Southeast Asian Journal of Economics Vol.14(1), April 2026: 165-192
Received: October 29, 2024
Revision: January 18, 2025
Accepted: April 28, 2025

Impact of Selected Macroeconomic Variables on Household Consumption in Eight ASEAN Countries

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Abstract

This paper identifies macroeconomic factors alongside income growth that influence changes in household consumption across ASEAN (excluding Lao PDR and Vietnam due to data limitations) from 2010 to 2022. We use a mix-order variable selection using Bayesian additive regression trees (BART) and Bayesian adaptive sampling for variable selection (BASAD) methods to choose the important input variables in explaining household final consumption (HFC). We then employ both cross-sectional autoregressive distributed lags (CS-ARDL) and Bayesian dynamic multivariate panel models to examine determinants of household consumption. The mix-order variable selection method reveals output growth in service sectors, population growth, and unemployment rates as important factors among input predictors influencing the changes in HFC, in addition to income growth during the studied periods. The Bayesian dynamic multivariate model shows two main findings: (1) Fixed effects show a positive correlation between income growth and service sector output growth with HFC, while population growth and unemployment rates have a negative nexus with HFC, and (2) time-varying effects of all independent variables are positively correlated with HFC. CS-ARDL model estimation results indicate a positive short-run effect of income growth, population growth, and unemployment, but a negative effect in the long run between income growth and unemployment with HFC. This paper not only contributes to a deeper understanding of the macroeconomic determinants of household consumption in ASEAN countries but also discusses the study's limitations and directions for future research.

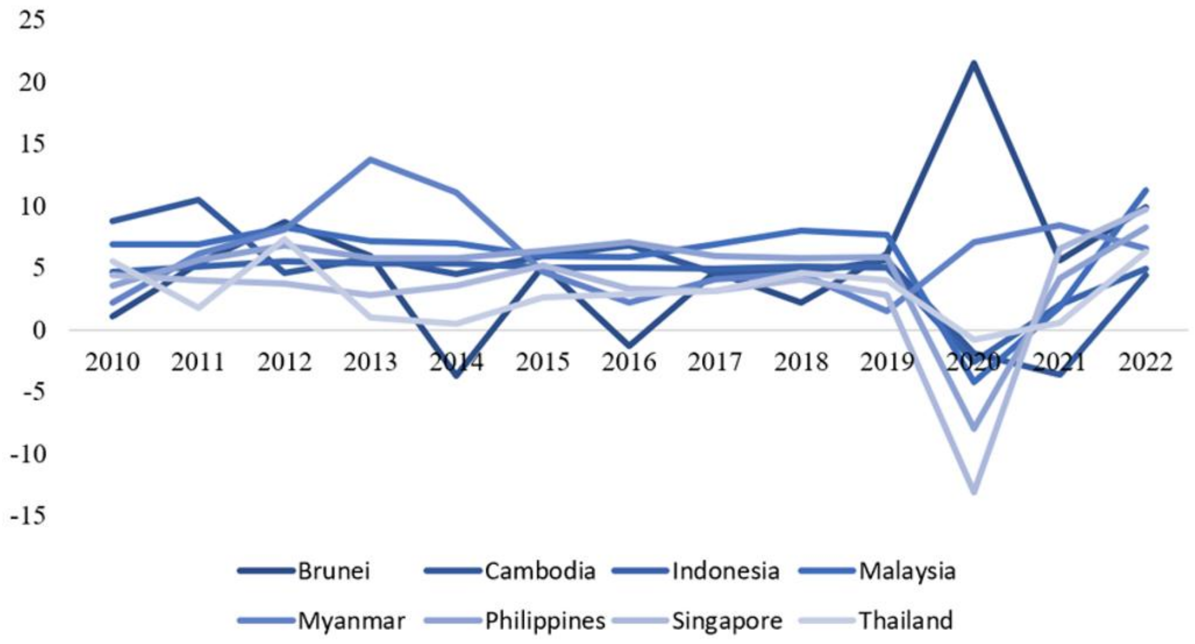
Keywords: household consumption, Bayesian variable selection methods, dynamic panel models, ASEAN.

1. Introduction

There is no doubt that every economy intends to achieve the highest level of aggregate welfare growth. The average consumption level per person is linked to the concept of GDP per capita, so it can be regarded as a measure of economic productivity. Household consumption or spending can be explained by the aggregate demand function. This important variable should be considered when a country reviews changes in its fiscal budget planning in macro policies. The focus of several studies on household consumption is different, but the concept always relates to the economic well-being (Cooper et al., 2023), and the study of household consumption signifies and reflects on overall economic performance analysis (Madudova & Corejova, 2024). Some people believe that consumption tends to increase as household incomes grow. We believe that consumption also grows statistically when currency devalues or there is higher inflation because households need to consume basic and essential commodities. When this happens, commercial banks play a role by lending money to households to operate and expand their businesses. Some of those households will deposit funds when the interest rates at the banks are satisfactory. Thus, this study investigates which of the selected factors drive household consumption more within eight ASEAN countries.

Figure 1 illustrates the changing rates in household final consumption (HFC) of eight selected ASEAN countries from 2010 to 2022. It shows that HFC patterns fluctuate differently in some countries over time. There will be different factors affecting the changes of each ASEAN nation studied. However, HFC in most ASEAN countries experienced a significant decline in 2020 (the year of the COVID-19 pandemic), with the notable contractions in Cambodia by -1.9%, Indonesia by -2.6%, Malaysia by -4.2%, the Philippines by -8%, Singapore by -13.1%, and Thailand by -0.8%. Brunei and Myanmar were exceptions, potentially due to the fact that households in these two countries in ASEAN are less associated with the tourism sector. Of the other ASEAN countries, Singapore and Thailand had the largest negative impact. Households in these two countries rely on tourism-based industries. HFC recovery was documented in nearly all eight ASEAN countries in 2021 and 2022, except for Myanmar, which is highly correlated with the political instability caused by the early 2021 military coup in the country. One study reported that the size of Myanmar's hidden economy under military regimes is a lot higher than during semi-democratic regimes (Ko et al., 2024). Obviously, this circumstance alone cannot answer the whole HFC pattern in Myanmar, so future studies should carefully explore the broader effects of political instability.

Figure 1. Average change in household final consumption in selected ASEAN countries, 2010–2022



Source: Authors adjusted the data collected from World Bank Open Data, 2024.

Although HFC patterns in ASEAN countries show considerable changeability, the precise macro country-specific factors influencing these fluctuations remain empirically underexplored. This paper aims to fill this gap for relevant agencies by proposing an effective policy formulation by examining the causal relationships between HFC and key macroeconomic variables across eight ASEAN countries. To accomplish this goal, we must first determine factors significantly affecting the changes in HFC; otherwise, bias is introduced when ideal variables are used for data analysis.

2. Literature Review

Household consumption or spending is considered a main indicator of overall economic activity because it reflects both household income levels and macroeconomic conditions. It is also a significant factor of aggregate demand. The Keynesian Consumption Theory argues that current income is the main driver of consumption. It shows that changes in income and employment directly affect how much people spend (Keynes, 1936). For example, GDP per capita and unemployment rates are key variables linked to this theory (Mankiw, 2014). The Permanent Income Hypothesis (PIH) suggests that people base their consumption on their expected lifetime income rather than temporary income changes (Friedman, 1957). In this context, per capita GDP can reflect long-term income expectations. The Life-Cycle Hypothesis (LCH) further explains that people save during their working years to fund consumption in retirement, and population growth influences long-term consumption patterns (Modigliani & Brumberg, 1954; Biorn, 1980). While the Financial Intermediation Theory emphasizes the role of commercial banks in providing credit, which boosts consumption, the number of banks plays a role (Schumpeter, 1911). Monetary Theory highlights how money supply, exchange rates, and inflation affect purchasing power and consumption (Friedman & Schwartz, 1963). Other theories, like the Service Economy Theory and Financial Intermediation Theory, also help explain consumption. The Service Economy Theory shows that growth in the service sector can lead to higher income and spending. This study combines these theories to better understand the factors driving HFC in ASEAN countries and to select variables. It aims to find what drives household spending in ASEAN. Keynesian theory and the Permanent Income Hypothesis explain income and unemployment through short-term and long-term effects. Demographic theory supports population growth and shapes spending patterns. Service Economy Theory and Baumol's ideas explain service sector growth, as services drive income in ASEAN. Financial Intermediation Theory includes banks, where loans help with spending. Monetary Theory adds inflation, exchange rates, and money supply, which affect buying power. These theory choices fit ASEAN's economy. Unlike past studies, we avoid random picks. However, it's important to note that blending these theories can be challenging, especially when trying to capture both short-term and long-term consumption behaviors, as well as demographic and institutional factors (Deaton, 1992).

Empirically, several studies have explored the relationships between macroeconomic variables and household consumption expenditure and found different results for different countries and regions. Recent research studies covered this field in different countries, but most did not focus on examining the most important variables influencing changes in HFC. In fact, many researchers studied particular consumption and its relationship with macroeconomic and microeconomic factors (e.g., Azam et al., 2015; Diehl et al., 2019; Sian et al., 2021; Islam et al., 2022; Anita, 2023; Mokal et al., 2023; Tran, 2024). These leave both empirical and methodological gaps, so this present study shall fill this gap by examining the most significant variables influencing consumption changes with advanced econometric models. Arapova (2018) examined the drivers of household expenditures in 13 Asian countries between 1991 and 2015. The study found that gross national income, population growth, lending interest rates, and government expenditures were key drivers of consumption among the selected macroeconomic variables. Additionally, Thailand, Indonesia, and the Philippines were identified as key contributors to consumption-led growth in the region. Rumbia et al. (2020) primarily studied the impact of household spending on economic growth in four ASEAN countries using the nonlinear ARDL approach from 1967 to 2018 and found only a short-term effect from consumption to economic growth in the studied countries. Similarly, Sudibyo (2024) found a significant and positive relationship between consumption and economic growth in ASEAN3+ and the United States from 1960 to 2020.

Other studies have examined the impact of various macroeconomic drivers on household consumption expenditure. Dilanchiev and Taktakishvili (2021) studied key macro drivers of household consumption in Georgia between 1983 and 2018 using the ARDL model, but did not specify which variables were most predictive of household consumption. Duarte et al. (2021) investigated the environmental impact of household consumption in EU countries, including the UK. They found that more income for low-income groups increases carbon emissions, highlighting the need for sustainable consumption. Iheonu and Nwachukwu (2020) studied the impact of household consumption on chosen macro variables in selected West African countries from 1989 to 2018 and found that GDP per capita could improve consumption levels. Zeynalova and Mammadli (2020) examined household expenditure in Azerbaijan from 1995 to 2017 and discovered that income tax and disposable income did not significantly increase consumption, while the exchange rate and corporate tax had a positive impact. Bonsu and Muzindutsi (2017) studied macro determinants of household expenditure using the VAR approach in Ghana from 1961 to 2013 and found that exchange rate and economic growth had a significant effect, but price levels caused the changes in consumption.

Most existing papers covering different countries and regions examined particular variables believed to have an impact on household consumption expenditure. However, we cannot agree with the assumptions made out of nowhere in selecting variables that potentially affect household consumption because they could have significant bias when selecting those ideal and fancy variables. In addition, to the best of our knowledge, no previous study has taken the steps of this present paper in determining the most significant factors before estimating key drivers of HFC. Consequently, this paper fills this gap with ASEAN as a focus with advanced econometric modelling by combining Bayesian and classical techniques. The rest of the study is structured as follows: It begins by describing the data collection and methods of study used. Next, we discuss the findings of the results, followed by conclusions and suggestions for future research in this field.

3. Data and Methods of Study

3.1 Data

For data analysis in this study, we used secondary publicly available data obtained from the World Bank and the Asia Development Bank. The sample period ranged from 2010 to 2022 across eight ASEAN nations. The average change in HFC was used as the dependent variable of this study. Independent variables included the total number of commercial banks, GDP per capita, money supply (M2), exchange rates, consumer price inflation, foreign direct investment (FDI) inflows, population growth, deposit interest rate, unemployment rate, food production index, and growth rates in three sectoral outputs (agriculture, industrial, and service). The selection of these input predictors was based on their theoretical relevance to the study. For example, the total number of commercial banks was chosen based on the Financial Intermediation Theory (Gurley & Shaw, 1960). Per capita GDP is included in accordance with Keynesian consumption theory and the permanent income hypothesis (Keynes, 1936; Friedman, 1957). Money supply (M2) follows the Monetary Theory by Friedman and Schwartz (1963), while exchange rates are guided by the Purchasing Power Parity Theory (Cassel, 1918). Consumer price inflation is included in line with inflation theory (Notestein, 1945). FDI net inflows are linked to economic growth models (Borensztein et al., 1998). Deposit interest rates follow Fisher's theory of interest (Fisher, 1930), while population growth is based on demographic transition theory (Notestein, 1945). Unemployment is analyzed based on Keynesian consumption theory (Keynes, 1936), and the food production index follows agricultural economics (Schultz, 1964). The growth of sectoral outputs (agriculture, industry, and services) is encouraged by the work of

Schultz (1964) and Baumol (1967). Notation, units of measurement, and sources of data and variables used in this study are provided in Appendix A. This study is designed only to explore the effect of chosen final independent variables on HFC by using the mix-order variable selection approach between the Bayesian additive regression trees (BART) and Bayesian adaptive sampling for variable selection (BASAD) methods. Once particular variables are chosen from this approach, we apply Bayesian dynamic multivariate and cross-sectional autoregressive distributed lags (CS-ARDL) models to examine an empirical nexus between dependent and independent variables.

3.2 Methods of Study

The primary goal of this study was to evaluate macro-specific factors driving the change in HFC across eight ASEAN countries between 2010 and 2022 by using both Bayesian and classical methods. Classical methods always struggle with limited data, and most other methods still struggle to suggest the significance of predictors. Consequently, we proposed to initially determine the significance of potential explanatory variables using the BART and BASAD methods. These models are employed to select important or relevant explanatory variables according to their probabilities of influencing household consumption patterns. The models work well with small datasets and uncertain predictor significance. They can identify the most relevant input variables, even in the absence of strong prior knowledge. BART, BASAD, and CS-ARDL match our goals. We want to find key factors and study short- and long-term effects. BART finds complex patterns in data. BASAD picks the best factors clearly. Together, they avoid mistakes. Old methods like stepwise regression pick incorrect factors and overfit data. CS-ARDL studies short- and long-term effects, so it handles ASEAN's mixed data well. Old panel models assume sameness and miss differences, but CS-ARDL fixes this. The Bayesian dynamic panel model tracks changing effects and beats old models.

These tools fit ASEAN's complex economy and improve on old ways. Bayesian formulation is based on posterior distribution, and it can be expressed as:

$$\mathbb{p}(\mathcal{M}_\gamma|\Upsilon) = \frac{\mathbb{p}(\Upsilon|\mathcal{M}_\gamma)\mathbb{p}(\mathcal{M}_\gamma)}{\sum_{\gamma\epsilon\Gamma}\mathbb{p}(\Upsilon|\mathcal{M}_\gamma)\mathbb{p}(\mathcal{M}_\gamma)} \quad (1)$$

Where $\mathbb{p}(\mathcal{M}_\gamma|Y)$ equals $\int \mathbb{p}(\Upsilon|\theta_\gamma, \mathcal{M}_\gamma)\mathbb{p}(\theta_\gamma|\mathcal{M}_\gamma)\, d\theta_\gamma$, which is relative to the marginal likelihood of $\mathcal{M}_\gamma$ that resulted from the joint likelihood with respect to the prior distribution on all parameters $\theta_\gamma = (\alpha, \beta_\gamma, \emptyset)$ given $\mathcal{M}_\gamma$; and $\mathbb{p}(\mathcal{M}_\gamma)$ refers to prior probabilities of models.

To address the limitations of traditional econometric approaches, this study employs a mixed-method Bayesian approach by using BART and BASAD. These methods are particularly useful when dealing with limited data and uncertain predictor significance, challenges often encountered in econometric studies. BART is adept at handling nonlinear datasets and incorporating interaction effects, while BASAD integrates adaptive sampling and model averaging to evaluate the importance of variables. Recognizing that BART can sometimes mix relevant and irrelevant predictors, the study uses a mix-order variable selection approach that combines BART and BASAD to ensure the selection of robust and significant variables. Although the study uses advanced econometric methods, the authors acknowledge limitations, including the length of the dataset and the omission of potentially significant variables.

3.2.1 Bayesian Additive Regression Trees (BART) Model

BART was first developed by Chipman et al. (2010) and later popularly cited in 2016 by Kapelner and Bleich. It is a non-parametric Bayesian regression approach that constructs an ensemble of trees to identify complex relationships between predictors and the response variable. One of the advantages of using BART is its ability to handle nonlinear datasets and incorporate interaction effects. One of the weaknesses of this model is overfitting the data; thus, only a small fraction of the variation of the overall relationship between dependent and independent variables in each tree can be explained. Brito Filho and Artes (2018) argued that BART is less effective because the model mixes relevant and irrelevant predictors. This model consists of three parts in estimation or prediction: additive trees, prior specification, and the stochastic process for the posterior distribution. Following Brito Filho and Artes (2018), the BART model can be written as follows:

$$\Upsilon_i = \sum_{j=1}^{\mathcal{M}} g_j\left(\chi_i; \Gamma_j, \mathcal{M}_j\right) + \varepsilon = G(\chi_i) \tag{2}$$

Where $\chi_i$represents the independent variables associated with each terminal node of Γ_j that represents the terminal node of the tree, and with j as the set of terminal nodes; $\mathcal{M}_j = \left(\delta_{1j}, \delta_{2j}, \dots, \delta_{ij}\right)$ represents parameters allied with the tree Γ_j; and $\varepsilon \sim N(0,1)$ represents the random error. Given $\Gamma_j\ and\ \mathcal{M}_j$, the function $g_j\left(\chi_i; \Gamma_j, \mathcal{M}_j\right)$ is used to allocate $\delta_{1j} \in \mathcal{M}_j$ to each. The joint prior distribution for parameters δ_{ij} and tree structure Γ_j used in this study are as follows:

$$\mathbb{p}[(\Gamma_1, \mathcal{M}_1), \dots, (\Gamma_m, \mathcal{M}_m)] = \prod_{j=1}^{\mathcal{M}} \mathbb{p}\left(\Gamma_j, \mathcal{M}_j\right) = \prod_{j=1}^{\mathcal{M}} \mathbb{p}\left(\mathcal{M}_j|\Gamma_j\right) \mathbb{p}\left(\Gamma_j\right), \mathbb{p}\left(\mathcal{M}_j|\Gamma_j\right) = \prod_{i=1}^{N} \mathbb{p}\left(\delta_{ij}|\Gamma_j\right) \tag{3}$$

$$\mathbb{p}[(\Gamma_1, \mathcal{M}_1), \dots, (\Gamma_m, \mathcal{M}_m)] = \prod_{j=1}^{\mathcal{M}} \mathbb{p}\left(\Gamma_j\right) \prod_{i=1}^{N} \mathbb{p}\left(\delta_{ij}|\Gamma_j\right) \tag{4}$$

$\delta_{ij} \sim N\left(0, \sigma_\delta^2\right)$ is assumed to be the prior distribution of $\delta_{ij}|\Gamma_j$ associated with the terminal nodes of the tree Γ_j. The mean of the parameters is supposed to be zero when it follows a normal distribution for the posterior distribution. Since given different parameters, δ_{ij} has prior independent distributions and is expressed as:

$$G(x) \sim N(0, \mathcal{M}\sigma_\delta^2) \tag{5}$$

If z is defined as confidence interval level, the confidence interval for $G(x)$ is $G_{min} = -z\sigma_\delta\sqrt{m}\ and\ G_{max} = z\sigma_\delta\sqrt{m}$. Brito Filho and Artes (2018) recommended the use of z between 1 and 3, so we used $-1 \le G(x) \le 1$. Thus,

$\sigma_\delta = \frac{1}{z\sqrt{m}}$. For the data analysis, the "bartMachine" package from RStudio was used, and the model was built upon a fully Bayesian probability as the ensemble of trees, which refers to the number of trees to grow, also known as the sum of trees model. The Markov chain Monte Carlo (MCMC) algorithm was used for data sampling in the Bayesian approach.

3.2.2 Bayesian Variable Selection with Adaptative Sampling (BASAD) Model

BART alone could be biased for the variable selection due to its weakness in mixing relevant and irrelevant input predictors when examining the most important predictors. Hence, we employed the BASAD model proposed by Clyde et al. (2011). Narisetty and He (2014) also mentioned that the Bayesian variable selection approach integrates adaptive sampling and model averaging to further evaluate the importance of variables. This model evaluates the importance of each variable by ranking based on their posterior inclusion probabilities. In this analysis, we used the "basad" package from RStudio software and a student's t prior distribution with Gibbs sampling. The model selection was guided by the BIC criterion to a maximum of 20 variables in the median probability model. The sampling involved 500 burn-in and 1000 iterations to ensure the reliability of posterior estimates. In this applied package, the regression coefficients follow the hierarchical structure shown as follows:

$$\beta|(Z = 0, \sigma^2) = N(0, \tau_0^2\sigma^2) \text{ and } \beta|(Z = 1, \sigma^2) = N(0, \tau_1^2\sigma^2) \quad (6)$$

Where Z_i represents the latent variable of 0 or 1. The coefficients of prior densities were generated based on those previously chosen. The student's t prior can be expressed as:

$$\beta|(Z = k, \sigma^2) = \frac{\tau(\frac{\nu + 1)}{2}}{\tau(\frac{\nu}{2}\sqrt{\pi\nu\tau_k\sigma}}(1 + \frac{1}{\nu}(\frac{\beta^2}{\tau_k^2\sigma^2}))^{-\frac{\nu+1}{2}} \quad (7)$$

Where ν represents the degree of freedom, and τ_k represents the scale for the prior distribution. Given the weakness in both the BART and BASAD methods, this paper proposes to choose final variables using the mix-order variable selection approach following Kaplan and Zhu (2017) and Pastpipatkul and Ko (2025), thereby ensuring robust, significant variable selection results.

3.2.3 Bayesian Dynamic Multivariate Panel Model

In this study, the use of a Bayesian dynamic multivariate model (Helske & Tikka, 2024) assumes response variables as continuous (T, i=1, …, N). This model is implemented in the R package "dynamite", where a Gaussian distribution is used for multiple response variables. Time-varying effects are defined using Bayesian panelized splines. It is a causal inference based on structural causal models (Pearl, 2009) defined through interventions, with external changes to the data-generating process. The Bayesian DNP model supports both time-varying, time-invariant, and individual-specific effects for multiple responses across various distributions, such as Gaussian, Poisson, binomial, and categorical, using MCMC simulation. However, this model is weak; for example, it lacks explicit error terms in the linear predictor. Following Helske and Tikka (2024), the linear predictors ($\eta_{c,t}$) for the dependent variable ($\gamma_{c,t}$) can be expressed as:

$$\eta_{c,t,i} = \alpha_{c,t} + \beta_c u_{c,t,i}^{\top} + \delta_{c,t} w_{c,t,i}^{\top} + \vartheta_{c,i} z_{c,t,i}^{\top} + \psi_{c,t} \lambda_{c,t,i}^{\top} \tag{8}$$

Where $\alpha_{c,t}$ denotes a time-varying intercept, β_c indicates time-invariant or fixed effect coefficients, $\delta_{c,t}$ indicates time-varying coefficients, $\vartheta_{c,i}$ indicates random effects within mean 0 and variance σ^2, and $\psi_{c,t}$ represents the latent dynamic factor for unobserved influences. The Bayesian penalized splines in this model is written as:

$$\tau_{c,t,k} = b_t^{\top} w_{c,k} \rightarrow w_{c,k,d} \sim N\left(w_{c,k,d-1}, \tau_{c,k}^2\right) \tag{9}$$

Where β_t is Bayesian panelized splines with a degree of freedom, and $w_{c,k}$ is spline coefficients with random walk priors. The coefficients ($\alpha_{c,t}, \beta_c, \delta_{c,t}, \vartheta_{c,i}, \psi_{c,t}$) are estimated using 1000 MCMC iterations with 250 warm-ups and a thinning rate of 1.

A smaller degree of freedom for posterior distributions allows the model to handle heavy tails and extreme values in dynamic and nonlinear panel datasets.

3.2.4 Cross-Sectional Autoregressive Distributed Lags (CS-ARDL) Model

In this study, we used a second-generation cross-sectional augmented ARDL (CS-ARDL) model developed by Chudik and Pesaran (2015). One advantage of the CS-ARDL model is that it can handle both stationary and nonstationary variables. Thus, the model is suitable for datasets where variables have different orders of integration. This model is used to study both long- and short-run relationships between dependent and final chosen independent variables (see Table 1). For the long-run estimation, equation (10) can be applied using the common correlated effects (CCE) estimation of heterogeneous dynamic panel data models (Chudik & Pesaran, 2015). The short-run coefficients can be computed using the ARDL-based error correction model (ECM), and it can be expressed as written in equation (11).

$$HFC_{i,t} = \alpha_0 + \alpha_1 LOGPCGDP_{i,t} + \alpha_2 SERVG_{i,t} + \alpha_3 PGR_{i,t} + \alpha_4 UNEMP_{i,t} + \varepsilon_{i,t} \tag{10}$$

$$\Delta HFC_{i,t} = \beta_0 + \sum_{j=0}^{n} \beta_1 \Delta LOGPCGDP_{i,t-j} + \sum_{j=0}^{n} \beta_2 \Delta SERVG_{i,t-j} + \sum_{j=0}^{n} \beta_3 \Delta PGR_{i,t-j}$$
$$+ \sum_{j=0}^{n} \beta_4 \Delta UNEMP_{i,t-j} + \vartheta ECT_{i,t} + \varepsilon_{i,t} \tag{11}$$

Where Δ denotes the first difference (*I(1)*), *n* indicates the number of optimal lags, $ECT_{i,t}$ represents the error correction term (ECT) derived from the long-run estimation, and $\varepsilon_{i,t}$ is assumed to be serially independent with a mean of 0 and a finite covariance matrix. The combination of CCE and ARDL-based ECM is known as the CS-ARDL approach. Therefore, the primary equation is given as:

$$Y_{i,t} = \sum_{I=0}^{py} \beta_{I,i} Y_{i,t-I} + \sum_{I=0}^{px} \delta_{I,i} X_{i,t-I} + \sum_{I=0}^{pz} \acute{\sigma}_i I \bar{Z}_{t-I} + \epsilon_{i,t} \tag{12}$$

According to Haussain et al. (2022), equation (12) can solve cross-sectional dependency and slope heterogeneity, whereas, $Y_{i,t}$ is the dependent variable (here

HFC), $X_{i,t}$ represents all independent variables (here LOGPCGDP, SERVG, PGR, and UNEMP), $\bar{Z}_{t-I}$ =($\bar{Y}_{i,t\bar{I}}, \bar{X}_{i,t\bar{I}}$) provides the averages of all cross sections, and $\bar{Z}$ is the dummy for the time period.

4. Estimated Results

This study explored the macro determinants of HFC across eight ASEAN countries by using Bayesian dynamic multivariate and cross-sectional autoregressive distributed lags models for the study period 2010 to 2022. We initially determined the important variables influencing HFC during the studied time period by using the BART, BASAD, and mix-order selection methods. The results are provided in Table 1. The mix-order method combined the results of posterior probabilities exceeding the 50th quantiles of input predictors, confirming their importance. Specifically, service sector output growth (SERVG) had a posterior probability of 0.1438 using BART, population growth (PGR) had a probability of 0.0781 using BASAD, and unemployment (UNEMP) had a probability of 0.0875 using BART. We concluded that SERVG, PGR, and UNEMP were identified as significant variables influencing HFC, alongside income growth. This partially aligns with Arapova (2018), who highlighted per capita GDP and population growth as key drivers of consumption in Asian countries.

Table 2 presents the estimated results of the nexus between selected macro variables and the HFC variable in ASEAN countries with both time-varying and fixed effects considered. Both fixed effects (β_1) and (β_3) and time-varying effects (δ_1) and (δ_3) for income growth and output growth in services were positively associated with HFC during the studied periods. The fixed effects (β_2) and (β_4) for population growth and unemployment rates were found to be negatively correlated with HFC. Regarding the robustness check of the Bayesian dynamic multivariate panel model estimation, the diagnostic checks confirm that the model converged with the trace and density plots for parameters (betas and deltas) and the R-hat statistics, suggesting that the parameter estimates and inferences derived from the model are robust (see Appendix E).

The results of the panel unit root tests were conducted using the CIPS and CADF tests (see Appendix B). The findings show that the variables HFC, PGR, and SERVG are stationary at level (I(0)) based on the CIPS test, while LOGPCGDP and UNEMP only become stationary after first differencing (I(1)). Specifically, LOGPCGDP has a test statistic of -1.125 at level and -2.317 at first difference, while UNEMP shows a test statistic of -1.259 at level and -4.100 at first difference. This shows that these variables are integrated of order one (I(1)), while others are either stationary at level or after differencing. The results for the CADF test similarly indicate that most variables, except LOGPCGDP and UNEMP, are stationary at level. The overall panel cointegration testing results using the Kao, Pedroni, and Westerlund reveal the presence of cointegration (see Appendix C), meaning that there is a long-run relationship among the studied variables. Furthermore, we found a slope homogeneity in the panel dataset (see Appendix D). These statistics validate the appropriateness of applying a CS-ARDL model to examine both short- and long-run associations while supplementing the findings from the Bayesian dynamic model.

Table 3 provides the estimated long-run and short-run relationships between dependent and independent variables. In the short run, income growth, population growth, and unemployment rates were found to be positively associated with HFC. The short-run effect of service output growth was negative and insignificant. In the long run, income growth and unemployment rates had a negative impact on HFC during the studied periods. However, these findings lack statistical significance. The ECT reveals that HFC adjusts back to its equilibrium over time after short-run shocks. Additionally, we found that CS-ARDL is weak when working with a very small sample size.

These findings suggest that while current income and unemployment are positively associated with household consumption in the short run, this effect does not persist in the long run. This aligns with Keynesian theory, which posits that current income drives short-term consumption. However, the insignificant long-run effect of income growth may be attributed to Friedman's Permanent Income Hypothesis, where consumption decisions are based on expected lifetime income rather than temporary fluctuations. Moreover, the study indicates that unemployment exhibits a positive association with household consumption in the short run, although this effect diminishes over time. This divergence from Keynesian predictions may be attributed to the heterogeneity in labor markets across ASEAN countries and the role of informal employment in moderating consumption during unemployment. The positive short-run correlation between unemployment and consumption could indicate the presence of social transfers or unemployment benefits. Additionally, the time-varying and positive effects of population growth align with the Life-Cycle Hypothesis, where demographic shifts influence consumption patterns over time.

In sum, these findings are consistent with some established theories. For example, Keynes (1936) argued that current income significantly drives consumption in the short term. However, the insignificant long-run effect of income growth could reflect the Permanent Income Hypothesis by Friedman (1957), in which households base consumption decisions on expected lifetime income, diminishing the effect of transient income changes over time. The time-varying and positive effects of population growth are consistent with the Life-Cycle Hypothesis (Modigliani & Brumberg, 1954), where demographic changes, such as population growth, influence consumption patterns over time. The insignificant short- and long-run effects of unemployment contrast with Keynesian predictions, likely due to the heterogeneity in labor markets across ASEAN countries and the role of informal employment in moderating consumption during unemployment. Notably, the mixed short-run and long-run effects revealed the complexity of consumption dynamics in ASEAN.

Table 1. Significant variable selection results by using BART, BASAD, and mix-order methods

From using BART*		From using BASAD**		From using MIX-ORDER***
Variable	Posterior Probability	Variable	Posterior Probability	Chosen Variable
SERVG	0.14384519	SERVG	0.075	SERVG
INDUSAG	0.08924524	INR	0.035	PGR
UNEMP	0.08755888	AGRG	0.032	UNEMP
TNCB	0.08356935	PGR	0.030	(LOGPCGDP)#
PGR	0.07806279	UNEMP	0.029	
EXR	0.07167950			
IRS	0.06952846			

Notes: * and **: both models estimated the posterior probabilities of input predictors based on 50^{th} quantiles; *: the model ran 20 times for the robust; **: the model used a students' t-distribution with a BIC of 20 and a 1000 burn in at 10000 iterations; ***: indicates the mix-order variable selection approach; and # is a main independent variable of this study.

Table 2. Estimated macro determinants of household final consumption in eight ASEAN countries

Parameter	Mean	SD	5 %	97.5 %	Rhat	ESS_Bulk	ESS_Tail
α Time-Varying_intercept	3.14	2.56	0.241	7.79	1.06	32	20.1
σ_1 Fixed Effects	3.28	0.269	2.92	3.74	1.01	58.6	297
σ_2Time-Varying	1.80	1.05	0.503	3.46	1.00	124	240
β_1LOGPCGDP	0.00951	4.25	-6.77	6.88	1.00	310	397
β_2 PGR	-0.478	4.00	-6.44	6.33	1.01	138	329
β_3 $SERVG$	0.339	1.06	-1.38	2.11	1.04	173	341
β_4 UNEMP	-0.314	1.99	-3.17	3.04	1.02	73.2	199
δ_1 LOGPCGDP	1.40	1.38	0.190	4.04	1.03	50.7	320
δ_2 PGR	3.30	2.70	0.211	7.92	1.03	123	339
δ_3 SERVG	0.447	0.510	0.0218	1.44	1.05	27.4	32.3
δ_4 UNEMP	0.863	0.811	0.102	2.46	1.00	89.8	176

Notes: Time-invariant parameters (β) were estimated based on 1000 iterations, 250 warm-ups, 1 chain, thinning rate of 1; τ_k,(k = 1, …, 4) are standard deviation parameters of a random walk prior for the spline coefficients of the time-varying effect Deltas (δ).

Table 3. Estimated short-run and long-run relationships
(dependent variable = household final consumption)

Variable	Short Run					Long Run				
	Coef.	Std. Err.	P-value	95 % Conf. Interval		Coef.	Std. Err.	P-value	95 % Conf. Interval	
LOGPCGDP	146.09	92.66	0.115	-35.51	327.67	-15.09	37	0.686	-88.24	58.06
PGR	2.04	3.21	0.526	-4.26	9.34	5.42	6.36	0.394	-7.05	17.89
SERVG	-16.62	24.19	0.492	-64.05	30.81	0.83	0.62	0.176	-0.38	2.04
UNEMP	0.61	0.65	0.354	-0.68	1.89	-0.87	2.16	0.687	-5.12	3.37
ECT	-1.18									
CD Statistic	0.26									
R^2	0.23									

Note: The model we used in this study is CS-ARDL with zero lags due to a small data sample size.

5. Conclusion

This study identifies the key factors influencing HFC in eight ASEAN countries from 2010 to 2022. Using a mixed-method Bayesian variable selection approach, we found that growth in services, population, and unemployment rates, along with income growth, were the primary drivers of changes in HFC, with probabilities exceeding the 50th quantile. In validating the CS-ARDL model specification, we considered panel unit root tests, panel cointegration tests, cross-sectional dependence, and slope homogeneity. The study highlights the significance of macroeconomic factors, i.e., income growth, unemployment, population growth, and service output growth, influencing household consumption patterns during this period. This contributes to a deeper understanding of the macroeconomic determinants of household consumption dynamics in ASEAN countries. Particularly, the study introduces an innovative mix-order selection approach using the BART and BASAD models, which enhances the methodological consistency in variable selection. Our main findings show that income growth and unemployment are negatively associated with household consumption in the long run, while population growth positively affects consumption in the long run. Services output growth was positively correlated with household consumption in both the short and long run. Overall, the results reveal the complexity of consumption dynamics in eight ASEAN countries.

The relationship between macroeconomic variables and HFC in ASEAN countries exhibits complexities across the short and long run. The results indicate that income growth has a positive association with household consumption in the short run, but this effect does not persist in the long run, which aligns with Keynes (1936). The insignificant long-run effect of income growth could reflect the Permanent Income Hypothesis (Friedman, 1957), while short-run consumption may depend on temporary income shocks. The results indicate that unemployment has a positive association with household consumption in the short run, but this effect does not persist in the long run. The insignificant short- and long-run effects of unemployment contrast with Keynesian predictions, likely due to the heterogeneity in labor markets across ASEAN countries and the role of informal employment in moderating consumption during unemployment. The positive association between unemployment and consumption in the short run could reflect increased social transfers, unemployment benefits, or other factors compensating for lost income. The time-varying and positive effects of population growth are consistent with the Life-Cycle Hypothesis (Modigliani & Brumberg, 1954), where demographic changes influence consumption patterns over time.

We acknowledge that this study has several limitations. While it examined key macro factors, other potentially significant variables, such as tax rates, the impacts of the COVID-19 pandemic, and political regime changes, were not included. Additionally, shifts in consumer behavior during periods of crisis (Molnar-Tankaka et al., 2023) were not explicitly analyzed. Moreover, the 13-year dataset could not fully capture structural changes over time, so it limits the study's ability to assess long-term consumption trends broadly. Future research should address these gaps by incorporating a broader range of variables and extending the analysis period to offer better insights into household consumption patterns across ASEAN economies.

Despite these limitations, the findings in this study still have the potential to propose the following: Policymakers should focus on job creation to reduce unemployment and promote growth in the service sector, which can boost both aggregate demand and supply through increased household spending. Furthermore, affordable social programs, such as free education and accessible healthcare, can help stabilize consumption patterns and mitigate the negative effects of demographic changes, particularly population growth. Policies aimed at expanding the service sector could also foster sustainable household consumption and support long-term economic growth in the ASEAN region.

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Appendices

Appendix A. Notation, units of measurement, and sources of data and variables used in this study

Notation	Variable	Unit	Source
HFC	Average change of household final consumption	%	WDI
TNCB	Number of commercial banks, total	Number	ADB
LOGPCGDP	Logged per capita GDP	U.S. Dollar	ADB
M2	Money supply (M2), local currencies	Millions	ADB
EXR	Exchange rates (1 US dollar against local currencies)	Number	ADB
INR	Consumer price inflation rate	%	WDI
FDI	Foreign direct investment net inflows % of GDP	%	WDI
PGR	Population growth rate	%	WDI
IRS	Deposit interest rate on 12-month period of savings	%	ADB
UNEMP	Unemployment rate of total labor force	%	WDI
FPI	Food production index	2010=100	ADB
AGRG	Growth rate of agriculture output	%	ADB
INDUSAG	Growth rate of industrial output	%	ADB
SERVG	Growth rate of service output	%	ADB

Note: WDI = World Bank Open Data; ADB = ADB Data Library

Appendix B. Panel unit root testing results by using CIPS and CADF tests

Variable	CIPS test (Pesaran, 2007)		CADF test (Im et al., 2003)	
	At level, (I(0))	At first difference, (I(1))	At level, (I(0))	At first difference, (I(1))
HFC	-2.877***	-4.475***	-1.493	-1.796
LOGPCGDP	-1.125	-2.317*	-1.390	-1.900
PGR	-3.530***	-5.393***	-1.421	-2.282*
SERVG	-3.515***	-3.875***	-3.194***	-3.597***
UNEMP	-1.259	-4.100***	-1.049	-1.942

Notes: * $p < 0.01$; ** $p < 0.05$; *** $p < 0.1$; these statistics were computed at lags (1) using Stata17; the LOGPCGDP and UNEMP variables become stationary only after first difference.

Appendix C. Panel cointegration testing results by using Kao, Pedroni, and Westerlund tests

Test	Dickey-Fuller	ADF	Phillips-Perron	G_τ	G_α
Kao (1999)	-1.1393	0.1362	-	-	
Pedroni (1999)	-	-5.2415***	-5.6621***	-	-
Westerlund (2005)	-	-	-	2.2891**	1.0687

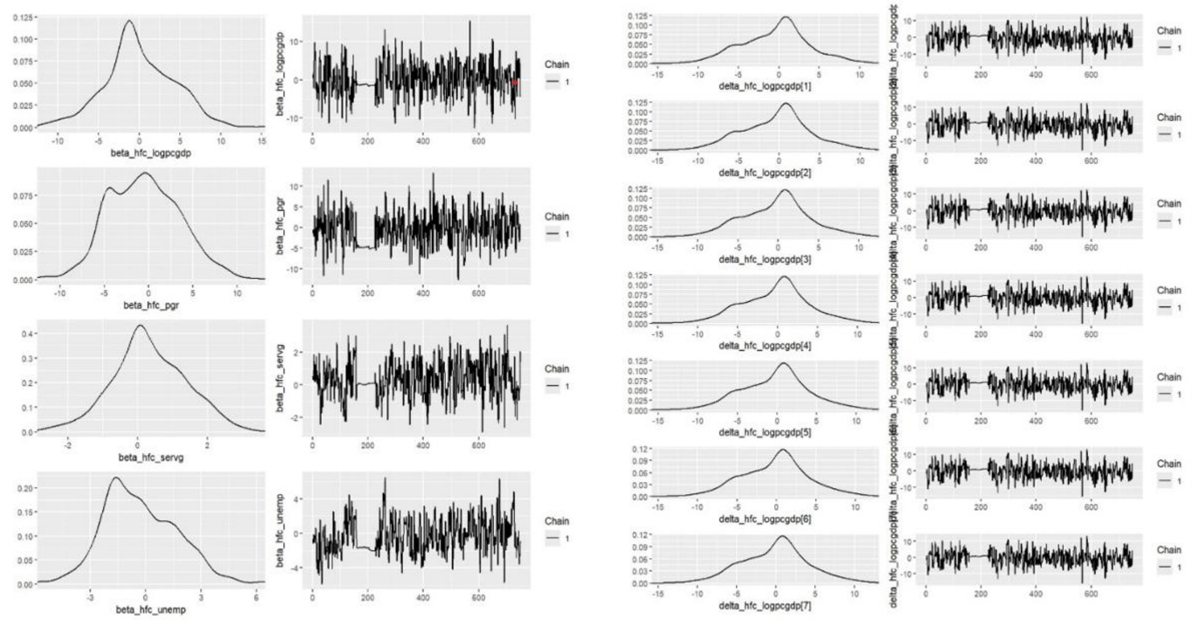
Notes: * $p < 0.01$; ** $p < 0.05$; *** $p < 0.1$; panel cointegration shows evidence of long-run relationship among variables.

Appendix D. Slope homogeneity testing results by using Pesaran and Yamagata (2008) test

Statistic	Value	P-Value
Delta (Δ)	2.895	0.0004
Adjusted Delta Adjusted ($\tilde{\Delta}$)	3.945	0.000

Note: There is a slope homogeneity in the panel dataset.

Appendix E. Model robust check of Bayesian dynamic nonlinear multivariate panel model estimation



Notes: The model used in this analysis has converged. The diagnostic checks, including trace and density plots for parameters (betas and deltas) and R-hat statistics, confirm that the samples generated are representative of true posterior distribution. Hence, the parameter estimates and inferences derived from this model are reliable and robust.