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Financing Pathways for Entrepreneurs in the Philippines: A Big Data Analysis using DSLOGIT Regression

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As echoed by many other authors and experts, micro, small, and medium enterprises (MSMEs) are crucial for economic development. This study uses the 2014 Consumer Finance Survey conducted by the Bangko Sentral ng Pilipinas and a double-selection lasso logistic regression model (DSLOGIT) to identify factors influencing the likelihood of starting and operating single proprietorships in the Philippines. The findings highlight the significant role of various financing sources and individual characteristics. Microfinancing is positively correlated with single proprietorship, while loans from commercial banks, cooperatives, and close relatives negatively affect business ownership. These insights can help policymakers design more effective support mechanisms for MSMEs.

Keywords: big data analysis, double selection Lasso Logistic Regression, MSME, consumer finance survey, entrepreneurship, proprietorship

1 Introduction

The existing literature highlights the crucial role that micro, small, and medium enterprises (MSMEs) play in achieving sustainable economic growth, job creation, and poverty alleviation (Raquiza, 2021; Oviatt & McDougall, 2005; Tamangan et al., 2004). This study aims to investigate the factors influencing the operation of MSMEs and assess whether available financing options affect the decisions of micro and small entrepreneurs to start, operate, and manage small enterprises as solo business owners. Specifically, the objectives of this research are to: (1) identify the key factors influencing the likelihood of starting and operating single proprietorships in the Philippines; (2) compare the relationships between various formal and informal financing options; and (3) provide insights for policymakers to design more effective support mechanisms for MSMEs.

Formal financing options include bank loans and government programs, while informal options encompass family loans and personal savings. In the Philippines, MSMEs are operationally defined by their size in terms of employment and assets. According to the Philippine Statistics Authority (PSA, 2022), a microenterprise has fewer than 10 employees; a small enterprise employs between 10 and 99 employees; and a medium enterprise employs between 100 and 199 employees. In terms of asset size, microenterprises have assets up to PHP 3 million, small enterprises range from PHP 3 million to PHP 15 million, and medium enterprises range from PHP 15 million to PHP 100 million (RA 6977, 1991). Figure 1 shows the number of MSMEs has grown by 38%, from 780,469 in 2006 to 1,076,279 in 2021. Employment generated by MSMEs increased by 64%, rising from 3.3 million in 2006 to 5.5 million in 2021, as shown in Figure 2. By 2022, MSMEs provided approximately 5.6 million jobs, with micro-enterprises contributing a 50% share, thus accounting for 65% of the country's total employment (PSA, 2022). In that same year, the sectoral distribution indicated that wholesale, retail, and repair of motor vehicles and motorcycles accounted for nearly 50% of MSME performance, followed by accommodation and food service activities at 14% and manufacturing at 12%. Overall, MSMEs contribute 40% to the Philippine GDP (UNDP, 2020).

Evidence from various studies demonstrates a positive impact of access to finance on MSME growth (Ayyagari et al., 2008; Beck et al., 2008; Berger & Udell, 2006; Beck & Demirguc-Kunt, 2006). In the Philippines, loans provided to MSMEs have increased, from a loan borrower-to-total MSME ratio of 0.55 in 2006 to 1.57 in 2020, while the incidence of non-performing loans has remained stable, growing at an average rate of 4% as shown in Figure 3. However, despite this increasing access to loans, one of the primary constraints faced by MSMEs continues to be the lack of access to capital. Figures 1, 2, and 3 are included in the appendix section.

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This study emphasizes the application of Big Data, which involves a vast array of information that is constantly and rapidly updated. However, the 2014 CFS data utilized in this study provides only a snapshot in time, raising questions about its classification as Big Data. Despite this limitation, the large volume and variety of data points justify its inclusion under the Big Data umbrella.

Thus, this study aims to empirically assess whether the financing options available to micro and small entrepreneurs affect their decisions to start, operate, and engage in small enterprises as solo business owners. The study also seeks to understand other determinants of running a small business to provide insights into the enabling and disabling factors affecting small business owners. Furthermore, it intends to compare the relationships between various formal and informal financing options. Formal financing sources, such as bank loans and government programs, are typically regulated by financial authorities, offering structured loan products with defined terms and conditions. Examples of these include commercial banks, microfinance institutions, and government-backed loan programs. Conversely, informal financing options encompass family loans and personal savings, which are less regulated and often involve more flexible, personal arrangements. Informal financing may include borrowing from relatives or friends or utilizing one's savings to fund business operations.

Finally, this study intends to leverage Big Data to enhance the robustness of its findings, making them relevant across a broad spectrum of contexts and applications. According to Davis (2014), Big Data involves the collection of vast amounts of information that is continuously and rapidly updated. In the digital age, where information is easily gathered and stored from customers and clients at every interaction point, the main challenge lies in effectively utilizing this data. Thus, Big Data analytics offers policymakers and decision-makers an opportunity to optimize the use and analysis of extensive data collections.

Davis (2014) emphasizes the importance of effectively utilizing vast amounts of information in the digital age. Big data analytics offers policymakers and decision-makers an opportunity to optimize the use and analysis of extensive data collections. Goldstein, Spatt, and Ye (2021) discuss how big data analytics can enhance financial decision-making and risk assessment within the finance industry. When analyzing Big Data, there is a corresponding challenge of dealing with an immense number of observations and predictors in the model. An ordinary regression model may be insufficient when many predictors are correlated, leading to multicollinearity, which can produce misleading or skewed results. As noted by Safi (2023), multicollinearity can inflate the standard errors of the coefficients, potentially rendering predictors that were previously statistically significant insignificant due to the presence of collinearity. Therefore, this study intends to employ double selection lasso logistic regression with shrinkage estimators to minimize multicollinearity.

2 Review of Related Literature

In the Philippines, MSMEs encompass a diverse range of business structures, with entrepreneurship serving as a common form, particularly among household-based business owners. These businesses are typically characterized by their small scale, limited resources, and the personal involvement of the owner in daily operations (Raquiza, 2021). The MSME sector is crucial to the Philippine economy, significantly contributing to employment and gross domestic product (GDP) (Guliman & Uy, 2019). Entrepreneurships, as a subset of MSMEs, benefit from various government programs designed to support and promote small business growth (Raquiza, 2021).

Numerous studies have examined the financing pathways available to entrepreneurs in the Philippines. Guliman and Uy (2019) explored the concepts of financial sophistication and the triple bottom line in their study on Filipino micro-entrepreneurs. They employed quantitative analysis to examine financial decision-making and literacy among these entrepreneurs. The context of their research focused on micro-entrepreneurs in the Philippines, aiming to understand how financial sophistication impacts business performance. Their findings revealed that higher financial sophistication is positively correlated with better business performance, highlighting the importance of financial literacy and informed decision-making in the success of micro-enterprises.

Enyi (2019) analyzed the impact of dependent variables on financial performance using multiple surrogates analysis. The study, conducted within the context of financial performance research, found that enhanced access to financing and elevated financial literacy positively impact business success. The findings emphasized the importance of financial resources and literacy in driving business performance, supporting the need for policies that improve access to finance and financial education.

Raquiza (2021) explored the financial difficulties faced by MSMEs and the role of public financing support in addressing these challenges. Using qualitative analysis, the study focused on MSMEs in the Philippines, highlighting the critical need for enhanced access to financial resources. The findings underscored that improved access to financing is essential for the growth and sustainability of MSMEs, emphasizing the importance of supportive financial policies and programs.

Further, Avila and Gonzalvo (2019) examined the relationship between financial literacy and business operations among micro-business owners in Ragay, Camarines Sur. Through a survey-based analysis, the study found a direct correlation between financial education and effective business operations. The research highlighted that higher levels of financial literacy among micro-business owners lead to better decision-making and improved business performance, stressing the importance of financial education programs. This aligns with the work of Goldstein, Spatt, and Ye (2021), who discussed how big data analytics can enhance financial decision-making and risk assessment within the finance industry.

Magid et al. (2024) investigated the impact of FinTech solutions and sustainable finance in the post-COVID-19 investment landscape. Utilizing big data analytics, the study demonstrated that FinTech and big data analytics significantly promote sustainable finance. The research provided insights into how technological advancements and data-driven approaches can enhance financial decision-making and support sustainable investment practices. Additionally, Emfevid and Nyquist (2018) focused on financial risk profiles through logistic regression analysis. The study aimed to identify critical factors influencing financial risk profiles within the context of financial risk assessment. The findings revealed key determinants of financial risk, providing valuable insights for financial institutions and policymakers to better understand and manage financial risks.

Kristanti and Dhaniswara (2023) compared the predictive accuracy of artificial neural networks and logistic regression in forecasting financial distress. The study, set in the context of financial distress forecasting, found that both traditional methods and modern analytical approaches are effective. The research highlighted the complementary strengths of these methods, suggesting that combining them could enhance predictive accuracy and reliability. Together, these studies provide a comprehensive view of the factors influencing entrepreneurial success in the Philippines, particularly the roles of financial literacy, access to financing, and advanced analytical tools.

In the context of financing pathways for entrepreneurs, the dependent variable may be the success or growth of the business, while independent variables could encompass access to financing, financial literacy, business experience, and prevailing market conditions (Enyi, 2019). These expectations can be substantiated through existing literature and theoretical frameworks. For example, research generally supports the notion that enhanced access to financing and elevated financial literacy yield positive impacts on business success (Enyi, 2019). Additionally, business experience and favorable market conditions are anticipated to significantly contribute to growth (Boyles, 2022).

3 Methodology

3.1 Data Source

This study utilizes data from the 2014 Consumer Finance Survey (CFS), conducted by the Bangko Sentral ng Pilipinas (BSP) every four years. The survey covers all 17 regions of the Philippines and achieved a response rate of 86.1%, resulting in a final sample of 15,503 respondents from an initial sample size of 18,000 (BSP, 2014). The CFS collects comprehensive information on respondents' demographic profiles, loan details, financing options, financial and non-financial assets, expenditures, and income.

Using secondary data such as the 2014 CFS offers several advantages. According to Ashikuzzaman (2025), the use of secondary data circumvents the time-consuming and resource-intensive process of primary data collection. The CFS provides a broad and detailed dataset rich in variables pertinent to the analysis of MSMEs in the Philippines, facilitating an in-depth examination of financing pathways and their impacts on proprietorship.

Although the 2014 Consumer Finance Survey (CFS) represents a static snapshot in time, it enables researchers to analyze trends and patterns over an extended period, offering valuable insights into the evolution of financing options and their effects on MSMEs. The data collected by the Bangko Sentral ng Pilipinas (BSP) is publicly accessible and has undergone rigorous validation, ensuring its reliability and accuracy for research purposes. While more recent CFS data is available, the 2014 CFS provides a comprehensive dataset with a high response rate and detailed information on respondents' demographic profiles, loan details, financing options, financial and non-financial assets, expenditures, and income. Despite its static nature, the large volume and variety of data points justify its inclusion under the Big Data umbrella. Additionally, the 2014 CFS offers a baseline for understanding the entrepreneurial landscape before the COVID-19 pandemic, which can be compared with post-pandemic data in future studies.

Despite its static nature, the 2014 CFS qualifies as Big Data due to its large volume and variety of information. The dataset includes extensive details on business success, access to financing, financial literacy, business experience, market conditions, and technological infrastructure. These variables are operationalized in line with the concepts discussed in the Review of Related Literature. For instance, business success is measured through indicators such as revenue growth, profit margins, and business expansion. Access to financing is assessed by the variety of financing options available and the total amount of funding received. Financial literacy is evaluated via standardized tests and self-assessment surveys, while market conditions are analyzed using relevant economic indicators and market reports.

3.2 Method

This study employs double-selection lasso logistic regression (DSLOGIT) to investigate the relationships among explanatory variables and proprietorship, representing MSMEs. The DSLOGIT model combines the Least Absolute Shrinkage and Selection Operator (Lasso) with logistic regression to select relevant predictor variables and estimate regression parameters. The DSLOGIT model is a sophisticated regression technique that first applies the Lasso to select relevant predictor variables. Following this selection process, the model estimates the regression parameters for the chosen variables of interest. This approach aids in addressing potential multicollinearity issues, enhancing the accuracy and interpretability of the findings.

3.2.1 Lasso Regression

The Lasso is a special type of regression that is used when there is a large volume of observation. According to Tibshirani (1996), Lasso only maintains the significant variables in the model by marking the coefficients of the predictors with minimal effect to zero. This model includes a shrinkage estimator that penalizes the model and minimizes the deviance thereby reducing the incidence of multicollinearity.

The objective function of Lasso that shrinks the model with a penalty is shown below (Simon et. al, 2011; McCullagh & Nelder, 1989):

$$OF_{Lasso} = \sum_{i=1}^{N_{IS}} \tilde{w_i}\,[-\,\tilde{y}_i(\beta_0 + \boldsymbol{x}_i\boldsymbol{\beta'}_i) + ln\,(1 + e^{(\beta_0 + \boldsymbol{x}_i\boldsymbol{\beta'}_i)})\,] + \lambda_{Lasso}\sum_{j=1}^{p} K_j(\beta_j) \qquad (1)$$

y_i is the ith observation of the dependent variable; x_i = (x_{i1},…., x_{iN}) are 1 x p vector of the the independent variables (note that the continuous regressors used in the model have been standardized so that mean =0 and standard deviation =1); β_0 is the intercept β_i is the 1 x p vector of the coefficients of the regressor; **$\boldsymbol{\lambda}$ is the lasso penalty estimator which is ≥ 0;** K_j are coefficient-level weights; xb_i is the linear prediction of the ith observation; w_i is the observation-level weights, N_{IS} is the number of observations of the in-sample subset and N_{OS} is the number of observations in the out-sample subset.

3.2.2 Logistic Regression

It is worthwhile to discuss the standard logit regression to explain the dslogit regression properly. This is the regression model that is apt to use when the dependent variable is binary which has a value of 1 or 0. A simple logit regression formula is written as (Agresti, 2015):

$$\hat{\rho}_i(\mathrm{y}=1|\mathrm{x})=\frac{\mathrm{e}^{(\sum_{j=1}^{p}\beta_j x_{ij})}}{1+\mathrm{e}^{(\sum_{j=1}^{p}\beta_j x_{ij})}} \tag{2}$$

where: $\hat{\rho}_i$ is the probability of the i[th] observation; i is the number of observations; j is the number of coefficient parameter β; x is the number of regressors.

3.2.3 Double-Selection Lasso Logistic Regression

The Lasso model is used to select the variables that will provide the least deviance or errors or mainly for the prediction of the best-fit model. However, this alone won't be useful when doing inferences. Since the outcome of Lasso is the various models showing different values of deviance, there is a need to account for sample-to-sample variability. Moreover, there might be omitted variable bias when Lasso dropped some predictor variables with a small impact on the dependent variable (Belloni et.al, 2014). Hence, the dslogit model employs a double selection using both lasso regression in equation (1) and the logit regression in equation (2). The dslogit gives the equation below (Belloni et.al, 2016):

$$\hat{\rho}_i(\mathrm{y}=1|\mathrm{x},\mathrm{d})=\frac{\mathrm{e}^{(\mathbf{d}\boldsymbol{\alpha}\prime+\boldsymbol{x\beta}\prime)}}{1+\mathrm{e}^{(\mathbf{d}\boldsymbol{\alpha}\prime+\boldsymbol{x\beta}\prime)}} \tag{3}$$

where d are the chosen variables of interest such as demographic characteristics and banking engagements of individuals; x are the variables selected by Lasso which are included in the control variables; and α are the coefficients reported from the dslogit regression model.

This study employs the Double-Selection Lasso Logistic (DSLOGIT) regression model to analyze the financing pathways for entrepreneurs in the Philippines. The primary dependent variable is business success, measured using indicators such as revenue growth, profit margins, business expansion, and market share. The independent variables include access to financing, financial literacy, business experience, market conditions, and technological infrastructure.

Access to financing is quantified by the number of available financing options, the total amount of funding received, and the terms of those financing arrangements. Financial literacy is evaluated using standardized tests, self-assessment surveys, and educational background. Business experience is represented by the number of years in business, previous ventures, and relevant work experience. Market conditions are assessed via market analysis reports and economic indicators, while technological infrastructure considers technology adoption, the use of digital platforms, and investments in technological upgrades.

By systematically defining and measuring these variables, this study aims to provide a comprehensive analysis of the factors influencing the financing pathways for entrepreneurs in the Philippines, ensuring that significant factors are considered, leading to reliable and actionable results.

The DSLOGIT regression method operates under several key assumptions: the presence of a binary response variable, independence of observations, absence of severe multicollinearity among explanatory variables, and the lack of extreme outliers. The 2014 Consumer Finance Survey (CFS) data align well with these assumptions, as it includes binary outcome variables for business success or failure and maintains independent observations by collecting data from individual businesses. Furthermore, Lasso regularization mitigates potential multicollinearity issues, while the data has been cleaned to remove extreme outliers.

The specific variables used in the DSLOGIT regression model include:

1. Business Success: Measured by revenue growth, profit margins, business expansion, and market share.
2. Access to Financing: Assessed by the number of financing options available, total funding received, and financing terms.

3. Financial Literacy: Evaluated through standardized tests, self-assessment surveys, and educational attainments.
4. Business Experience: Gauged by years in business, previous ventures, and related work history.
5. Market Conditions: Evaluated using market analysis reports and relevant economic indicators.
6. Technological Infrastructure: Measured by the level of technology adoption, usage of digital platforms, and investment in technological upgrades.

The application of big data within this regression analysis enhances the ability to uncover patterns, trends, and relationships among extensive datasets. Big Data refers to large, complex datasets that surpass traditional processing capabilities. In the context of financing pathways for entrepreneurs, Big Data allows for the inclusion of numerous variables and observations, thereby improving the robustness and predictive power of the regression models.

The DSLOGIT model is particularly well-suited for big data applications, as it combines logistic regression with the Lasso (Least Absolute Shrinkage and Selection Operator), effectively managing high-dimensional settings with a multitude of potential predictors. The Lasso technique facilitates the selection of the most relevant variables while controlling for multicollinearity, ensuring the model remains interpretable and reduces the risk of overfitting. The 2014 CFS serves as a secondary data source, providing a comprehensive dataset that fits the assumptions of the DSLOGIT regression model. The operationalization of variables such as business success, access to financing, financial literacy, business experience, market conditions, and technological infrastructure aligns with concepts discussed in the Review of Related Literature.

By leveraging Big Data, this study captures a detailed and nuanced understanding of the factors influencing financing pathways for entrepreneurs. The DSLOGIT model's capacity to manage large datasets and select pertinent variables ensures that the analysis is both thorough and precise, yielding valuable insights for theoretical research, practical applications, and methodological advancements.

4 Results and Discussion

Among the 15,503 respondents, a total of 2,687 individuals (17%) identified as entrepreneurs operating their own businesses. The demographic profile of these entrepreneurs indicated a gender distribution of six females for every four males. In terms of age, 19% of the respondents fell within the 31-40 age range, while 25% were aged 51-60. Educational attainment revealed that 70% of these entrepreneurs had completed high school or lower levels of education.

Nearly half of the businesses operated by these entrepreneurs had been in operation for five years or less, with a significant majority classified as micro-sized enterprises (97%). Among the respondents, 37% reported having availed of loans to support their businesses. The average age of these borrowers was 48, which is notably younger than the average age of 51 for non-borrowers. Furthermore, individuals who secured loans demonstrated higher educational attainment compared to those who did not.

Both groups had businesses with an average operational duration of 11 years. However, the businesses of loan recipients were slightly more skewed towards the micro-enterprise category, with 98% classified as such, compared to 96% of non-borrowers during the study period.

These findings highlight significant trends in loan utilization among entrepreneurs, indicating that younger, better-educated individuals are more likely to secure loans for their business ventures. This suggests that financial literacy and access to education play crucial roles in enabling entrepreneurs to obtain financing. Table 1 presents the profile of these solo business owners categorized by loan availment in 2013.

Table 1. Socio-Demographic Profile of Single Proprietorship by Loan Availment in 2013, Philippines

	Loan=0 n = 1,703	Loan=1 n = 984	Total N = 2,687
Total	**63%**	**37%**	**100%**
Sex			
Male	24%	13%	38%
Female	39%	23%	62%
Age			
17-30	3%	2%	5%
31-40	12%	7%	19%
41-50	17%	11%	29%
51-60	15%	11%	25%
over 60	16%	6%	22%
Average age	51	48	
Educational level			
Elem	20%	10%	30%
High School	25%	15%	41%
College	14%	8%	23%
Others	4%	3%	7%
Number of years of operation			
0 to 1 year	9%	6%	15%
2 to 5 years	19%	10%	29%
6 – 10 years	10%	7%	17%
11 – 15 years	9%	5%	14%
16 – 20 years	5%	3%	9%
over 21 years	11%	6%	17%
Average years of operation	11.4	11.5	
Employed			
Micro (1-9 employees)	61%	36%	97%
Small (10-99 employees)	2%	1%	3%

Source: 2014 Consumer Finance Survey

In terms of industry breakdown, most of the entrepreneurs are traders in wholesale & retail businesses (31%), farmers (24%), and operators of food and accommodation businesses (11%) as shown in Figure 4 (in the appendix section). Almost the same industry mix is found in both groups of loan availment as shown in Table 2.

Table 2. Top Three Industry Breakdowns of Proprietorship by Loan Availment in 2013, Philippines

	Loan=0 n = 1,703	Loan=1 n = 984	Total N = 2,687
Wholesale & Retail	20%	11%	31%
Agriculture	15%	9%	24%
Food and Accommodation	7%	4%	11%

Source: 2014 Consumer Finance Survey

Access-to-capital is ranked first as the most essential factor for the health of their businesses at 61% in the two groups. This is followed by perseverance (12%), product knowledge (5%), and having the right price (2%) as shown in Figure 5 (in the appendix section). Between the two groups, those who secured loans gave more weight to access-to-capital at 63% compared to 59% of those who did not avail of loans as shown in Table 3.

Table 3. Most Essential Requirements of a Successful Business by Loan Availment, 2013

	Loan=0 n = 1,703	Loan=1 n = 984	Total N = 2,687
Access to Capital	59%	63%	61%
Perseverance	12%	10%	12%
Product knowledge	5%	5%	5%
Right Price	2%	3%	3%
Total	100%	100%	100%

Source: 2014 Consumer Finance Survey

In Table 4, there were more MSMEs (37%) who took out loans than the other non-MSME (18%) respondents, further supporting the previous result of the importance placed by entrepreneurs on capital accumulation through financing. Interestingly, the highest source of financing for MSME came from microfinance banks (31%), followed by commercial banks at 25% and cooperatives at 16%. In contrast, non-MSE borrowers preferred commercial banks (17%) and cooperatives (14%) as their source of loans.

Table 4. Source of Financing for Entrepreneurs in 2013, Philippines

	Secured Loans*		
	MSME**	Non MSME**	Total
No. of observations	984	2,262	3,246
Total Observation	2,687	12,816	15,503
Percent to total	37%	18%	21%
Commercial bank	25%	17%	20%
Microfinance bank	31%	6%	13%
Rural/cooperative bank	7%	4%	4%
Savings/Thrift bank	3%	1%	2%
Total banked sources	66%	28%	40%
Cooperatives	16%	14%	15%
Family/relatives/friends	4%	4%	4%
Total	100%	100%	100%

Note:
*Multiple responses
** MSMEs are the entrepreneurs in the dataset
Source: 2014 Consumer Finance Survey

When asked about the most important reason why they preferred their bank/ financial institutions, the proximity to home (30%) and efficient service (26%) were the two most important considerations considered by both MSMEs and non-MSMEs as shown in Table 5.

Table 5. Reasons for Choosing Bank/Financial Institution for Single Proprietors in 2013, Philippines

	MSME	Non-MSME	Total
Proximity to home	32%	29%	30%
Efficient service	28%	25%	26%
It is a major bank	5%	6%	6%
Personal acquaintances/ relatives	5%	5%	5%
Proximity to workplace	3%	6%	5%
Attractive charges for services	3%	4%	3%
High interest rates	2%	2%	2%
Others	21%	23%	22%
Total	100%	100%	100%

Source: 2014 Consumer Finance Survey

4.1 Double Selection Lasso Logistic Regression Analysis

The Double Selection Lasso Logistic regression model is employed to investigate the determinants of an individual's decision to operate a proprietorship in the Philippines using the 2014 Consumer Finance Survey with 15,503 respondents. The dslogit model includes a total of 209 variables and retains 136 final regressors in the final Lasso model. The model is statistically significant at a 1% level with a Wald chi-square test statistic of 375.35 and a p-value of 0.0000 as shown in Table 6.

Table 6. Table DSLOGIT Regression Result

No. of Observations	15,503
Number of Controls	209
Number of Selected Controls	161
Wald chi2 (18)	375.35
Prob > chi2	0.0000

Selected Variables	Single proprietorship/ MSME	
	Coefficient	z-value
Avail loan (dummy)	0.6359**	2.4471
Ranked access to capital as the primary need of a business (dummy)	6.1657***	13.8843
Microfinance (dummy)	4.1534***	5.8979
Commercial bank (dummy)	-1.6031*	-1.6692
Coop (dummy)	-11.7003***	-7.5579
Family loan (dummy)	-1.5026*	-1.8448
Age (continuous)	0.0091***	3.8642
Own vehicle (dummy)	0.7389***	3.135
Spend more (dummy)	-0.4441*	-1.9404
Female (dummy)	-0.2472	-1.2153
Risk taker (dummy)	0.1534	0.7156
Savings deposit (dummy)	-0.0578	-0.0677
Bank client longer than 5 years (dummy)	0.2107	0.3052
High school or higher (dummy)	-0.1315	-0.6126
Own house (dummy)	0.0618	0.2897
Rated health condition as very good (dummy)	0.1336	0.5426
Rated house's condition as very good (dummy)	-0.0185	-0.0875
Thrift bank (dummy)	1.2124	0.7143

***, ** and * denote significance level at the 1%, 5%, and10% levels, respectively.

4.1.1 Securing a Loan

Several factors significantly influence the decision to become a small solo business owner. Specifically, obtaining a loan is associated with a higher likelihood of establishing a sole proprietorship in the country. Those who view access to capital as the most critical determinant of their business health and success are more likely to be micro and small business owners. This study corroborates prior research emphasizing the pivotal role of credit in facilitating entrepreneurial activities and fostering economic growth (Aghdam et al., 2023; Hodgson, 2021; Karlan & Morduch, 2010; Trew, 2010; King & Levine, 1993).

4.1.2 Financing Options

Among the formal and informal financing options available to small business owners, borrowing from microfinance institutions stands out as positively correlated with proprietorship. Banerjee and Duflo (2014) also highlighted the beneficial impact of microfinancing on small businesses, noting that these products are often more accessible, flexible, and less restrictive compared to traditional bank offerings.

Conversely, this study reveals a negative relationship between financing from commercial banks, cooperatives, and family or friends and the establishment and operation of small businesses. This finding mirrors the study by Vrablova (2021), which reported that only 20% of small businesses in

Hungary obtained loans from banks. Additionally, Robb (2002) evidenced that younger firms tend to rely heavily on informal financing due to concerns about being denied loans from traditional banking institutions.

Unexpectedly, the study also indicates a negative association between cooperative financing and engaging in small business activities. Cooperatives, which are user-owned and user-controlled organizations designed to fulfill common needs and aspirations (ICA, n.d.), generally provide financial benefits, information, support, and networking opportunities to their members (Ghauri et al., 2021). However, this finding aligns with Nwankwo, et al's (2012) assertion that although cooperatives aim to assist small businesses, their relatively small scale often prevents them from having a significant impact on micro and small enterprises. Future research could further explore this unexpected result.

The negative association between loans from family and friends is consistent with findings from Lee and Persson (2016), who noted that, despite being less expensive and sometimes interest-free, family loans are often less preferred than formal financing due to associated shadow costs, which can limit the entrepreneurial risk-taking necessary for successful business management.

4.1.3 Individual Characteristics

Regarding the socio-demographic characteristics of the respondents, older individuals and those who own vehicles are more inclined to become solo business owners. This finding resonates with Bai et al. (2022), who established a positive correlation between age and successful entrepreneurship, suggesting that more mature individuals are likely to pursue proprietorship compared to their younger counterparts.

5 Conclusion

This study highlights the critical role of access to capital for micro and small businesses, particularly through microfinance institutions. The findings suggest that promoting microfinance and integrating it into financial systems can enhance its availability and accessibility, even in remote areas. In contrast, traditional financing options, such as commercial banks, cooperatives, and informal loans from family and friends, are negatively correlated with the propensity to be a solo business owner. These findings suggest that microfinance should be further promoted and integrated into financial systems to enhance its availability and accessibility, even in remote areas. It is imperative that public and private support is institutionalized to help financial institutions provide better rates and services to their clients.

The insights derived from this research underscore the significance of access to capital while suggesting directions for future investigations. Understanding why loans from commercial banks and other sources are negatively correlated with proprietorship could inform policymakers in designing more suitable and effective financing and support mechanisms for MSMEs. Additionally, further research could explore how gender and cultural norms influence individuals' likelihood of engaging in entrepreneurial ventures. Assessing the sustainability and longevity of small businesses receiving different types of financing would also be valuable. A longitudinal study could trace the factors affecting individuals' tendencies to start and operate businesses over time and across various policy interventions.

5.1 Implications for Theoretical Research

This study contributes to the theoretical understanding of financing pathways for entrepreneurs in the Philippines by integrating big data analytics and the DSLOGIT regression model. This research highlights the importance of financial literacy and access to financing in determining business success. Policymakers should focus on enhancing financial education programs and improving access to microfinance institutions. Future research could explore additional variables such as gender and cultural norms to provide a more nuanced understanding of entrepreneurial success. The findings support existing theories about the roles of financial literacy and access to capital in business performance, while also introducing new insights regarding the impact of technological infrastructure. Future theoretical research could build upon these findings by exploring additional variables and refining the models used to analyze financing pathways.

5.2 Implications for Practice

For practitioners, this research offers actionable insights into the factors influencing entrepreneurial success. Financial institutions can utilize these findings to develop targeted financial products and services that address the specific needs of entrepreneurs. Policymakers can leverage these insights to design programs that enhance financial literacy and improve access to financing for small businesses. Financial institutions can develop targeted financial products and services that address the specific needs of entrepreneurs. For example, microfinance institutions can offer flexible loan products with lower interest rates and longer repayment periods. Policymakers can design programs that provide financial literacy training and support for small businesses, particularly in remote areas. Furthermore, entrepreneurs can benefit from recognizing the importance of financial literacy and technological adoption in their operations, enabling them to make informed decisions that enhance their chances of success.

5.3 Implications for Research Methods

The application of the DSLOGIT regression model in this study demonstrates its effectiveness in handling large datasets and identifying significant predictors of business success. This methodological approach allows for the selection of relevant variables while controlling for potential endogeneity, producing robust and reliable results. The DSLOGIT regression model demonstrates its effectiveness in handling large datasets and identifying significant predictors of business success. Researchers should consider applying this model in other contexts and datasets to validate its versatility. Additionally, comparing the DSLOGIT model with other advanced statistical and machine learning frameworks can enhance analytical approaches. Future research could benefit from applying the DSLOGIT model in other contexts and datasets, exploring its versatility and potential across various aspects of financial analysis. Moreover, researchers should consider comparing the DSLOGIT model with other advanced statistical and machine learning frameworks to validate and enhance their analytical approaches.

This study has multiple implications for theoretical research, practice, and research methods. The findings contribute to the understanding of factors influencing MSME operations while underscoring the significance of access to financing. For practitioners, the results suggest that improving access to formal financing options can significantly boost business performance. The DSLOGIT regression method showcases its applicability in analyzing large datasets, providing essential insights for future research.

Additionally, further research could focus on comparing the success rates of businesses operated by younger versus older entrepreneurs to gain a deeper understanding of the variables affecting their respective successes or failures. Supporting evidence from Karlan and Morduch (2010) indicates that personal spending habits can limit individuals' financial capacity to engage in entrepreneurial endeavors, warranting further exploration in future studies.

6 Limitations of the Study

This study on financing pathways for proprietors in the Philippines, utilizing big data analytics and the DSLOGIT regression model, acknowledges several limitations that must be considered. The accuracy and reliability of the analysis are influenced by the availability and quality of big data; inconsistent or incomplete data may restrict the scope and depth of the study. Additionally, the findings may not be generalizable to all entrepreneurs due to the diversity in business types, sizes, and geographic locations, potentially introducing biases into the results.

While the DSLOGIT regression model is a powerful analytical tool, its effectiveness relies on the correct specification of variables and data quality. Issues such as mis-specification or multicollinearity could impact the model's performance. Moreover, external factors—including economic conditions, government policies, and market dynamics—that influence financing pathways may not be fully accounted for, resulting in variability that is challenging to control.

Furthermore, implementing big data analytics necessitates advanced technological infrastructure and expertise. Limited access to such resources can impede effective application. To address these limitations, future studies could enhance data collection efforts by collaborating with government agencies, financial institutions, and industry associations to obtain more comprehensive datasets. Expanding the sample size to incorporate a larger and more diverse group of proprietors could improve the generalizability of the findings. Including external factors, such as economic indicators, policy changes, and market trends, would provide a more holistic understanding of the influences on financing pathways.

Additionally, exploring alternative models alongside the DSLOGIT regression model could validate and compare results, thereby identifying the most effective analytical approaches. Investing in technological infrastructure and developing expertise in big data analytics through training programs and academic collaborations is crucial for improving the implementation of advanced analytical techniques. Addressing these limitations and following these recommendations will enable future research to achieve a more comprehensive and accurate understanding of financing pathways for proprietors in the Philippines.

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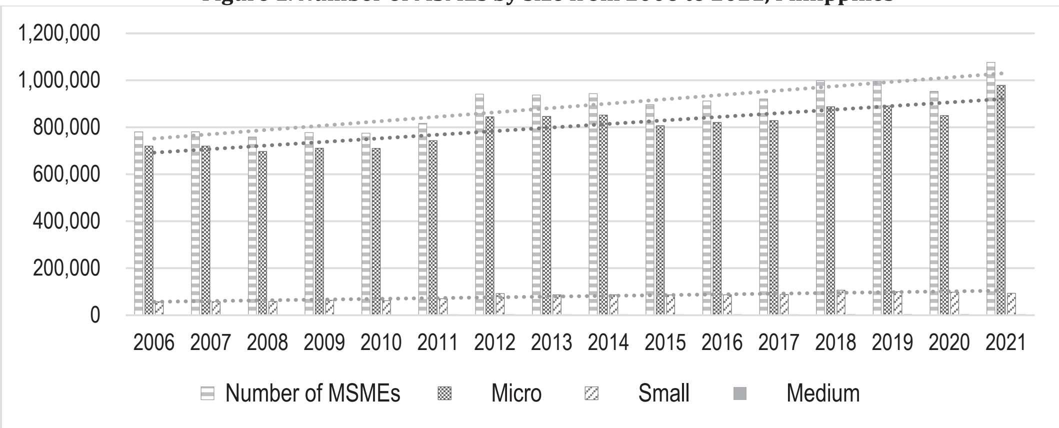
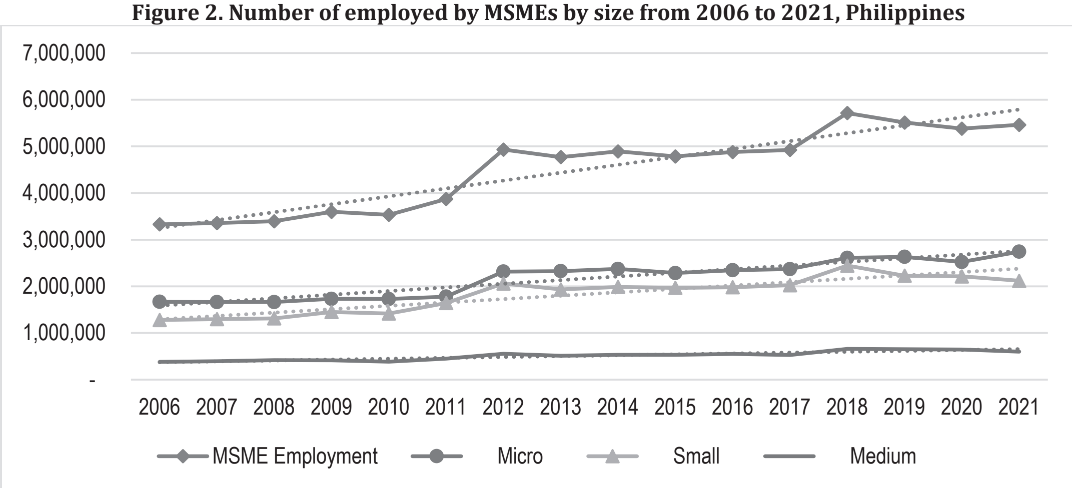
Appendices

Figure 1. **Number of MSMEs by size from 2006 to 2021, Philippines**



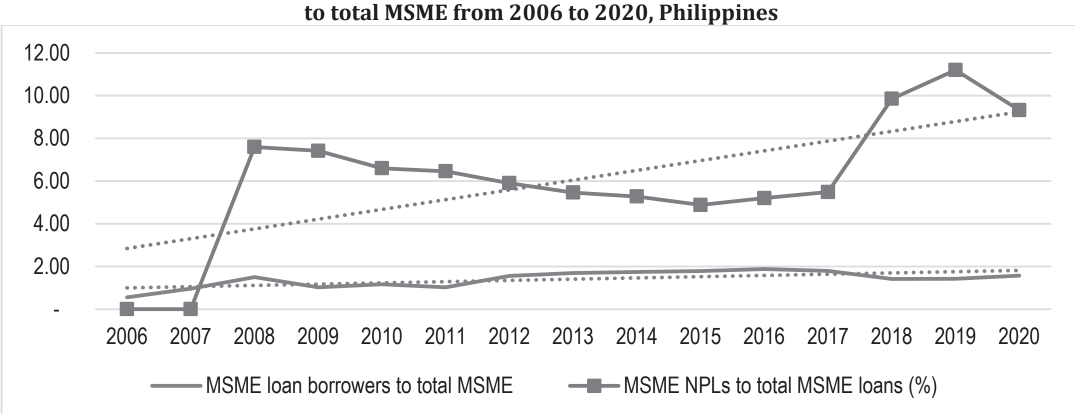
Source: Asian Development Bank, Asia SME Monitor 2023

Figure 2. Number of employed by MSMEs by size from 2006 to 2021, Philippines



Source: Asian Development Bank Asia SME Monitor 2023

Figure 3. **Share of MSME loan borrowers and Incidence of Non-performing Loans to total MSME from 2006 to 2020, Philippines**



Source: Asian Development Bank Asia SME Monitor 2023

Figure 4. Breakdown of industry sector of the businesses in 2013, Philippines

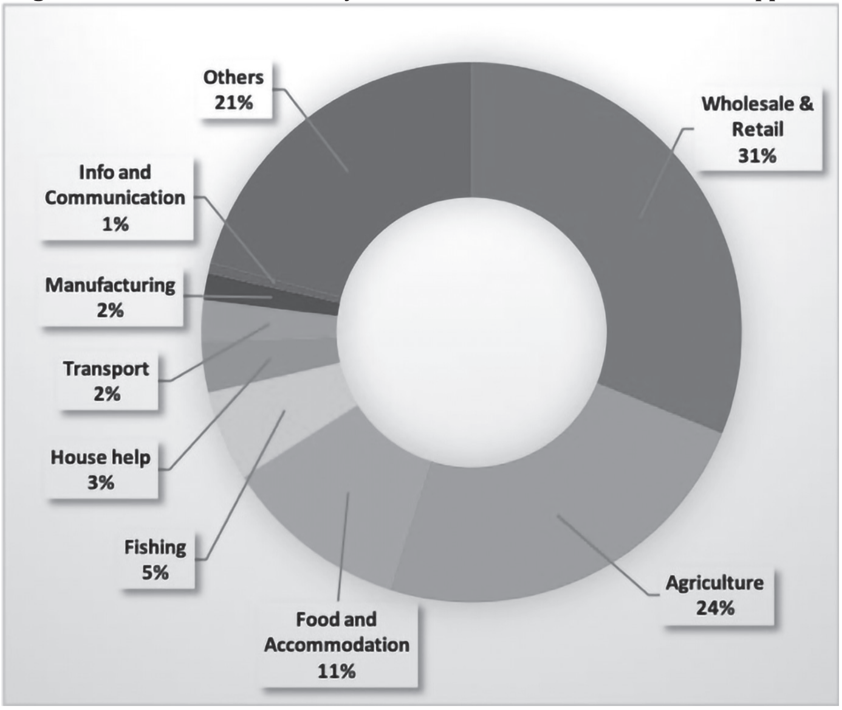


Figure 5. Rankings of the most essential requirements for a successful business among entrepreneurs in 2013, Philippines