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Binary logistic regression analysis on determinants of capacity utilization in medium and large manufacturing industries in Ethiopia

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ABSTRACT

Most manufacturing industries in Ethiopia are not operating at full capacity. The manufacturing industry is one of the main determinants of the economic growth of a country; therefore, the reasons why they are not operating at full capacity have to be assessed. The aim of this study is to assess determinant factors associated with Ethiopia's large and medium manufacturing industries (henceforth referred to as LMMIs in this study) not working at full capacity based on 2020 LMMI survey data. In this study, 3,067 large and medium manufacturing industries were examined. Among these industries, 78.71% were not working at their full capacity, while the remaining 21.29% were. Binary logistic methods were used to analyze the data. Study results found that the region, the number of months the establishment operated during the study period, the workplace of the manufacturing company, the effect of Covid-19, and the current most serious problem facing the establishment were statistically significant predictors for working at full capacity. LMMI intervention programs, including regional work, increasing the number of working months in the year, workplace, the effect of unexpected external influences (e.g., COVID-19) and major problems among LMMIs, should be put in place to increase the production to full capacity.

Contribution/Originality: Most studies on manufacturing industries use direct measures of capacity utilization. By taking the preceding illustration into account, this study includes some indirect estimating measures of capacity usage, such as logistic regression analysis.

1. INTRODUCTION

Ethiopia's economy has experienced rapid growth since 2019 with gross domestic product (GDP) growth rates of 6.1% per annum compared to Sub-Saharan Africa's rate of 3.5% (Commercial Bank of Ethiopia Annual Report, 2014; Ethiopian Economics Association, 2015; Yared, Alemayehu, & Seid, 2015; Yared, Alemayehu, Seid, Bhorat, & Tarp, 2016). Industry has grown by 9.6% per year since 2016 and contributed 29% of GDP (Commercial Bank of Ethiopia Annual Report, 2014).

Among the sectors, agriculture, which is the mainstay of Ethiopia's economy, grew by 6.6%, while industry and services grew by 20.2% and 10.8%, respectively, indicating that Ethiopia's economic growth is becoming more diversified (National Planning Commission, 2016; Seid, 2015).

Agriculture contributed 44.7% to GDP in 2010/11, industry contributed 10.5%, and services contributed 45.5%, but these figures changed to 38.5%, 15.1%, and 46.3% in 2014/15, respectively (International Monetary Fund, 2014; National Planning Commission, 2016).

According to Narasimha and Ramesh (2015), manufacturing drives economic growth and structural transformation. Since the early 2000s, Ethiopia has been one of the few African countries to formulate and implement a comprehensive industrial development strategy. Manufacturing is an essential part of industrial growth, and it is essential for building national technological and industrial capabilities, technological progress, productivity, and capital accumulation (McKinsey Global Institute, 2012; United Nation Industrial Development Organization, 2014; United Nation Industrial Development Organization, 2015).

Transfer of surplus resources from agriculture to manufacturing is important for economic growth, and manufacturing has different advantages, such as broadening job opportunities and improving the total factor productivity and increasing the competitiveness of the economy (McKinsey Global Institute, 2012; United Nation Industrial Development Organization, 2014; United Nation Industrial Development Organization, 2015). The second Growth and Transformation Plan focuses on the development of light and small manufacturing enterprises that are globally competent and leading in Africa, which will provide a solid foundation for further growth of heavy industries that will ultimately make Ethiopia a middle-income country by 2025 (National Planning Commission, 2016). Natural resource endowments have given Ethiopia a comparative advantage when it comes to exporting textiles and garments, leather and leather products, and processed agricultural products (Kefyalew & Tarkegne, 2013; Tsegaye, 2011). However, the manufacturing sector in Ethiopia is underdeveloped, even by African standards. There are only a few successful cases in leather and textiles, and the sector is small and highly import-dependent (Peter & Lamin, 2010) and Assefa, Bienen, and Ciuriak (2013).

One of the fundamental problems facing less developed countries today, such as Ethiopia, is the backwardness of their economies as well as the lack of resources necessary to match their ambitions. The industrial sectors of these countries are allegedly plagued by technical inefficiency (Tybout, 1990). Similarly, Pickett (1991) pointed out that Ethiopia has not had an efficient industrial sector. Given this situation, there is a strong desire to document the patterns and magnitudes of these issues so that suitable policies can be developed.

Manufacturing capacity utilization peaked at 78.70% in the late 1970s and plummeted to 43.80% in the 1980s. Between 2000 and 2005, it fluctuated between 34.60% and 52.78%. Manufacturing value addition and employment generation, which determined industrial development, also fluctuated during the same period. It remains uncertain how the utilization of manufacturing capacity contributes to industrial development. This study aims to assess the trend of individual firms working at full capacity in Ethiopian large and medium manufacturing industries and identify the causes of industries not working at full capacity.

Capacity utilization is important in many developing countries, especially in Nigeria, where capital is scarce and underused (Adeyemi & Olufemi, 2016). Deb (2014) found that utilizing plant capacity is one way in which economic reforms in India enhanced productivity growth in the manufacturing sector. According to the study, Indian manufacturing sector capacity utilization rates were estimated. The result showed that capacity utilization rates were lower in the pre-reform period but grew faster after the reform.

The manufacturing sector has not yielded many benefits for Ethiopia due to a lack of productivity, high labor turnover, and an inability to effect structural changes (Tigabu, Gebrehiwot, Balineau, & Fikru, 2018).

Even though small and medium enterprises (SMEs) play a crucial role in creating jobs and alleviating extreme poverty in Ethiopia, many of them are unable to reach their full potential (Nega & Hussein, 2016).

Technology plays a significant role in enabling the future of production, with emerging technologies providing the crux of the industrial revolution. The World Economic Forum (2018) emphasizes that countries should continuously upgrade their technology infrastructure so that they can fully utilize emerging technologies. There are several reasons why underproduction occurs: a lack of electricity, a lack of foreign currency, a lack of working capital, a lack of a market, inadequate management and leadership, a shortage of skilled manpower, unfair competition against imported products, a monopolistic nature of local manufacturing, and an unwillingness of public procurement offices to purchase products from local manufacturers (Mulugeta, 2018). A market-based approach is required to optimize capacity utilization among furniture manufacturing SMEs (Mapetere & Thelmaer, 2018). Furthermore, emerging technologies are one of the key enablers of the industrial revolution as they are adopted and diffused throughout the industry. This requires countries to continually upgrade their technology infrastructure in order to ensure that their platform is advanced enough for emerging technologies to operate effectively and efficiently (World Economic Forum, 2018).

Having a well-functioning supply chain will keep a business efficient, effective, and smooth (Basu, Jeyasingam, Habib, Letchmana, & Ravindran, 2017). A collaborative approach to supply chain management increases both performance and capacity utilization (Seo, Dinwoodie, & Roe, 2015).

As a result of the policies, different sectors develop and national industries become stronger (World Economic Forum, 2018). Analyses of the possible causes of under-capacity utilization of the sector in Nigeria cited shortage of power, lack of foreign currency, lack of working capital, lack of market, inadequate management, lack of appropriately skilled manpower, unfair competition with imported products, the monopolistic nature of competition among local manufacturers, and the reluctance of public procurement offices to buy from local manufacturers as some factors that could be causing under-capacity utilization (Mulugeta, 2018).

Research has been carried out on whether improving the capacity utilization of furniture manufacturing SMEs through a market-based approach in the case of Gweru, Zimbabwe, by examining only the market effect on the capacity utilization of SMEs, and it was recommended that the sector develop a new market strategy in order to improve its capacity utilization (Mapetere & Thelmaer, 2018).

Raw material inadequacy, workers' problems, financing problems, energy shortages, and tariffs are factors that affect capacity utilization, according to Turhan (2018). Manufacturing industries face shortages of domestic and imported raw materials as well as inadequate imports (Turhan, 2018).

In food manufacturing, Ndemezo, Ndikubwimana, and Dukunde (2018) found that the main reasons for underutilization of capacity are shortages of raw materials, the lack of specialized technology, the tax administration, and standards. In addition to fixed assets, beverage manufacturing is also undermined by a lack of working capital and standards and insufficient demand. As a result of inadequate output from one industry, there is a lack of raw materials in another (Turhan, 2018). This study examines the determinant factors associated with Ethiopia's large and medium manufacturing industries (LMMI) not operating at full capacity. Based on 2020 data from the Ethiopian survey of large and medium manufacturing industries, we quantified the extent and variation of under-capacity operation across regions. However, because we use the LMMI survey data, we are limited to specific variables, and the data was also limited in 2020.

2. MATERIALS AND METHODS

The 2020 Large and Medium Scale Manufacturing Survey (LMSMIS) data were used in this study. The dependent variable is a binary variable measuring operations, either at full capacity or otherwise. Region, total sales value, value of raw materials, the number of months during which the establishment operated, place of work, Covid, and the most serious problem facing the establishment at present were all considered as explanatory variables.

2.1. Binary Logistic Regression Model

The data in this study were analyzed using binary logistic regression. This study uses logistic regression since the dependent variable is the capacity of LMSMIS industries, which is determined by whether or not a firm is working at full capacity. As a function of covariates, we can model a binary or dichotomous variable with logistic regression (Hosmer & Lemeshow, 1989). The dependent variable's two responses have been coded as follows:

$$Y = \begin{cases} 1, if\ the\ industry\ working\ at\ full\ capacity \\ 0, if\ the\ industry\ not\ working\ at\ full\ capacity \end{cases}$$

By using binary logistic regression, the explanatory variables can be related to the outcome variable through a suitable transformation of the probability of success. In this study, "success" means "working at full capacity". The model with p explanatory factors/variables is given by Equation 1 as:

$$logit(\pi) = g(X) = X'\beta = \beta 0 + \beta 1 x 1 + \cdots + \beta p x p \quad (1)$$

Equation 1 presents the logistic regression model. For more details about this model, please refer to the standard work by Hosmer and Lemeshow (2000).

2.2. Binary Logistic Regression Analysis (BLRA)

In a regression analysis, the response variable is associated with one or more explanatory variables. In many cases, the outcome variable is discrete and has two or more possible values (Hosmer & Lemeshow, 2000). The binary linear regression analysis (BLRA) is used when the explanatory variables are quantitative or qualitative and the response is binary rather than continuous (Hair, Black, Babin, & Anderson, 2010). In the 1970s, this method was proposed to overcome the difficulties of ordinary least squares (OLS) regression in treating binary outcomes (Peng, Lee, & Ingersoll, 2002). According to logistic regression (LR) the probability (p) will be 1 rather than 0. This is based on binomial probability theory; thus, the event is more likely to be associated with one group rather than another. According to the maximum likelihood approach, LR presents the best fitting function, which maximizes the probability that the observed data will belong to the correct category given the regression coefficient (Burns & Burns, 2008).

2.3. Assumptions of BLRA

Linear relationships between the response and the explanatory variables are ignored in logistic regression. Furthermore, the response must be binary variables, explanatory variables need not be interval variables, the distribution must be normal, the relationship should be linear, and there must be no inequality of variance within groups. Furthermore, each group should be mutually exclusive and detailed, with each case belonging to only one group. Furthermore, the maximum likelihood coefficients are large estimates since LR must have a much larger sample size than the maximum likelihood. At least 50 cases are required for each explanatory variable (Burns & Burns, 2008; Hair et al., 2010; Kleinbaum & Klein, 2010).

2.4. The Logistic Model

In order to investigate implied associations between response variables and explanatory variables, logistic regression analysis (LRA) can be used assuming one explanatory variable X and one binary outcome variable Y; the logistic model predicts Y from X as a natural logarithm of the odds of Y. As a simple formula, it looks like this:

$$\ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta x \quad (2)$$

The logit is on the left-hand side. In the LR model, X is linear in the logit. As a result, we get:

$$\pi(x) = E\left(\frac{Y}{X}\right) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} \quad (3)$$

Where π represents the probability of the outcome of interest, given that X = x, α is a parameter which represents the Y-intercept, β is a parameter of the slope, X can be a qualitative (categorical) or quantitative variable, and Y is always qualitative or categorical. From simple linear regression to multiple linear regression, the formula (2) is expressed as follows:

$$\ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 x_{1+} \beta_1 x_{1+} \beta_2 x_{2+\ldots+} \beta_k x_k \quad (4)$$

Therefore,

$$\pi(x) = \frac{e^{\alpha+\beta_1 x_1+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k}}{1+e^{\alpha+\beta_1 x_1+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k}}, \quad (5)$$

Where α is the Y-intercept, the βs are parameters of the slope, the Xs are combinations of explanatory variables, and π denotes the event probability. The maximal likelihood estimator approach is used to estimate α and the β parameters.

2.5. Hosmer–Lemeshow Goodness of Fit Test

The Hosmer–Lemeshow test, commonly known as the X^2 (Chi-square) test, determines if a model fits the data. The null hypothesis states that the model is adequate to fit the data, and it will only be rejected if there are sufficiently compelling reasons to do so (traditionally, if the p-value is less than 0.05). See Hosmer & Lemeshow (2000) for details.

2.6. Likelihood Ratio Test (LRT)

The test is based on the log-likelihood ratio. With this test, we check the significance of the difference between the likelihood ratio for the reduced model with explanatory variables and the likelihood ratio for the current model with only a constant in it. The reduced model with explanatory variables differs significantly from the one with only the constant if the significance level is 0.05 or less (all 'b' coefficients being zero). It measures how well the explanatory variables fit the null model compared to the explanatory variables. We do not reject the null hypothesis that the explanatory variables do not affect the prediction of the response variable when the probability is unable to reach the 0.05 significance level (see Bergerud (1996); Bewick, Cheek, & Ball (2005)).

2.7. Goodness of Fit Test by R^2

In linear regression methods based on OLS, the coefficient of determination R^2 can be used as a measure of goodness of fit, which represents the variation ratio explained by the model. Since logistic regression lacks a similar statistic, several pseudo-R^2 statistics have been developed. The Cox and Snell pseudo R^2 and Nagelkerke pseudo R^2 are used in this paper (see Nagelkerke (1991) and StatSoft (2013) for details).

2.8. Statistical Significance Test

In linear regression, we want to determine how well the model fits the data overall as well as the contributions made by the explanatory variables. In logistic regression, we use the Wald test, which is similar to a t-test that is performed on the coefficients in a linear regression in order to determine whether a variable is contributing to the prediction of the outcome, specifically determining if the coefficient of the explanatory variable is significantly different from zero. A logistic regression model is evaluated by calculating the area under the curve, which ranges between 0.5 and 1.0, with larger values indicating a better fit (Kleinbaum & Klein, 2010).

2.9. Average Marginal Effects

In most studies that utilize logistic regression, the focus is more on relative risks and odds ratios. However, both could be misleading. As a result, we have no sense of magnitude of the odds ratios and relative risks (that is, no intuitive sense of the size of the difference).

Nonlinear models are commonly manipulated by marginal effects to give a more intuitive sense of their effect on the variables. Logistic regression models are more informative since they express the effects in probability scales (whereas coefficients are estimated in log-odds scales), i.e., we can better interpret the model by using the scale that makes the most sense. A marginal effect can be defined as the instantaneous effect that a change in an explanatory variable has on the conditional mean of the response (y) (Cameron & Pravin, 2010). For a continuous variable x_j, the marginal effect is calculated by computing its derivative with respect to the covariate:

$$\frac{\partial E(\frac{y}{x})}{\partial x_j} = \frac{\partial F(x'\beta)}{\partial (x'\beta)} \cdot \frac{\partial (x'\beta)}{\partial x_j} = f(x'\beta)\beta_j \quad (6)$$

Where f is the density function that corresponds to the cumulative distribution function F. In a linear regression, marginal effects are simply functions of slope coefficients. Nevertheless, in nonlinear regression models, marginal effects of explanatory variables (x_j) on response variables depend not just on the regression coefficient attached to them (β_j) but also the associated parameter vectors (β) and covariates (x). The marginal effect of x_j on the logit model can be expressed as follows:

$$\frac{\partial E(\frac{y}{x})}{\partial x_j} = F(x'\beta)[1 - x'\beta]\beta_j \quad (7)$$

Equation 7 shows that the marginal effects will vary with the value of x. As a result, an expression can be evaluated using the sample means of the data, or the marginal effects can be estimated at every observation and their average marginal effects can be calculated from the sample average of each marginal effect. These two approaches generally lead to different results because marginal effects are nonlinear functions of the explanatory variables $(F(E[Y]) \neq E[F(Y)])$, parameters and levels. In small or moderate-sized samples, it is preferable to average the marginal effects of each participant (Greene, 2003).

The presence of dummy variables in the covariate vector (x) complicates the computation of marginal effects in a binary choice model. For such variables, it might not be appropriate to take the derivative as if they were continuous. For an independent binary variable of x_k , a marginal effect would be as follows:

$$\text{Marginal effect} = \Pr\,(y = 1/\vec{x}\,, x_k = 1) - \Pr\,(y = 1/\vec{x}\,, x_k = 0) \quad (8)$$

where $\vec{x}$ denotes a vector of the means of all other variables in the model.

The predicted probabilities and the estimated marginal effects can be computed as $F(x'\hat{\beta})$ and $f(x'\hat{\beta})\hat{\beta}$, respectively. Note again that both are nonlinear functions of the parameter estimates. Greene (2003) shows that the estimators are asymptotically normal under certain regularity conditions. To compute the standard errors, we can use linear approximation approaches, such as the delta method (linear Taylor series expansion). In this study, the impact of covariates was explored using average marginal effects (AMEs).

3. RESULTS

3.1. Goodness of Fit

The model summary in Table 1 shows the variation in the outcome variable production at full capacity explained by the independent variables with the Cox and Snell R^2 and Nagelkerke R^2 (Pseudo R^2) values. The Cox & Snell R^2 = 0.631, which indicates that 63.1% of the variation in production at full capacity is explained by the predictors but the remaining 36.9% is unexplained. These R^2 values demonstrate the explained variation in production at full capacity, which ranges from 63.1% (Cox and Snell R^2) to 71.8% (Nagelkerke R^2).

Table 1. Model summary.

Cox & Snell R-squared	Nagelkerke R-squared
0.631	0.718

Table 2 presents the results of the Hosmer–Lemeshow test, which tests the null hypothesis that the predictions made by the model fit absolutely with the observed group memberships. A chi-square statistic (10.44, df = 8) was computed by comparing the observed frequencies with those expected under the linear model. It shows the non-significant chi-square value and indicates that the model is good fit for the data.

Table 2. Goodness of fit (Model diagnostic).

Hosmer–Lemeshow Test	Chi-square	Df	Sig.
	10.441	8	0.235

3.2. Results of Logistic Regression Analysis (Marginal Effects Analysis)

As discussed earlier, interpreting the coefficients of the fitted logistic regression model using the odds ratios (or the log-odds scale) may be misleading since odds ratios do not account for actual differences in the probabilities of outcomes among groups (categories). On the other hand, marginal effects are more informative since they express effects on a probability scale. Using marginal effects, we examine the impact of covariates on the outcome.

3.3. Average Marginal Effect

The average marginal effect (AME) shows how a covariate affects the probability of an outcome. In the case of a continuous covariate, it refers to the average change in probability when the covariate increases by one unit. When categorical variables are considered, the AME shows the difference in the predicted probabilities for one category relative to the reference category (discrete change effects). Unlike linear models, the effect varies based on individual differences (since logits are nonlinear models). The AME computes the predicted probability of an individual based on the observed levels of covariates. Averages of these values are then calculated for all individuals.

Table 3 presents the average marginal effects for the covariates considered in this study. The results indicate that, on average, a one-month increase in the production of industries is associated with a 2.4% increase in the probability of working at full capacity. Moreover, industries not affected by COVID-19 have a 4% higher probability of producing at full capacity compared to industries affected by COVID-19.

Table 3. The average marginal effects from the fitted binary logistic regression model (For significant covariates) (Delta method).

Variable/Covariate	dy/dx	Std. err.	Z	P > z	[95% Conf. interval]	
Region: Addis (Ref.)						
Amhara	0.005	0.019	0.240	0.813	-0.032	0.041
Oromia	-0.0396	0.128	-3.10	0.002	-0.065	-0.014
Somalie	-0.023	0.060	-.390	0.696	-0.140	-0.093
Benishangul	0.330	0.284	1.160	0.245	-0.226	0.887
S.N.N.P.R. (Southern Nations, Nationalities, and Peoples' Region)	-0.029	0.021	-1.34	0.179	-0.068	0.012
Sidama	0.207	0.102	2.03	0.042	0.007	0.406
Gambela	0.106	0.162	0.660	0.0512	-0.212	0.424
Harari	0.024	0.106	0.230	0.818	-0.183	0.232
Dire Dawa	0.135	0.052	2.60	0.009	0.033	0.237
Sales	0.000	0.000	-0.70	0.485	0.000	0.001
Raw materials	0.000	0.000	1.760	0.078	0.000	0.002
Month	0.024	0.004	6.58	0.000	0.017	0.031
Place of work (Industrial park ref.)						
Industrial shade	-0.102	0.077	-1.33	0.184	-0.252	0.048
Other	-0.067	0.077	-0.87	0.382	-0.217	0.082
Covid effect: affected by Covid ref.						
Not affected	0.041	0.021	1.93	0.044	-0.001	0.082
Major problem (Other ref.)						
Newly established	0.014	0.026	0.53	0.599	-0.037	0.063
Shortage of raw materials	0.014	0.044	0.31	0.759	-0.073	0.10
Shortage of spare parts	-0.057	0.026	-2.17	0.030	-0.109	-0.005
Shortage of foreign exchange	-0.236	0.035	-0.67	0.501	-0.092	0.045
Acquiring market or customers	-0.002	0.052	-0.03	0.973	-0.103	0.099
Lack of working capital	0.012	0.069	0.17	0.868	-0.125	0.14
Shortage of electric and water	0.149	0.065	2.29	0.022	0.0212	0.276
Repeated breakage of machinery	-0.018	0.029	-0.60	0.551	-0.075	0.040
Government rules and regulations	0.018	0.032	0.55	0.584	-0.045	0.080

Industries found in industrial parks have a 10.2% and 6.7% higher probability of producing at full capacity compared to industrial shade and others, respectively.

Regarding region, industries in Sidama and Dire Dawa have a 20.7% and 13.5% higher probability of working at full capacity compared to those found in Addis Ababa. Industries found in Addis Ababa have a 3.4% higher probability of working at full capacity compared to those found in Oromia. However, there is no significant difference in the probability of the outcome among Amhara, Benishangul, S.N.N.P.R., Gambela, Harari and Addis Ababa.

4. DISCUSSION

This study showed that LMMI productivity is significantly associated with region, the number of months the establishment operated during the study period, workplace, Covid, and most serious problems faced by the establishment (shortage of raw materials, electricity shortage, lack of working capital, and government rules and regulations). On the other hand, the study revealed that total sales value and the value of raw materials were not significant predictors for working at full capacity.

This study aimed to identify correlates of LMMIs on hinderances to working at full capacity in Ethiopia based on LMMI 2020 data. The likelihood of not working at full capacity for LMMIs in Amhara, Benishangul, S.N.N.P.R., Gambela, Harari were not significantly different from LMMIs in Addis Ababa regional state (the reference region). LMMIs in Oromia were less likely to work at their full capacity than LMMIs in Addis Ababa. LMMIs in Sidama and Dire Dawa were more likely to operate at full capacity than LMMIs in Addis Ababa. There were significant differences across regions in LMMIs working at full capacity. This finding is supported by other studies that also found a productivity efficiency difference across regions (Hulten & Schwab, 1984; Moomaw, 1981).

The results of this study revealed that the number of working months in a year was significantly correlated with LMMIs working at full capacity. LMMIs working at full capacity increased as the number of working months in a year increased. LMMIs working for all 12 months were more likely to work at full capacity than those that did not. LMMIs with more working hours were found to be more productive than those that operated for fewer hours. This finding is in agreement with McKinsey Global Institute (2012) and Sreekumar, Chhabra, and Yadav (2018).

Compared to LMMIs affected by Covid, those not affected by Covid were more likely to operate at full capacity. The result shows that Covid had a significant effect on companies, causing them to operate below capacity. LMMIs have been particularly affected by Covid, which has had a lasting impact on their productivity. This finding agrees with studies conducted by the World Bank group, which showed that enterprises have been affected by Covid (De Nicola, Mattoo, Timmis, & Tran, 2021). The association between Covid and not working at full capacity was also investigated by Yayeh and Ferede (2020), whose findings are similar to those in this study.

Our results show that the most serious issues faced by LMMIs, such as a shortage of power/electricity, shortages of raw materials and working capital, and government rules and regulations, significantly affected LMMIs not working at full capacity. This finding is consistent with Mojekwu & Iwuji (2012), who found that electricity supply has a significant positive impact on capacity utilization, and also that electricity and raw material shortages cause poor performance of infrastructural facilities, mainly due to frequent power cuts and the high cost of raw materials. This finding is also in agreement with a study done in Ethiopia which suggests that shortage of raw materials was the main cause of the relative technical inefficiency of the sector (Erena, Kalko, & Debele, 2021; Hailu & Tanaka, 2015). Another study in Nigeria by Ekwochi, Ejim, and Agbaji (2021) found that working capital management has an impact on the productivity of manufacturing.

This study also shows that premises/workplaces were significantly associated with LMMI productivity and their ability to operate at full capacity. LMMI working in shade/clusters and industrial parks were more likely to work at full capacity compared to LMMIs in other locations. A similar finding was obtained by Strøjer Madsen, Smith, and Dilling-Hansen (2003) in Denmark. A study in Nigeria by Charles, Ifeyinwa, Somkenechi, and Emmanuel (2021) also showed that provision of a conducive working environment improves manufacturing productivity.

5. CONCLUSION

The study results show that socioeconomic and proximate variables in Ethiopia have a significant impact on companies' ability to operate at full capacity. Particularly, region, the number of months the establishment operated during the study period, Covid, and the most serious problems faced by the establishment at present are significantly associated with full capacity production in LMMIs. These can be considered as the major significant factors influencing the patterns of productivity of LMMIs in Ethiopia.

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