this challenge, we used three estimation techniques that allows us to estimate the impact of microcredit on sales in the absence of a valid instrument. These techniques are the Generalised Difference-in-Difference (GDiD) (Cerulli and Ventura, 2017), the heteroskedasticity based instrumental variable approach (Lewbel, 2012), the panel Fixed Effect (FE) model and the Endogenous Switching Regression (ESR).

The use of each of the techniques for estimation is justified by the lack of information about the nature of the unobservable factor generating the endogeneity bias. The FE models are sufficient only if the unobservable factor is assumed to be fixed at firm level. The Lewbel model is more appropriate where the model is heteroscedastic and the endogenous regressor contributes to this heterogeneity with a specific random error. The ESR is appropriate when the variable generating the endogeneity bias is a dummy variable. This
implies that using the multiple techniques enhance the robustness of the results. For instance, where the family FE models (FE, DDID and DID) fail to account for endogeneity due to low observed fixed effects, the ESR and Lewbel become relevant. The following sections discuss these techniques.

3.2.1 Generalised Difference in Difference approach

In addition to the instrumental variable technique, we employed the difference-in-difference (DiD) technique to estimate the impact of microcredit uptake on the performance of youth enterprises in Benin. Two different models were estimated using the standard DiD procedure and the generalised DiD procedure. While the standard DiD procedure is popular in the literature, the generalised DiD is fairly new and deserves further comments. The generalised models allow for the estimation of pre and post intervention effects. For instance, while the standard DiD estimates that impact of an intervention at time $t$, the generalised version allows for the impact of the intervention at times $t+1$ and $t-1$. A formal presentation of the model is given in outcome equation in (6):

$$ Y_{it} = \mu_{it} + \beta_{-1} D_{it-1} + \beta_0 D_{it} + \beta_{+1} D_{it+1} + \gamma X_{it} + u_{it} \quad (6) $$

Where $D_{it}$ is a binary treatment indicator that takes the value of 1 if a firm $i$, is treated at time $t$ and 0 otherwise. This implies that the coefficient of the $D_{it}$, $\beta_0$, measures the impact of the treatment in the current period. In similar fashion, the coefficients $\beta_{+1}$ and $\beta_{-1}$ capture the impact of the intervention one period before and after the treatment occurred, respectively.

Too further appreciate this, we assume that treatment can occur only over the interval $[t-1, t+1]$. This allows us to define the following sequence of treatment:

$$ \{w^j\} = \{D_{it-1}, D_{it}, D_{it+1}\} = \begin{cases} w^1 = (0, 0, 0) \\ w^2 = (1, 0, 0) \\ w^3 = (0, 1, 0) \\ w^4 = (0, 0, 1) \end{cases} \quad (7) $$

$w^j$ represents the treatment sequence with $j = 1, \ldots, 4$ and each treatment sequence is associated with a potential outcome $Y(w^j)$. For instance, the first sequence, $w^1$, represents no-treatment and is associated to the potential outcome $Y(w^1)$. Given this background, we can then define the Average Treatment Effect (ATE), between two potential outcomes $Y(w^j)$ and $Y(w^k)$, as:

$$ ATE_{jk} = E[Y_{it}(w^j) - Y_{it}(w^k)] \quad (8) $$

Equation (8) shows the ATE of sequence $j$ against the counterfactual, sequence $k$. Against this backdrop and using equation (6) we can present the ATE for any of the sequences with treatment against the benchmark of no treatment. By taking expectation, we derive the coefficients of interest. For sequence $w^2$ against the benchmark of $w^1$, we have

$$ ATE_{21} = [E(Y_{it}|w^2) - E(Y_{it}|w^1)] = (\bar{\mu} + \beta_{-1} + \bar{\gamma} \bar{x}) - (\bar{\mu} + \gamma \bar{x}) = \beta_{-1} \quad (9) $$

It, therefore, follows that $ATE_{31} = \beta_0$ and $ATE_{41} = \beta_{+1}$.

As indicated earlier, the coefficient of $\beta_{+1}$ can be interpreted as the effect of current treatment on past outcome. It hypothesises that outcomes in pretreatment period is affected by current treatment. Cerulli and Ventura (2017) call this the “anticipatory effect”. Similarly, $\beta_0$ can be interpreted as the effect of current treatment on current outcomes. Finally, $\beta_{-1}$ captures the lagged effect and suggests that current treatment has an effect on future outcomes. That is,
post-treatment period outcome is affected by current treatment. The Stata routine \textit{ddid} is used to estimate these impacts.

### 3.2.2 Heteroscedasticity based instrumental variable approach

In estimating the impact of a non-experimental intervention/treatment, a crucial challenge is eliminating the potential biases from the non-random nature of the data. As discussed earlier, similar challenge arises in this study as microcredit update is non-random and is likely to suffer from self-selection bias. In the presence of a valid instrument, the estimates can be purged from the bias and interpretations will be valid. However, like in many other empirical studies, identifying a good instrument is a daunting task. To avert this, we turn to the use of heteroscedasticity-based instruments to correct for the bias. This approach developed firstly by Lewbel (2012) is particularly relevant in situations where external instruments are insufficient or not available.

The Lewbel (2012) technique relies on some identifying assumptions that justify the proposed artificial instrumental variables. The key assumptions are:

\begin{align}
E[X\varepsilon_1] &= 0 \quad (2) \\
E[X\varepsilon_2] &= 0 \quad (3) \\
E[\text{Centered}_1 IV \cdot \varepsilon_i] &= 0 \text{ for } i = 1, 2. \quad (4) \\
E[\text{Centered}_1 IV \cdot \varepsilon^2_i] &\neq 0 \quad (5)
\end{align}

The fourth assumption suggests that the generated IV must be correlated with the square of the residuals. This holds in presence of heteroscedasticity. Indeed, as emphasised by (Baum et al., 2012), identification can be achieved if heteroscedasticity is present in, at least, some elements of $X$. Lewbel (2012) also showed that, with the first three assumptions, the artificial IVs can easily be generated by using the auxiliary equations’ residuals ($\partial y_2$). These residuals can be predicted from the ‘first-stage regression’ of each endogenous regressor $y_2$ on all exogenous regressors ($X$), by the centred endogenous: $IV = \text{Centered}_1 y_2, \partial y_2 = 0$. To estimate this, we used the Stata \textit{ivreg2h} routine developed by Baum and Schaffer (2017).

An important prerequisite for the application of this technique is the presence of scale heteroscedasticity in the regressors. Baum et al. (2013) noted that the higher the scale heteroscedasticity, the higher the correlation between the generated instruments and the included endogenous variables. We test and confirm the presence of scale heteroscedasticity in our data using the Breusch-Pagan type test - “\textit{ivhettest}”. We also used various post estimation tests to confirm the validity of the technique. These include the Sargan overidentification restriction, under identification and Weak identification tests (Stock and Yogo, 2005).

The Sargan-Hansen test is a test of overidentifying restrictions. Under the null hypothesis, the error term is supposed to be uncorrelated with the instruments that are considered thereby confirming the validity of the instruments. A rejection of the Sargan test casts doubt on the validity of the instruments. Under the null hypothesis that the equation is under-identified, the under-identification test shows that the excluded instruments are relevant. In our case, it tests if the generated instrument is correlated with the endogenous treatment variable (access to microcredit). The weak IV test checks if the excluded instruments are correlated with the endogenous regressors, but only weakly. It is expected no correlation between the excluded instruments and the endogenous regressor. The models are valid as the test statistics showed consistent estimates. This implies that for most of the models, the instruments are valid and satisfy all the necessary conditions.
3.2.3 Endogenous Switching Regression

The main assumption behind the ESR is that individuals can be sorted into two states using a switching equation. In our case, firms can be sorted into those that received credit and those that did not. It is also assumed that the outcome variable is continuous. Here we consider a criterion function \( T_i \) that determines which regime a firm faces.

\[
\begin{align*}
T_i = 1 & \quad \text{if} \quad yZ_i + u_i > 0 \\
T_i = 0 & \quad \text{if} \quad yZ_i + u_i \leq 0 \\
\end{align*}
\]

Regime 1: \( y_{1i} = X_{1i}\beta_1 + \epsilon_{1i} \) and \( y_{1i} = I[y_{1i} \geq 0] \)

Regime 2: \( y_{0i} = X_{0i}\beta_0 + \epsilon_{0i} \) and \( y_{0i} = I[y_{0i} \geq 0] \)

Where \( y_{1i} \) and \( y_{0i} \) are the two observed outcome variables. For the ESR model, the distribution of the three residuals \( u_i, \epsilon_{1i} \) and \( \epsilon_{0i} \) with a jointly three variants normally distributions, with a mean-zero vector and correlation matrix:

\[
\Omega = \begin{bmatrix}
\sigma_u^2 & \sigma_{1,u} & \sigma_{0,u} \\
\sigma_{1,u} & \sigma_{1}^2 & . \\
\sigma_{0,u} & . & \sigma_{0}^2 \\
\end{bmatrix}
\] (12)

Where \( \rho_l = \text{Cov}(u_i, \epsilon_i) \) and \( l \in \{0,1\} \). Since \( y_{1i} \) and \( y_{0i} \) are not observed simultaneously, and then the joint distribution of \( (\epsilon_1, \epsilon_0) \) cannot be identified. In the estimation, it is assumed that \( \rho_0 = 1 \). The estimation can be done by the Full specification of Maximum Likelihood model.

The results of the ESR model can also be used to generate conditional expectations. With the help of equation (13) to (16), we estimate the ATT and ATU in equations 17 and 18.

\[
\begin{align*}
E(y_{1k} | I_k = 1, X_{1,k}) &= X_{1,k}\beta_1 + \rho_1\sigma_1 f(Z_k\gamma)/F(y_Zk) \\
E(y_{0k} | I_k = 1, X_{1,k}) &= X_{1,k}\beta_0 + \rho_0\sigma_0 f(Z_k\gamma)/F(Z_k\gamma) \\
E(y_{1k} | I_k = 0, X_{0,k}) &= X_{0,k}\beta_1 - \rho_1\sigma_1 f(Z_k\gamma)/[1 - F(Z_k\gamma)] \\
E(y_{0k} | I_k = 0, X_{0,k}) &= X_{0,k}\beta_0 - \rho_0\sigma_0 f(Z_k\gamma)/[1 - F(Z_k\gamma)]
\end{align*}
\]

This follows that:

\[
\begin{align*}
\text{ATT} &= E(y_{1k} | I_k = 1, X_{1,k}) - E(y_{0k} | I_k = 1, X_{1,k}) \\
\text{ATU} &= E(y_{1k} | I_k = 0, X_{0,k}) - E(y_{0k} | I_k = 0, X_{0,k})
\end{align*}
\]

5. Results in progress

5.1 Descriptive statistics
Table 1 presents the summary statistics of the main variables used in the analyses, for the general sample and by year. A clean sample of 1119 observations for each wave of data was used for the study. This adds up to a panel of 3357 observations over the three years. Average weekly sales in the panel is 85424 FCFA. The yearly statistics show that the average sales almost double from 52,998 to 105,594 FCFA between 2014 and 2015. However, bigger size firms with sales above 300,000 FCFA mainly drive this increase. When we exclude these outliers, the average sale reduces to 56,336 FCFA and the difference across years is smaller. The average age of SME owner in the sample was approximately 30 years.

The proportion of male owners among the studied sample remained largely unchanged during the period of the study at 47%. Respectively, 18%, 36%, 38% and 8% of the SMEs’ owners have no education, primary, secondary and tertiary education level. We observe a smooth progression across the educational ladder over the years. While there is a decline in owners with primary education, there is an increase in secondary and tertiary education across the years. This suggests that some owners progressed in their education while they were in business.

The average number of hours worked per week among these firms is 51 hours. The proportion of SMEs with access to electricity has increased from about 62% in 2014 to 64% in 2015 and has remained constant in 2016. About 63% of firms had access to electricity and 4.2% had access to informal and family credit, respectively. Between 2015 and 2016, there was a significant increase in the number of firms, which were relied on the informal credit to finance their activities, whereas the number of those with to access family credit almost stayed constant.

### Table 1: Mean and standard deviation by year

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Main outcome variable:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales (CFA)</td>
<td>85424</td>
<td>212218</td>
<td>52998</td>
<td>47245</td>
</tr>
<tr>
<td>Sales (&lt;300000)</td>
<td>56336</td>
<td>56302</td>
<td>52420</td>
<td>45494</td>
</tr>
<tr>
<td><strong>Owner characteristics:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex of owner (Male)</td>
<td>0.470</td>
<td>0.499</td>
<td>0.467</td>
<td>0.499</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>0.178</td>
<td>0.482</td>
<td>0.178</td>
<td>0.383</td>
</tr>
<tr>
<td>Primary</td>
<td>0.357</td>
<td>0.480</td>
<td>0.381</td>
<td>0.486</td>
</tr>
<tr>
<td>Secondary</td>
<td>0.379</td>
<td>0.484</td>
<td>0.366</td>
<td>0.482</td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.085</td>
<td>0.279</td>
<td>0.076</td>
<td>0.265</td>
</tr>
</tbody>
</table>

$1=FCFA 550$
Firm characteristics:

<table>
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<tr>
<th></th>
<th>0.633</th>
<th>0.482</th>
<th>0.622</th>
<th>0.485</th>
<th>0.638</th>
<th>0.481</th>
<th>0.637</th>
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<td>Access to electricity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hours worked per week</td>
<td>51.180</td>
<td>34.922</td>
<td>54.34</td>
<td>33.39</td>
<td>54.54</td>
<td>33.29</td>
<td>45.50</td>
<td>35.75</td>
</tr>
<tr>
<td>Number employed</td>
<td>0.227</td>
<td>0.710</td>
<td>0.198</td>
<td>0.650</td>
<td>0.225</td>
<td>0.722</td>
<td>0.259</td>
<td>0.757</td>
</tr>
<tr>
<td>Informal credit</td>
<td>0.041</td>
<td>0.199</td>
<td>-</td>
<td>-</td>
<td>0.049</td>
<td>0.215</td>
<td>0.075</td>
<td>0.264</td>
</tr>
<tr>
<td>Family credit</td>
<td>0.041</td>
<td>0.199</td>
<td>-</td>
<td>-</td>
<td>0.063</td>
<td>0.243</td>
<td>0.062</td>
<td>0.241</td>
</tr>
<tr>
<td>Observations</td>
<td>3357</td>
<td>1119</td>
<td>1119</td>
<td>1119</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Produced by the authors using firm Data from Benhassine et al., (2017)
* p < 0.1, ** p < 0.05, *** p < 0.01

To further understand the dynamics in the key variables of interest, we present various graphs to unpack relationships and explain the objectives under investigation. Each of the graphs was constructed using non-parametric regression techniques (Local Linear Nonparametric Regression). In Figure 1, we plot the relationship between each of the three different forms of credit (formal, informal and family credit) and the firm’s sales. The idea is to identify which types of firms (in terms of sales levels) have access to which type of credits. This was also disaggregated by gender of the firm’s owner. Panel 1 in the figure shows that as the level of sales increased firms tend to take up formal credit. By contrast, firms that received family credit were those with lower levels of sales. This suggests that, youth start up enterprises mostly receive credit from family while larger firms are considered for credit from formal sources. This underscores the challenges faced by many start-up enterprises in developing countries regarding credit. In many countries, the requirements to access formal credit are costly, including various forms of assets for collateral. This limits small sized firms from having access to this kind of credit. Family credits, on the other hand, do not require too much in collateral and in terms of payment are much more flexible for smaller firms. The expected proportion of informal credit uptake remains, in general, constant and low compared to formal and family credit at different levels of sales. The informal credit uptake is higher only for high levels of sales. This suggests that informal credit may be less attractive for small-sized firms because of its high rate of interest compared to formal and family credit and the constraints in reimbursement.

In panel 2, we observe that the proportion of female owners who received formal credit was higher at all levels of sales compared to males. This can be explained by the fact that in recent times, policies have been introduced to improve access to credit with particular focus on women. Such policies include the programme of microcredit for poor launched in 2007 by the government of Benin. At lower levels of sales, men are likely to receive more informal credits than women (panel 3). Panel 4 suggests that expected proportion with access to family credit was higher at lower levels of sales and was higher for females relative to males. While females dominated access to family credit at higher levels of sales, the expected proportion was lower (Panel 4). The pattern, however, reverses at higher levels of sales where women are more likely to receive informal and family credit, compared to men. We explore further these gender dynamics later on in this paper with the empirical analysis.

Figure 1: Firm Sales and access to credit
In Figure 2, we explore the dynamics between credit access, age and sales. It can be observed that as age increases, the expected proportion of firms that received formal credit also increases. By contrast, the expected proportion of firms that received informal and family credit remained almost constant for different levels of age. The second panel of figure 2 shows that the sales of firms increase as the owner’s age increases.

Figure 2: Credit access, firm sales and owner’s age

The density curves by gender and credit types are presented in Figure 3. The density curves in panel 1 show that the concentration for female-owned firms is at higher levels of sales compared to those of male-owned firms. Similar conclusion for those with formal and informal credit, and where, the concentration of sales level is higher for firms with this type of credit compared to firms without credit (Panel 2 and 3). This was the inverse for the case of family credit, and where firm sales are relatively low (Panel 4).

Figure 3 : Density curves by gender and credit types
4.2 Econometric results

4.2.1 Impact of Credit Uptake on Firm Performance

We begin the econometric analyses with estimates of the impact of formal credit uptake on firm sales. As indicated earlier, we used both the standard difference-in-difference (DiD) and the generalised DiD (GDiD) techniques. The results present in table 2 suggest that, from the standard DiD the impact of formal credit access on sales (log) is 2.92. Disaggregating this by gender suggests an impact of 3.22 and 3.21 for male and female-owned firms, respectively. We also disaggregated the analysis by age interval and the estimated impacts are 2.20, 3.06 and 2.89 for age intervals [17, 25], [26, 30] and [31, 35], respectively.

Using the generalised GDiD the impact at time $t$ of receiving formal credit at time $t-1$ is estimated at 1.71, 1.07 and 2.13 for the whole population, male and female samples, respectively and 2.30, 2.18 and 2.20 for age intervals [17, 25], [26, 30] and [31, 35] respectively. However, the impact is not significant for owners aged between 17 and 25 years. Therefore, in general the impact of receiving formal credit is relatively more important for female owners and owners aged between 26 and 30 years old. However, the anticipated effect of access to formal credit is not significant across the entire population, and across both gender and age groups. The non-significance of the anticipated effect strengthens the parallel trend assumption on which we have based our estimation.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Male</th>
<th>Female</th>
<th>[17-25]</th>
<th>[26-30]</th>
<th>[31-35]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DiD</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ATE</td>
<td>2.919***</td>
<td>3.229***</td>
<td>3.208***</td>
<td>2.200*</td>
<td>3.062***</td>
<td>2.887***</td>
</tr>
<tr>
<td>Observations</td>
<td>2238</td>
<td>1051</td>
<td>1187</td>
<td>330</td>
<td>938</td>
<td>970</td>
</tr>
<tr>
<td><strong>GDiD</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ATE (t-1)</td>
<td>1.714***</td>
<td>1.076</td>
<td>2.129***</td>
<td>2.305</td>
<td>2.177***</td>
<td>2.198***</td>
</tr>
<tr>
<td>Observations</td>
<td>2238</td>
<td>1037</td>
<td>1168</td>
<td>227</td>
<td>697</td>
<td>892</td>
</tr>
</tbody>
</table>
Tables 3 to 5 present the results of the estimations of the impact of access to microcredit on firm’s sales using the OLS, the fixed effect, and the Lewbel (2012) instrumental variable models. Table 3 presents estimates per year while tables 4 and 5 present the results by gender and per age respectively for the different types of credit (formal, informal and family).

The results in Table 4 show a positive and statistically significant relationship between access to formal credit and firm sales except for year 2014 in the Lewbel Model. This implies that firms that had access to formal credit are more likely to have higher sales, compared to their counterparts without access. Estimates from OLS model shows impact of 1.6, 0.1, 1.7 and 1.7 for the pooled data, 2014, 2015 and 2016, respectively. These estimates are significant at 1% statistical level except for 2014 where the effect is significant at 5%. The estimated impacts of access to formal credit on firm sales, however, decreased when we corrected for endogeneity using the Lewbel technique. The estimated impacts are 1.02, 0.02, 1.4 and 1.5 respectively for the pooled data, 2014, 2015 and 2016. Except for the 2014 estimate which did not show statistical significance, all other estimates are significant.

The Sargan test is only checked for 2014 but the under-identification and the weak IV tests are checked for all models. The reduction in the estimates from the Lewbel technique underscores the need to correct for endogeneity bias in the model. This may be explained by the fact that the estimates are driven by firms who self-select themselves to access credit. These firms may be privileged by set of the unobserved characteristics, and hence bias the estimates upwards. Correcting for this bias avoids the self-selection and hence drives down the estimates.

Compared to the results of the Lewbel model, we noticed an increase in the impact of access to credit on firm’s sales, and it is estimated at 1.7. For the Lewbel model the impact of access to credit on firm’s performance is only significant across years but not for the general sample. The implication of these estimates is consistent with previous discussions. Firms that accessed formal credit were more likely to have higher sales levels. These findings can be explained by the fact that absorbing the fixed effects removes unobservable factors that do not change over time. This implies that firms that received credit in all years of the panel influence the estimates as much as firms whose status changed from no credit to receiving credit. In this case, the impact on such firms is expected to be higher.
<table>
<thead>
<tr>
<th>Table 3: Access to Formal Credit and Firm Performance (Log of Sales)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OLS</strong></td>
</tr>
<tr>
<td>Treatment:</td>
</tr>
<tr>
<td>Access to formal Credit</td>
</tr>
</tbody>
</table>

**Owner firm characteristics:**

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</tr>
</thead>
<tbody>
<tr>
<td>Sex of owner</td>
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<td>-0.215***</td>
<td>-0.081</td>
<td>-0.208</td>
<td>-0.278**</td>
<td>-0.227***</td>
<td>-0.117</td>
<td>-0.244</td>
<td>-0.039</td>
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<tr>
<td>Age of owner in 2014</td>
<td>0.025</td>
<td>0.011*</td>
<td>0.012</td>
<td>0.069**</td>
<td>0.030</td>
<td>0.012*</td>
<td>0.014</td>
<td>0.070**</td>
<td>-1.944***</td>
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**Education level:**

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<td>Primary</td>
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<td>-0.083</td>
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<td>-0.145</td>
<td>0.122**</td>
<td>-0.084</td>
<td>-0.371</td>
<td>0.634**</td>
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<td>Tertiary</td>
<td>0.455*</td>
<td>0.332***</td>
<td>0.604</td>
<td>0.437</td>
<td>0.458*</td>
<td>0.334***</td>
<td>0.613</td>
<td>0.431</td>
<td>0.042</td>
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**Firm characteristics:**

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</thead>
<tbody>
<tr>
<td>Access to electricity</td>
<td>-0.190</td>
<td>-0.061</td>
<td>-0.448*</td>
<td>-0.189</td>
<td>-0.184</td>
<td>-0.064</td>
<td>-0.438*</td>
<td>-0.185</td>
<td>0.616**</td>
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<tr>
<td>Hours worked per week</td>
<td>0.063***</td>
<td>-0.002***</td>
<td>0.086***</td>
<td>0.099***</td>
<td>0.064***</td>
<td>-0.002***</td>
<td>0.086***</td>
<td>0.099***</td>
<td>0.060***</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Number of employees</td>
<td>0.280***</td>
<td>0.131***</td>
<td>0.326**</td>
<td>0.343**</td>
<td>0.279***</td>
<td>0.131***</td>
<td>0.326**</td>
<td>0.342**</td>
<td>0.166</td>
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</tr>
<tr>
<td>Informal credit</td>
<td>2.547***</td>
<td>-</td>
<td>1.219**</td>
<td>2.468***</td>
<td>2.543***</td>
<td>-</td>
<td>1.199**</td>
<td>2.473***</td>
<td>2.353***</td>
<td></td>
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<td></td>
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<tr>
<td>Family credit</td>
<td>1.408***</td>
<td>-</td>
<td>0.653</td>
<td>0.966**</td>
<td>1.377***</td>
<td>-</td>
<td>0.630</td>
<td>0.951**</td>
<td>1.906***</td>
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**Constant term:**

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<td>9.995***</td>
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<td>-0.202</td>
<td>5.883***</td>
<td>10.101***</td>
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<td>-0.000</td>
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<td>No</td>
<td>No</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
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<tr>
<td>District</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Observations | 3357 | 1119 | 1119 | 1119 | 3357 | 1119 | 1119 | 1119 | 3357 |
| R-Squares | 0.447 | 0.152 | 0.417 | 0.569 | 0.445 | 0.150 | 0.417 | 0.569 | 0.378 |

| Over-identification Test | | | | | | | | | | | | |
| (>5%) | × | √ | × | x | × | √ | √ | √ | √ |
| Under-identification P-Value | | | | | | | | | | | | |
| Weak IV Test (5%) | | | | | | | | | | | | |

Source: Produced by the authors using firm Data from Benhassine et al., (2017)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
In Table 4, we replicate the analyses for the three types of credit (Formal, Informal and Family credit) considered in this study. We also disaggregated the analysis by gender. This is to show whether the impact of credit uptake varied across gender of the firm's owner. We present only estimates of the key variable (credit access) in the table in addition to the summary statistics of the models. The summary statistics suggests that the models are well fitted and instruments (in the case of the Lewbel models) are valid for some of the models.

It can be observed from the fixed effect models that the estimated impacts of access to credit were significant for all the models and for the different types of credit. As in the model without accounting for the fixed effect, the impact for access to credit is higher for females than for males and access to informal credit has higher impact compared to family credit that also has higher impact than formal credit. The impact of access to credit by female-owned firms on the performance of their business is significantly estimated at 1.8 for formal credit, 2.9 for informal credit and 2.1 for family credit. The estimates for the total and male samples across the three types of credit are 1.7 and 1.5; 2.3 and 1.6; 1.9 and 1.8 respectively for formal, informal and family credit. For the Lewbel model with fixed effect, we did not find any statistically significant results at the conventional 5% level. Only the estimate for female-owned enterprises showed statistical significance at 10%.
<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Lewbel Model</th>
<th>Fixed Effect Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Female</td>
<td>Male</td>
</tr>
<tr>
<td>Formal credit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3357</td>
<td>1778</td>
<td>1579</td>
</tr>
<tr>
<td>R-Squares</td>
<td>0.446</td>
<td>0.462</td>
<td>0.437</td>
</tr>
<tr>
<td>Sergan P-value (5%)</td>
<td>×</td>
<td>×</td>
<td>x</td>
</tr>
<tr>
<td>Under-identification P-Value</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Weak IV Test (10%)</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Informal credit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3357</td>
<td>1778</td>
<td>1579</td>
</tr>
<tr>
<td>R-Squares</td>
<td>0.446</td>
<td>0.461</td>
<td>0.438</td>
</tr>
<tr>
<td>Sergan P-value (5%)</td>
<td>×</td>
<td>×</td>
<td>x</td>
</tr>
<tr>
<td>Under-identification P-Value</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Weak IV Test (10%)</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Family Credit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3357</td>
<td>1778</td>
<td>1579</td>
</tr>
<tr>
<td>R-Squares</td>
<td>0.446</td>
<td>0.461</td>
<td>0.438</td>
</tr>
<tr>
<td>Over-identification Test (&gt;5%)</td>
<td>×</td>
<td>×</td>
<td>x</td>
</tr>
<tr>
<td>Under-identification P-Value</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Weak IV Test (10%)</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>

Source: Produced by the authors using firm Data from Benhassine et al. (2017)

*p < 0.1, ** p < 0.05, *** p < 0.01
The impact of formal credit on firm’s performance was also estimated by age intervals of the owners. Table 5 presents results using OLS and Lewbel model as well as Fixed effects model. It shows that, for the OLS model, there was a significant impact of access to credit across all age groups that relied on formal credit. In both the OLS and Fixed effect models, we found significant impact for the 26-30 and 31-35 age groups. The impact of formal credit on performance of firms with owners between 26 and 30 years was 1.4 in the OLS model and 1.5 in the FE models. For owners 31-35 years, the impact was 1.8 and 2.1 for the OLS and FE models, respectively. Statistical significance in the Lebel model was generally low with only owners in ages 31-35 showing significance.

In the case of informal credit access, statistical significance was largely prevalent. There was generally positive impact on performance of firms, irrespective of age’s owner. There was no clear pattern on the impact of credit and age of owner. It was, however, evident that firm owners within the age range of 31-35 were generally better off in terms of impact. This seems to be consistent for both informal and formal credit access. For instance, in the FE model, while the impact of informal credit was 2.38 and 2.17 for [17-25] and [26-30], respectively, it was 2.41 for age range [31-35]. For family credit, the estimates were 1.97 and 1.81 for ages [17-25] and [26-30], compared to 1.89 for age [31-35]. The use of the Lewbel model for the impact of family credit did not show any statistical significance.
Table 5: Access to Formal Credit and Firm Performance per age interval

<table>
<thead>
<tr>
<th></th>
<th>OLS All</th>
<th>Lewbel Model All</th>
<th>Fixed Effect Model All</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[17 25]</td>
<td>[26 30]</td>
<td>[31 35]</td>
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<tr>
<td>Formal credit</td>
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<tr>
<td>Observations</td>
<td>3357</td>
<td>467</td>
<td>1377</td>
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<tr>
<td>R-Squares</td>
<td>0.446</td>
<td>0.487</td>
<td>0.44</td>
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<tr>
<td>Sergan (5%)</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Under-id P-Value</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Weak IV (10%)</td>
<td>√</td>
<td>×</td>
<td>√</td>
</tr>
</tbody>
</table>

| Informal credit       |         |                  |                        |
| Observations         | 3357    | 467              | 1377                   |
| R-Squares            | 0.446   | 0.487            | 0.44           |
| Sergan (5%)          | ×       | ×                | ×                       |
| Under-id P-Value     | √       | √                | √                       |
| Weak IV (10%)        | √       | ×                | √                       |

| Family Credit         |         |                  |                        |
| Observations         | 3357    | 467              | 1377                   |
| R-Squares            | 0.446   | 0.487            | 0.44           |
| Over-identification Test (>5%) | × | ×                | ×                       |
| Under-id P-Value     | √       | √                | √                       |
| Weak IV (10%)        | √       | √                | √                       |

Source: Produced by the authors using firm Data from Benhassine et al. (2017)

*p < 0.1, ** p < 0.05, *** p < 0.01
Table 6 presents results from the endogenous switching regression model. As mentioned earlier, this model was adopted as a complementary model in addressing the selection and endogeneity bias problems. Estimates for the average treatment effect on the treated (ATT), untreated (ATU) and the entire sample (ATE) are reported. The results show that there was a protective impact of credit uptake on the treated, untreated and the combined average. The impacts were also strongly significant. As expected, the magnitude of the impact was higher for the treated (7.5) compared to the untreated (2.5) and the combined average (3.2). This confirms our earlier findings that formal credit uptake improves firm performance in Benin. The estimates also suggest that the treatment impact was largely driven by female-owned enterprises. The gender disaggregation showed that treatment effect on the treated and average treatment effect was higher for females.

<table>
<thead>
<tr>
<th></th>
<th>ALL</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimated impact</td>
<td>Standard error</td>
<td>Estimated impact</td>
</tr>
<tr>
<td>ATT</td>
<td>7.523***</td>
<td>0.157</td>
<td>-0.140</td>
</tr>
<tr>
<td>ATU</td>
<td>2.505***</td>
<td>0.018</td>
<td>2.888***</td>
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<tr>
<td>ATE</td>
<td>3.197***</td>
<td>0.040</td>
<td>2.470***</td>
</tr>
<tr>
<td>p0</td>
<td>0.997***</td>
<td>0.001</td>
<td>-0.240</td>
</tr>
<tr>
<td>p1</td>
<td>0.141</td>
<td>0.157</td>
<td>-0.084</td>
</tr>
</tbody>
</table>

Source: Produced by the authors using firm Data from Benhassine et al., (2017)

* p < 0.1, ** p < 0.05, *** p < 0.01

6. Conclusion

The study set out to estimate the impact of credit uptake on youth enterprise performance. This question fits in recent policy discourse across the continent on youth employment and its potential impact on well-being. Using data from an RCT experiment, we explored both instrumental variable and DiD techniques to achieve our stated objective. In general, the results indicate a positive and significant relationship between access to credit and firm performance (measured by level of sales). The magnitude of the impact differed between males and females as well as age groups. There were also some variations with regards to the various forms of credit – formal, informal and family credit. Specifically, we found evidence that firms at their early stages benefit better from informal and family credit relative to formal credit. This may be justified by the fact that informal and family credit are usually more flexible than formal credits and require less collateral. Payment terms are also generally flexible and therefore likely to favour these firms.

The results generally suggest that, if given the right attention and commitment, easy access to credit uptake could improve the performance of youth enterprises. Unfortunately, many formal credit sources in Benin (and by extension developing countries), require collateral that hinder SMEs from accessing such credits. Our results also show that credit from informal sources and family could be important for small enterprises. Providing appropriate regulations for these sources may be a step in the right direction. While government policies have only focused on formal sources of credit, the findings of this study underscore the need to pay attention to informal sources. This may be achieved through community-based interventions that provide support to small-scale firms through informal moneylenders while ensuring some regulation of their activities.
7. References


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