RESEARCH ARTICLE

Nexus Between Electrical and Electronic Export Values With Exchange Rate Among Southeast Asian Countries: An Evidence From Finite Mixture Model

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In recent years, the electrical and electronic sector has monopolized the world's top three export products. Asian developing countries are the most influential countries exporting electrical and electronic products. Nevertheless, many external issues, such as competitors and unexpected incidents, specifically the coronavirus pandemic in 2019, affected international trading performance. This study aims to model the export price of electrical and electronic with exchange rates among Malaysia, Thailand, and the Philippines by fitting the Bayesian approach to the normal mixture model. Results depicted a negative effect between electrical and electronic export value and exchange rate for sampled countries. Meanwhile, brand new probability density functions are generated for future forecasting purposes. The input of this study can guide investors and traders in making a successful investment by understanding the factors that affect the performance of trade exports. Lastly, this study greatly impacts the adequacy of policies against several risks, which helps sustain economic stability.

Keywords: finite mixture model, Bayesian analysis, time series data

JEL Classification: C11, C13, C51

The mixture model is a probabilistic model employed to represent the presence of a subpopulation within an overall population (Phoong et al., 2022). The finite mixture model, a mixture model with finite dimension introduced by Newcomb (1886), has been proposed in a wide range of areas, including finance, economics, marketing, biology, and psychiatry, as shown in the increasing rate of articles regarding finite mixture model in the statistical and general scientific literature (McLachlan & Peel, 2001). In statistics, it has been implemented in the analysis of image, discriminant, and latent classes (McLachlan & Peel, 2001). Meanwhile, the finite mixture model provides a natural classification of heterogeneity in a finite number of latent classes. With its popularity, various distributions have been introduced to fit the finite mixture model, including normal, Poisson, and Weibull models. In this article, a normal mixture model is applied because it has the strength to capture the leptokurtic, skewed, and multimodal properties of financial data.

The Bayesian method is an extension of Bayes' theorem. It has gained popularity in data analysis, especially during the advent of computer technology. The Bayesian method is a famous statistical approach used to fit with the finite mixture model and has been proposed in a broad range of fields such as finance, economics, statistics, and meteorology. It functions as a parameter estimation tool to determine the reliable parameters of a model. The main reason for applying the Bayesian analysis is its asymptotically unbiased, consistent, and efficient properties, which yield significant findings. Theoretically, the Bayesian method holds three important concepts in analyzing data: prior distribution, likelihood function, and posterior distribution. Each concept plays a crucial role in parameter estimation with a different motivation. The prior distribution is a former information source before the implementation of observed data. The likelihood function denotes information with the application of observed data, whereas the posterior distribution is the multiplication results of prior information and likelihood function. In Bayesian analysis, a model's parameter estimates are developed from the association of prior information and likelihood function.

Besides, the previous posterior distribution can be transformed and used as a prior distribution when new datasets exist. It is a unique part of Bayesian in which other statistical methods do not have this kind of strength. Furthermore, the Bayesian method holds great consistency and asymptotic normality in large sample studies, as it can furnish significant results. Therefore, in this study, the Bayesian approach is introduced to fit with the normal mixture model in addressing the financial interaction between the electrical and electronic export prices and the exchange rate for Malaysia, Thailand, and the Philippines. Concurrently, modeling equations among variables are developed as a reference for statisticians and policymakers to forecast the variables' nexus during different conditions.

The electrical and electronic industries play a prominent role in economic development. At present, electrical and electronic goods are the main contributors to the world's exports. However, most electrical and electronic products are manufactured in Asian countries (Errighi & Bodwell, 2017). Goods, including smartphones and cables, are under the electrical and electronic category. This illustrates that electrical and electronic products cover all essential goods in our daily lives. Because electrical and electronic goods are important in this era of technology, all countries, especially developing countries such as Malaysia, Thailand, and the Philippines, are trying to boost electrical and electronic export rates. This is because the effects of dynamic growth in developing nations can be further improved through the expansion of exports (Geiger, 1991).

Nonetheless, much research has focused on the competitiveness and performance of electrical and electronic exports, which is insufficient to provide useful information for policymakers in maintaining economic growth, as shown by Mamun et al. (2015) and Chavosh et al. (2011). Subsequently, developing countries' electrical and electronic export performance is always influenced by other developed countries, such as China, which offers cheap labor and raw materials. In addition, the coronavirus pandemic, which started in 2019 and became the hottest issue of 2020, has disrupted the world's economic performance as many countries implemented lockdown rules, such as temporarily closing company and factory premises. These actions are believed to have a great negative impact on electronic and electrical exports among developing countries.

Another financial variable employed in the present study is the exchange rate. The exchange rate is defined as the rate of change of currency. In international trading, the exchange rate plays a crucial role (Chowdhury & Hossain, 2014) because it can influence a country's trade performance (Hada et al., 2018). Any fluctuation in the exchange rate might affect a nation's trading activities and economic growth. For instance, the export rate will increase when the exchange rate depreciates as goods become cheaper and vice versa. Nevertheless, the exchange rates are often influenced by financial crises such as the Asian Contagion in 1997, which was largely caused by the currency rate collapse and the hot money bubble. It started in Thailand before spreading to other Asian countries. As a result, most Asian countries fixed the exchange rate to the United States Dollar (USD) for a few years to stabilize the economy. This scenario shows that a global crisis easily affects the exchange rate. The study by Phoong et al. (2016) asserted that the exchange rate could be easily affected by economic changes in Asian countries. Research can further focus on Southeast Asia to investigate the changes in the exchange rate. Because Asia is the greatest electrical and electronic manufacturer, the flow of exchange rates should be monitored because it could affect the performance of international trading. According to Choi (2017), the exchange rate will affect the international trade balance and real gross domestic product (GDP), mainly in OECD-developed countries. In addition, Ng and Chin (2021) also found that changes in the exchange rate can influence international trade between Malaysia and China. Therefore, in the present study, nominal exchange rate datasets are used. The main concern of implementing a nominal exchange rate is its ability to determine economic growth because it is always used in international trading activities.

The primary contribution of the present study is to analyze the relationship between electrical and electronic export prices with exchange rates among Malaysia, Thailand, and the Philippines. At the same time, this article also develops a new equation among electrical and electronic export prices with the exchange rate that allows for forecasting purposes through Bayesian analysis.

In short, this present article is organized as follows. Section 2 emphasizes the previous studies of the Bayesian method. Section 3 highlights the research methodology, whereas the results and discussion are displayed in Section 4. Lastly, Section 5 summarizes the conclusion of the present study, followed by contributions and recommendations.

Literature Reviews

In 1886, the finite mixture model was introduced by Newcomb (1886). After that, Pearson (1894) explored the parameters of the finite mixture model using moments before the advent of computer technology. However, the method of moments showed weakness in large sample sizes due to its inadequate properties. Moreover, the finite mixture model has been introduced in the Gaussian mixture model, as shown in a study by Schork et al. (1996). According to Schork et al. (1996), the normal mixture model addresses human genetics. A normal mixture model is also employed to examine the model's parameters and determine vector quantization with a high approximation rate (Hedelin & Skoglund, 2000).

Subsequently, the Bayesian approach proposed by Laplace (1986) has become a popular method for modeling time series data due to its excellent properties in handling large sample sizes. As a result, the Bayesian method has been applied in various fields. For instance, in medicine, the Bayesian method has been introduced in magnetic resonance images (MRI) to enhance image quality and reduce noise and artifacts (Hu et al., 1991). In addition, the Bayesian method is associated with the EM algorithm and proposed in brain MRI segmentation to minimize energy (Marroquin et al., 2002). Both studies have a similarity where the Bayesian approach is a plausible method for MRI segmentation.

Aside from that, Cooper and Herskovits (1992) reviewed the Bayesian approach to making probabilistic networks. At the same time, with its versatilities, Bayesian is then applied in studying missing datasets and hidden variables (Cooper & Herskovits, 1992). Meanwhile, the Bayesian method can be proposed in the dynamic stochastic general equilibrium (DSGE) model, as referred to by Smets and Wouters (2003) and Liu et al. (2018). Both studies utilized quarterly data. In this regard, the main difference between both studies is the variables used in which Smets and Wouters (2003) implemented seven macroeconomic variables, whereas Liu et al. (2018) examined tourism and economic growth.

The Bayesian method also shows its attractiveness in handling different datasets, as in the study of Cai et al. (2019). The Bayesian method is proposed to analyze latent Markov models with a non-ignorable missing mechanism to analyze multivariate, non-ignorable missing and longitudinal data.

In genetics, Yeung et al. (2005) have modified the existing Bayesian model averaging method for gene selection purposes on binary and multiclass microarray datasets. This study is similar to Do et al. (2005), in which the Bayesian method is utilized to classify genes. According to Do et al. (2005), Bayesian with non-parametric is studied to classify differentially and non-differentially expressed genes. In short, these studies revealed that the Bayesian approach is a convenient statistical method in genetics.

Besides that, the Bayesian method is strong in handling and identifying unobserved heterogeneity datasets. With this, Rodrigues (2003) applied the Bayesian method to modeling augmented datasets with the zero-inflated Poisson model.

Apart from that, Ghosh et al. (2006) studied the Bayesian method in modeling the zero-inflated Poisson regression model by adopting Nortel data. The findings showed that Bayesian is a great method for modeling finite samples compared with conventional approaches, especially in interval estimates and convergence. According to Ghosh et al. (2006), the Bayesian method is a statistical tool that can be employed easily; with this, it has been extended to other zero-inflated distributions.

The usefulness of the Bayesian method can be shown in the pharmaceutical field. In the study of Madigan et al. (2010), drug safety issues are investigated through the Bayesian approach. At the same time, according to Madigan et al. (2010), the Bayesian approach with high dimensionality data is beneficial in pharmaceuticals. In migration, the Bayesian approach is utilized to model binary response data according to generalized logistic regression to analyze immigration in Europe (Valle et al., 2020).

In finance, the Bayesian method is a common statistical tool applied in modeling time-series datasets as it always furnishes a natural framework to evaluate central issues (Jacquier & Polson 2012). Meanwhile, the Bayesian approach is introduced to estimate the pricing issue of exchange options with stock liquidity (Gao et al., 2020).

Furthermore, the Bayesian method examines the optimal number of components by fitting with the Gaussian mixture model (Roberts et al., 1998). As a result, the Bayesian method provides reliable findings in selecting a model through comparison with another five model selection methods.

In sociology, Tuke et al. (2019) introduced the Bayesian method of investigating social unrest events on Twitter. However, this method can be implemented in other social media. This finding indicates that a Bayesian method is flexible in utilizing social media.

Subsequently, Hasegawa and Ueda (2019) presented the Bayesian method in identifying Japanese married couples' time. The primary reason for using the Bayesian method is its attractiveness in analyzing compositional data. As a result, the Bayesian approach furnishes superior performance. The Bayesian method also presented its strength in live birth registrations, as shown by Akomolafe et al. (2019). In the study of Akomolafe et al. (2019), the Poisson regression model was fitted by the Bayesian approach in analyzing the birth registration in Ondo State between 2012 and 2015.

In summary, the Bayesian method has been utilized in many fields, as shown in previous studies. Therefore, in the present study, the normal mixture model is fitted by the Bayesian method in modeling nonlinear financial time series data.

Comparison Between the Present Study and Existing Literature

The existing literature often discusses the relationship between variables using statistical methods, such as generalized auto regressive conditional heteroskedasticity (GARCH) and autoregressive distributed lag (ARDL). Aftab and Rehman (2017) contributed to East Asian countries by investigating the influence of exchange rates on bilateral trade between Malaysia and Singapore through GARCH and ARDL models. The findings revealed that the exchange rate impacts many industries in the short run. Bahmani-Oskooee and Aftab (2018) investigated the exchange rate and trade balance between Malaysia and China by implementing ARDL. The results showed that the largest industry benefited from the Ringgit depreciation against the Yuan.

Aftab et al. (2017) utilized the GARCH (1,1) and ARDL to model the exchange rate volatility and trade flow between Malaysia and Thailand. The study period was set from 2000 to 2013. The findings revealed that large industries experience negative influences from the exchange rate volatility.

Furthermore, Wiseman et al. (2021) employed nonlinear ARDL to study the influence of exchange rates on rice trade in Southeast Asia. The study considered Malaysian, Indonesian, Philippines, and China importing rice from Thailand. As a result, the importing countries did not follow profit-maximizing behavior during exchange rate volatility.

Unlike the existing studies, the present study applied a finite normal mixture model to model the electrical and electronic export price with exchange rates among selected Southeast Asian countries. Compared to the existing literature, the current model has the strength to discover the data pattern without supervision (Bishop, 2007). Because the finite mixture model is an unsupervised learning model, it would be interesting to discuss the time series variables under this model, especially in the digital age, where a prodigious flow of data is generated daily.

Methodology

The finite mixture model is proposed to identify the interaction between electronic and electrical export prices with the exchange rate among Malaysia, Thailand, and the Philippines via the Bayesian method. The monthly data from July 2005 until August 2020 were collected and obtained from CEIC (https://www.ceicdata.com/en/malaysia/exports-by-major-commodities-and-miti-classification/exports-value-electrical--electronic-products). Therefore, a total of 182 observations are conducted in the present study. These monthly data are then analyzed through SAS OnDemand for Academics. At the same time, all currencies were converted to USD to standardize the unit because all sampled countries have different currency units.

In the mixture model study, the selection of component numbers is a primary stage before data analysis. According to Eirola and Lendasse (2013), improper component number selection can potentially yield invalid results. Hence, the Bayesian Information Criterion (BIC) is presented to determine the study's most plausible number of components. The equation of BIC is displayed in Equation 1.

$$BIC = -2\,log\,L\left(\hat{k}\right) + mlog(t) \tag{1}$$

where $L\left(\hat{k}\right)$ is the maximized value of joint likelihood, refers to the number of parameters, whereas *m* denotes the sample sizes used in this study.

Subsequently, using BIC, the Bayesian method is employed to analyze data after the number of components is recognized. In Bayesian analysis, there are number of observations that is $y = y_1, y_2, y_3, \dots, y_n$. It has been drawn randomly from the finite mixture distribution to generate an inference for mixture distribution. Equation 2 presents the Bayesian inference for the finite mixture model.

$$P\langle\phi|\chi\rangle = \sum_{s=1}^{n} n_s P\langle\phi|\chi\rangle \tag{2}$$

where $P\langle\phi|\chi\rangle$ represents the probability density with $y_1, y_2, y_3, \dots, y_n$ and known components numbers n_s denotes as the *s*th observations in sample sizes *n*.

Aside from that, the likelihood function is utilized in the Bayesian method to summarize all information regarding the parameters of the datasets. The equation of the likelihood function is computed as

$$Likelihood = f(ID, \theta) + E \tag{3}$$

where $f(ID, \theta)$ refers to the function of the observed input data called *ID*, whereas *E* is the error in the present study, and the likelihood function is integrated and associated with normal distribution with *m* observations. Equation 4 is shown as:

$$P(\theta) = \frac{1}{\sigma^m(\sqrt{2\pi})^m}\exp \left\{-(2\sigma^2)^{-1}\sum_{ID=1}^{m}(Likelihood - f(ID, \theta)^2\right\} \tag{4}$$

The multiplication products of prior information and likelihood function, posterior distribution, is the final result of Bayesian analysis. The posterior distribution equation of the Bayesian method is highlighted in Equation 5.

$$P\langle\varpi|\beta\rangle = \{P\langle\beta|\varpi\rangle \cdot P\langle\varpi\rangle\}/P\langle\beta\rangle \tag{5}$$

Where ϖ, β denotes as events occurred, $P\langle\varpi\rangle$ is prior distribution, $P\langle\beta\rangle$ refers to a constant, $P\langle\varpi|\beta\rangle$ represents the posterior distribution of the Bayesian method, and $P\langle\beta|\varpi\rangle$ refers to the likelihood function.

Results and Discussion

In this section, the components number of electrical and electronic with the exchange rates for sampled countries are analyzed and listed in Table 1 with several components, $m = 2, 3, 4$. Note that *p* represents the number of parameters, whereas -2LL denotes the values of -2 log-likelihood.

Theoretically, BIC with the smallest values denotes a true model. Based on Table 1, the model with two components yields the lowest BIC value compared to other components. This scenario indicates that the two-component model is the true model to identify the relationship of selected financial variables for Malaysia, Thailand, and the Philippines. Therefore, the

Table 1. *Components Evaluation*

Number of		Malaysia		Thailand		The Philippines	
m	*p*	-2 LL	BIC	-2 LL	BIC	-2 LL	BIC
2	7	-1440.14	-1403.75	-2280.47	-2244.08	-2445.11	-2408.72
3	11	-1428.05	-1370.87	-2281.64	-2224.45	-2444.84	-2387.65
4	15	-1428.05	-1350.07	-2289.39	-2211.41	-2445.86	-2367.89

Bayesian method is adopted to fit with two components normal mixture model throughout this study.

Table 2. *Bayes Information*

Bayes Information	
Sampling Algorithm	Conjugate
Burn-In Size	2000
MC Sample Size	10000
Parameters in Sampling	7
Mean Function Parameters	4
Scale Parameters	2
Mixing Prob Parameters	1
Number of Threads	2

Table 2 details Bayes's information used in the present study. Table 2 shows a conjugate sampling algorithm with 2000 burn-in size and 10000 MC sample sizes implemented through finite mixture model procedures. Moreover, there are four mean function parameters, two scale parameters, and a mixing weight parameter, which sums up the seven parameters. Besides, there are two threads utilized for multithreading purposes.

Furthermore, Table 3 displays a detailed prior distribution for Malaysia, Thailand, and the Philippines. This prior distribution table includes distribution families and initial values for components 1 and 2. The mean electronic and electrical export values with the exchange rate for sampled countries exhibit a normal distribution. Based on Table 3, the scale parameters present an inverse gamma distribution, whereas mixing probability for selected nations displays a Dirichlet distribution.

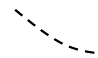
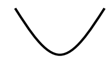
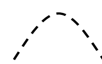
Table 4 displays the posterior distribution results of sampled countries. Based on the graph plotted, it can be found that there is a negative relationship between electrical and electronic export prices with the exchange rate for Malaysia, Thailand, and the Philippines. It indicates that the appreciation of electrical and electronic export prices is along with the exchange rate depreciation in these nations. This finding is supported by Tuck and Wong (2008), who mentioned that the exchange rate has an inverse effect on electrical and electronic exports.

Additionally, variance parameters have been presented to illustrate how the datasets obtained spread out from their mean. In the present study, the variances of components 1 and 2 for Malaysia, Thailand, and the Philippines were found to be small. This depicts that the results obtained are convincing, valid, and significant. The mixing probabilities for component 1 in Malaysia and the Philippines are 0.9946, whereas in Thailand, it

Table 3. *Prior Distribution*

Component	Effect	Distribution	Initial Value		
			Malaysia	Thailand	The Philippines
1		Normal	-0.0083	0.0026	-8.2E-6
1		Normal	0.0009	-0.0003	2.9E-6
2		Normal	-0.0083	0.0026	-8.2E-6
2		Normal	0.0009	-0.0003	2.9E-6
1		Inverse Gamma	2.2E-5	2.1E-7	8.1E-8
2		Inverse Gamma	2.2E-5	2.1E-7	8.1E-8
1		Dirichlet	0.6180	0.6180	0.6180

Table 4. *Posterior Distribution*

Component	Parameter	Estimates			Coefficient Plot
		Malaysia	Thailand	The Philippines	
1	μ_{EXCHG}	-0.0076	0.0014	0.0028	
1	μ_{EEP}	0.0009	-0.0002	-0.0003	
2	μ_{EXCHG}	-0.0211	-0.1283	0.1311	
2	μ_{EEP}	-0.6428	0.5391	0.2253	
1	σ_1^2	0.0111	0.0111	0.0111	
2	σ_2^2	0.9971	0.9622	0.9817	
1	π	0.9946	0.9945	0.9946	

is 0.9945. In addition, the probability density function equation for Malaysia and the Philippines can be expressed as $0.9946h_1 + 0.0054h_s$, whereas Thailand is $0.9945h_1 + 0.0055h_s$ where h_1 and h_2 are probability density functions of components 1 and 2, respectively. In short, in the first normal distribution, 99.46% of the returns were exhibited in Malaysia and the Philippines, and Thailand recorded 99.45%. The second normal distribution for Malaysia and the Philippines was 0.54%, whereas Thailand recorded 0.55%.

Conclusion

In the present study, the two components normal mixture model is introduced to elucidate the relationship between the electrical and electronic export prices and exchange rates among Malaysia, Thailand, and the Philippines via the Bayesian approach. As a result, these financial variables have a negative effect on selected countries. Moreover, the new probability density functions generated from the present study can benefit statisticians who wish to discuss the relationship between these variables for Malaysia, Thailand, and the Philippines more deeply. This is because these equations can be used for forecasting purposes. The empirical findings of this research contribute to investors and traders making smart investments by considering the factors that affect electrical and electronic export performance. Statisticians interested in financial time series variables via Bayesian analysis are believed to benefit from this study. Additionally, further research can be conducted by comparing other Asian electrical and electronic export-oriented countries to comprehensively view the world's largest exports. Besides that, further study is encouraged to introduce different statistical methods such as maximum likelihood estimation and generalized method of moments to address the interaction between electrical and electronic export price with exchange rate because these methods favor large sample study.

Disclosure of Statement

There is no potential conflict of interest reported by the authors.

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