Testing the Keynesian consumption hypothesis on European panel data

Authors:
Rodica IANOLE*,
Elena DRUICĂ**

Abstract: *The aim of the paper is to explore to what degree the main hypothesis of the Keynesian model of consumption – current real income represents the most important determinant for consumption, in the short run – is still valid in current European economies. While there is a fairly extensive economic literature discussing different theoretical versions of this initial model, we believe there is yet not enough empirical evidence to rely upon for clearly accepting or rejecting one of them. The added value of our work is particularly salient in the contemporary context of declining rates of savings, augmented by the extending pressures of overconsumption. The analysis is based on a set of panel data available for 42 European countries, for the time period 2000-2013, including final consumption expenditures as dependent variables, regressed against GDP and a dummy variable for the financial crisis. A random effect model offers the best explanation for the consumption trends depicted by the data, offering a clear quantification for the impact of income: each 1% increase in income results in roughly 0,58% increase in consumption, thus confirming the theory, and also pointing out to the remaining percentage as unobserved individual influences, not correlated with our independent variables.*

Keywords: *Keynesian model, random effects, consumption and savings theories, panel data analysis, European economies*

JEL Classification: C33, E12, E21

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* *Rodica IANOLE, Lecturer, PhD, e-mail: rodica.ianole@faa.unibuc.ro.*
** *Elena DRUICĂ, Professor, PhD, e-mail: elena.druica@faa.unibuc.ro.*

1. Introduction

The consumption trends observed in the last decades in most European countries confront the Keynesian income equation and its subsequent consumption law with a type of behavior that became in short time the new norm and not an exception: declining, and even negative, savings (Brenner *et. al*., 1994, Callen & Thimann, 1997, Attanasio & Banks, 1998) along with boosting consumption rates (Hooimeijer & Schutjens, 1991, Migone, 2007). While this is a pervasive result, the excessive consumerist phenomenon seems to fall outside the interests and predictions of standard economic models (Stiglitz, 2008), being either marginalized to the realm of social theories (Ritzer & Stepnisky, 2007), or simply accounted as a natural product of the market.

Recently, Bertrand and Morse (2013) have proposed a theory of trickle-down consumption for explaining this situation with respect to the US, arguing that 25% of the decline in savings in the last three decades may be determined by this exposure to the consumption patterns of the rich, and not by increase in income, unobserved for the non-rich. This result is highly significant from a policy point of view but in order to gain a higher interest on public agendas, further empirical work must be done for building a more consistent consumption theory.

However, the existing econometric findings, generated through somewhat more complicated theoretical models, usually have a narrow contextual focus and thus fail to point out towards a unitary framework of understanding, relevant enough as a solid theoretical piece of information. Without this, we continue to encounter a lot of noise regarding the optimal choice and efficiency of level of certain economic policies. A more acute need of proper quantitative documentation is noticed for the European economies, most of the existing work being conducted on US data sets (complemented by Japan and China studies).

In this context, even if it is a recognizable difficult attempt to determine the real trigger of the consumer behavior from aggregate data (Hall & Mishkin, 1980), the paper primarily attempts to check the validity of income as a key determinant for private consumption, understood in the Keynesian classical spirit. Moreover, given that one of the main effects of the financial crisis of 2007-2008 was the decrease in household's consumption, it is important to reassess the explanatory power of one of initial and most persistent theories regarding consumption. Another important aspect is that previous studies were mostly conducted on individual countries, thus making the panel analysis a good fit with potential for supplementary clarification and country-specific fixed effects. This is especially appropriate in the current context when longitudinal data is the subject of one of the most dynamic topics in econometrics (Greene, 2002).

The data set is a balanced panel consisting of 42 European countries, for the period 2000-2013. On the one hand, we expect various countries to be bound to a certain heterogeneity which panel data analysis can easily capture by allowing for individual specificities to be taken into consideration. On the other hand, not only that the time component increases the number of available data, but also allows for a higher variability in data, less coliniarity, more information and more degrees of freedom. The proxy used for private consumption were the final expenditures at the household level, while the determinants included in our model consists of GDP as proxy for income, and one categorical variable (whether or not the year is before or after 2009), to check for potentially immediate effects of the financial crisis.

The quantitative analysis employed the extended range of models used for panel data – pooled OLS, fixed effects, first difference, between and random effects – discussing their specific output and including the necessary statistical tests for choosing the most appropriate framework. The random effect performs better taking into consideration the cumulative criteria of explanatory power and coefficient significance. This opens up the floor for vast theoretical underpinnings regarding the existence of unobserved individual effects that are not correlated with our independent variables – GDP and the time momentum before and after the crisis.

The paper is structured as follows. Section 2 discusses the relevance of the variables, in relation to the existing theories and empirical work regarding consumption. Section 3 describes the data and the models, followed by discussions and interpretations presented in section 4. We conclude in section 5 by formulating extended implications and further paths of development.

2. Determinants of private consumption

The literature abounds in different investigations focused on the determinants of consumption, incorporating to different degrees relative income, habit formation, social interdependencies or rational expectations (Keynes, 1936; Duesenberry, 1949; Modigliani & Brumberg, 1954; Friedman, 1957). However, this diversity does not seem to translate into too many concrete results, usually because the previous work is still under a certain veil of ignorance and shadowed by a more appealing variable, centrally positioned but not necessary built-in as an addition to the existing work. Palley (2010) brought up a hybrid framework called a synthetic Keynes–Duesenberry–Friedman model, which offers a more comprehensive view of the major stylized facts on consumer spending. He is in line with other opinions stating that the main consumption theories are not competing but in fact are complementary (Darby, 1987).

As usually with the richer theoretical models, this also falls under a relatively complicated approach regarding the data collection process for testing its implications outside the US and on a large number of different countries. Having a parsimonious mindset, we explore the Keynesian belief that once we account for changes in the price levels, the only important factor influencing consumption expenditures is the level of income. Naturally, we acknowledge the famous work of Kuznets (1952) and Goldsmith (1955) for US data, both of them illustrating how savings did not increase even when real income grew significantly (in the interval 1899-1949). However, we also believe that the dynamics of the socio-economic environment had undergone drastic transformation in the second half of the last century (especially for the group of Central and Eastern European countries), opening the path for new investigations of the consumption patterns.

From a slightly different perspective, Campbell and Mankiw (1989), even suggested the existence of two different categories of consumers (still for the US): one that is guided by the principles of the life-cycle theory, and the other that has a more Keynesian nature and simply consumes the current income. The simplicity of the categorization is definitely appealing in terms of analogies for the European space and in more realistic terms we think that this property can be symbolically expressed by the significance of fixed and random effects. Their relevance will be discussed in the final section.

Going back to the aim of the paper, the dependent variable of our models, private consumption, is expressed through the World Bank indicator of household final consumption expenditure. In their working definition, this number encompasses the market value of the goods and services purchased by households (the data is measured in constant 2005 US dollars). Following the observations of Johnsson and Kaplan (1999), we also consider this pure consumption as a proper measure for generating correct estimations.

Secondly, the main independent variable is GDP, a cornerstone variable proxy for most of the research in consumption and savings research. The standard models postulate a significant and positive relationship between GDP and household consumption, while according to the Keynesian hypothesis the increase in consumption will be lower than the increase of the GDP. To comply with the independent variable, in our study the GDP data are also measured in constant 2005 US dollars (retrieved from the same source, The World Bank).

Thirdly, we took into account one potentially relevant categorical variable: the period before the crisis, the years 2000-2008 (0) and after the crisis, the years 2009-2013 (1). Even if it is hard to identify precise discrete time moments for reporting upon the effects of the financial crisis in Europe (Jackson, 2010), the threshold year was chosen based both on the intensity of policy responses and observable public events. Also, the use of such a specific variable was found in other recent studies (Niculescu-Aron & Mihaescu, 2014) and we postulate a negative relationship between this dummy and the consumption expenditures.

3. Data and models

3.1. Data

The panel data for our empirical application is collected from the World Bank, for 42 countries from the group of 50 internationally recognized states of Europe, either considered European on the basis of their territorial location or due to their membership to international European organizations. The analyzed period was 2000-2013. Due to partial data unavailability, we have counted out Albania, Andorra, Bosnia&Herzegovina, Georgia, Lichtenstein, Monaco, and San Marino.

Besides, 16 values of final expenditures Iwere initially missing in our data set, therefore we imputed them based on the rest of the variables: GDP, the income level, and three dummy variables (whether or not the country is a EU member, an Eastern European country, or whether the time is after crisis or not). To conduct our work, we used R – software and several specific packages for imputation ("mice") and for basic panel data analysis ("plm").

In panel data analysis we need to account for tree types of variations. The overall variation takes all the data into account as if they were cross–sectional data. No differences between countries will be isolated, and no influence of time variable. The between variation will count in our case for differences between countries, but will neglect the time component. The last, within variation, will emphasize the time impact within each country and may help provide insights about specific consumption patterns.

Tables 1 and 2 present the summary statistics (after imputation) for our panel data variables. Both the values of GDP and households' final expenditures are measured in 1000.000 constant 2005 US$. The overall evaluation of the available data shows that GDP ranges from 1.965 in Montenegro in 2000, to 3.161.913 in Germany in 2000. The mean is 399.129, while the median is 111.257, warning for a right skewed distribution of this variable. The household final expenditures range between a minimum of 1.467 reached in Montenegro the same year 2000, to a maximum of 1.758.736 for Germany. Similar to the previous case, there is a significant difference between the average value of households' final expenditures, which is 236.365, and the median of 67.288. The histograms show indeed that these two numerical variables are not normally distributed, thus we log final expenditures and GDP data. The results are recorded in the fourth and fifth row of Table 1.

In reporting the variance between units we see that the minimum average GDP over the period of time taken into account is 2.479, reached by Montenegro, while Germany again is responsible for the maximum average value of 2.962.000. For the households' final expenditures, the minimum average value is 2.104 while the maximum is 1.676.000.

Table 1. Sample statistics for the numerical variables in the panel dataset

Variable	Variance	Obs.	Minimum	Median	Mean	Maximum	Standard deviation
Households Final Expenditures (1000.000's US$ 2005)	Overall	N = 588	1467	67288	236365	1758736	410773,5
	Between	n = 42	2104			1676000	404338,2
	Within	T = 14	198800			298000	29812,1
GDP (1000.000's US$ 2005)	Overall	N = 588	1965	111257	399129	3161936	691627,1
	Between	n = 42	2479			2962000	697589,9
	Within	T = 14	352200			427900	27619,49
Log Households Final Expenditures	Overall	N = 588	7,3	11,1	11,0	14,4	1,8
	Between	n = 42	7,6			14,3	1,8
	Within	T = 14	10,69			11,34	0,21
Log GDP	Overall	N = 588	7,6	11,6	11,5	14,97	1,9
	Between	n = 42	7,8			14,9	1,9
	Within	T = 14	11,25			11,62	0,13

Source: own calculations.

As regards the dummy variable, Table 2 shows that 378 of the observations out of 588 were recorded before 2009, while the rest of 210 were recorded between 2009 and 2013. As we will explain in the next paragraphs, the dummy variable will make sense in our study only for three of the five analyzed models.

Table 2. Sample statistics for the "after crisis" variable

Variable	Variance	0 (no)	1 (yes)
After Crisis	Overall	378	210

Source: own calculations.

Models – General description

We have considered the three main approaches of the basic regression analysis with panel data: the pooled, fixed effects, and random effect models, in several different variants that we describe below. The main model for our panel data can be described as follows:

$$Y_{it} = \beta_0 + \beta_1 * X_{1it} + \beta_2 * D_{2it} + \beta_3 * w_{it} + \varepsilon_{it} \quad (1)$$

Here, Y_{it} is the dependent variable, the households' final expenditures measured for the cross–sectional unit i at time t, X_{1it} is GDP measured for unit i at time t and D_{2it} is the "after crisis" dummy variable corresponding to unit i at time t. We also included a variable w_{it} that accounts for all the unobservable variables coming from potential country specificities. If omitted, this variable can bias the results in case of a pooled model by either under or over-evaluation of the impact of X on Y, or by indicating a wrong direction of that impact.

Based on the original model, we expect to find a positive value for β_1, which stands for a positive relationship between GDP and households final expenditures. Also, we expect a value β_1 below unit, which means that one unit increase in GDP will result in increased households final expenditures – but with less than one. However, since these two variables are not normally distributed, a log–log model is rather recommended to describe the relationship between them:

$$Log(Y_{it}) = \beta_0 + \beta_1 * Log(X_{1it}) + \beta_2 * D_{2it} + \beta_3 * w_{it} + \varepsilon_{it} \quad (2)$$

The log-log version of the model will be interpreted in terms of elasticity rather than in terms of absolute monetary units, but since the normality of the independent variable is a recommendation in case of using parametric methods, we will keep both models, with and without logarithm, for final discussions and interpretation. In supporting our approach we plot the scatter diagrams in both cases (Figure 1 and 2 in Appendix 1) and calculate the correlation coefficient between the dependent and independent variable, as shown in Table 3. As it can be observed, in both cases a strong linear relation is indicated.

Table 3. Correlation coefficients between the variables: log–version and simple (non–log) version

Model	Correlation coefficient	Strength of linear relation
Simple	0.9702456	Very strong
Log-log	0.9644138	Very strong

Source: own calculations.

The main differences in estimating the coefficients for both models (1) and (2) come from the assumptions imposed on the error term, on the intercept and the slope. There are several approaches specific to panel data analysis, as we briefly describe below. The pooled OLS model, the first and most simple approach in panel data analysis, will treat all the data as cross – sectional. This model does not account for any differences between countries and for any influence of the time variable, its coefficients are therefore constants, and in our study, as much as in most of the econometric studies on panel data, we expect it to have a good explanatory power but to be affected by serial correlations or misspecifications.

For the category of the models that take into account the individual–specific factors, we estimate the regression coefficients using the first difference estimator, the fixed effects estimator and the random effects estimator. In such models, we assume that it may be something specific to each country that may impact or bias either the final expenditures as the output variable, or the GDP as the predictor, and we control for this. Particular to this sort of models is the removal of time-invariant specific characteristics and the pure assessing of the predictor effect on the dependent variable.

According to the econometric theory, the fixed effects model and random effect models will test for the existence or the inexistence of a correlation between the regressors and the specificities. The output in case of the fixed effects estimator will help decide whether the individual-specific factors concentrated in the intercept reflect the leftover variance in the dependent variable that cannot be explained by the regressors, while the random effects estimator will be based on the assumption that the individual specific effects are independent of the regressors and any differences between intercepts are due to random influences and can be included in the error term. Which of the models is a best fit for our data will be tested later in this paper.

We will pay a particular attention to the between model. Seldom used in literature, this type of model will remove the time component by taking the average of the dependent and independent variable for each country and will regress them against each other. The reason that we include it in our paper is the unexpected high explanatory power, similar to the model that will prove to be the best fit for our data. Section 4 will host discussions and interpretations of this result.

Building the models

The standard approaches in basic panel data analysis that we used in this paper is: the pooled OLS models, the fixed effects models, the first difference models, the random effects models and the between models. A complete summary of the results, including the level of significance of each variable and the corresponding t – values can be found in Tables 1 and 2, Appendix 1, at the end of the article, but partial references about each model will be discussed in the next subsections.

Model 1. Pooled OLS Model

With this model we assume that all the coefficients are constant (intercepts as well as slopes) across time and units. All the variations over time and individuals are captured by the error term in a pooled OLS model and we do not allow for specificities related to countries or time in our dataset. The general form of the models is already mentioned in (1) and (2).

The results of the simple model, recorded in Table 4, show that the adjusted R-squared is 94%, which is a very high value, and both variables are significant. Moreover, there is a positive correlation between the household final expenditures and the GDP in the sense that one unit increase in income results in 0,576 units increase in consumption. At 1% level of significance, the dummy variable seems to have an unexpected positive sign: for the same level of income, the consumption after crisis is 26.744 units (1000.000's) higher than the consumption before crisis. Similar results are obtained from the log-log model, with an adjusted R-squared of 93% and both variables highly significant. An increase of 1% in GDP leads to 0,94% increase in consumption, which still supports the idea that consumption increases with income, but this increase is inelastic. The dummy variable has also a positive sign, showing an increased consumption after crisis, at the same level of income.

Table 4: Main results of the pooled OLS models

Model	**Intercept**	**GDP**	**After Crisis**	**Adjusted R-sq**
Simple Pooled OLS	-301,2	0,58***	26.744***	0,94
Log Pooled OLS	0,18	0,94***	0,16***	0,93

Source: own calculations.

Both models are in line with the original Keynesian model and at a first glance everything seems to be reasonable with them. The only concern is a low Durbin Watson statistic, with high p-values that point out in the direction of serial autocorrelations in the errors that are not necessarily idiosyncratic. Table 5 resumes the main results for our pooled OLS models and shows that for both cases we fail to reject the null hypothesis stated below.

H_0: serial correlation in errors due to individual specificities
H_1: serial correlation in idiosyncratic errors

Table 5: Main results of Durbin Watson test for pooled models

Model	DW statistic	p-value	Results
Simple Pooled OLS	1,3406	0,76	Fail to reject H_0
Log Pooled OLS	1,2559	0,76	Fail to reject H_0

Source: own calculations.

As observed in the table, the p-value in this case is the same for both tests and it has a high value of 0,76, meaning that the data are compatible with the null hypothesis, and the serial correlations in errors are most likely the result of individual specificities. In theory, it is not only autocorrelation that can result in a low value of Durbin-Watson statistics: specification errors are also possible, which in our case means that the intercept or the slopes are perhaps variable and not constant as we assumed, but in what follows we try to allow first for individual specificities in each country.

Model 2. The Fixed Effects Model

In this model, also known as a "within" approach, the slope coefficients will be constant, but the intercept varies over individuals. This name of the model comes from the fact that the model doesn't take into consideration the time component: the intercept may differ across individuals, but not over time. If we denote the average of the observed values for the variables within each country by mean(Y_i) and mean (X_i), the next step is to regress the differencesc $Y\tilde{}_{it}$= Y_{it} – mean(Y_i) against the difference: $X\tilde{}_{it}$ = X_{it} – mean(X_i) and add the dummy variable. The general form of the simple model is:

$$Y\tilde{}_{it} = \beta_i + \beta_1 * X\tilde{}_{it} + \beta_2 * D_{it} + \varepsilon_t \tag{3}$$

or the similar log form. What is particular to this model is the intercept β_i, which in this case depends on the corresponding unit. We expect that each country has its own intercept, capturing some unobserved characteristics that can explain the variations in the predicted variable and are correlated with the predictors. It is also important to note that the fixed effects included in the variable w difference out.

The summary both for the simple and log fixed effects models is shown in Table 6, were we can see that there are no intercepts indicated in these two regressions, as a consequence of different intercepts for different countries. Table 3 in Appendix 1 at the end of the paper presents the intercepts for each country, resulted from this model. As in Figure 6, at least two of the values are statistically different, which supports the idea that there are specific factors in each of the 42 analysed countries that could explain the variation in the household final expenditures, besides GDP and the dummy variable. Another important thing is that the adjusted R-squared in both cases is low: 12% for the simple model and 20% for the log model.

Table 6: Main results of the fixed effects model

Model	Intercept	GDP	After Crisis	Adj R-sq
Simple FE	No constant	0,54***	2.8070***	0,12
Log FE	No constant	1,10***	0,13**	0,20

Source: own calculations.

Compared to the pooled model, the variables are equally significant and the sign of the coefficients are intuitive, but the explanatory power of the fixed effect model is very low both for the simple and the log-case. We explain this result in the Discussions section of the paper.

The results of Durbin-Watson test in this case are reported in Table 7 and from the very low p-values it becomes obvious that the data doesn't support anymore the null. We decide therefore to reject the hypothesis stating that the correlations in errors are due to individual specificities and accept that any remained serial correlation comes from idiosyncratic errors. However, some supplementary tests will be conducted later in the paper, for a final decision regarding the model that fits best our data.

Table 7: Main results of Durbin Watson test for fixed effects model

Model	DW statistic	p-value	Results
Simple Pooled OLS	1,5753	1.328e-07	Reject H_0
Log Pooled OLS	1,5462	1.632e-08	Reject H_0

Source: own calculations.

Model 3. The Between Model

Seldom used in the literature, the between model will remove the time component by taking the average of the dependent and independent variables for each country and then regressing one against the other. The reason why we include it in this paper is its rather high explanatory power, which is expressed through a R-squared value of about 98%, very close to the OLS model. Table 8 below shows the main outputs of this model, while the results at large are included in Table 1 and 2, Appendix 1, at the end of the paper.

Table 8: Main results of the between model

Model	Intercept	GDP	Adj R-sq
Simple Between	6465,9	0,576***	0,941
Log Between	0,245	0,935***	0,935

Source: own calculations.

The R-squared in both models is as high as 98%, with the adjusted values shown in Table 8 around 94%, and the independent variable is significant. The intercept is not significant, but since a value of 0 for the predictor is anyway meaningless in our context we are not concerned with this result. One important thing to notice is that we cannot estimate a between model using the dummy variable "after crisis", as it doesn't make any sense to calculate its average value. However, Figure 3 in Appendix 1 shows not only that the relation between the analyzed variable is indeed very strong, but also a certain peculiarity arising between 2008 and 2010. We will discuss it at large in the Discussions Section.

Model 4. The First Difference Model

In this model we take into consideration differences between values at successive moments, for the variables included in the model and then regress the differences in the dependent against the differences in the independent. This will help remove individual heterogeneity that is constant in time, and take into consideration only the variations that remain from one moment to the next one. The general form of the model is:

$$\Delta Y_{it}= \beta_1 * \Delta X_{it} + \Delta \varepsilon_{it} \quad (3)$$

Table 9 includes the main partial output of the coefficients estimation, while details can be found in Tables 1 and 2 in Appendix 1.

Table 9: Main results of the First Difference model

Model	Intercept	GDP	After crisis	Adj R-sq
Simple First difference	6016,1	0,33	-3922,1	0,0055
Log First difference	0,003	1,4 **	0,03	0,017

Source: own calculations.

We notice that there is almost no explanatory power in this model. The adjusted R-squared is very low, and the variables are hardly significant. That “after crisis” variable has no significance is not surprising in this case: it is an almost time invariant variable, except for the difference between 2009 and 2008. It is worth mentioning that the explanatory capacity seems to become weaker as we remove the unobserved heterogeneity specific to individuals, and allow only for the differences of the variables that are not constant in time to be considered.

Model 5. The Random Effects Model

The random effects estimator relies on the assumption that the variations across entities is assumed to be random, and uncorrelated with the predictors. This is, in fact, the main distinction between the fixed effects model and the random effect model and the results of this estimation can be found in the Table 10. The general form of this model is:

$$Yit = \beta_0 + \beta_1 * X_{1it} + \beta_2 * D_{2it} + v_{it}, \tag{4}$$

where: $v_{it} = w_i + \varepsilon_{it}$ stands for an error term that includes both the idiosyncratic error ε_{it} (a completely random element that is not associated with the cross–sectional units) along with w_i, the unobserved effects correlated with each particular cross–sectional unit. Unlike the fixed effect model, here an important assumption is that the unobserved individual effects are not correlated with the independent variables. In other words, the unobserved individual effects specific to each country should not be related with the GDP or with the analyzed period of time. For instance, we can expect that in a certain country the consumption behavior is related to the income level (in which case we admit that this is an individual effect that is correlated with the independent variable), but we can also admit that the attitude toward consumption within a cross-sectional unit is a specific factor that may not be related to the GDP.

The results in the table above show that both variables are highly significant for both of the models and, that their coefficients have values very similar to those obtained in the pooled OLS model. Table 2 and 3 in Appendix 1 display a synthesis of the results. The explanatory power of the models seems to be high, with an adjusted R-squared of 84% for the simple model and one of 79% for the log – model. There is also a similarity between the coefficients obtained in the fixed effects model and the random effects model, but the difference in the explanatory power of models built by the two methods of estimation is very different.

Table 10: Main results of the Random Effects model

Model	Intercept	GDP	After crisis	Adj R-sq
Simple Random Effects	-2.836,5	0,58***	26.759***	0.84337
Log Random Effects	0.14	0.94 ***	0.156***	0.79357

Source: own calculations.

The results included in Tables 1 and 2, Appendix 1, show that the share of the idiosyncratic error in the overall variance of the error term is 0,848 for the simple model and 0,799 for the log model, leaving only 0,152 and 0,201 respectively for the error coming from individual specificities.

3.2. Choosing the most appropriate model

In the previous paragraphs we built a number of regression models based on several standard methods of estimation in panel data analysis, and discussed their explanatory power along with the significance of the corresponding independent variables. None of the investigations above tell us which of the five models is a better fit for our data. The aim of this sub-section is to conduct some tests in order to make a final recommendation regarding the model that should be used in the final interpretation of the result.

The first test to be conducted is the Lagrange Multiplier test, to decide first between random effects model and OLS model, and then between fixed effects model and pooled OLS model. The hypotheses that we are going to test are the following:

H_0: there are no significant individual and/or time effects to be considered

H_1: there are significant individual and/or time effects to be considered

The results for the Lagrange Multiplier test are included in the table below:

Table 11: Main results of the Lagrange Multiplier test

Models	p-value	Decision
Simple models		
Random effects versus OLS (Honda)	< 2.2e-16	Reject H_0
Fixed effects versus OLS (F-Test)	< 4.658e-11	Reject H_0
Log – models		
Random effects versus OLS (Honda)	< 2.2e-16	Reject H_0
Fixed effects versus OLS (F-Test)	< 2.2e-16	Reject H_0

Source: own calculations.

When testing for differences in the results provided by the random effect estimator and the pooled OLS for the simple models, we find that the p-value is very small, which makes us reject the null hypothesis and accept that there are significant effects, time effects and/or individual, that must be taken into consideration. We reject, consequently, the pooled OLS model and admit that the random effect model is better. In a similar manner, when comparing the fixed effects model and the pooled OLS model we find that the fixed effect model is better than the pooled model. We conduct the same tests for the log-models and draw similar conclusions.

Now, that we know that the pooled model is not the best approach, we go further and test whether there are significant differences in terms of coefficient estimations between fixed effects and random effects models. The hypotheses that we test below are:

H_0: there are no significant differences between the coefficients estimated using random effects and fixed effects estimators;

H_1: the fixed effects estimation is reliable, while the random effect estimation is not.

The results of the Hausman test can be found in Table 12.

Table 12: The main results of the Hausman test

Models	p-value	Decision
Simple models		
Random effects versus Fixed effects	0,8867	Reject H_0
Log – models		
Random effects versus Fixed effects	0,4269	Reject H_0

Source: own calculations.

The p-value is high in both cases, which is an indication that we fail to reject the null hypothesis. That means that we should admit that there are no significant differences between the coefficients estimated through fixed and random estimators.

4. Discussions and interpretations

The pooled models have a high explanatory power in both versions – 94% for the simple model (without log), respectively 93% for the log-model, which confirms the standard theory that income is the main determinant of consumption.

In the simple pooled model, regressing the final consumption expenditures against GDP and the "after crisis" dummy variable, both independent variables are significant. The model depicts that one unit increase in GDP (a highly significant variable) results in 0,58 units increase in consumption – a result that complies with the original model that states that with each unit increase in income, the consumption will increase but with less than one unit. The dummy variable is also significant, at 1% level, but the sign of the coefficient is unexpected: the model suggests that the consumption expenditures seem to increase after the crisis.

In the log-pooled model, regressing the log of final consumption expenditures against the log of GDP and against the "after crisis" dummy variable, both independent variables are highly significant. A one percent increase in GDP results in about 0,94% increase in consumption, which shows the same inelasticity as in the previous case, and the "after crisis" variable has again a positive coefficient. However, the Durbin-Watson test for these models shows a high p-value of 0,76 that points out to a serial correlation that may be the result of some individual effects.

The first difference estimator attempted for demeaning the fixed effects in the dataset, and resulted in two regression models with a remarkably low explanatory power. In the case of simple model, only 0,55% of the variation in the dependent variable is explained by the variations in the independent variables, and none of the explanatory variable is statistically significant. For the log–model, the explanatory power "increases" to an R-squared of 1,7%, and the variable log of GDP becomes significant at 1% level. Similarly, the fixed effects estimator led to models with low explanatory power: R-squared of 12,8% for the no-log model and of 21,5% for the log model. Unlike the first difference estimator, in this case the independent variables are highly significant, but the dummy variable preserves a positive sign for its coefficients in both models.

The random effects estimator aims to make the fixed effect estimation more consistent, by including the effects related to the cross–sectional units in a composite error term, and imposing the assumption that these effects are not correlated with the predictors. This method of estimation leads to a model where the explanatory power is high (84,8% for the simple model and 79,4% for the log – model) and both variables are significant at 0,1% level. The sign of the coefficients are positive in both cases, indicating an increased GDP and the period "after crisis" alike lead to increased final consumption expenditures.

Another result to be mentioned is the value of the coefficients of the independent variables estimated by different methods. Table 2 in Appendix 1 shows that except for the simple first difference model, the coefficients of GDP estimated by the other methods are very similar, with a slight tendency of underestimation for the fixed effect model. The same conclusion can be drawn for the "after crisis" coefficient, which is slightly overestimated for the fixed effect model by comparing to the OLS and the random effects methods.

For the log–model the conclusions are very similar, except for the fact that the GDP is slightly lower in the fixed effects case than in the OLS and random effects cases, and *vice versa* for the "after crisis" coefficient.

The between model has a high explanatory power both in the simple and log – case but its stance in the literature is usually purely theoretical and most commonly ignored, causing the lack of correlation with reality.

The tests conducted in order to choose the model with the best-fit show that the pooled OLS model is not recommended, but the Hausman test shows that there are no significant differences in the coefficients in case of the fixed effects models and random effects models. Since the explanatory power is higher for the random effect model, we can decide that this is the model that will be used in the final section of the paper, to draw the conclusions and discuss the implications.

5. Conclusions and implications

Consumption spending roughly accounts for two-thirds of the GDP in many developed countries and its growth pace has been increasing for the economies in the following income classes. Thus it is more than justified to have a closer look at the dynamics of the phenomenon, using the range of econometric tools available in order to generate a better understanding of the factors determining private consumption in Europe, striving particularly for capturing the effect of income and respectively other types of relevant influences.

The panel analysis conducted in this study allowed us to control for variables that cannot be observed, or measured, like specificities of consumption behavior in each country, cultural factors, social practices, factors that apart from other economic variables acknowledged by the literature, are supposed to have an impact on how much people spend.

The basic panel data analysis used data on 42 countries from 2000 to 2013, to examine the relationship between GDP and household expenditure consumption. A dummy variable standing for whether the analyzed period of time is before or after the economic and financial crisis was taken into consideration as "0" for all the periods before 2008 and "1" for all the periods starting with 2009.

While many of them provide a high explanatory power – pooled OLS, between model and random effects – there are other technicalities to consider, showing also the robustness of the coefficients for the case of fixed effects. The extensive analysis filters for both these important criteria and supports the validity of random effects.

The descriptive force of the numerical manipulations stops here, setting the ground for further explorations on what may we include in this type of effects. The postulated answers, inspired from behavioral economics, can include the role of cognitive biases and heuristics. While their impact may be considered a fixed one in terms of universal predictable irrationalities, the randomness can be viewed in the light of different level of salience in their manifestations. Of course, along them we need to mention the role of social norms and social preferences, the impact of trust and also the way inequality shapes the decision-making processes.

Acknowledgement

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Appendix. Figures and Tables

Figure 1. Scatter plot of gdp (x-line) versus final expenditures (y-line)

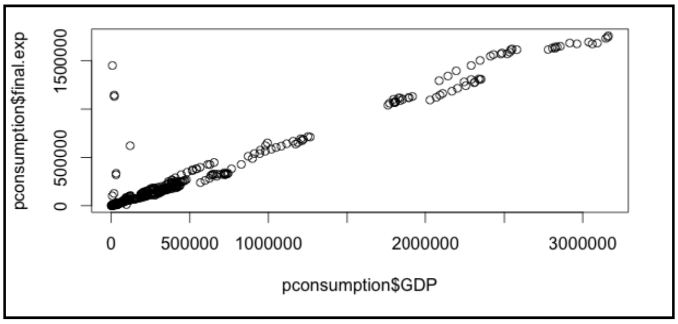

Figure 2. Scatter plot of log – gdp (x-line) versus log – expenditures (y-line)

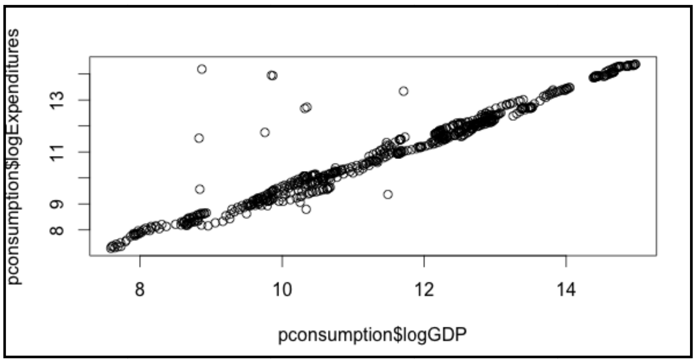

Figure 3. The trends in average consumption and income between 2000 and 2001

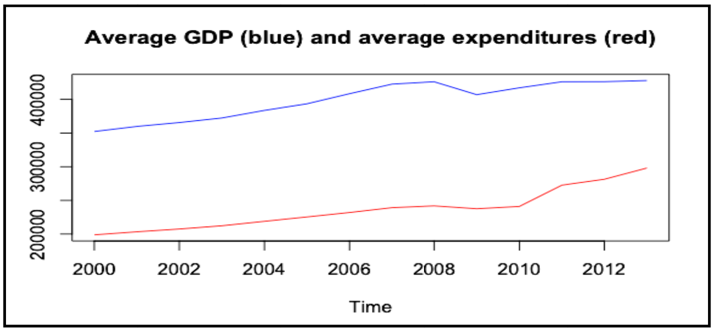

Figure 4. Heterogeneity across years – household's final expenditures

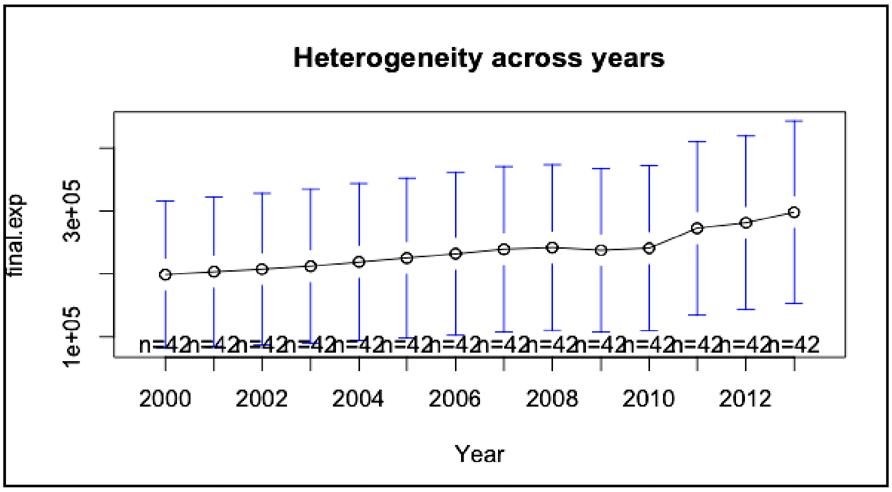

Figure 5. Heterogeneity across years – GDP

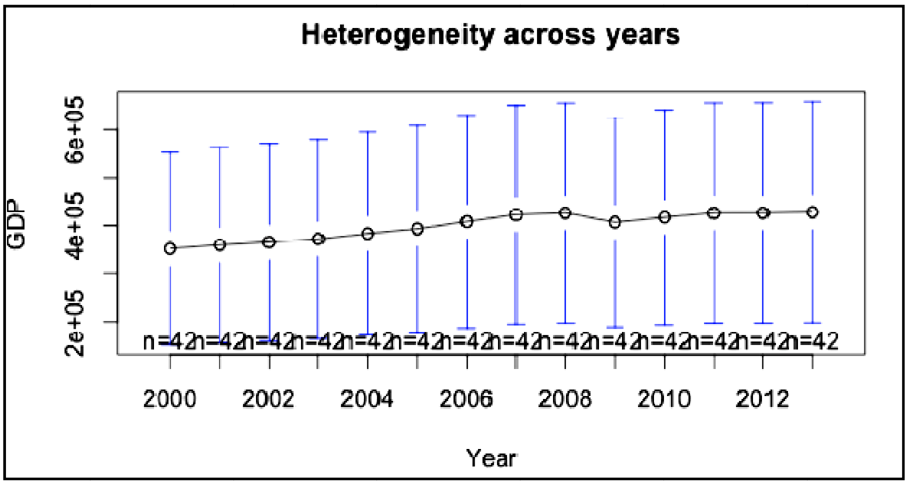

Figure 6. The fixed effects simple model: the differences between the intercepts for each of the 42 countries

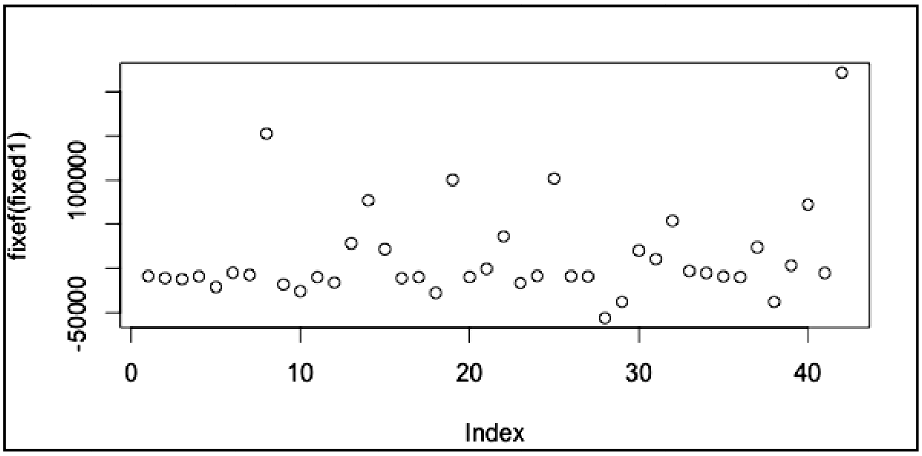

Table 1. Comparison between the estimators for the simple panel regression model

Final expenditures	Pooled OLS Regression	First differences	Within, or fixed effects	Random Effects	Between
Intercept	-3.011,9 (t= -0.541)	6016,1 (1.3035)	No intercept	-2.836,5 (t=-0.3322)	6.465,9 (t=0.7938)
GDP	0,576 *** (97.638)	0.329 (1.5253)	0,537 *** (t=6.722)	0,575 *** (t=56.7566)	0.576 *** (t=56.322)
After Crisis	26.744 ** (t= 3.1443)	-3922,1 (t=-0.2372)	28.070 (t=3.377)	26.759 (t=3.403)	-
R2	0.942	0.0055	0.128	0.847	0.988
Adjusted R2	0.938	0.0055	0.118	0.843	0.941
Idiosyncratic error (share)	-	-		8.344e+0 (0.848)	
Individual error (share)	-	-		1.491e+09 (0.152)	
Rho	-	-			
Theta (λ)	-	-		0.4656	

Table 2. Comparison between the estimators for the log – panel regression model

Log(Final expenditures)	Pooled OLS Regression	First differences	Within or fixed effects	Random Effects	Between
Intercept	-0,178648 (t= 1,4580)	0,0029 (0,107)	No intercept	0.142 (t=0.615)	0.245 (t=1.048)
Log(GDP)	0,936 *** (t=89,07)	1,400 ** (2,757)	1,100*** (t=8,794)	0.939 *** (t=47.265)	0.935*** (t=46.487)
After Crisis	0,156 *** (t= 3,814)	0,030 (t=0,3483)	0,129 ** (t=3,057)	0.156 *** (t=4.221)	-
R2	0,932	0,017	0,215	0.798	0.982
Adjusted R2	0,927	0,017	0,199	0.794	0.935
Idiosyncratic error (share)	-	-	-	0,18253 (0,799)	-
Individual error (share)	-	-	-	0,04597 (0,201)	-
Rho	-	-	-	0,030	-
Theta (λ)	-	-	-	0,5299	-

Table 3. The fixed effects simple model: the differences between the intercepts for each country are significant for at least two countries.

1	8	15	22	29	36
-8762,94	152695,54	21822,43	-16716,34	-37889,65	-9936,53
2	**9**	**16**	**23**	**30**	**37**
-10955,46	-18273,28	-11045,20	-16716,34	20187,40	23956,53
3	**10**	**17**	**24**	**31**	**38**
-12210,90	-25861,55	-9948,55	-8577,39	10542.96	-37930,56
4	**11**	**18**	**25**	**32**	**39**
-9049,97	-9950,70	-27825,84	101648,84	53852,26	3278,64
5	**12**	**19**	**26**	**33**	**40**
-21096,92	-16073,45	100337,12	-8887,98	-3024,53	72247,73
6	**13**	**20**	**27**	**34**	**41**
-4994,64	28371,98	-9797,43	-9250,41	-5313,90	-5318,11
7	**14**	**21**	**28**	**35**	**42**
-7355,06	76897,37	-409,20	-56138,96	-9174,97	221659,07