Indonesian Capital Market Review 15 (2023) 57-69

INDONESIAN
CAPITAL MARKET REVIEW

Assessing the Impact of Financial Obstacles on Manufacturing Firm's Capacity Utilization: A Bayesian Approach

Arab Dahir Hassan[1*] and Rasim Ozcan[2]
[1] Department of Economics, Ibn Haldun University, Turkey
[2] Department of Management Information Systems, Istanbul University, Turkey

(Received: April 2023/ Revised: August 2023 / Accepted: October 2023 / Available Online: October 2023)

This study investigates the relationship between financial obstacles and the capacity utilization of manufacturing firms. It departs from previous studies by employing a Bayesian linear regression analysis. The results demonstrate the considerable negative effect that financial constraints have on the capacity utilization of manufacturing enterprises, while access to credit lines has a positive effect. The sample consists of 1,494 private manufacturing firms in 31 European and Central Asian countries. Financial obstacles were perceived as a major impediment to business operations by 65% of the enterprises surveyed. Furthermore, 52% of enterprises in the sample have access to loans from financial institutions, while 47% have no access to credit lines. This implies that the manufacturing sector's capacity to tap into financial market resources and surmount financial barriers both is vital to its survival and presents a significant challenge.

Keywords: *Manufacturing enterprises; financial obstacles; financial access; capacity utilization; Bayesian approach*

JEL Classification: C11, G00, C50

Introduction

Manufacturing-led development has proven to be a successful approach due to the direct contribution of the manufacturing sector to economic growth, its spillover effect, and the increases in dynamic productivity in terms of scale, transferability, and job creation (Felipe et al., 2019). In developing countries, manufacturing development is accompanied by process enhancements and structural reforms within the sector (Haraguchi, 2015). The process of modernizing the sector, which is seen as a useful strategy for applying the most recent technological developments, depends on additional investment. Hence, capacity utilization is linked to the generation of new investments. Highly efficient capacity utilization boosts depreciation rates and encourages the replacement of existing facilities with new ones (Liu & Wang, 2014a). However, credit markets are often underdeveloped in developing nations, where enterprises are typically hindered by a lack of financial resources, preventing them (particularly private firms) from making value-enhancing investments and updating their existing facilities to increase productivity (Chen et al., 2017).

Credit constraints can impact a business's operations and investment decisions by affecting its capacity utilization. For example, firms with high-capacity utilization rates, given their

* Corresponding author's email:

capital availability and productivity levels, are more likely to enter the global market (Tian, 2016a). Capacity utilization influences businesses' decisions to invest, export, and hire workers, all of which further impact economic growth in developing countries. The relationship between financial conditions and capacity utilization provides fundamental insights into how organizations behave when faced with stringent credit constraints.

According to Talberg et al. (2008), a firm's debt ratio is influenced by the industry in which it operates. This is evidenced by the significant differences in the capital structures of manufacturing subsectors. Additionally, manufacturing sub-sectors differ in terms of capital expenditures, the proportion of tangible assets in total assets, and the availability of trade credit, all of which influence their need for external financing (Chor & Manova, 2012). Credit constraint conditions have varied effects on tangible and intangible capital as well as human capital, depending on the types of manufacturing sub-sectors in which they occur. These inputs on capacity utilization play different roles. For example, in the short term, credit constraints affect labor productivity more when a firm experiences them, as labor input tends to respond to financial friction more promptly and directly than physical capital. Most importantly, the heterogeneity of the manufacturing sub-sectors may have an impact on the relationship between credit constraints and capacity utilization.

In this study, capacity utilization is used as a measure of the efficiency with which a firm utilizes its resources, specifically its production capacity. This is a crucial indicator of a firm's performance and can have a significant impact on its financial health. Financial constraints, on the other hand, refer to any financial challenges that a firm may encounter, such as inadequate funding or high levels of debt. These constraints can hinder a firm's ability to invest in new capital, which can thereby affect its capacity utilization. Most previous studies on this topic have primarily employed frequentist statistical methodology. However, this study aims to explore the influence of financial constraints and access to finance on firm capacity utilization through Bayesian estimation methods. The Bayesian statistical approach provides 95% credible interval estimates, yielding results that are comparable to those obtained through frequentist methods. In contrast to frequentist statistics, in which estimators are used to approximate the true values of unknown parameters, Bayesian statistics provide a complete distribution of parameters. Bayesian inference offers a more intuitive and straightforward interpretation of results in terms of probabilities. For instance, credible intervals are understood as intervals within which parameters fall with a certain probability, as opposed to the less intuitive interpretation of confidence intervals based on repeated sampling.

The remainder of the paper is organized as follows: Section 2 provides a concise review of the relevant literature on financial constraints and manufacturing firms' capacity utilization. Section 3 describes the data and methods used. Section 4 reports the Bayesian empirical results and interpretation. Section 5 presents the Bayesian model diagnostics or robustness test. Finally, Section 6 concludes.

Literature Review

A well-established financial market efficiently allocates capital to enterprises with high-value initiatives, fostering economic growth (Fisman & Love, 2003). However, limited access to external financing often poses a challenge for manufacturing enterprises in developing countries. According to Liu and Wang (2014), a credit-constrained productive firm is likely to suffer from increased negative effects and decreased equity value, causing a reallocation of resources from productive to unproductive enterprises.

The modernization of the manufacturing sector in developing nations is influenced by labor market policies, technology dissemination, and product market policies (Dutz et al., 2018). Modernization in different sub-sectors of the manufacturing sector leads to an enhanced industry structure, essential for growth and development in developing countries. According to Greenwood et al. (1988), high levels of capac-

https://scholarhub.ui.ac.id/icmr/vol15/iss1/5
DOI: 10.21002/icmr.v15i1.1156

ity utilization and high rates of capital utilization interact with investment shocks, impacting firm productivity and employment by accelerating the depreciation of aging equipment and promoting new investment formation.

Several studies have examined the relationship between capacity utilization and macroeconomic factors such as income distribution, savings-to-investment ratio, inflation rates, and productivity changes (Nikiforos & Foley, 2012; Schoder, 2014). Nikiforos and Foley (2012) investigated the causal relationship between income distribution and capacity utilization using aggregate data. Further study reveals that capacity utilization impacts an enterprise's employment, tendency to export, and investment choices on both micro and macro levels (Tian, 2016b).

Given their crucial role in macroeconomic indicators and firm performance, the drivers behind capacity utilization across sectors have been investigated. Financially constrained enterprises face greater challenges in making investment decisions and have fewer options for selecting the optimal degree of capacity utilization (Ahn & McQuoid, 2017). Along with changes in demand, physical and financial restrictions prevent enterprises from producing at their maximum capacity (Ahn & McQuoid, 2017). We propose that financial constraints lead to poor capacity utilization. In other words, when enterprises are subject to rigid financial constraints, they face a constrained ability to set an optimal rate of capacity utilization.

Different manufacturing sub-sectors have varying levels of external financial dependence, thus affecting their loan demand (Manova, 2013). High-tech companies are typically young, small, and fast-growing, and these characteristics can impact their need for external funding and loan applications (Farre-Mensa & Ljungqvist, 2016). Some enterprises facing financial challenges may establish a secure relationship with banks to expand their access to credit (Braun et al., 2019).

As previously noted, capital and labor inputs, which react differently to financial friction, are necessary for capacity utilization. For instance, enterprises with limited access to finance often substitute physical assets, which banks require as collateral, for investment in intangible assets. The relationship between credit constraints and capacity utilization may vary across industries since the function of different assets and human resources in capacity utilization depends on the types of manufacturing sectors involved. Lower capacity utilization in the production process indicates inefficient capital and labor allocation. In general, firms with limited access to capital cannot maximize their investments, indicating a conflict between credit constraints and production (Ganau, 2016).

Research Methods

Data Description

The data for this study was obtained from the World Bank's Enterprise Surveys (ES) for Europe and Central Asia. The survey was conducted using a standardized methodology and involved face-to-face interviews between firm representatives and trained field researchers. The World Bank's Enterprise Surveys (ES) methodology is designed to provide comprehensive data on the business environment of an economy's private sector. The surveys cover a broad range of topics, including access to finance, corruption, infrastructure, crime, competition, and performance measures. This study is based on surveys conducted in 2013, 2014, 2018, 2019, and 2021.

The World Bank's Enterprise Surveys (ES) are not conducted at a fixed frequency within each year. Instead, the surveys are carried out in different countries at different times. Despite this variation in timing, the ES follows uniform data processing procedures and data collection instruments, and the same firms are interviewed across time using unique firm IDs. We first downloaded the data from the World Bank Enterprise Surveys in STATA format, using the country name and survey type as filters. The columns were the same for all surveys, as the survey was based on a uniform methodology. We then merged the data from different countries into a single dataset using the unique IDs of the firms. Finally, we filtered the data

Table 1. Operationalization of Variables

Variable	Description
Capacity (DV)	Output produced relative to the maximum amount that could be produced
Exper (IDV)	Top manager's years of experience in the industry
Femalemanager (IDV)	Dummy variable: takes 1 if the top manager is female and 0 otherwise.
Expfemale (IDV)	Interaction of female top management and experience
finance-obst (IDV)	Ordinal scale from 0 to 5; No obstacle ‘0’, Minor obstacle ‘1’, Moderate obstacle ‘2’, Major obstacle ‘3’, and Very Severe Obstacle ‘4’.
Loan (IDV)	Dummy variable: takes 1 if the firm accesses a bank loan and 0 otherwise.
fixed asset (IDV)	Dummy variable: takes 1 if the firm acquires fixed assets and 0 otherwise.
licensed tech (IDV)	Dummy variable: takes 1 if a firm has licensed technology and 0 otherwise.

Source: Author’s calculation

to include only responses from the manufacturing sector. This resulted in a final dataset with survey responses from all of the manufacturing firms in the countries that we surveyed.

Using the variables outlined in the table above, the standard linear regression model is formulated as follows. Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. In this case, the dependent variable is capacity utilization, and the independent variables are financial obstacles and access to credit lines.

$$\begin{aligned} capacity_i = {} & \beta_0 + \beta_1 exper + \beta_2 femalemanager \\ & + \beta_3 expfemale + \beta_4 finance{-}obst \\ & + \beta_5 loan + \beta_6 fixed{-}asset \\ & + \beta_7 licensed{-}tech + \varepsilon_1 \end{aligned} \tag{1}$$

Expfemale is an interaction variable derived from the product of two variables: female manager and experience. The purpose is to examine whether the effect of a manager’s experience on capacity utilization differs depending on the gender of the manager.

The interpretation of β_1 for *exper* is the same as in traditional linear regression. *Exper* is a continuous variable that represents the number of years of experience the manager has in the working sector. The interpretation of β_2 is in terms of probability since it is a binary variable. Initially, we added the experience (experience of managers regardless of gender) and *femalemanager* (if the manager is female). The β_1 for experience is positive and statistically significant, showing that the sectoral experience of the manager significantly matters in the capacity utilization of a firm. However, we found the β_2 for *femalemanager* negative, showing that female managers have negative effects on capacity utilization. This is somewhat difficult to translate into economic terms.

Then, we tried to check if the experience of female managers matters or not. That is why we employed an interaction variable of female managers and experience. After adding the interaction variable, the β_2 changed to positive but was not statistically significant. This shows that the experience of female managers matters, but the interaction variable is negative, which is a little ambiguous. However, our interest variable *experience* did not change with gender; it remains significant across the models. Therefore, managerial experience is a crucial factor for a firm’s capacity utilization, regardless of gender.

Financial obstacles (*finance−obst*) are measured using an ordinal variable ranging from 0 to 4, with equal intervals.

Methodology

This study employs a Bayesian approach to explore the relationship between financial constraints and the capacity utilization of manufacturing firms. The Bayesian and frequentist approaches have distinct philosophies about what is considered fixed, leading to different interpretations of the results. In the Bayesian approach, the data sample is assumed to be fixed, while the model parameters are considered random. The posterior distribution of the parameters is estimated based on the observed data and the prior distribution of the parameters, and this is used for inference. In contrast, the frequentist approach assumes that the data are a repeatable random sample and that the parameters are unknown but fixed and constant across repeated samples (Best, 1996). Despite the ongoing debate between Bayesian and frequentist statistics, the use of Bayesian methods in various fields of study is gaining momentum (McShane et al., 2019; Ruiz-Ruano García & López Puga, 2018; Wasserstein et al., 2019). The present study's analysis is based on the conditional distribution of parameters in the observed sample rather than on the distribution of statistics obtained from repeated hypothetical samples. As such, the Bayesian approach is well suited to the nature of this study. Additionally, this study employs a Bayesian statistical approach, diverging from previous studies that utilized a frequentist statistical methodology to investigate the influence of financial constraints and external financing on firm capacity utilization (Ndiaye et al., 2018).

The Bayesian approach is founded on the well-established principle of Bayes' theorem. Bayesian analysis begins by specifying a posterior model, which describes the probability distribution of all model parameters given the observed data and any prior knowledge. This posterior distribution is composed of two parts: a likelihood, which incorporates information about the model parameters based on the observed data, and a prior, which represents any prior information about the model parameters before the data was observed (Rosenberg et al., 2022). The Bayesian rule, often known as Bayesian analysis, mixes previous knowledge through conditional probability:

$$Pr\ (\theta|Y) = \frac{Pr\ (\theta)\ Pr\ (\theta|Y)}{Pr\ (Y)} \tag{2}$$

$Pr\ (\theta|Y)$ is the posterior probability of the hypothesis adjusted based on observed data.

Posterior distributions reflect a prior probability of a hypothesis or parameter that has been updated with new information. $Pr\ Pr\ (\theta)$ is the probability of a parameter or hypothesis based on prior information. $Pr\ (Y\,|\theta)$ is the likelihood of the hypothesis-conditioned data. $Pr\ (Y)$ is the normalization constant.

Bayes' rule is expressed as a proportion to make it more understandable:

$$Pr\ (\theta|Y) \propto Pr\ (\theta)\ Pr\ (\theta|Y) \tag{3}$$

According to equation (3), the posterior distribution is the weighted average of the knowledge of previous parameters for the data and the information about the parameters in the observed data (Thach, 2021).

We employ a normal prior distribution in the first stage because researchers consider that it provides a decent representation of the distribution of effects (Oanh et al., 2022; Permai & Tanty, 2018). As a result, we employ the prior distribution N (0, 1), which describes the preceding default normal with a mean of 0 and a variance of 1. Block et al. (2011) claim that, if a normal prior distribution is employed, the results of the Bayesian analysis of the study's hypotheses will not be skewed either positively or negatively.

In the following steps of the procedure, we assume normal distributions with the parameters derived from the econometric model in Eq. (1). Finally, the Bayesian estimator generates posterior distributions of the parameters using the MCMC and Gibbs sampling techniques. Additionally, when using the Gibbs sampling procedure to generate posterior distributions, researchers should assess the stability and convergence of the MCMC (Kruschke, 2014).

Bayesian Linear regression model Specification

One method for parameter estimation in regression modeling that uses the Bayesian approach is Bayesian linear regression. The work of Permai and Tanty (2018) is followed to set the Bayesian linear regression equation in this study. The Bayesian method includes a prior, likelihood distribution, and posterior distribution. The Bayesian technique for parameter estimation entails working with the posterior distribution, obtained by multiplying the prior distribution by the likelihood. Using the OLS estimation method, a linear regression model has the normal distributed error assumption, which is $\epsilon \sim N(0,\sigma^2)$. Because the error is normally distributed, the variables (X, β, σ^2) are similarly normally distributed.

As a result, the variables $(Y|X, \beta, \sigma^2) \sim N(0,\sigma^2)$ and these variables' probability density functions (pdf) are as follows:

$$\rho(X,\beta,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} exp[-\frac{1}{2\sigma^2}(Y-X\beta)^T(Y-X\beta)] \quad (4)$$

Equation (4) shows the probability distribution of Y given X, B, and o², assuming a linear regression model. It is also known as the likelihood function. In other words, the equation demonstrates that the probability of observing a value of Y given X, β, and o² is proportional to the probability density of a normal distribution with mean Xβ and variance o².

1 / (2πσ²) ^(1/2) is a normalizing constant that ensures that the probability distribution integrates to 1, while exp(-1/2 * (Y - Xβ)^T(Y - Xβ)) is the probability density function of a normal distribution, with mean Xβ and variance o².

The likelihood function of these variables can be defined based on the probability density function (pdf) above:

$$\rho(Y|X, \beta, \sigma^2) = \Pi_{n=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} exp[-\frac{1}{2\sigma^2} (Y-X\beta)^T(Y-X\beta)] \quad (5)$$

$$\rho(X, \beta, \sigma^2) = (\sigma^2)^{-n/2} exp[-\frac{1}{2\sigma^2} (Y-X\beta)^T(Y-X\beta)] \quad (6)$$

Equations (5) and (6) are the same equation, just written in different forms. Equation (5) is the sum of squared errors formula for linear regression, while Equation (6) is the probability density function of the normal distribution. Both equations represent the likelihood function of the Bayesian linear regression model.

$$\rho(X, \beta, \sigma^2) \propto (\sigma^2)^{-\frac{v}{2}} exp[-\frac{vs^2}{2\sigma^2}]\times(\sigma^2)^{-n/2} exp[-\frac{1}{2\sigma^2} (Y-X\beta)^T(Y-X\beta)] \quad (7)$$

Equation (7) is the posterior distribution of the Bayesian linear regression model, which is obtained by multiplying the prior distribution by the likelihood function and then normalizing the result.

The distribution of the prior conjugate is one of the prior distributions that can be employed in the Bayesian approach of a linear regression model. The Bayesian technique can be used to estimate the regression model parameters by iterating at the marginal posterior. By multiplying the prior distribution by the likelihood function, the posterior distribution is calculated.

$$Posterior \propto likelyhood\ x\ prior \quad (8)$$

$$\rho(Y, X) \propto \rho(X, \beta, \sigma^2)\rho(\sigma^2)\ \rho(\sigma^2) \quad (9)$$

Equation (9) is a Gibbs sampling algorithm, a type of Markov Chain Monte Carlo (MCMC) method, which is used to estimate the posterior distribution of a Bayesian linear regression model.

$$\rho((Y,X) \propto (\sigma^2)^{-n/2} exp[-\frac{1}{2\sigma^2} (Y-X\beta)^T(Y-X\beta)]\times (\sigma^2)^{-(\frac{v}{2}+1)} exp[-\frac{vs^2}{2\sigma^2}] \times (\sigma^2)^{-\frac{k}{2}} exp[-\frac{1}{2\sigma^2}(\beta-\mu)^T(\beta-\mu)] \quad (10)$$

Equation (10) is the joint posterior distribution of the Bayesian linear regression model with a normal prior distribution for the coefficients and an inverse gamma prior distribution for the variance. The term vs²/2σ² is a scaling factor that adjusts the shape of the distribution to match the prior beliefs about the variance of the error term. The larger the value of v, the more spread out the distribution and the more uncertainty there is about the variance.

The mathematical symbols used in the above equations are specified as follows:

X: A matrix of independent variables.
Y: A vector of dependent variables.
β: The Greek letter beta, which is used to represent the regression coefficients.
σ²: The Greek letter sigma squared, which is used to represent the variance of the error term.
N: The sample size.
π: The Greek letter pi, which is used to represent the product of a set of numbers.

https://scholarhub.ui.ac.id/icmr/vol15/iss1/5
DOI: 10.21002/icmr.v15i1.1156

$\propto$: The symbol for proportionality.
V: The degree of freedom is the number of observations minus the number of parameters in the model.
s^2: The sample variance of the residuals in the linear regression model.
Λ: A matrix that depends on the shape parameter k. The matrix Λ is used to penalize the variance o^2 for being too large.
T: The superscript that refers to the transpose of a matrix.

The MCMC algorithm can be used to estimate regression model parameters with a Bayesian approach. Gibbs sampling is a typical MCMC algorithm. The process then iterates until the burn-in conditions are met.

Results and Discussions

Our findings indicate that both financial access and financial obstacles have a significant impact on the capacity utilization of enterprises. In particular, the mean parameter of the loan variable is 0.05459, with a posterior mean probability of 95% and a credible interval of (0.0073, 0.102). This suggests that, with 95% certainty, we expect the true value of the coefficient to lie within the range from 0.0073 to 0.102. The analysis further reveals a positive correlation between a firm's ability to access bank loans and its capacity utilization or performance. This implies that financial access strongly influences the capacity utilization of manufacturing firms, consistent with prior studies in the literature (Fowowe, 2017; Mayordomo et al., 2021). The mean coefficient of the financial obstacle is negative 0.022, with a credible interval of (-0.040, -0.0042). This means that the true value of the coefficient is likely to fall within this interval with 95% certainty. The negative coefficient indicates a negative relationship between financial obstacles and firm capacity utilization. This means that, as financial obstacles increase, firm capacity utilization decreases. This finding is consistent with our expectations and corroborates findings from other studies in the literature (Fowowe, 2017; Wang et al., 2022).

The association between firm capacity utilization and female top management (female_manag) is positive, but this is contrary to the expectations of this study. The mean coefficient of 0.012 is not statistically significant, as zero falls within the 95% credible interval of (-0.065, 0.088). This means that there is not enough evidence to conclude that there is a statistically meaningful relationship between the gender of managers and the capacity utilization of firms. To verify this relationship, we examined the effect of experienced female managers on capacity utilization by using the interaction between top female management and experience (expfemale). We found that the mean coefficient of this interaction was negative, -0.00258, with 95% certainty and a credible interval of (-0.00495, -0.0002). The zero falling outside the confidence intervals indicates a statistically weakly significant relationship between factors. On the other hand, the acquisition of fixed assets such as equipment and land have a positive effect on firm capacity utilization. However, since zero falls between the lower and upper credible intervals, the relationship is not statistically significant.

Firm size also has a significant effect on how well a firm uses its capacity, so in this study, we used the number of employees as a measure of firm size (employee). The mean coefficient of employees is 0215 with 95% certainty. The zero falls outside the 95% credible interval, which implies a significant relationship. This implies that, as business size grows, so does firm capacity use. This is because larger organizations can often distribute fixed costs across a greater number of units, making them more efficient. Furthermore, larger organizations may have greater resources, such as money and labor, which can help them use their capacity more effectively. Similarly, the application of technology (licensed_tech) also positively affects the capacity utilization of firms, as the mean coefficient shows 0.0322 with 95% certainty. This implies that enterprises that use licensed foreign technology have higher capacity utilization. This is because licensed foreign technology can give enterprises access to new and innovative manufacturing processes, allowing them to create more output with the

Table 2. The Bayesian method's estimates of the research model's results

Variable	Mean	Std. Dev	MCSE	Median	Equal-tailed [95% Cred. Interval]	
Experience	0.1093302	0.0387570	0.000194	0.1095488	0.0333224	0.1852724
Female_manag	0.0120872	0.0393309	0.000197	0.0120727	-0.0652114	0.0888117
Expfemale	-0.0025810	0.0012057	60.0e-06	-0.0025890	-0.0049477	-0.0002034
Loan	0.0545909	0.0242664	0.000122	0.0544078	0.0073935	0.1023207
Finance-obstac	-0.0222798	0.0091568	0.000046	-0.0223024	-0.0402410	-0.0042068
Fixed_asset	0.0242815	0.0236109	0.00012	0.0243003	-0.0223245	0.0704014
Employee	0.0215567	0.0086400	0.000043	0.0215871	0.0047703	0.0385861
Licensed_tech	0.0321788	0.0191365	0.000096	0.0321380	-0.0054169	0.0695884
Constant	3.8354220	0.1419317	0.000712	3.8346640	3.5578560	4.1173170
Var	0.1863127	0.0068631	0.000034	0.1861528	0.1733063	0.2001679
Avg acceptance rate	1					
Avg efficiency: min	0.972					
Max Gelman-Rubin Rc	1					

Source: The author's calculations

same amount of input. Additionally, licensed foreign technology can assist firms to promote their quality control and efficiency, which can also lead to higher capacity utilization.

The findings of the present study reveal that the managerial experience in the sector in which the firm operates significantly affects the capacity utilization of firms. The mean coefficient of experience is 0.1093302, with a credible interval of 0.0333224 and 0.1852724. Zero falls outside the credible interval, which shows that the true coefficient falls between the upper and lower intervals with 95% certainty. This implies that managerial experience related to the sector in which the firm operates leads to higher capacity utilization.

Table 2 shows that the average acceptance rate is 1, exceeding the allowable minimum value of 0.1 (Roberts & Rosenthal, 2001). The Max Gelman-Rubin Rc, the estimation results, are guaranteed to converge when the convergence statistics of all the parameters in the model are less than 1.1 (Gelman and Rubin 1992). The average efficiency (min) reached a value of 0.972, exceeding the allowable minimum of 0.01. The greater the efficiency, the smaller the Monte Carlo Standard Error (MCSE), resulting in a more precise posterior mean estimate. The estimation results show that the MCSE of all variables is much smaller than the allowable maximum of 0.05, which ensures the robustness of the model (Flegal et al., 2008). Therefore, our findings are robust, and our estimates are reliable.

MCMC Diagnostics

This study uses Bayesian analysis with MCMC to estimate the parameters for the dynamic system, as described in the previous section. We ran a total of 12,500 MCMC iterations to carry out the Bayesian regression. The results of the Bayesian linear regression are shown in Table 1. To construct the posterior distributions using the MCMC sampler, stability and convergence are required. The effective sample size determines the stability of the estimations (ESS). The ESS for all parameters is close to the MCMC sample size, which is 40,000, as Table 4 shows. As a result, all model parameters have MCMC efficiencies that are near 1.0, which shows model robustness (Oanh et al., 2022). The estimates are stable as a result. In this study, we use a widely applied test known as the Gelman-Rubin (Rc) convergence diagnostic for multiple series. Rc contrasts the variability among chains with the variability within chains. Chains with a value below 1.1 are fully converged (Thach, 2021). The convergence diagnostic of the MCMC algorithm is assessed using the Gelman-Rubin statistic (Rc). The Rc values reported in Table 4 are all less than 1.1, which indicates that the MCMC chains have converged. This means that the chain values match the posterior distribution, which is a necessary condition for the posterior simulation to comply with the Bayesian analysis's requirements.

For the hypothesis test, Bayesian credible intervals (BCIs) are used to summarize the un-

Table 3. Bayestest Interval

Interval test	Pr (mean)	Std. dev.	MCSE
Experience	0.95	0.21795	0.0010936
Female_manag	0.95	0.21795	0.0010897
Expfemal	0.95	0.21795	0.0010927
Loan	0.95	0.21800	0.0010961
Finance	0.95	0.21795	0.0010898
Fixed_asset	0.95	0.21795	0.0011022
Fmployee	0.95	0.21795	0.0010897
Licensed_tech	0.95	0.21795	0.0010897
Constant	0.95	0.21574	0.0010897

Source: The author's calculations

Table 4. Gelman–Rubin convergence diagnostic & ESS

Variable	Rc	ESS	Corr. time	Efficiency
Experience	1.0000170	40000.00	1.01	1.0000
Female_manag	0.9999773	40000.00	1.00	1.0000
Expfemale	1.0000390	39767.81	1.00	0.9942
Loan	1.0000810	39832.17	1.00	0.9958
Finance	1.0001160	39507.32	1.00	0.9877
Fixed_asset	0.9999753	38880.39	1.01	0.9720
Employee	0.9999961	39538.91	1.00	0.9885
Licensed_tech	1.0000350	40000.00	1.00	1.0000
Constant	0.9999692	39698.04	1.00	0.9925
Var	1.0000560	39670.57	1.01	0.9918
Number of chains	4			
MCMC size, per chain	10,000			
Max Gelman–Rubin Rc	1.000192			
MCMC sample size		40,000		
Efficiency: min		0.972		
Avg		0.9922		
Max		1		

Convergence rule: Rc < 1.1
Source: The author's calculations

certainty around the mean coefficients. Table 3 shows the probability mean coefficients, standard deviation (Std. dev.), Monte Carlo standard error (MCSE), and 95% BCIs for the mean coefficients. As the table shows, all coefficients of the variables lie within their 95% credible intervals. This means that we are 95% confident that the true value of each coefficient lies within the interval. This indicates the stability and reliability of these estimates. The MCSE of all variables is minimal, which indicates the robustness of the estimates.

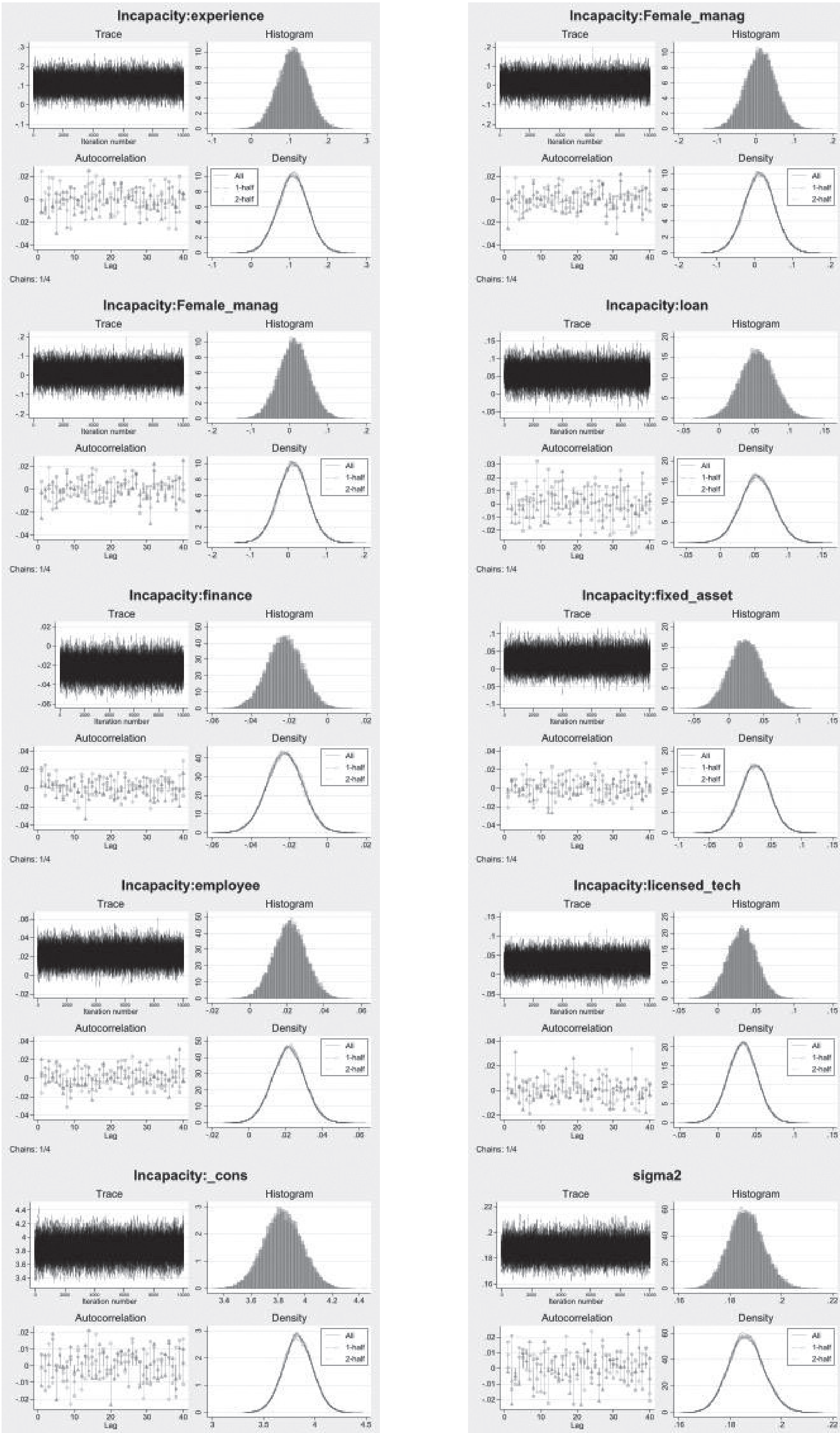
Visual Convergence Test of the model

To evaluate the effectiveness and validity of Bayesian inference, the study used the MCMC series convergence diagnostic test. Figure 1 shows the convergent series between capacity utilization and financial access, financial obstacles, and other controlled variables. To assess convergence, the MCMC series convergence diagnostic test utilizes trace plots, posterior distribution charts (histograms), autocorrelation plots, and kernel density plots. The visual diagnostic of the graphs demonstrates that all model parameters are credible, and trace and correlation plots show low correlation. The chart appears to have a normal distribution and has a uniform shape.

The convergence of the MCMC series is significant since it ensures the reliability of the Bayesian inference results. If the MCMC series does not converge, the Bayesian inference estimates may be incorrect and unreliable.

The trace plot depicts the MCMC chain's progress over time. If the trace plot shows that the chain is randomly moving, the chain has not converged. If, on the other hand, the trace plot reveals that the chain is convergent to a single

Figure 1. Visual convergence test



https://scholarhub.ui.ac.id/icmr/vol15/iss1/5
DOI: 10.21002/icmr.v15i1.1156

value, the chain has converged.

The post-distribution chart displays the distribution of the MCMC chain, with a normal distribution indicating convergence. The autocorrelation chart shows the correlation between the MCMC chain at different time points, with decreasing correlation over time indicating convergence. In short, these charts are used to evaluate MCMC chain convergence. Convergence is indicated by a normal distribution in the posterior distribution chart and a decreasing correlation in the autocorrelation chart.

The kernel density (plot density) chart shows the density of the MCMC chain. If the kernel density chart is a smooth curve, then the chain has converged. However, if the kernel density chart is not a smooth curve, then the chain has not converged. From this, we can infer that the Bayesian inference is robust (Nam et al., 2022).

Conclusions

Capacity utilization measures the efficiency with which a firm utilizes its production capacity and other resources. It can significantly impact a firm's financial health and serve as a critical performance indicator. Financial constraints, such as insufficient funding or high debt levels, may impede a firm's ability to invest in new capital, thereby affecting its capacity utilization. This study highlights the relationship between firm capacity utilization and financial obstacles. Firms with high debt levels and insufficient funding are more likely to have lower capacity utilization rates. Robust estimates from the Bayesian regression analysis indicate that financial constraints have a negative effect on the capacity utilization of manufacturing firms. Conversely, the study found that access to loans or credit lines has a strong positive effect on the capacity utilization of manufacturing enterprises. These results contradict some of the studies in the literature that used frequentist statistical approaches, such as Ndiaye et al. (2018).

By strengthening their financial infrastructure, developing countries can overcome some of their most challenging growth and development obstacles, such as energy. This includes removing financial barriers, which can significantly increase the production capacity of manufacturing firms. These enterprises are vital to the economic development and long-term growth of emerging countries. The acquisition of efficient technology, equipment, and land is crucial for achieving optimal and efficient production levels in the manufacturing sector. However, the ability to procure these resources is conditional on the financial health of the enterprises operating within this sector. In developing countries, where the manufacturing industry plays a vital role in driving economic growth, a robust financial infrastructure is essential. This infrastructure provides the necessary support for enterprises to invest in the resources needed to enhance their production capabilities, thereby contributing to the growth and development of the manufacturing sector as a whole.

References

Ahn, J., & McQuoid, A. F. (2017). Capacity Constrained Exporters: Identifying Increasing Marginal Cost. *Economic Inquiry*, *55*(3), 1175–1191. https://doi.org/10.1111/ecin.12429

Best, N. (1996). Bayesian Data Analysis. *Statistics in Medicine*, *15*(19), 2123–2124. https://doi.org/10.1002/(SICI)1097-0258(19961015)15:19<2123::AID-SIM364>3.0.CO;2-K

Block, J. H., Jaskiewicz, P., & Miller, D. (2011). Ownership versus management effects on performance in family and founder companies: A Bayesian reconciliation. *Journal of Family Business Strategy*, *2*(4), 232–245.

Braun, M., Briones, I., & Islas, G. (2019). Interlocking directorates, access to credit, and business performance in Chile during early industrialization. *Journal of Business Research*, *105*, 381–388. https://doi.

org/10.1016/j.jbusres.2017.12.052

Chen, Y., Hua, X., & Boateng, A. (2017). Effects of foreign acquisitions on financial constraints, productivity and investment in R&D of target firms in China. *International Business Review*, *26*(4), 640–651. https://doi.org/10.1016/j.ibusrev.2016.12.005

Chor, D., & Manova, K. (2012). Off the cliff and back? Credit conditions and international trade during the global financial crisis. *Journal of International Economics*, *87*(1), 117–133. https://doi.org/10.1016/j.jinteco.2011.04.001

Dutz, M. A., Almeida, R. K., & Packard, T. G. (2018). *The Jobs of Tomorrow: Technology, Productivity, and Prosperity in Latin America and the Caribbean*. World Bank Publications.

Farre-Mensa, J., & Ljungqvist, A. (2016). Do measures of financial constraints measure financial constraints? *The Review of Financial Studies*, *29*(2), 271–308.

Felipe, J., Mehta, A., & Rhee, C. (2019). Manufacturing matters…but it's the jobs that count. *Cambridge Journal of Economics*, *43*(1), 139–168.

Fisman, R., & Love, I. (2003). Trade Credit, Financial Intermediary Development, and Industry Growth. *The Journal of Finance*, *58*(1), 353–374. https://doi.org/10.1111/1540-6261.00527

Flegal, J. M., Haran, M., & Jones, G. L. (2008). Markov chain Monte Carlo: Can we trust the third significant figure? *Statistical Science*, 250–260.

Fowowe, B. (2017). Access to finance and firm performance: Evidence from African countries. *Review of Development Finance*, *7*(1), 6–17. https://doi.org/10.1016/j.rdf.2017.01.006

Ganau, R. (2016). Productivity, Credit Constraints and the Role of Short-Run Localization Economies: Micro-Evidence from Italy. *Regional Studies*, *50*(11), 1834–1848. https://doi.org/10.1080/00343404.2015.1064883

Gelman, A., & Rubin, D. B. (1992). Inference from Iterative Simulation Using Multiple Sequences. *Statistical Science*, *7*(4), 457–472. https://doi.org/10.1214/ss/1177011136

Greenwood, J., Hercowitz, Z., & Huffman, G. W. (1988). Investment, Capacity Utilization, and the Real Business Cycle. *The American Economic Review*, *78*(3), 402–417.

Haraguchi, N. (2015). Patterns of structural change and manufacturing development. In *Routledge Handbook of Industry and Development*. Routledge.

Kruschke, J. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*.

Liu, Z., & Wang, P. (2014). Credit Constraints and Self-Fulfilling Business Cycles. *American Economic Journal: Macroeconomics*, *6*(1), 32–69. https://doi.org/10.1257/mac.6.1.32

Manova, K. (2013). Credit Constraints, Heterogeneous Firms, and International Trade. *The Review of Economic Studies*, *80*(2), 711–744. https://doi.org/10.1093/restud/rds036

Mayordomo, S., Moreno, A., Ongena, S., & Rodriguez-Moreno, M. (2021). Bank capital requirements, loan guarantees and firm performance. *Journal of Financial Intermediation*, *45*, 100825.

McShane, B. B., Gal, D., Gelman, A., Robert, C., & Tackett, J. L. (2019). Abandon Statistical Significance. *The American Statistician*, *73*(sup1), 235–245. https://doi.org/10.1080/00031305.2018.1527253

Nam, P. H., Ngoc Thach, N., Van Tuan, N., Nhat, N. M., & Nhung, P. T. H. (2022). Does Internal Control Affect Bank Profitability in Vietnam? A Bayesian Approach. In N. Ngoc Thach, V. Kreinovich, D. T. Ha, & N. D. Trung (Eds.), *Financial Econometrics: Bayesian Analysis, Quantum Uncertainty, and Related Topics* (pp. 219–238). Springer International Publishing. https://doi.org/10.1007/978-3-030-98689-6_14

Ndiaye, N., Abdul Razak, L., Nagayev, R., & Ng, A. (2018). Demystifying small and medium enterprises' (SMEs) performance in emerging and developing economies. *Borsa Istanbul Review*, *18*(4), 269–281. https://doi.org/10.1016/j.bir.2018.04.003

Nikiforos, M., & Foley, D. K. (2012). Distribution and capacity utilization: Conceptual issues and empirical evidence. *Metroeco-*

nomica, *63*(1), 200–229.
Oanh, T. T. K., Diep, N. V., Truyen, P. T., & Chau, N. X. B. (2022). The impact of public expenditure on economic growth of provinces and cities in the Southern Key Economic Zone of Vietnam: Bayesian approach. *Prediction and Causality in Econometrics and Related Topics*, 328–344.
Permai, S. D., & Tanty, H. (2018). Linear regression model using bayesian approach for energy performance of residential building. *Procedia Computer Science*, *135*, 671–677.
Roberts, G. O., & Rosenthal, J. S. (2001). Optimal scaling for various Metropolis-Hastings algorithms. *Statistical Science*, *16*(4), 351–367.
Rosenberg, J. M., Kubsch, M., Wagenmakers, E.-J., & Dogucu, M. (2022). Making Sense of Uncertainty in the Science Classroom. *Science & Education*, *31*(5), 1239–1262. https://doi.org/10.1007/s11191-022-00341-3
Ruiz-Ruano García, A. M., & López Puga, J. (2018). Deciding on Null Hypotheses using P-values or Bayesian alternatives: A simulation study. *Psicothema*, *30*(1), 110–115. https://doi.org/10.7334/psicothema2017.308
Schoder, C. (2014). Effective Demand, Exogenous Normal Utilization and Endogenous Capacity in the Long Run: Evidence from a Cointegrated Vector Autoregression Analysis for the USA. *Metroeconomica*, *65*(2), 298–320. https://doi.org/10.1111/meca.12041
Talberg, M., Winge, C., Frydenberg, S., & Westgaard, S. (2008). Capital Structure Across Industries. *International Journal of the Economics of Business*, *15*(2), 181–200. https://doi.org/10.1080/13571510802134304
Thach, N. N. (2021). How Values Influence Economic Progress? Evidence from South and Southeast Asian Countries. In N. Ngoc Thach, V. Kreinovich, & N. D. Trung (Eds.), *Data Science for Financial Econometrics* (pp. 207–221). Springer International Publishing. https://doi.org/10.1007/978-3-030-48853-6_15
Tian, X.-L. (2016). Participation in export and Chinese firms' capacity utilization. *The Journal of International Trade & Economic Development*, *25*(5), 757–784.
Wang, C., Zhao, S., Zheng, H., & Bai, Y. (2022). Does Financial Constraint Hinder Firm Growth? *Emerging Markets Finance and Trade*, *58*(15), 4195–4206.
Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a World Beyond "p < 0.05." *The American Statistician*, *73*(sup1), 1–19. https://doi.org/10.1080/00031305.2019.1583913

Statements and Declarations
The authors declare that they did not receive funding, grants, or other support for the writing of this work.

Conflict of Interest
No conflict of interest is present in this study.

Data availability
The data utilized in this study is publicly available in the World Bank Enterprise Surveys, and the authors are willing to provide it upon request.