Learning-by-doing effect: Evidence from firms of an emerging economy

Nguyen Ngoc Thach[a*]

[a]*Institute for Research Science and Banking Technology, Banking University HCMC, Vietnam*

C H R O N I C L E	A B S T R A C T
	In the learning theory, the vast majority of both theoretical and applied research have concentrated on the developed world. In contrast, developing, in particular, emerging economies have drawn much less attention. Moreover, empirical outcomes are conflicting, with some studies revealing learning-by-doing to have a positive impact, but others finding learning-by-doing to have a negative effect on the performance. Therefore, this study is conducted through the Metropolis-Hastings and Gibbs samplers in the context of a Cobb-Douglas specification to evaluate the effects of learning-by-doing on firm performance on a panel data of the 227 manufacturing firms listed on the Vietnamese stock market. A Bayesian mixed-effects regression used allows for capturing the varying effects of all the researched firms. The study found that firm-specific learning-by-doing has a strong positive influence on firm performance. This finding is accordant with the predictions of the learning theory, many previous investigations, as well as the fact that in a fast-growing economy like Vietnam, firm-specific learning-by-doing is closely associated with economic growth. Some helpful policy implications proposed are aimed at increasing productivity for firms in emerging economies.

1. Introduction

As widely known, among the significant stylized facts on economic growth is the following: technical progress, education, and skills of the workforce play an increasingly crucial role in ensuring the high speed of economic growth. The importance of labor qualifications has been noted by the classics of economic theory, such as Adam Smith, Jean Baptiste Say, John Stuart Mills, Leon Walras, Arthur Pigou, and others. The concept of human capital was introduced in economics in the 1960's in the works of Jacob Mincer, Theodore Schultz, Gary Becker, and Mark Blaug. At an early stage of development of the growth theory, a focus was traditionally on only such economic factors as land, physical capital, and raw labor (the number of workers involved in production). Nowadays, human capital has become a primary determinant of economic growth. Human capital refers to a combination of professional knowledge and skills acquired in education and training programs, which subsequently may be profitable. In the modern growth theory, the mechanism of human capital accumulation is an essential part of endogenous growth models. The fundamental concepts of the effects of human capital and technical progress on the dynamics of economic systems go back to the works of Kenneth Arrow, Paul Romer, Hirofumi Uzawa, and Robert Lucas. The first concept of human capital was included in a classical article by Arrow (1962). In that work, increases in knowledge are "unintentional" through physical investment. That is a by-product of mechanization, or in other words, the mechanism of human capital accumulation is training in the process of work or on your own experience ("learning-by-doing"). This mechanism differs from that described

in Becker's theory and connected with an increase in employees' qualifications via paid education. Arrow associated the mechanism of human capital accumulation with physical investment by businesses or capital learning. In a broad meaning, however, learning-by-doing is also related to labor learning (or the learning of semi-manual and manual tasks) and organization learning. Research on labor learning has a long history starting with empirical analyses devoted to aircraft- and shipbuilding or another machine manufacturing (e.g., Wright, 1936; Montgomery, 1943; Alchian, 1950; Hirsch, 1952; Baloff, 1966). Later, learning-by-doing is examined as a productivity-enhancing determinant in a production specification (e.g., Rapping, 1965; Sheshinski, 1967). Organization learning, with its capacity to form organization capital, was analyzed by, among others, Conway & Schultz (1959), Prescott & Visscher (1980), Tomer (1981), Gort et al. (1985). Human capital accumulated through learning-by-doing leads to an increase in labor productivity, which in turn fosters a rise of output. According to Killingsworth (1982), since the costs of learning-by-doing are less than those linked with the acquisition of knowledge through educational programs, older enterprises achieve superiority over beginners. In this case, the stock of knowledge and skills or experience accumulated in production activities is proxied by time elapsed from the enterprises' birth, i.e., firm age (e.g., Bahk & Gort, 1993; Papatogonas, 2007; Coad et al., 2007; Akinomi & Olagunja, 2012; Hui et al., 2013). As noted, the above analyzed theoretical and empirical works focus on firms or industries in developed economies. Few studies on learning-by-doing in the manufacturing firms of an emerging economy like Vietnam were carried out. Furthermore, Vietnam is still a specific economy in the process of economic transformation from plan to market, where the overwhelming majority of firms are comprised of newly established private and restructured state-owned ones. Moreover, distinct from previous studies conducted based on the frequentist approach, where the stock of knowledge, skills, or experience in production was specified as an independent variable in linear regression models, the present work will be aimed at accessing learning-by-doing within the context of a Cobb-Douglas specification based on a corporate dataset. For this goal, the research will employ the Bayesian mixed-effects regression. The application of Bayesian methods brings about some great advantages as highlighted in Section 3. Lastly, the inconsistency of different empirical results requires further consideration of the problem.

The remainder of the article is organized as follows. Analytical framework and empirical research are presented in the second section. The third section introduces research methodology, specifies the model, and describes the data sample. The fourth section provides Bayesian simulation results and discussions. The fifth section derives the conclusions of the study.

2. Analytical Framework and Related Empirical Studies

In his own learning-by-doing hypothesis, Arrow (1962) views the accumulation of knowledge (methods, skills, mastery, and other innovations applicable to production) as a byproduct of mechanization (represented by a capital-labor ratio). Maximizing long-term profit, firms make decisions on physical investment. Generating great production opportunities for firms in coming times, physical investment is restrained by the law of positive and diminishing productivities. Working environment alters with a new apparatus brought in. Operating it, workers learn the latest technology. More particularly, learning to use the new machine, the workers find out new forms of production organization and implement improvements upon it. That is, by increasing mechanization level, firms accumulate the knowledge stock via learning-by-doing process. Therefore, A_{it} grows by φ percent each one percent increase in K_{it}/L_{it}:

$$A_{it} = \omega \left(\frac{K_{it}}{L_{it}}\right)^{\varphi}, \tag{1}$$

where A_{it} represents the knowledge stock of firm $i = 1, 2, \ldots, N$, $\frac{K_{it}}{L_{it}}$ stands for its mechanization level, φ denotes the learning-by-doing elasticity of A_{it} relative to $\frac{K_{it}}{L_{it}}$ and positive, ω is a parameter. It is noteworthy that the learning-by-doing process cannot be perpetual; learning-by-doing effects will be gone over time. Let us notice that Arrow was not the first to invent learning-by-doing. Learning-by-doing has been a principle for millenniums; it was supported by numerous scholars, such as Plato, Thomas Hobbes, Karl Marx and Mao Zedong, English and Spanish epigrammatists, cultural anthropologists, Maria Montessori, Burrhus Skinner, and John Watson (Reese, 2011). Further, it is useful to distinguish labor learning-by-doing, capital learning-by-doing, and organization learning-by-doing. Concerning labor learning-by-doing, we agree with Bahk and Gort (1993) considering that the workforce's skills in specific assignments are obtained through experience. Repetition routinizes jobs and workers achieve better adaptation to their jobs. This kind of learning becomes more important in labor-intensive production activities (Hirsch, 1952; 1956; Hartley, 1965). Capital learning contains multiplying through experience engineering information about the level of mechanization, about the application of specialized instruments and devices, as well as about improvements in factory arrangement and the manipulation of materials. Organization learning may comprise the following essential components: First, the matching of workers and their duties relying on knowledge cumulated via the competencies and restrictions of workers; second, acquisition of interdependent understanding of production in some members' possession but not accessible to others in a group; third, the development of social capital as a combination of real or potential social resources related to maintaining

trustful relationships among members of the organization; and last, managerial learning expressed in the development of coordination between divisions (Bahk & Gort, 1993).

Additionally, we make the second distinction between firm-specific learning-by-doing and economy-wide or industry-wide learning-by-doing. Firm-specific learning is proprietary to firms with the returns not captured by labor, while returns to aggregate human capital, once acquired, are appropriated by employees and reflected in wage rates. In the current paper, we pay the main attention to firm-specific learning-by-doing. Here, economy-wide or industry-wide learning-by-doing as well as the effects of knowledge accumulation from the growth of human capital and the technical level embodied in physical capital are excluded from the analysis. Regarding firm-specific learning, growth economists perhaps know about "Horndal effect" (David, 1973; Lazonick & Brush, 1985), i.e., verified by numerous empirical studies the effect of increasing productivity of workers and firms as the output of the same products grows under almost constant organizational and technological conditions. For example, labor productivity when manufacturing the aircraft body № N (counting them from the start of production) is approximately proportional to $N^{1/3}$. Graphical representation of the corresponding dependency (say, a relationship between the labor productivity of a representative worker and the number of units produced by a company) is called learning curve. Such dependency reflects labor learning. Since the research of Wright (1936) corresponding to the airframe industry, learning-by-doing has been analyzed through a progress function determining variations in production costs through the years. Together with the work of Montgomery (1943) relative to shipbuilding, Alchian (1950) investigated aircraft. Besides, Hirsch (1952) and Baloff (1966) analyzed machine manufacturing, while Preston and Keachie (1964) studied radar equipment, or Lieberman (1984) – chemical products. All the mentioned works are considered classical in this strand. Specifically, in Rapping (1965), Sheshinski (1967), learning-by-doing is first referred to as a productivity-enhancing factor in a production function. The link between company age and entrepreneurial performance has become a topic of diverse conceptual research, not only the learning theory but also the liability of obsolescence and liability of senescence theories. From the learning theory, it is logical to expect that there exists a positive relationship between firm age and business performance. This is because as firms exist longer, they gain more experience and become more productive than newcomers. Contrary to the learning-by-doing hypothesis, the liability of obsolescence theory indicates a mismatch between company targets and the business environment, whereas the liability of senescence concept points out internal inefficiency resulting from age (Hannan & Carrol, 1992). A lot of empirical analyses have been performed against the backdrop of the mentioned theories. It turns out that the correlation between company age and entrepreneurial performance is contentious. While some studies found that firm age is positively connected with entrepreneurial performance (e.g., Bahk & Gort, 1993; Papadogonas, 2007; Rosli, 2011; Halil & Hasan, 2012; John et al., 2012), others revealed a negative correlation (e.g., Gardner, 1965; Majumdar, 1997; Dogan, 2013; Pervan et al., 2016). A negative linkage between company age and profitability was shown by Gardner (1965). Majumdar (1997) examined the effects of age and size on entrepreneurial performance on a dataset of 1020 Indian companies. The empirical result showed that Indian older companies work more productively. Relying on a sample of 200 firms listed on the Istanbul Stock Exchange between 2008 and 2011, Dogan (2013) revealed a negative relationship between age and profitability. Pervan et al. (2016) affirmed that as companies become older, benefits from their experience in all primary activities of business were overwhelmed by the inertia and osseous caused by the accumulation of routines, organizational structure, and rules. On the contrary, among others, Bahk & Gort (1993), Garnsey (1998), Kristiansen et al. (2003), Harvie et al. (2010), Rosli (2011), Cowling et al. (2012), and Okunbo & Oghuvwu (2019) yielded the opposite results. Bahk & Gort (1993) discovered a positive relationship between firm age and entrepreneurial performance on the data set of plants in 41 U.S. manufacturing industries. Kristiansen et al. (2003) asserted that firm age is associated with business performance for Indonesian businesses because entrepreneurs from older firms have more experience and are very independent. Harvie et al. (2010) (for ASEAN small and medium enterprises), Rosli (2011) (for Malaysian firms) established that firm age greatly impacts on entrepreneurial performance. Cowling et al. (2012) investigated the relationship between firm age and performance for UK companies and revealed that firm age is positively significant to firm performance. Okunbo & Oghuvwu (2019), based on Small and Medium Enterprise Development Agency of Nigeria Survey, affirmed a positive impact of firm age on the performance of a hundred small and medium business entrepreneurs from the wholesale, retail, and manufacturing sector. Nonetheless, Coad et al. (2007), applying various estimation techniques (LAD, OLS, and VAR) to a panel of Spanish manufacturing firms for 1998-2006, found the conflicting evidence, on the one hand, better performance of enterprises with age and, on the other hand, reduction of their productivity with age. In sum, the aforementioned mixed results have induced an inconclusive debate. The controversy over the firm age-performance relationship is one of the main factors encouraging us to carry out this research.

3. Research Method and Data

3.1. Method and Model Specification

Bayesian statistical methods have been becoming ever more popular in social and behavioral science research over the last three decades while using the p-value to test hypotheses has confronted severe criticism. According to many studies (see, e.g., Hung & Thach, 2018; Anh et al., 2018; Hung & Thach, 2019; Hung et al., 2019a; Hung et al., 2019b; Sriboonchitta et al., 2019; Svítek et al., 2019; Kreinovich et al., 2019; Thach et al., 2020; Thach, 2020a; Thach, 2020b), Bayesian methods have the advantages

over the standard frequentist approach. First, universality is the great superiority of the Bayesian methods because the Bayes rule can be applied to all regression models, whereas a frequentist method is often appropriate only for one model class, but not for different classes. Second, contrast to frequentist inference, the Bayesian approach provides a straightforward and intuitive probabilistic interpretation of results. Bayesian inference using noninformative priors and frequentist inference produce similar results, but their interpretations differ in probabilistic sense. For instance, 95% confidence intervals mean that, if we repeat the same experiment many times, then the confidence intervals of 95% of the experiments will contain a population parameter of interest. But in Bayesian analysis, 95% credible intervals allow for making a probability statement that the true value of a particular parameter falls into a prespecified interval with a probability of 95%. Third, Bayesian result is an entire posterior distribution, while frequentist inference yields point estimates derived from a likelihood function. In Bayesian modeling, there is no need for the application of any approximation to evaluate uncertainties as the entire posterior distribution of the parameter is at hand. For the above reasons, we access a Bayesian approach via the Metropolis-Hasting and Gibbs samplers as the MCMC methods to estimate the firm-specific learning-by-doing effects on firm performance in this work. We begin our Bayesian analysis with forming a posterior distribution that encompasses two sources of information: out-of-data, prior belief, and information concluded in data:

$$\text{Posterior} \propto \text{prior} \times \text{likelihood,} \tag{2}$$

where Eq. (2) is called Bayes' theorem, which is mathematically defined as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}, \tag{3}$$

where with events A and B, $P(A|B)$ denotes the conditional probability that event A takes place given the occurrence of event B, ($P(B|A)$ is also the conditional probability, but the roles of A and B are reversed, $P(A)$ and $P(B)$ are the marginal probabilities of occurrence of event A and event B respectively. The flexibility of Bayesian analysis is that Bayes' theorem allows for involving prior beliefs in the model. Prior choice is crucial in Bayesian analysis as priors affect posterior distribution. While Yang & Berger (1998) support objectivity, several other researchers (e.g., Gelman & Hill, 2007; Kruschke, 2010; German et al., 2013; Hobbs & Hooten, 2015; Lemoine, 2019) favor a middle perspective, according to which weakly informative priors should include sufficient information to regularize estimates: the priors should rule out unreasonable values of a parameter but need not be so strong as to rule out its meaningful values. In the current research, we advocate the middle perspective, accounting for its capability of providing more unbiased and robust estimation results. Therefore, prior choice is proposed as follows:

- As we have a sufficiently big sample size of 227 firms for 11 years, the likelihood can overwhelm the information included in the priors. In Bahk & Gort (1993), the coefficient for the learning-by-doing variable is positive. In the meanwhile, others (e.g., Gardner, 1965; Majumdar, 1997; Dogan, 2013) found that the firm age-performance relationship is inconsistent. So, we select a normal prior on the coefficient for variable learning-by-doing with the zero mean such that the Bayesian results concerning our hypotheses in either positive or negative direction will not be biased. Using the sensitivity analysis proposed by Korner-Nievergelt et al. (2015), we rerun a Bayesian inference with progressively narrower prior distributions. Following Block et al. (2011), we set an error variance of 1 and to vary the mean in a range from -0.5 to 0.5 in order to examine sensitivity on posterior distributions to prior choice. 11 simulations are performed accordingly (see the simulation results in Table 4).

- For the case of elasticities in a neoclassical production function, priors are expected to be between 0 and 1. So, prior uniform (0,1) is appropriate. If we, however, want to ease restraints, then N(0.5,0.5) is a reasonable choice too. Referring to Thach (2020b), we select the uniform prior.

In agreement with Rapping (1965), Sheshinski (1967), to estimate learning-by-doing effect, we regard learning-by-doing as a productivity-enhancing factor in a Cobb-Douglas function, where firm-specific learning-by-doing is simply modeled as a separate argument. In our case, firm-specific learning-by-doing and the Solow residual are considered the sources of disembodied technical change. The Solow residual represents Hicks-neutral technical change. Such that a multiplicative productivity term A(t) is involved in our Cobb-Douglas function (see Function 4 below), which captures the residual proportion of output augmentation that emerges from aggregate learning-by-doing and other qualitative changes, except for firm-specific learning-by-doing. Applying the Cobb-Douglas specification to our panel data, we obtain:

$$Q_{it} = A(t)E_{it}^{\beta}K_{it}^{\alpha}L_{it}^{1-\alpha}, \tag{4}$$

where Q denotes output, K denotes physical capital, L denotes labor, A is Hicks-neutral technical change, E is learning-by-doing (experience), the subscripts i and t are firm and period, respectively. Furthermore, Eq. (4) is expressed in its econometric specification:

$$lnQ_{it} = b0 + \beta E_{it} + \alpha lnK_{it} + (1 - \alpha)lnL_{it} + \varepsilon_{it}, \tag{5}$$

where Q is output proxied by net revenue, L is labor proxied by the number of employees, K is stock of physical capital, E is learning-by-doing proxied by firm age. Hence, our Bayesian mixed-effects model is specified as follows:

Likelihood:

$$lnQ_{it} = b_0 + \beta lnage_{it} + \alpha lnk2010_{it} + (1 - \alpha)lnl_{it} + u_{1t} + \varepsilon_{it}. \tag{6}$$

Priors:
$$
\begin{aligned}
&b_0 \sim N(0, 100), &&\beta \sim normal(0,1) &&\alpha \sim uniform(0,1) \\
&u_{1t} \sim N(0, \sigma_{id}^2) &&\sigma_0^2 \sim Igamma(0.001, 0.001) &&\sigma_{id}^2 \sim Igamma(0.001, 0.001)
\end{aligned} \tag{7}
$$

where $lnk2010, lnl, lnQ$ refer to, respectively, natural log of capital, labor, output at constant prices, b_0 denotes efficiency parameter, α denotes income share of capital, ε_{ij} is random error, u_{1t} is random effects, year $t = 2008,…, 2018$, and enterprise $i = 1, 2, 3,…, 227$. Note that Cobb-Douglas specifications are popularized in empirical growth literature, especially regarding growth decomposition problems. Besides, Bayesian mixed-effects models are useful for the analysis of individual impacts of firms on the model outcome thanks to the grouping structure of data, where multiple levels of nested groups encompass both random effects and fixed effects. The two-level mixed-effects models account for variability among firms identified by the variable id. As emphasized by Nezlek (2008), if the multilevel nature of data is not taken into account, the results of multilevel data analysis may not be accurate.

3.2 Data Description

The present work utilized a firm-level panel of the 227 manufacturing firms listed on the Vietnamese stock market between 2008 and 2018. The data sources are the annual financial statements and annual reports of the studied firms for the relevant years. According to Ilaboya & Ohiokha (2016), "the choice of panel data approach is premised on the fact that it provides larger data points, increase the degree of freedom and reduces the problem of collinearity of the explanatory variables." The firms in the research sample operate in a variety of manufacturing industries, and hence, their varying effects on the outcome are captured through a mixed-effects regression. The data has a frequency of years. The dataset consists of 1,974 observations. Firm capital and output are represented by fixed assets and net revenue recalculated on the 2010 producer price index (Vietnam General Statistics Office, 2019). Labor is represented by the number of employees, age is represented by the number of years from a firm's foundation. The manufacturing firms are selected for analysis, for they are a driving force of Vietnamese economic growth. The application of a dataset on the listed companies enables labor and capital shares not to be biased because of statistical errors often occurring as mixed incomes from the households' labor and capital contributions, and those in the public sector are hardly measured correctly (Karabarbounis & Neiman, 2014). Owing to the skewed distributions of the variables, we log age, output, capital, and labor in our regression model. Table 1 provides the measurements of the research variables, most of which were used by Thach (2020a).

Table 1
Measurements of research variables

Variable		Notation	Measurement	Data Source
Input	Labor	lnl	Natural logarithm (number of employees)	Firms' annual report
	Capital	lnk2010	Natural logarithm (net fixed assets/Producer price index)	Firms' financial statement
Output	Product	lnQ	Natural logarithm (net revenue/Producer price index)	Firms' financial statement
Learning-by-doing	Firm age	lnage	Natural logarithm (number of years from firm establishment)	Firms' annual report
PPI	Producer price index	PPI	2010 as a base year	Vietnam General Statistics Office

4. Regression Results

4.1 Bayesian Posterior Simulations

In Bayesian analysis, acceptance rate and efficiency are practiced to judge the efficiency of MCMC estimators, which influences MCMC convergence. Rate of acceptance, by definition, is the fraction of accepted proposals in the total proposals, whereas efficiency indicates how well Markov chains mix. Bayesian information criteria show that the specified simulations get the almost same DIC estimates. Therefore, we choose simulation 3 having the lowest DIC value for further analysis as a typical illustration. The Bayesian results for simulation 3 report that this model reaches an acceptance rate of 0.58. The smallest, average, and largest efficiency reported is equal to 0.04, 0.47, and 1, respectively and all these initial indicators higher than the warning rate of 0.01. These levels can be accepted, according to Roberts and Rosenthal (2001). Most posterior means of the parameters, as well as random effects, obtain reasonable Markov chain standard errors (MCSEs) of less than one tenths (Tables 2 and 3). In general, the lower the MCSE estimates, the more precise the posterior mean values of the parameters. Moreover, the Bayesian approach provides a straightforward and intuitive probabilistic interpretation for credible intervals. For instance, in our model, a Bayesian credible interval [0.33, 0.39] is interpreted as the interval, which parameter alpha (capital share) belongs to with a probability of 95% (Table 2).

Table 2

Bayesian posterior simulations

Parameter	Mean coefficient	Std. Dev	MCSE	Posterior probability of coefficient >0	Equal-tailed [95% Cred. Interval]	
Natural log (capital)*	.3633044	.0145531	.000981	1	.3333752	.3924041
Natural log (A)	3.811807	.1230542	.010694	1	3.582262	4.060153
Natural log (learning-by-doing)	.3766484	.032601	.002449	1	.3120829	.4379703
Overall uncertainty	.1233717	.0042337	.000077	1	.1154946	.131996
Random intercepts uncertainty	.6361844	.0637335	.001718	1	.5257349	.7706273

Note: * Posterior probability of the coefficient of log (capital) in the interval (0,1) is 100%.

Source: The author's computations

Also, regarding simulation 3, random intercepts for u_{1t} (id) imply variations in the individual effects of the researched firms on the outcome of the model. All the random effects achieve the sufficiently low MCSE estimates for MCMC methods, which point at the highly efficient MCMC simulations. For illustration, the first 20 firms' estimates of the random intercepts are presented in Table 3.

Table 3

Posterior simulations of random intercepts of 20 firms

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred.	Interval]
lny2010						
id						
1	-.0402059	.1326178	.003383	-.0374557	-.2945865	.2189321
2	-.3829814	.1174514	.003303	-.3845203	-.6076356	-.1537845
3	-.4448979	.1207932	.003663	-.4437505	-.6856812	-.2151446
4	.6781612	.1288561	.005238	.6793082	.4262275	.926714
5	-.1586318	.1178592	.00341	-.1614853	-.3887248	.073654
6	.4433483	.1794721	.003986	.4461544	.0829891	.7815247
7	-.3071653	.1283132	.003394	-.3075616	-.5532817	-.0564984
8	1.311922	.1214479	.003397	1.311191	1.06827	1.551771
9	-.8049211	.1211782	.002972	-.8044031	-1.046562	-.5698457
10	-.5708233	.1255111	.003104	-.5741194	-.8086729	-.3199843
11	.3522455	.1427323	.00381	.3551475	.0740645	.6296982
12	.7002935	.1231915	.003032	.7009352	.4661121	.9409311
13	-.4279527	.1166162	.003137	-.4314988	-.6504045	-.1977667
14	.1397481	.1409215	.003336	.1388848	-.1382145	.41616
15	-.4638785	.1427042	.003171	-.4680294	-.7387795	-.1769516
16	1.236439	.1838869	.004171	1.231219	.8793809	1.607156
17	-.0695661	.1575895	.005722	-.0719153	-.3749977	.2421988
18	-.5634294	.1336612	.003302	-.5631914	-.8312518	-.3064052
19	.7355271	.1158373	.002889	.7373313	.507306	.9615617
20	.4880821	.139683	.003646	.4897209	.2157439	.756033

Source: The author's computations

4.2 Robustness Checks

Importantly, the posterior distributions, which are not sensitive to various prior choices, indicate a sign of model robustness. This is proven by the results recorded in Table 4, where there are inconsiderable differences between summaries of posterior distributions, posterior means, their MCSEs, and credible intervals of the learning-by-doing variable when the mean of the normal prior is adjusted step-by-step from -0.5 to 0.5 with even spacing of 0.1.

Table 4

Sensitivity analysis with respect to prior choice

Variable of interest	Summaries of posterior distributions	Mean of prior distributions										
		-0.5	-0.4	-0.3	-0.2	-0.1	0	0.1	0.2	0.3	0.4	0.5
Learning-by-doing	Mean coefficient	.374	.373	.377	.375	.374	.375	.375	.375	.375	.370	.352
	Standard deviation	.033	.035	.033	.033	.032	.035	.035	.035	.035	.034	.034
	MCSE	.003	.004	.002	.003	.003	.003	.003	.003	.003	.003	.003
	Credible interval	[.313, .441]	[.307, .441]	[.312, .438]	[.310, .442]	[.312, .437]	[.308, .449]	[.308, .449]	[.308, .449]	[.308, .449]	[.306, .438]	[.285, .417]

Source: The author's computations

As analyzed in the above, simulation 3 is acceptable for inference. Before proceeding to inference, we should verify whether MCMC chains have converged to a stationary regime. The ideal Monte Carlo algorithm employs independent *successive* random values. In the application of MCMC samplers, successive draws are not independent, which makes the methods converge slower than the ideal Monte Carlo. The faster they mix, the faster the dependence decays in successive iterations, and the faster they converge. The successive draws are rapidly "almost independent" of the initial state. We are motivated for well mixing chains as we are wary about time consuming and, more importantly, we desire a representative sample from the marginal posterior distribution. The former are dependent on the complexity of the model: if the model is simple, it may not matter much whether our algorithm is efficient. The latter is very significant if we are interested in posterior uncertainty or acquiring posterior means with high precision. The chain convergence to the desired distribution enables us to conclude that Bayesian iterations produce consistent estimations once the model has achieved validity. In Bayesian analysis, two conventional diagnostic techniques of convergence most often practiced are formal and graphical. We apply cusum lines and effective sample size in this research. Fig. 1 graphically describes the properties of MCMC convergence for simulation 3. For all the model parameters, their diagnostic graphs are reasonable in terms of convergence because the cusum lines are jagged, but not smooth, which definitely indicates the convergence of Markov sequences.
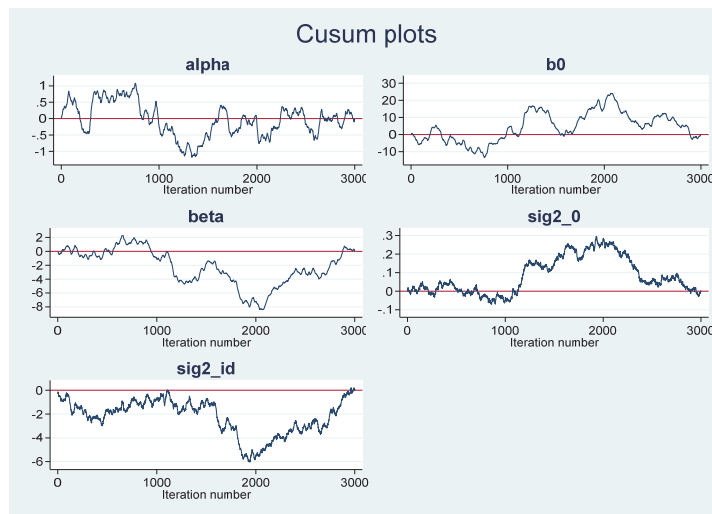

Fig. 1. Visual diagnosis of MCMC convergence
Source: The author's computations

In addition to the graphical inspection, we can monitor effective sample size for checking MCMC convergence. Because of an efficiency estimate of more than 0.01, we acquire a satisfactory result. According to the estimation results, the efficiency of all the parameters is higher than this level.

In sum, chain mixing looks convincing and our Bayesian simulations tackle no convergence problems.

4.3 Discussion

In the present research, relying on the middle view to specify suitable priors, we could increase model robustness. Accordingly, weakly informative priors were included in our Bayesian regression model to regularize parameter estimates and stabilize posteriors. Regularization priors allows for reducing or avoiding common errors corresponding to noninformative or frequentist analyses. Based on the results of the sensitivity analysis (Table 4), we can affirm that prior choice has a minimal effect on the posterior inference and thus, our specified model is valid. In addition, visual and formal checks for the chain convergence ensure our conclusion about model robustness. Moreover, concerning all our simulations, the standard deviation of all the parameters is small, while all the MCSE values are less than one decimal position. These are sufficient for the preciseness of the posterior means. It follows that our model can be employed for further inference. As claimed before, a substantial advantage of the Bayesian approach is to allow for probability statements what a standard frequentist framework cannot do. In our case, the summaries reported in Table 2 permit a statement that the probability of a positive impact of the predictor variable learning-by-doing as well as the remaining variables on the response variable output is 100%; the coefficient for the learning-by-doing variable belongs to the interval [0.31, 0.44] with a probability of about 95%; capital share falls into the interval [0,1] with a 100% probability. Importantly, the Bayesian simulation results demonstrate that because no credible intervals contain the zero value (Table 2), variable *lnage* (firm-specific learning-by-doing) correlates positively and strongly with variable *lnQ* (output). In other words, firm-specific learning-by-doing has a positive and strong effect on firm performance. It means that without any doubt, the firms become more productive with their age. This finding, which is in line with many earlier studies (see, among others, Gardner, 1965; Majumdar, 1997; Dogan, 2013; Okunbo & Oghuvwu, 2019), shows that the learning-by-doing hypothesis is accordant with the Vietnamese manufacturing firms. A probable explanation is that the majority of Vietnamese businesses are in nascent stages, which is a common feature of emerging economies. In a fast-growing economy like Vietnam, firms achieve a coincident increase in learning-by-doing and performance. In such a dynamic business environment, firms must manage to achieve rapid advancements, from immaturity to vitality and flexibility, from a lack of experience to learning capability, from external financing to accumulation of internal resources, and from institutional uncertainty and opacity to an established settlement. Besides, the Vietnamese state-owned enterprises should effectively restructure themselves to develop further in a market-oriented economy. And what's more, as indicated by the simulation results, the labor share equals roughly 0.64 (Table 4). This finding seems paradoxical for a capital-intensive manufacturing sector in an emerging economy. A probable explanation is that the contribution of human capital embodied in labor may not be accounted for in our model. This omission is considered a main limitation of our study.

5. Conclusion

Learning-by-doing effect is recognized to exist in the production processes of firms from ancient times to nowadays. Nevertheless, conflicting empirical findings cause a continuing controversy, which motivates us to conduct the current research. Specifically, few studies on learning-by-doing effects are dedicated to emerging countries. By utilizing a panel data of the 227 manufacturing firms listed on the Vietnamese stock market, the study employed the Bayesian mixed-effects regression in the context of a Cobb-Douglas production function to access the impact of firm-specific learning-by-doing on their firm performance, where individual effects of the studied firms on the model outcome are taken into account. Cobb-Douglas specifications are most relevant to the analysis of growth problems. In our Cobb-Douglas framework, beside the disembodied Hicks-neutral technical change, the learning-by-doing variable enters the production function as a separate predictor. Such settings enable the model to capture the distinct impact of firm-specific learning-by-doing on firm performance. Along with a sensitivity analysis, the MCMC convergence tests performed confirm that our Bayesian simulations are robust. According to the posterior simulation results, firm-specific learning-by-doing measured by company age positively and strongly affects firm performance. Our findings are consistent with the learning-by-doing hypothesis and many empirical investigations finding a positive relationship. The fact that the learning-by-doing effects exist in the Vietnamese manufacturing firms is obvious. This is because the Vietnamese economy has been growing rapidly in recent decades, which stimulates the development of the firms, encouraging them to raise productivity. Based on the empirical results obtained, the study recommends the Vietnamese firms to enhance productivity growth through motivating workers to accumulate human capital in many ways, including learning-by-doing in all its forms. Additionally, there is an essential need to foster the restructuring of the state-owned enterprises. In this regard, the state has to keep in its ownership only economically or socially important enterprises. Moreover, to increase the effectiveness of the firms, it is crucial to improve the institutional quality and to create an environment of fair competition. Last but not least, as medium and small firms account for more than 90% of businesses in Vietnam, the state should increase access to credit for this group of firms. All the above mentioned measures are aimed, in general, at enhancing firm productivity. Notably, policy implications suggested for the Vietnamese firms may be adopted by firms from other emerging economies.

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