Journal of
Risk and Financial Management

Article

Revisiting the Determinants of Consumption: A Bayesian Model Averaging Approach

Pinar Deniz [1,*] and Thanasis Stengos [2]

[1] Department of Economics, Marmara University, Istanbul 34722, Turkey
[2] Department of Economics, University of Guelph, Guelph, ON N1G 2W1, Canada
[*] Correspondence: pinar.deniz@marmara.edu.tr

Abstract: This study revisits the widely researched area of the consumption function using Bayesian Model Averaging (BMA) for a panel of EU countries to deal with the uncertainty of potential determinants, using the convergence club analysis to construct homogeneous groups by income. BMA suggests that income is the only variable that is found to be a strong determinant across different country groups, whereas other variables have varying importance for different country groups.

Keywords: consumption function; bayesian model averaging

check for updates

Citation: Deniz, Pinar, and Thanasis Stengos. 2023. Revisiting the Determinants of Consumption: A Bayesian Model Averaging Approach. *Journal of Risk and Financial Management* 16: 190. https://doi.org/10.3390/jrfm16030190

Academic Editor: Gulasekaran Rajaguru

Received: 8 February 2023
Revised: 3 March 2023
Accepted: 7 March 2023
Published: 10 March 2023

1. Introduction

Consumption expenditures constitute the highest share of GDP and policies targeting consumption directly or indirectly are used to control the level of economic activity. Hence, it is not surprising that the most basic and widely employed expansionary fiscal policies aim to trigger consumption expenditures as a transmission channel to revive a stagnant economy. As such, identifying the factors that affect consumption has been central to macroeconomics.

After the basic Keynesian formulation, the earliest theories that examined the consumption function were the permanent income hypothesis (Friedman 1957) and the life-cycle hypothesis (Modigliani and Brumberg 1954). There are many empirical and theoretical models in the literature that investigate potential drivers of consumption expenditures employing a variety of variables. Other than income, which is common in all models, variable selection changes depending on the model used. Our study argues that there is uncertainty that stems from the variable selection in this context and as a result we propose using Bayesian Model Averaging (BMA) methodology to identify the most important variables out of a large set of variables found in the literature. To the best of our knowledge, this is the first study to use BMA for consumption function.

Using the BMA method with a motivation to define the most important variables, our main aim is to examine whether we can derive a general modeling framework for the consumption function. To answer the problems stemming from non-standard data measurement across countries, we concentrate on a group of countries with standardized measurements for the variables of interest, the European Union (EU). The EU dataset is collected from a single source, the Eurostat, hence it provides consistency in terms of data measurement due to similar legislation, economic policies and social standards. In our analysis, we examine a panel of EU27 for 2001–2020 period and for certain subgroups constructed using the Phillips and Sul (2007, 2009) convergence club analysis. Since income is observed to be the common variable in the literature for investigating the determinants of consumption, we construct the subgroups of EU27 using income, specifically GDP per capita.

Our key findings are as follows: (i) the BMA approach suggests that income is the only variable that is consistently found to be important across country groups, (ii) variables other than income have varying importance for different country groups. As a conclusion, we disregard a standardization for consumption function and suggest a methodological novelty to construct homogeneous groups to investigate the drivers of consumption.

The organization of the paper is as follows. Section 2 reviews the literature on the potential determinants of consumption. Section 3 gives an overview of the data and the model. Section 4 introduces the econometric framework. Section 5 presents the results, and the last section concludes the paper.

2. Potential Determinants of Consumption

This section summarizes the potential determinants of consumption. The main theories on consumption function are based on the life-cycle and permanent income hypotheses. The life-cycle hypothesis, proposed by Modigliani and Brumberg (1954), suggests that economic agents are forward-looking. Consumers receive utility from life-time consumption and assets and the resulting consumption function considers factors of current income, expected average income and initial assets. The permanent income hypothesis, proposed by Friedman (1957), decomposes consumption into permanent and transitory components with the intention to interpret actual behavior, which is taken to be permanent consumption. Accordingly, with a direct and almost one-to-one link with permanent income, the theory defines a function for permanent consumption with interest rates and wealth-to-income ratio as important factors. However, an important study by Hall (1978), predicting current consumption via stock prices as a proxy for wealth, empirically rejects life-cycle and permanent income hypotheses, since these hypotheses assume a random walk for consumption, arguing that all other variables are irrelevant in predicting current consumption.

Besides the basic consumption function that examines the impact of income, a wealth effect is also examined to be a potential factor especially due stock market volatility. In the consumption model with the current income model of Sierminska and Takhtamanova (2012), wealth is decomposed by the impact of housing wealth, measured with house prices, and financial assets, besides using several control variables such as socio-demographic characters, employment and share of stock in financial assets. Due to the fluctuations in housing prices, several empirical studies examine the impact of house price inflation on house wealth and, further, on consumption (Attanasio et al. 2009; Calomiris et al. 2009; Dynan and Maki 2001). Similarly, the total financial asset liabilities of households is used as a proxy for financial wealth in consumption function (Boone and Girouard 2003; Gholipour Fereidouni and Tajaddini 2017). Macro-financial variables such interest rate and inflation rate are also frequently employed in the determination of consumption function (Gylfason 1981; Mankiw 1981; Raut and Virmani 1989).

In an attempt to stimulate the economy by boosting consumption growth, policymakers discuss the impact of fiscal policies under conventional or unconventional routes, see for example (Feldstein 2002; Hall 2011; Ludvigson 1996; Cho and Rhee 2013). From another angle, Katona (1974) argues that consumption (of durable goods) is volatile, not only dependent on income volatility, and introduces the concept of "willingness (confidence) to buy" as a determinant of consumption expenditures. Acemoglu and Scott (1994) also explore the predictive power of consumer confidence as it captures future expectations of agents. In their work, several other variables, such as income growth, real interest rate, current inflation rate and change in housing wealth, are also used under sensitivity analysis. Another prominent work by Blanchard (1993) takes a closer look at confidence by arguing that the index can be interpreted as foresight or animal spirits, a reference to Keynes, since consumption shocks are positive or negative anticipations by consumers. A highly cited empirical study by Carroll et al. (1994) decomposes the impact of uncertainty on consumption in terms of (i) precautionary savings, which have the power to lower consumption, and (ii) habit formation, which hampers this decline in consumption. The predictive power of consumer confidence is investigated and empirically asserted in the recent literature (Acuña et al. 2020; Ahmed and Cassou 2016; Dees and Brinca 2013; Juhro and Iyke 2020).

3. Data and the Model Specification

All data are obtained from the Eurostat database. Table A1 provides the data description in details. This study employs quarterly and annual datasets for the 2001–2020 period[1] with an aim to examine the distinction from data frequency. We test consumption modeling under relatively higher frequency and lower frequency data as a way to compare short run to long run. We assume that higher (lower) frequency captures the short run (long run) perspective.

The main contribution of this study is to reconsider the consumption function under a variety of variables. To do so, BMA is employed, which is a useful methodology under model uncertainty. We define consumption function for a panel as follows:

$$C_{it} = f(Income_{it}, Sentiment_{it}, Finance_{it}, Fiscal_{it}, Other_{it}), \tag{1}$$

where C is the consumption, $Income$ is the income as used in a standard consumption function or other income proxies. Control variables are given under different groups, such as sentiment, financial, fiscal and other variables.

EU27 is a relatively homogeneous country group due to similar economic policies in addition to sharing common trade agreements and social programs and having geographical proximity. However, there are still differences that can be observed with income per capita levels as a proxy. To deal with the potential heterogeneity in the panel data, income per capita of EU27 is examined under convergence analysis. A rejection of overall convergence enables the construction of convergence clubs under the approach of Phillips and Sul (2007, 2009). Our study argues that convergence clubs according to income per capita of EU27 provide country groups that are homogeneous in terms of income. Variable selection for country group specification is attributed to the observation on the literature, where income per capita stands out as the main theoretical determinant of consumption. Finally, the BMA approach is applied for EU27 overall and the country groups to compare the findings across groups.

4. Econometric Framework

4.1. Convergence Club Analysis

Phillips and Sul (2007, 2009) propose a time-varying factor model allowing for a wide range of possible time paths and individual heterogeneity to identify convergence clubs. The panel data X_{it}, with i denoting the cross-sectional unit and t the time unit, can be decomposed into the permanent common component (μ_t) and the transitory component (δ_{it}). Hence, $X_{it} = \delta_{it}\ \mu_t$. The common component ($\mu_t$) can be removed by scaling to obtain the relative transition component (h_{it}), which measures the individual trajectory of i relative to the average at time t (deviation from the common component), i.e., the relative transition path:

$$h_{it} = \frac{X_{it}}{\frac{1}{N}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \tag{2}$$

Under the assumption that the cross-sectional average of the transition parameter and its limit to infinity are different from zero, the cross-sectional average of h_{it} is unity by definition, and h_{it} converges to unity if δ_{it} converges to δ for all i. Hence, the cross-sectional variance of h_{it}, which is symbolized as H_t, converges to zero in the long run.

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \tag{3}$$

Phillips and Sul (2007) use a semiparametric model for the transition coefficients that allows for heterogeneity over t and i as

$$\delta_{it} = \delta_i + \sigma_i \xi_{it} L(t)^{(-1)} t^{(-\alpha)} \tag{4}$$

where $t \geq 1$, $\sigma_i > 0$ for all i; δ_i is fixed, ξ_{it} is iid(0, 1) across i but may be weakly dependent over t, and $L(t)$ is a slowly varying function[2] , i.e., $logt$, for which $L(t) \rightarrow \infty$ as t→∞; α is the decay rate for the cross-section variation.

With this formulation, δ_{it} converges to δ_i for all $\alpha \geq 0$, which is the null hypothesis of convergence against the alternative hypothesis of divergence.

$H_0 : \delta_i = \delta$ and $\alpha \geq 0$

$H_1 : \delta_i \neq \delta$ for all i or $\alpha < 0$

To put it differently, there exists relative convergence (not absolute convergence) when $H_{it} \rightarrow 0$ as t→∞, which is tested running the following $logt$ regression:

$$log(H_1/H_t) - 2logL(t) = a + blogt + u \tag{5}$$

for t = $T_0, \ldots$,T.

Phillips and Sul (2007) recommend starting the regression with the initial observation T_0 = [rT] for some r > 0, where the first r% of the data is trimmed[3]. $L(t) = log(t)$, $b = 2\alpha$, where b is the speed of convergence parameter of δ_{it} and α is the rate at which the cross-section variation over the transition decays to zero over time. The convergence test is one-sided with standard normal critical value, which is -1.65 for 5% significance level, i.e., the null hypothesis is rejected if $t_b < -1.65$.

If $b \geq 2$, i.e., $\alpha \geq 1$, and the common component, μ_t, is random walk, then b implies convergence in level form of the data; if $2 > b \geq 0$, then the speed of convergence corresponds to conditional convergence, growth rates of the data converge over time.

Finally, a clustering mechanism is applied when the convergence is rejected for the overall sample, which is referred to as convergence club analysis. First, the cross-sectional units are sorted in descending order according to the last period. Second, a core group is created and tested for convergence. Third, the convergence test is replicated for the group by adding cross-sectional units one by one. Finally, for the cross -ectional units that do not converge, a new subgroup is created and the procedure is replicated[4]. Hence, convergence club analysis is the second step when the overall sample is not converging.

4.2. Bayesian Model Averaging

Assume a linear model with C as the consumption, X_γ as the vector of k regressors, B_γ as the vector of coefficients and ϵ as the vector of error terms of $\epsilon \sim N(0, \sigma^2)$.

$$C = \alpha_\gamma + X'_\gamma B_\gamma + \epsilon \tag{6}$$

In the availability of a large number of potential regressors given in the literature, inclusion of all variables is not feasible and may end up causing erroneous interpretations by inflating standard errors.

Under such an uncertainty regarding the true model, Bayesian Model Average (BMA) helps us to select the best model out of all possible combinations of models, i.e., (2^k), using the highest posterior probabilities, i.e., $p(M_\gamma|C, X)$, by using a specified prior model, i.e.,$p(M_\gamma)$, and the data, i.e., $p(C|M_\gamma, X)$, through Bayes' theorem:

$$p(M_\gamma|C, X) = \frac{p(C|M_\gamma, X)p(M_\gamma)}{p(C|X)} = \frac{p(C|M_\gamma, X)p(M_\gamma)}{\sum_{s=1}^{2^k} p(C|M_s, X)p(M_s)} \tag{7}$$

The model weighted posterior distribution for θ becomes:

$$p(\theta|C, X) = \sum \gamma = 12^k p(\theta|M_\gamma, C, X)p(M_\gamma|X, C) \tag{8}$$

Posterior distribution is dependent on the model prior $p(M_\gamma)$. Hence, a varying number of model priors can be checked for a robust analysis. This study employs uniform model prior, however binomial, beta-binomial and a custom form of model priors are also investigated under the robustness check. Out of 2^k number of possible models, uniform model prior refers to a common prior model probability of $p(M_\gamma) = 2^{-k}$; whereas it is

$p(M_\gamma) = \theta^{k_\gamma}(1-\theta)^{k-k_\gamma}$ for the binomial model prior, where θ is a common and fixed inclusion probability on each regressor; θ is drawn from a beta distribution for the beta-binomial model prior; and lastly θ is chosen by the researcher for the custom form of model priors.

Using Zellner (1986)'s g prior (commonly used estimation technique where g represents a hyperparameter that reflects certainty on $B_\gamma = 0$, which is common to assume when no information is available), the expected value of the posterior distribution of B_γ given g is $\frac{g}{1+g}\hat{B_\gamma}$ with variance defined as $\sigma^2(\frac{1}{g}X_\gamma' X_\gamma)^{-1}$ for model B_γ. Lower (higher) g means lower (higher) variance, hence higher (lower) certainty on $B_\gamma = 0$. The choice for the form of g is important. Following the standards used in the literature, unit information prior (UIP) on Zellner's g is utilized.

BMA provides three crucial statistics: (1) Posterior Inclusion Probabilities (PIP), which is the sum of posterior model probabilities (PMP) including a covariate, (2) Post Mean and (3) post standard deviation (Post SD). PIP shows the importance of the variables as regressors, Post Mean shows the coefficients averages over all models.

5. Empirical Findings

We begin by presenting the convergence clubs[5] given in Table 1 and Figure 1. We propose a long-run approach for the construction of country groups as the fluctuations in higher frequency data may be misleading[6]. Results reflect five subgroups within EU27 using the annual dataset. The subgroups are in line with the convergence analysis of Nowak and Kochkova (2011) as they propose that the "new Europe", namely Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia,and Slovenia, joining by 2004, and Bulgaria and Romania, joining by 2007[7], and the "old Europe", as Belgium, France, Germany, Italy, Luxembourg, and the Netherlands, joining by 1958; Denmark, Ireland, and the UK, joining by 1973; Greece, joining by 1981; Portugal and Spain, joining by 1986; Austria, Finland and Sweden, joining by 1995, converge within each other. It is observed that clubs 2 and 3 form the "new Europe", whereas clubs 4 and 5[8] form the "old Europe".

Table 1. Club Convergence Analysis.

Tests	Countries	Beta	Standard Error
Convergence test	EU27	−7.238	2.303
Club Tests			
club 1	IE, LT	−3.307	3.140
club 2	RO, LV, PL, EE, MT, HU, BG	−3.331	2.109
club 3	SK, CZ, HR	−3.717	2.305
club 4	SI, DE, DK, SE, PT, ES, NL	−5.025	3.163
club 5	CY, BE, FR, AT, FI	−3.323	3.247

IE: Ireland, LT: Lithuania, RO: Romania, LV: Latvia, PL: Poland, EE: Estonia, MT: Malta, HU: Hungary, BG: Bulgaria, SK: Slovakia, CZ: Czechia, HR: Croatia, SI: Slovenia, DE: Germany, DK: Denmark, SE: Sweden, PT: Portugal, ES: Spain, NL: Netherlands, CY: Cyprus, BE: Belgium, FR: France, AT: Austria, FI: Finland, IT: Italy, LU: Luxembourg, EL: Greece. IT, LU and EL are divergent countries. Relative transition paths for the convergence clubs are depicted in Figure A1.

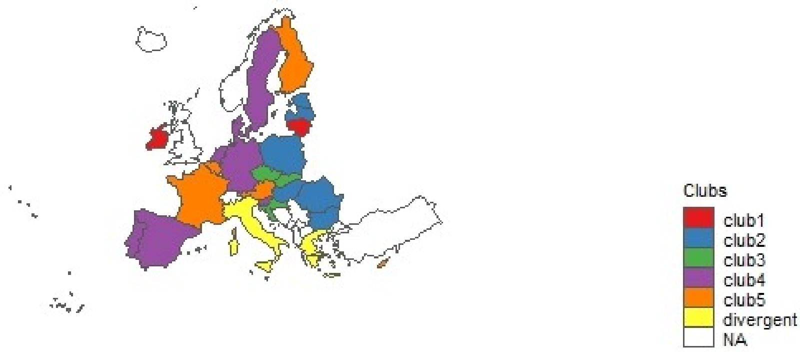

Figure 1. Convergence Clubs.

BMA results for Equation (1) are presented in Table 2 for the short-run approach and Table 3 for the long-run approach. Both analyses include constant coefficient[9] and utilize uniform model prior. For the key statistic, Posterior Inclusion Probability (PIP), we follow a rule of highlighting variables (given in bold font) with PIP larger than 0.5. The results also include the posterior mean of the coefficients (Post Mean) and the corresponding posterior standard deviations (Post SD). The highlighted variables are also consistent with the $|$Post Mean/Post SD$| > 1$ rule for statistical significance as depicted by Raftery (1995). For the quarterly (annual) dataset, using 13 (17) candidate predictors of consumption, we have 2^{13} = 8192 (2^{17} = 131,072) different models[10].

Short-run results, given in Table 2, reflect the main income variable, GDP per capita (*income*), as the only valid variable across country groups, providing a PIP of 1 both for overall EU27 and all subgroups. The sign of the coefficient is in line with the main theory of higher income meaning higher consumption expenditure. The coefficients are also significant using either $|$Post Mean/Post SD$| > 1$ rule or that the threshold for the ratio is taken as 2, which is the classical significance level at 95% as depicted by Sala-i Martin et al. (2004). As for proxies of income, (i) industrial production index (*ipi*) is selected for EU27 and for the clubs between 3 and 5; (ii) real wage, labor productivity (*wage*) is selected only for clubs 1 and 5; (iii) unemployment rate (*ur*) is selected for EU27 and club 4. For all income proxies, we observe negative sign. The sign for *ur* is expected following Okun's law.

As for sentiment variables: (i) index reflecting the intention to buy a car within the next 12 months (*car*) is selected only for club 3; (ii) consumer confidence index (*cci*) is selected for clubs 1 and 3; (iii) index reflecting the intention to purchase or build a home within the next 12 months (*house*) is selected for club 1 only. *cci* is a leading indicator that collects information regarding income expectations and future consumption decisions on durable goods of the agents. Hence, a positive coefficient for *cci* is expected as stated by Acemoglu and Scott (1994), since consumer confidence captures preference shocks and the precautionary saving, which asserts that agents lower their consumption and develop a habit to save more if they are unsure about the future.

Regarding fiscal variables[11]: (i) government debt (*debt*) is selected only for club 3; (ii) general government financial assets/liabilities (*gasset*) is selected for EU27, clubs 4 and 5. All significant coefficients reflect negative signs for both variables. A negative sign may be perceived as lower future funds for the households as government debt and asset accumulation rise, which may create a precautionary saving motive.

Finally, for financial variables, (i) housing price (*hprice*) is selected for EU27, clubs 1 and 2; (ii) inflation rate (*inf*) is selected for clubs 2 and 5; (iii) interest rate (*int*) is selected only for EU27. Positive sign for *hprice* is consistent with the main theories and the later empirical studies (Alp and Seven 2019; Bootle 1981; Jaramillo and Chailloux 2015; Koop et al. 2008; Kundan Kishor 2007). Bootle (1981) explains the positive effect through higher inflation expectations in the future when wealth increases. Theoretically, we may expect positive and negative signs for inflation. Positive signs may be attributed to a wealth effect link, whereas a negative sign to an uncertainty effect link as defined by

Gylfason (1981). Similarly, the negative impact of inflation can be attributed to the delay of discretionary expenditures as depicted by the promising work of Katona (1974). Raut and Virmani (1989) also explain that inflation may raise uncertainty which in turn creates precautionary savings. The sign is observed to be negative for club 2, which are post-Soviet or post-Soviet-sphere countries similar to club 3 countries. On the other hand, the sign is positive for club 5 which are mainly high-income Western countries. Here, we may argue that the prior country group is more prone to reflect a precautionary motive due to its past links, whereas it may reflect a wealth effect for the latter richer country group. Lastly, the positive impact of interest rate on consumption seems unexpected. However, an earlier work by Weber (1970) attributes it to the domination of the income effect over substitution effect.

As for other variables, trade balance (*trade*) is selected for EU27 and all subgroups except for clubs 1 and 3. The positive sign is line with the standard national income model since higher trade balance refers to higher GDP which may further lead to higher consumption through the income channel.

Long-run results, given in Table 3, are similar to the short-run results; however, there is more room for potential drivers due to the advantages of lower frequency data. Hence, the following variables are included in BMA: income inequality (*inequal*), household total financial assets/liabilities (*hasset*), total environmental taxes (*environ*) and natural gas prices (*gprice*). Out of four new variables, only *inequal* (for club 4) and *gprice* (for EU27 and club 5) are selected. Negative sign for income inequality may reflect the relatively higher saving tendency of the richer household when inequality is increasing. Our finding is in line with the Keynesian belief that equalization of income distribution would increase consumption. Finally, a positive sign for gas prices is expected considering the dependence of households on natural gas for energy and heating purposes if no short-term substitute is available.

Table 2. BMA results—short-run approach.

	EU27		**Club 1**		**Club 2**		**Club 3**		**Club 4**		**Club 5**	
	PIP	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**
(Intercept)	1.000	−2.810	1.000	−4.039	1.000	−0.894	1.000	−1.707	1.000	−4.115	1.000	−2.878
income	**1.000**	0.779	**0.996**	0.885	**1.000**	0.714	**0.999**	0.591	**1.000**	1.060	**1.000**	1.260
	(0.036)		(0.226)		(0.057)		(0.118)		(0.078		(0.147	
ipi	**1.000**	−0.169	0.171	−0.010	0.059	0.001	**0.883**	−0.194	**1.000**	−0.450	**0.994**	−0.271
	(0.022)		(0.036)		(0.011)		(0.099)		(0.049)		(0.070)	
wage	0.094	−0.006	**0.953**	−0.430	0.065	0.000	0.092	0.002	0.104	−0.013	**0.960**	−0.257
	(0.021)		(0.161)		(0.019)		(0.035)		(0.053)		(0.111)	
ur	**1.000**	−0.160	0.204	−0.030	0.206	−0.022	0.215	0.023	**0.948**	−0.169	0.359	0.047
	(0.025)		(0.091)		(0.052)		(0.057)		(0.054)		(0.074)	
car	0.195	−0.008	0.334	−0.071	0.222	0.018	**0.979**	−0.265	0.061	−0.001	0.082	0.000
	(0.018)		(0.132)		(0.040)		(0.080)		(0.010)		(0.014)	
cci	0.058	0.002	**0.713**	0.216	0.397	−0.045	**0.989**	0.460	0.084	0.003	0.194	0.014
	(0.010)		(0.173)		(0.065)		(0.125)		(0.016)		(0.034)	
house	0.036	0.000	**0.757**	−0.200	0.067	0.000	0.105	0.004	0.057	−0.001	0.389	0.027
	(0.006)		(0.141)		(0.013)		(0.019)		(0.009)		(0.040)	
debt	0.045	−0.001	0.236	0.029	0.070	−0.002	**0.931**	−0.248	0.064	−0.002	0.074	0.001
	(0.006)		(0.071)		(0.016)		(0.110)		(0.014)		(0.016)	
gasset	**0.998**	−0.073	0.358	−0.032	0.145	−0.008	0.145	−0.008	**0.946**	−0.095	**0.884**	−0.090
	(0.017)		(0.052)		(0.023)		(0.027)		(0.036)		(0.045)	
hprice	**0.998**	0.094	**0.693**	0.250	**0.893**	0.152	0.084	0.001	0.196	−0.012	0.099	−0.004
	(0.021)		(0.206)		(0.072)		(0.020)		(0.028)		(0.017)	
inf	0.035	0.000	0.405	0.049	**0.708**	−0.079	0.134	−0.007	0.066	−0.002	**0.656**	0.055
	(0.004)		(0.076)		(0.062)		(0.025)		(0.010)		(0.048)	
int	**0.935**	0.067	0.467	0.080	0.105	0.006	0.247	0.025	0.052	0.000	0.067	0.000
	(0.026)		(0.105)		(0.026)		(0.052)		(0.008)		(0.012)	
trade	**1.000**	0.115	0.166	−0.010	**0.656**	0.065	0.092	0.003	**0.983**	0.104	**0.992**	0.130
	(0.015)		(0.035)		(0.056)		(0.018)		(0.031)			(0.036)

Post standard deviations are given in parenthesis.

Table 3. BMA results—long-run approach.

	EU27		Club 1		Club 2		Club 3		Club 4		Club 5	
	PIP	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**	**PIP**	**Post Mean**
(Intercept)	1.000	−5.503	1.000	−1.342	1.000	−0.283	1.000	−1.972	1.000	−1.373	1.000	−6.776
income	**1.000**	0.863	**0.907**	1.556	**0.983**	0.801	0.243	0.054	**1.000**	1.141	**0.786**	0.815
	(0.079)		(0.849)		(0.179)		(0.140)		(0.172)		(0.536)	
ipi	**1.000**	−0.213	0.243	0.016	0.129	−0.001	0.125	0.004	**1.000**	−0.642	**0.786**	−0.276
	(0.051)		(0.080)		(0.033)		(0.056)		(0.109)		(0.195)	
wage	0.070	−0.008	**0.864**	−0.897	0.175	0.028	0.178	0.008	0.240	−0.043	0.431	0.282
	(0.041)		(0.536)		(0.101)		(0.078)		(0.120)		(0.416)	
ur	**0.953**	−0.180	**0.538**	0.148	0.255	−0.041	0.241	0.026	**0.826**	−0.208	0.347	−0.059
	(0.065)		(0.433)		(0.118)		(0.113)		(0.125)		(0.110)	
car	**0.626**	−0.074	0.273	0.002	0.224	−0.019	**0.847**	−0.395	**0.552**	−0.116	0.207	0.000
	(0.072)		(0.177)		(0.052)		(0.240)		(0.129)		(0.057)	
cci	0.090	0.002	0.143	0.005	0.148	−0.006	**0.752**	0.516	0.138	−0.006	0.365	0.037
	(0.019)		(0.094)		(0.043)		(0.406)		(0.039)		(0.071)	
house	0.166	0.014	0.237	−0.014	0.148	0.002	0.322	0.068	0.249	−0.027	0.250	−0.017
	(0.041)		(0.172)		(0.032)		(0.135)		(0.083)		(0.064)	
debt	0.199	−0.016	0.160	−0.010	0.118	0.002	**0.886**	−0.545	0.122	−0.009	0.245	0.005
	(0.042)		(0.090)		(0.036)		(0.293)		(0.052)		(0.094)	
gasset	**0.633**	−0.075	0.237	−0.027	0.124	0.003	0.239	−0.030	**0.863**	−0.211	0.213	−0.029
	(0.067)		(0.094)		(0.030)		(0.126)		(0.115)		(0.091)	
hprice	0.360	0.037	0.380	0.160	0.352	0.056	0.194	0.016	0.171	−0.011	0.455	−0.066
	(0.058)		(0.296)		(0.096)		(0.080)		(0.038)		(0.094)	
inf	0.089	0.000	0.383	0.054	**0.609**	−0.089	0.278	−0.022	0.156	−0.001	0.194	−0.009
	(0.013)		(0.108)		(0.089)		(0.073)		(0.025)		(0.042)	
int	0.325	0.033	0.383	0.098	0.238	−0.018	**0.539**	0.153	0.118	0.005	0.221	−0.008
	(0.056)		(0.182)		(0.066)		(0.175)		(0.032)		(0.050)	
trade	**1.000**	0.148	0.231	0.007	0.158	0.008	0.201	0.024	0.350	0.034	**0.719**	0.115
	(0.032)		(0.110)		(0.039)		(0.086)		(0.057)		(0.094)	
inequal	0.235	0.014	0.271	0.051	0.223	0.020	0.153	0.009	**0.733**	−0.139	0.226	0.019
	(0.031)		(0.154)		(0.048)		(0.068)		(0.108)		(0.067)	
hasset	0.035	0.000	0.299	0.033	0.156	0.001	0.413	−0.116	0.257	−0.014	0.126	0.003
	(0.007)		(0.084)		(0.028)		(0.172)		(0.038)		(0.033)	
environ	0.068	0.002	0.285	0.038	0.233	−0.011	0.181	−0.001	0.226	0.013	0.241	0.017
	(0.011)		(0.123)		(0.037)		(0.070)		(0.051)		(0.064)	
gprice	**0.504**	0.042	0.246	−0.003	0.349	0.039	0.402	0.061	0.191	0.013	**0.616**	0.097
	(0.050)		(0.084)		(0.070)		(0.104)		(0.037)		(0.101)	

Post standard deviations are given in parenthesis.

6. Robustness Checks

This section provides a set of robustness check. The main analysis employs uniform model prior in short- and long-run BMA. As for the first robustness check, different prior models are utilized so as to compare the PIPs for uniform, binomial and beta-binomial model prior. Secondly, as income is observed to be an important regressor for EU27 and all country group models, its persistence is examined under a poor prior of $\theta = 0.01$ while the parameter is kept at a standard level of $\theta = 0.5$ for the rest of the variables. Hence, PIP comparisons for uniform, binomial and beta-binomial and the latter custom form of the model are given in Figure 2. The results reflect very similar findings as the prior model as uniform[12].

Thirdly, we control for the endogeneity of income in the consumption function as discussed in the literature[13]. To do so, BMA are examined in a model where income is expressed as a lagged variable, shown in Equation (9) below. The results presented in Table 4 display similar patterns except for the decline in the PIP of the lagged income and increase in the PIP of the sentiment variables. Last but not least, all variables indicate the same signs.

$$C_{it} = f(Income_{it-1}, Sentiment_{it}, Finance_{it}, Fiscal_{it}, Other_{it}), \tag{9}$$

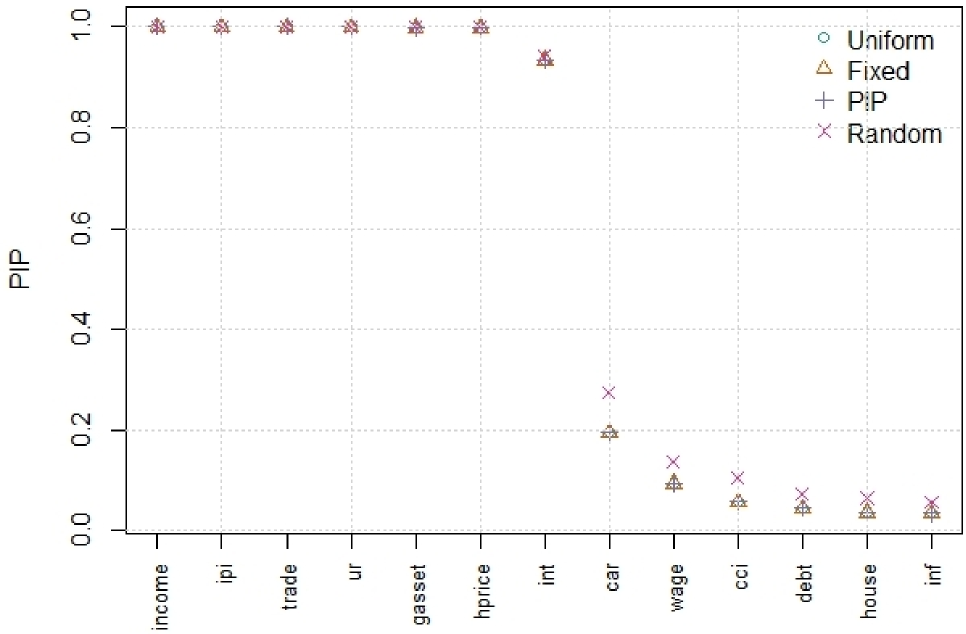

Figure 2. Model prior comparison—EU27.

Table 4. BMA results with lagged income variables.

	EU27		Club 1		Club 2		Club 3		Club 4		Club 5	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
(Intercept)	1.000	−2.196	1.000	−5.815	1.000	0.225	1.000	−2.238	1.000	−0.789	1.000	−3.399
lincome	**0.953**	0.283	0.366	−0.100	0.387	0.134	**0.833**	0.254	**0.971**	0.515	**0.997**	0.389
	(0.110)		(0.177)		(0.188)		(0.152)		(0.138)		(0.112)	
lipi	0.283	−0.019	0.162	−0.011	0.217	0.021	0.164	−0.017	**0.989**	−0.289	0.105	−0.011
	(0.034)		(0.042)		(0.048)		(0.053)		(0.080)		(0.045)	
lwage	**0.580**	0.084	0.197	0.014	**0.721**	0.205	0.228	0.028	0.142	0.005	0.193	−0.029
	(0.085)		(0.091)		(0.143)		(0.076)		(0.088)		(0.075)	
lur	**1.000**	−0.191	**0.615**	−0.152	**0.679**	−0.153	0.185	0.019	**0.833**	−0.160	0.081	−0.004
	(0.050)		(0.153)		(0.121)		(0.054)		(0.099)		(0.025)	
car	0.334	−0.027	0.141	0.010	0.184	0.016	**0.999**	−0.354	0.093	−0.002	0.070	0.002
	(0.042)		(0.070)		(0.041)		(0.078)		(0.029)		(0.018)	
cci	**1.000**	0.183	**0.961**	0.437	0.082	0.003	**1.000**	0.595	**0.991**	0.280	**0.997**	0.292
	(0.034)		(0.163)		(0.022)		(0.129)		(0.079)		(0.072)	
house	**0.685**	−0.059	**0.998**	−0.486	0.072	−0.002	0.100	0.004	**0.748**	−0.124	0.059	0.001
	(0.046)		(0.118)		(0.017)		(0.020)		(0.089)		(0.013)	
debt	0.361	−0.027	0.136	0.006	0.464	−0.076	**0.858**	−0.284	0.317	−0.050	0.314	−0.050
	(0.040)		(0.045)		(0.096)		(0.160)		(0.085)		(0.086)	
gasset	**1.000**	−0.171	0.491	−0.055	**0.827**	−0.112	**0.626**	−0.083	**0.998**	−0.218	**1.000**	−0.258
	(0.022)		(0.068)		(0.065)		(0.077)		(0.049)		(0.048)	
hprice	**1.000**	0.210	**1.000**	0.678	**1.000**	0.316	0.114	−0.007	0.098	0.006	0.234	−0.022
	(0.028)		(0.147)		(0.072)		(0.031)		(0.025)		(0.046)	
inf	**0.541**	−0.033	0.155	−0.005	**0.868**	−0.145	0.161	−0.011	0.063	0.000	0.070	−0.001
	(0.034)		(0.039)		(0.081)		(0.031)		(0.014)		(0.016)	
int	**1.000**	0.190	**0.710**	0.167	**0.515**	0.084	0.361	0.047	**0.666**	0.091	**0.848**	0.159
	(0.033)		(0.135)		(0.096)		(0.074)		(0.077)		(0.090)	
trade	**0.933**	0.065	**0.673**	−0.114	0.112	0.007	0.077	0.000	0.054	0.001	**0.879**	0.151
	(0.026)		(0.099)		(0.025)		(0.015)		(0.011)		(0.077)	

Post standard deviations are given in parenthesis.

7. Conclusions

This study revisits the widely researched area of the determinants of the consumption function to examine whether a general model for consumption can be derived, since there is a clear uncertainty regarding its main factors. In this manner, we determine the potential drivers following the literature and identify the most important variables. To deal with the heterogeneity across countries, we collect a dataset for a highly homogeneous country group, the European Union. Considering further heterogeneity within the EU, we employ convergence clubs analysis according to income per capita. Further, we use BMA to investigate the most important drivers of consumption. To the best of our knowledge, this is first study to apply BMA for the consumption function. Moreover, we believe to have made methodological contribution by constructing country groups using convergence analysis to deal with the heterogeneity issue of the panel data framework. The methodology is applied for EU27 and its subgroups for the 2001–2020 period using annual and quarterly frequency to examine whether there exists a distinction between high (assumed as short run) and low frequency (assumed as long run) data.

Our findings are as follows. First, income per capita is highlighted as the key driver of consumption, controlling for the subgroups and additional robustness checks. Second, the importance of other potential drivers clearly varies across country groups. Third, we find that several variables other than macroeconomic fundamentals can be important. All in all, we argue that consumption may have many drivers and the researcher should meticulously search for the best model suitable for the homogeneous group under investigation. As for future research, nonlinearities and inclusion of interaction terms may be investigated, which is currently an ambiguous area in the BMA approach.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/jrfm16030190/s1.

Author Contributions: P.D. and T.S. have contributed to each section equally. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are available on demand.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Relative Transition Paths for Convergence Clubs

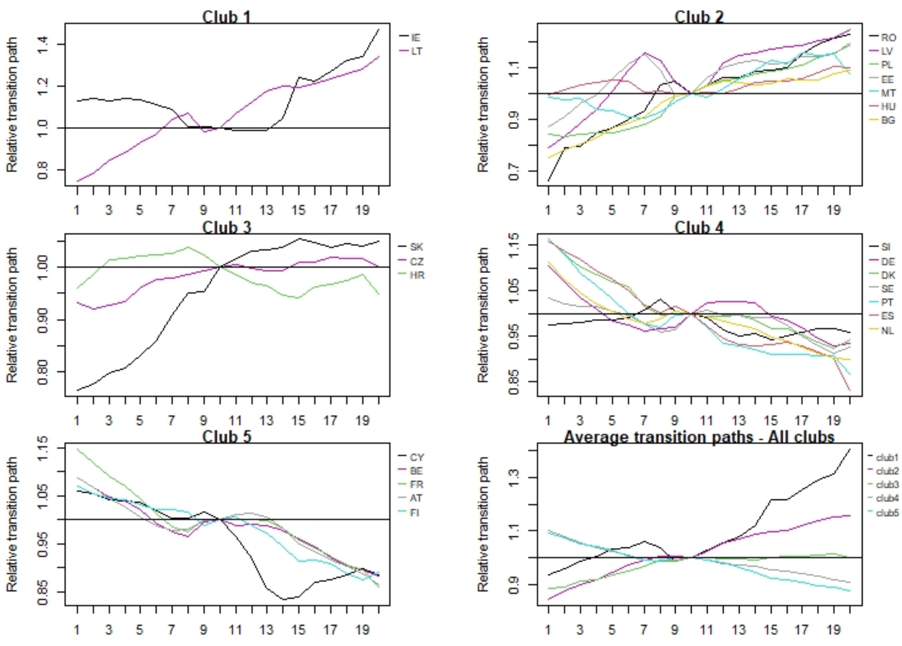

Figure A1. Convergence clubs—long-run approach.

Appendix B. Variable Definitions

Table A1. Dataset Description.

Variable	Original Data	Original Frequency	Transformation from Original to Quarterly	Transformation from Original to Annual
cons	Final consumption expenditure: chain-linked volumes, Index 2010 = 100, per capita	Quarterly	seasonal adjustment and annual growth (%)	seasonal adjustment, annual growth (%) and annual averages
income	GDP at market prices: chain-linked volumes, Index 2010 = 100, per capita	Quarterly	seasonal adjustment and annual growth (%)	seasonal adjustment, annual growth (%) and annual averages
ipi	Volume index of production (manufacturing) seasonally adjusted data, 2015 = 100	Monthly	annual growth (%) and quarterly averages	annual growth (%) and annual averages
wage	Real labor productivity per person, Index, 2015 = 100, seasonally adjusted	Quarterly	annual growth (%)	annual averages
ur	% of population in the labor force, seasonally adjusted	Monthly	annual change and quarterly averages	annual change and annual averages
car	Intention to buy a car within the next 12 months	Quarterly	level	annual averages
cci	Consumer confidence indicator (seasonally adjusted)	Monthly	quarterly averages	annual averages
house	Purchase or build a home within the next 12 months	Quarterly	level	annual averages
debt	Government consolidated gross debt (% of GDP)	Quarterly	annual difference	annual difference and annual averages
gasset	General government financial assets/liabilities % GDP	Quarterly	level	annual averages
hprice	Housing price index *, 2010 = 100	Quarterly	annual growth (%)	annual growth (%) and annual averages
inf	HICP Index, 2015 = 100	Monthly	annual growth and quarterly averages	annual growth and annual averages
int	EMU convergence criterion bond yield	Quarterly	levels	annual averages
trade	Trade balance for values (ratio for indices) Unit value index (2015 = 100)	Monthly	quarterly averages	annual averages
inequal	Income quintile share ratio S80/S20 for disposable income	Annual	-	level
hasset	Household total financial assets/liabilities (% of GDP)	Annual	-	differenced
environ	Total environmental taxes (% of GDP)	Annual	-	level
gprice	Natural gas prices for household consumers: Band D3-Gigajoule	Bi-annual	-	annual growth and annual averages

Whole dataset is from Eurostat. * Hprice data for Greece are received from OECD database under multi-family dwellings.

Notes

1. Pandemic period is excluded from the analysis.
2. $L(t)$ can be $log(t)$, $log^2(t)$, $log(log(t))$. Phillips and Sul (2007) reflects that the prior function has the best test under Monte Carlo simulations.
3. Phillips and Sul (2007), r = 30% is recommended for small sample case, where T $\geq$ 50.
4. There can be divergent units not fitting into any club.
5. We use R-package "ConvergenceClubs" for convergence club analysis of described by Sichera and Pizzuto (2019).
6. Convergence club analysis is replicated for short-run approach using quarterly data. The country groups are observed to be similar with annual data.
7. We can add Croatia to the "new Europe" definition, joining by 2013. Additionally, Nowak and Kochkova (2011) excludes Cyprus and Malta from their analysis due to their different transition patterns.
8. Except for Slovenia, which is in club 4 and the divergent countries.
9. All regression models utilize pooled OLS since homogeneity of the panels is ensured using convergence club analysis.

10 We use R-package "BMS" for BMA analysis of described by Zeugner and Feldkircher (2015).

11 Instead of including government expenditure or taxation variables individually, we concentrate on net effect variables since the prior will provide insufficient inference in the availability of adverse shocks from expansionary and contractionary fiscal policies.

12 The robustness check using different model priors for subgroups of EU27 are available in the Supplementary File to this document.

13 The earlier work of Hall (1978) states the importance of non-exogeneity of income.

References

Acemoglu, Daron, and Andrew Scott. 1994. Consumer confidence and rational expectations: Are agents' beliefs consistent with the theory? *The Economic Journal* 104: 1–19. [CrossRef]

Acuña, Guillermo, Cristián Echeverría, and Cristian Pinto-Gutiérrez. 2020. Consumer confidence and consumption: Empirical evidence from chile. *International Review of Applied Economics* 34: 75–93. [CrossRef]

Ahmed, M. Iqbal, and Steven P. Cassou. 2016. Does consumer confidence affect durable goods spending during bad and good economic times equally? *Journal of Macroeconomics* 50: 86–97. [CrossRef]

Alp, Esra, and Ünal Seven. 2019. The dynamics of household final consumption: The role of wealth channel. *Central Bank Review* 19: 21–32. [CrossRef]

Attanasio, Orazio P., Laura Blow, Robert Hamilton, and Andrew Leicester. 2009. Booms and busts: Consumption, house prices and expectations. *Economica* 76: 20–50. [CrossRef]

Blanchard, Olivier. 1993. Consumption and the recession of 1990–1991. *The American Economic Review* 83: 270–74.

Boone, Laurence, and Nathalie Girouard. 2003. The stock market, the housing market and consumer behaviour. *OECD Economic Studies* 2002: 175–200. [CrossRef]

Bootle, Roger. 1981. How important is it to defeat inflation-the evidence. *Three Banks Review* 132: 23–47.

Calomiris, Charles, Stanley D. Longhofer, and William Miles. 2009. *The (Mythical?) Housing Wealth Effect*. Technical Report. Cambridge: National Bureau of Economic Research, Inc.

Carroll, Christopher D., Jeffrey C. Fuhrer, and David W. Wilcox. 1994. Does consumer sentiment forecast household spending? if so, why? *The American Economic Review* 84: 1397–408.

Cho, Dooyeon, and Dong-Eun Rhee. 2013. Nonlinear effects of government debt on private consumption: Evidence from oecd countries. *Economics Letters* 121: 504–7. [CrossRef]

Dees, Stephane, and Pedro Soares Brinca. 2013. Consumer confidence as a predictor of consumption spending: Evidence for the united states and the euro area. *International Economics* 134: 1–14. [CrossRef]

Dynan, Karen E., and Dean M. Maki. 2001. Does the stock market matter for consumption? *Finance and Economics Discussion Working Paper* 23: 1–44.

Feldstein, Martin S. 2002. *The Role for Discretionary Fiscal Policy in a Low Interest Rate Environment*. Cambridge: National Bureau of Economic Research, Inc.

Friedman, Milton. 1957. *The Permanent Income Hypothesis*. Princeton: Princeton University Press.

Gholipour Fereidouni, Hassan, and Reza Tajaddini. 2017. Housing wealth, financial wealth and consumption expenditure: The role of consumer confidence. *The Journal of Real Estate Finance and Economics* 54: 216–36. [CrossRef]

Gylfason, Thorvaldur. 1981. Interest rates, inflation, and the aggregate consumption function. *The Review of Economics and Statistics* 63: 233–45. [CrossRef]

Hall, Robert E. 1978. Stochastic implications of the life cycle-permanent income hypothesis:Theory and evidence. *Journal of Political Economy* 86: 971–87. [CrossRef]

Hall, Robert E. 2011. The long slump. *American Economic Review* 101: 431–69. [CrossRef]

Jaramillo, Laura, and Alexandre Chailloux. 2015. *It's Not All Fiscal: Effects of Income, Fiscal Policy, and Wealth on Private Consumption*. Washington, DC: International Monetary Fund.

Juhro, Solikin M., and Bernard Njindan Iyke. 2020. Consumer confidence and consumption expenditure in indonesia. *Economic Modelling* 89: 367–77. [CrossRef]

Katona, George. 1974. Psychology, and consumer economics. *Journal of Consumer Research* 1: 1–8. [CrossRef]

Koop, Gary, Simon M. Potter, and Rodney W. Strachan. 2008. Re-examining the consumption–wealth relationship: The role of model uncertainty. *Journal of Money, Credit and Banking* 40: 341–67. [CrossRef]

Kundan Kishor, N. 2007. Does consumption respond more to housing wealth than to financial market wealth? if so, why? *Journal of Real Estate Finance & Economics* 35: 427–448

Ludvigson, Sydney. 1996. The macroeconomic effects of government debt in a stochastic growth model. *Journal of Monetary Economics* 38: 25–45. [CrossRef]

Mankiw, N. Gregory. 1981. The permanent income hypothesis and the real interest rate. *Economics Letters* 7: 307–11. [CrossRef]

Modigliani, Franco, and Richard Brumberg. 1954. Utility analysis and the consumption function: An interpretation of cross-section data. *Franco Modigliani* 1: 388–436.

Nowak, Jan, and Olena Kochkova. 2011. Income, culture, and household consumption expenditure patterns in the european union: Convergence or divergence? *Journal of International Consumer Marketing* 23: 260–75.

Phillips, Peter C. B., and Donggyu Sul. 2007. Transition modeling and econometric convergence tests. *Econometrica* 75: 1771–855. [CrossRef]

Phillips, Peter C. B., and Donggyu Sul. 2009. Economic transition and growth. *Journal of Applied Econometrics* 24: 1153–85. [CrossRef]

Raftery, Adrian E. 1995. Bayesian model selection in social research. *Sociological Methodology* 25: 111–63. [CrossRef]

Raut, Lakshmi K., and Arvind Virmani. 1989. Determinants of consumption and savings behavior in developing countries. *The World Bank Economic Review* 3: 379–93. [CrossRef]

Sala-i Martin, Xavier, Gernot Doppelhofer, and Ronald I. Miller. 2004. Determinants of long-term growth: A bayesian averaging of classical estimates (bace) approach. *American Economic Review* 94: 813–35. [CrossRef]

Sichera, Roberto, and Pietro Pizzuto. 2019. Convergenceclubs: A package for performing the phillips and sul's club convergence clustering procedure. *R Journal* 11: 142. [CrossRef]

Sierminska, Eva, and Yelena Takhtamanova. 2012. Financial and housing wealth and consumption spending: Cross-country and age group comparisons. *Housing Studies* 27: 685–719. [CrossRef]

Weber, Warren E. 1970. The effect of interest rates on aggregate consumption. *The American Economic Review* 60: 591–600.

Zellner, Arnold. 1986. On assessing prior distributions and bayesian regression analysis with g-prior distributions. *Bayesian Inference and Decision Techniques* 6: 223–43.

Zeugner, Stefan, and Martin Feldkircher. 2015. Bayesian model averaging employing fixed and flexible priors: The bms package for r. *Journal of Statistical Software* 68: 1–37. [CrossRef]