SCIENTIFIC LETTERS

Econometrics Letters Volume (7), 2, 2020, December

ISSN=2148-6212

Effects of Religiosity on the Growth and the Wealth in OECD Countries

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Abstract

The main purpose of this paper is analyzing the effects of religiosity on the economic growth and the wealth in OECD countries under the light of deriving new factor augmented panel data models. The first distinguished part of this work is to investigate the role of religious diversity on the growth and the wealth in a set of relatively rich countries instead of a set of mixture of rich and poor countries. Second attempt of this work is to measure the religious diversity effect not only on the income growth but also on the wealth by using public and government consumption as the proxies for the wealth. In a broad sense, empirical applications show that religious diversification has negative impact on the wealth and income growth.

Keywords: Growth; Wealth; Factor Model; Panel Estimation.
JEL Codes: C23; E01

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Acknowledgement: My thank go to Beren Uçar who has organized Survey Data and produced Indices

1. Introduction

Religious diversification is one of the important factor that leads to the social conflict, political instability and civil war with long lasting economic distortions.

When the society involves the discriminations due to the religious, ethnolinguistic or race differences, social tensions emerge along these groups. Religiously polarized societies may be affected negatively due to the fall of the rate of investment and increase in the public consumption. On the other hand, armed conflicts induces the government consumption which is also ended up with a negative effect on economic development. Hence, not only income growth variable but also public and government consumption variables are under the impact of religious conflicts.

Rent seeking models show that the resources spent by the groups in order to have a political power can be realized as a social cost with a negative effect on the income growth. This clearly reduces the investment in the production sector. The use of resources inefficiently is to have a adverse effect on the wealth of citizens. Hence, it is expected that private consumption falls dramatically in the time of violence and civil war. By departing from these models, the studies on the relationship between economic development and religious indeed try to gather information about the effect of beliefs, norms and values of the religious groups on the growth rate of the countries.

Many economists have studied the effect of religiosity on growth. Robert Barro is one of the most active researchers in the field of religion and economy, with Rachel McCleary. In their paper Religion and Political Economy in an International Panel (2002) they arrive an important result with the common belief. In the study they find church attendance and belief in heaven or hell are positively related to education level, which shows an opposite result from what major of people believe to be – that people who received higher education and thus with more scientific knowledge will hold opposite thoughts to religious belief. Besides Barro and McCleary, many of the economists and sociologists have reached to a similar conclusion, that it is an important to argue that religious activities, beliefs, or affiliations have significant effects on economic growth. Marcus Noland (2002) studied India, Malaysia, and Ghana, and found that religious affiliation is correlated with economic performance. The regressions do not yield any significant influence from a specific religion, and the results do not support the notion that Islam is inimical to economic growth. Rather he found out positive correlations between Islamic shares and economic growth, in both cross-country and within-country tests. In case of fertility rate, McQuillan (2004) and Lehrer (2004) state that “religious values are likely to play a critical role in shaping demographic behavior only when religious authorities have at their disposal a menu of rewards and sanctions that will encourage the faithful to conform” and such conditions are relevant not only to fertility, but to other demographic outcomes. Robert Grier (1997) looks at 63 former colonies in Latin America, and speculates the political and social-economic perspective of the region’s underdevelopment. Many literatures have argued that the Spanish-speaking countries inherited characteristics of Spain which are not especially conducive to growth and development. Grier had an empirical test the relation between economic growth and Catholicism or Protestantism, with the datasets from former British, Spanish, French colonies. He has observed that Protestantism has a significant correlation with growth and development, and also controlling for Protestantism does not have any effect on the gap between British and French and Spanish colonies’ development. Moreover, Reynal-Querol (2002) shows that the religious polarization is significant in explaining ethnic civil wars. Montelvo and Reynal-Querol (2003) using the model of Mankiw et.al. (1992) show that religious polarization is statistically significant while religious fractionalization is not going to be significant. Alesina et al.(2003) propose new measures for ethnic, linguistic and religious fractionalization for 190 countries in their extensive study. They also try to measure the effects of ethnic, linguistic and religious heterogeneity on the quality of institutions. They obtain the partial results such that those type of heterogeneities create barriers to the nations in showing good economic performance. Hence, their results could not completely support to the early work of Easterly and Levine (1997) who has concluded that per capita GDP growth is affected negatively from ethno linguistic fractionalization.

This study is also analyze the effects of religiosity on the economic growth and even on the wealth in OECD countries. The first distinguished property of this work is to investigate the role of religious diversity on the growth and the wealth in a set of relatively rich countries instead of a set of mixture of rich and poor countries. OECD sample is particularly is chosen because I want to answer the question such that “Is the religious really inducing (negative or positive) advanced capitalistic economies?”. Second attempt of this work is to measure the religious diversity effect not only on the income growth but also on the wealth by using public and government consumption as the proxies for the wealth.

In the empirical applications, religious effect is involved into the econometric models by using polarization and fractionalization indices as the exogenous variables. Some macroeconomic models are also included in the regressions and parameters are estimated via pooled OLS to increase number of observations and reduce the parameter biases. An interesting result is to obtain the insignificant parameter estimations when both polarization and fractionalization indices are located into the same regression model whereas significant parameters are estimated when these variables are located into the different regression model.

In a broad sense, after being many performed many econometric applications, empirical results serve that religious diversification has negative impact on the wealth and income growth in the examined a set of 32 OECD countries.

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2. Econometric Methodology

The empirical literature based on the panel data approach for the determinants of income growth is one of the important research area since the work of Islam(1995) has directed to the importance of country-specific effects between heterogeneous countries. Within the analysis of empiriacal growth models that rely on the use of panel data approach, pooled OLS estimation is usually preferred without regarding heterogeneities and correlations between cross section units. Excluding individual effects leads to both biased and inconsistent Pooled OLS estimation. Instead, fixed and random effect models can be used as a remedy for heterogeneity problem. However, fixed/random effect estimation procedures do not overcome the inconsistency problem since there may still exist cross sectional dependence. Moreover, another approach used in panel data analysis, GMM, has also an assumption that the error terms are cross sectionally independent which leads to biased and inconsistent estimators. On the other hand, since the cross section dimension is small and time series observations are large, usual approach is to implement seemingly unrelated regression equations (SURE) and estimate the system by generalized least squares (GLS). Notice here that, as stated by Pesaran (2006), the SURE approach is also not usable if the cross section observations become large because it will include nuisance parameters which rise up at a quadratic rate in a case of large cross section observations ($N \to \infty$).In addition to that, if the errors are correlated with the regressors and/or you believe that they are cross sectionally correlated then the estimators become inconsistent even for both large time dimension ($T \to \infty$) and cross section ($N \to \infty$) observations. This issue may be achieved with implementing unobserved factor models where cross section correlations are set up with factor loadings. More recently, a vigorous researches have been performed on dealing with cross sectional dependency in panel data. For instance, Coakley et al. (2002) propose a principal components estimation procedure advocated by

Stock and Watson (2002). Phillips and Sul (2003) suggests a GLS-SURE procedure for dynamic panel data model defining a single factor structure in the error terms. In addition to these, factor modeling issues, are also studied in the articles of Bai and Ng (2002), Bai (2003) and among others.

Besides of those approaches, instead of estimating both factors and their loadings, Pesaran (2006) and Kapetanious et al. (2011) propose a different new approach that yields consistent pooled OLS estimates even when T is fixed and $N \to \infty$. Their approach are based on the approximation for the unobserved factors with the linear combination of the averages (over the cross section) of dependent and explanatory variables. This is well known as common correlated effect (CCE) estimator in the literature.

In this paper, I adopt the analysis of Pesaran (2006) to the static fixed effect (FE), first difference, as a last one, Arellano and Bond (1991) and Blundell et al.(2000) models. I have obtained the proxy variables for unobserved factors and I have included these regressors into the pooled panel data model to remove the cross section dependency and then estimate the slope coefficients. The simple derivations for the resultant panel data models and their corresponding estimators are summarized below.

I consider linear heterogeneous panel data model such that :

$$y_{it} = \boldsymbol{\alpha}_i' + \boldsymbol{\beta}'\boldsymbol{x}_{it} + \boldsymbol{\gamma}_i'\boldsymbol{f}_t + \varepsilon_{it} \tag{1}$$

$$\boldsymbol{x}_{it} = \boldsymbol{A}_i' + \boldsymbol{\varphi}_i'\boldsymbol{f}_t + \boldsymbol{v}_{it} \tag{2}$$

where $\boldsymbol{x}_{it}$ is a $k \times 1$ vector of regressors, $\boldsymbol{f}_t$ is the $m \times 1$ vector of unobserved common effects, and ε_{it} are idiosyncratic errors which are orthogonal to the $\boldsymbol{x}_{it}$ while the unobserved factors $(\boldsymbol{f}_t)$ are to be correlated with $\boldsymbol{x}_{it}$.

Combining (1) and (2) will serve

$$\boldsymbol{z}_{it} = \begin{pmatrix} y_{it} \\ \boldsymbol{x}_{it} \end{pmatrix} = \boldsymbol{B}_i' + \boldsymbol{C}_i'\boldsymbol{f}_t + \boldsymbol{u}_{it} \tag{3}$$

where $\boldsymbol{u}_{it} = \begin{pmatrix} \varepsilon_{it} + \boldsymbol{\beta}'\boldsymbol{v}_{it} \\ \boldsymbol{v}_{it} \end{pmatrix} = \begin{pmatrix} 1 & \boldsymbol{\beta}' \\ 0 & I_k \end{pmatrix}\begin{pmatrix} \varepsilon_{it} \\ \boldsymbol{v}_{it} \end{pmatrix}$, $\boldsymbol{B}_i = (\boldsymbol{\alpha}_i \quad \boldsymbol{A}_i)\begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta} & I_k \end{pmatrix}$ and $\boldsymbol{C}_i = (\boldsymbol{\gamma}_i \quad \boldsymbol{\varphi})\begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta} & I_k \end{pmatrix}$.

To remove individual heterogeneity, having been taken the first difference of the equation (3), I arrive at the following equation:

$$\Delta\boldsymbol{z}_{it} = \boldsymbol{C}_i'\Delta\boldsymbol{f}_t + \Delta\boldsymbol{u}_{it} \tag{4}$$

Pesaran (2006) has proposed using the cross section averages of $\Delta\boldsymbol{z}_{it}$ as the proxy variables for unobserved factor $\Delta\boldsymbol{f}_t$. Hence,

$$\Delta\bar{\boldsymbol{z}}_{it} = \boldsymbol{C}_i'\Delta\boldsymbol{f}_t + \Delta\boldsymbol{u}_{it} \tag{5}$$

where $\Delta\bar{\boldsymbol{z}}_t = N^{-1}\sum_{i=1}^{N}\Delta\boldsymbol{z}_{it}$, $\Delta\bar{\boldsymbol{u}}_t = N^{-1}\sum_{i=1}^{N}\Delta\boldsymbol{u}_{it}$ and $\bar{\boldsymbol{C}} = N^{-1}\sum_{i=1}^{N}\boldsymbol{C}_i$. Since the rank condition $rk(\bar{\boldsymbol{C}}) = m \leq k+1$ is satisfied for $N \to \infty$, then directly,

$$\boldsymbol{f}_t = (\bar{\boldsymbol{C}}\bar{\boldsymbol{C}}')^{-1}\bar{\boldsymbol{C}}(\Delta\bar{\boldsymbol{z}}_t - \Delta\bar{\boldsymbol{u}}_t) \tag{6}$$

where $\bar{\boldsymbol{C}} \xrightarrow{p} \boldsymbol{C}$ and $\Delta\bar{\boldsymbol{u}}_t$ converges to zero in quadratic mean ($\Delta\bar{\boldsymbol{u}}_t \xrightarrow{q.m} 0$) as $N \to \infty$ for each t=1,2,…,T. Therefore, in a sense of quadratic mean convergence,

$$\boldsymbol{f}_t - (\bar{\boldsymbol{C}}\bar{\boldsymbol{C}}')^{-1}\bar{\boldsymbol{C}}(\Delta\bar{\boldsymbol{z}}_t - \Delta\bar{\boldsymbol{u}}_t) \xrightarrow{q.m} \boldsymbol{0} \tag{7}$$

Hence, there is a conclusion such that it is valid to use $\Delta\bar{\boldsymbol{z}}_t$ as observable proxy instead of $\boldsymbol{f}_t$.

In my empirical part, I have used the survey data set with having fixed time period as T=2. Therefore, $\Delta\bar{\boldsymbol{z}}_t = (\Delta\bar{\boldsymbol{x}}_t, \Delta\bar{y}_t)$ is to be included only one observation through time that the panel data equations (1) and (2) are turned out to be cross section regressions. Since $\Delta\bar{\boldsymbol{x}}_1$ and $\Delta\bar{y}_1$ include only one observation in time dimension for each cross section, they may treat as an intercept term and even there is possible to be correlated with each other so that I have added an intercept term as a proxy variable for the unobserved factors. Thus, the resultant model becomes

Model (A) : $\Delta y_{it} = \alpha'\tau + \boldsymbol{\beta}'\Delta \boldsymbol{x}_{it} + \varepsilon_{it}$ (8)

where $\tau = (1,1,\dots,1)$ $1 \times n$ vector of ones and the corresponding pooled OLS estimator is written simply as follows:

$$\hat{\beta}_p = \left(\sum_{i=1}^{N} \Delta \boldsymbol{x}_{i1}' M_\tau \Delta \boldsymbol{x}_{i1}\right)^{-1} \left(\sum_{i=1}^{N} \Delta \boldsymbol{x}_{i1}' M_\tau \Delta y_{i1}\right) \tag{9}$$

where $M_\tau = I_T - \tau(\tau'\tau)^{-1}\tau'$.

Moreover,as a different approach, Arellano and Bond (1991) and Blundell et al. (2000) have transformed the data in terms of the cross section deviations which leads to involve the time specific effects to capture the common variations in the short panel data regression model. I have applied Pesaran's CCE modeling set up to their traditional approach by implementing the following regressions:

$$y_{it} - \bar{y}_t = (\boldsymbol{\alpha}_i' - \bar{\alpha}) + \boldsymbol{\beta}'(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_t) + (\boldsymbol{\gamma}_i' - \bar{\boldsymbol{\gamma}})\boldsymbol{f}_t + (\varepsilon_{it} - \bar{\varepsilon}_t) \tag{10}$$

$$\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_t = (\boldsymbol{A}_i' - \bar{\boldsymbol{A}}') + (\boldsymbol{\varphi}_i' - \bar{\boldsymbol{\varphi}}')\boldsymbol{f}_t + (\boldsymbol{v}_{it} - \bar{\boldsymbol{v}}_t) \tag{11}$$

where $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, $\bar{\boldsymbol{\alpha}} = N^{-1}\sum_{i=1}^{N} \boldsymbol{\alpha}_i$, $\bar{\boldsymbol{\gamma}} = N^{-1}\sum_{i=1}^{N} \boldsymbol{\gamma}_i$, $\bar{\boldsymbol{A}} = N^{-1}\sum_{i=1}^{N} \boldsymbol{A}_i$,$\bar{\boldsymbol{\varphi}} = N^{-1}\sum_{i=1}^{N} \boldsymbol{\varphi}_i$, $\bar{\boldsymbol{v}}_t = N^{-1}\sum_{i=1}^{N} \boldsymbol{v}_{it}$ and $\bar{\varepsilon}_t = N^{-1}\sum_{i=1}^{N} \varepsilon_{it}$.

Combining (10) and (11) equations will serve the following single equation:

$$\boldsymbol{z}_{it}^* = \begin{pmatrix} y_{it} - \bar{y}_t \\ \boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_t \end{pmatrix} = \boldsymbol{B}_i^{*\prime} + \boldsymbol{C}_i^{*\prime}\boldsymbol{f}_t + \boldsymbol{u}_{it}^* \tag{12}$$

Sarafidis and Robertson (2009) has taken the first difference of the equation (12) to remove heterogeneity parameter $(\boldsymbol{B}_i^{*\prime})$ and construct instrumental variable (IV) estimator for the case of dynamic panel data setting. However, this does not provide consistent estimation for $\boldsymbol{\beta}$ because $\Delta\boldsymbol{f}_t$ and its loading could not dropped from the model. Instead, since CCE approach is directly applied to the regression given in (12), nuisance parameter $\boldsymbol{\varphi}_i$ is cancelled out from the model and turn back to the original model of (12) without factor variable. This has been shown via defining factor variable in terms of linear combinations of the deviated variables. First consider the simple cross-section averages of the equation (12) such that

$$\bar{\boldsymbol{z}}_t^* = \bar{\boldsymbol{B}}^{*\prime} + \bar{\boldsymbol{C}}^{*\prime}\boldsymbol{f}_t + \bar{\boldsymbol{u}}_t^* \tag{13}$$

and then,

$$\boldsymbol{f}_t = \left(\bar{\boldsymbol{C}}^*\bar{\boldsymbol{C}}^{*\prime}\right)^{-1}\bar{\boldsymbol{C}}^* \;\left(\bar{\boldsymbol{z}}_t^* - \bar{\boldsymbol{B}}^* - \bar{\boldsymbol{u}}_t^*\right) \tag{14}$$

Furthermore, it can be hold the following results by simple algebra,

$$\bar{\boldsymbol{z}}_t^* = \boldsymbol{E}(\boldsymbol{z}_{it}^*) = \begin{pmatrix} N^{-1}\sum_{i=1}^{N}(y_{it} - \bar{y}_t) \\ N^{-1}\sum_{i=1}^{N}(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_t) \end{pmatrix} = \boldsymbol{0}$$

$$\bar{\boldsymbol{B}}^* = \boldsymbol{E}(\boldsymbol{B}_i^*) = \left(N^{-1}\sum_{i=1}^{N}(\boldsymbol{\alpha}_i - \bar{\boldsymbol{\alpha}}) \quad N^{-1}\sum_{i=1}^{N}(\boldsymbol{A}_i - \bar{\boldsymbol{A}})\right)\begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta} & I_k \end{pmatrix} = 0$$

$$\bar{\boldsymbol{u}}_t^* = \boldsymbol{E}(\boldsymbol{u}_{it}^*) = \begin{pmatrix} 1 & \boldsymbol{\beta}' \\ 0 & I_k \end{pmatrix}\begin{pmatrix} \sum_{i=1}^{N}(\varepsilon_{it} - \bar{\varepsilon}_t) \\ \sum_{i=1}^{N}(\boldsymbol{v}_{it} - \bar{\boldsymbol{v}}_t) \end{pmatrix} = 0$$

These results render to suggest that $\boldsymbol{f}_t \xrightarrow{p} 0$ as $N \to \infty$. By using this result, the last form of the regression is represented as follows:

Model (B): $\tilde{y}_{it} = \boldsymbol{\beta}'\tilde{\boldsymbol{x}}_{it} + \varepsilon_{it}$ (15)

where $\tilde{y}_{it} = y_{it} - \bar{y}_t$ and $\tilde{\boldsymbol{x}}_{it} = \boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_t$.

The corresponding pooled estimator can be formulized as

$$\tilde{\hat{\beta}}_p = \left(\sum_{i=1}^{N} \tilde{\boldsymbol{x}}_i' \tilde{\boldsymbol{x}}_i\right)^{-1}\left(\sum_{i=1}^{N} \tilde{\boldsymbol{x}}_i' \tilde{y}_i\right) \tag{16}$$

where $\tilde{\boldsymbol{x}}_i = (\tilde{\boldsymbol{x}}_{i1}, \tilde{\boldsymbol{x}}_{i2})'$ and $\tilde{y}_i = (\tilde{y}_{i1}, \tilde{y}_{i2})'$.

My last model can be considered as an augmented fixed effect set up and suppose that it is generated according to the following specification:

$$y_{it} - \bar{y}_i = \boldsymbol{\beta}'(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i) + \boldsymbol{\gamma}_i'(\boldsymbol{f}_t - \bar{\boldsymbol{f}}) + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{18}$$

$$\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i = \boldsymbol{\varphi}_i'(\boldsymbol{f}_t - \bar{\boldsymbol{f}}) + (\boldsymbol{v}_{it} - \bar{\boldsymbol{v}}_i) \tag{19}$$

Solving the equations (18) and (19) simultaneously, then I have

$$\ddot{\boldsymbol{z}}_{it} = \begin{pmatrix} y_{it} - \bar{y}_i \\ \boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i \end{pmatrix} = \ddot{\boldsymbol{C}}_i'(\boldsymbol{f}_t - \bar{\boldsymbol{f}}) + \ddot{\boldsymbol{u}}_{it} \tag{20}$$

where $\ddot{\boldsymbol{u}}_{it} = \begin{pmatrix} 1 & \boldsymbol{\beta}' \\ 0 & I_k \end{pmatrix} \begin{pmatrix} \varepsilon_{it} - \bar{\varepsilon}_i \\ (\boldsymbol{v}_{it} - \bar{\boldsymbol{v}}_i) \end{pmatrix}$ and $\ddot{\boldsymbol{C}}_i = \begin{pmatrix} \boldsymbol{\gamma}_i & \boldsymbol{\varphi}_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta} & I_k \end{pmatrix}$.

Furthermore, in the case where the rank condition is satisfied, the unobserved factors might be defined as the following representation.

$$\boldsymbol{f}_t - \bar{\boldsymbol{f}} = \left(\bar{\ddot{\boldsymbol{C}}}\bar{\ddot{\boldsymbol{C}}}'\right)^{-1} \bar{\ddot{\boldsymbol{C}}}(\bar{\ddot{\boldsymbol{z}}}_t - \bar{\ddot{\boldsymbol{u}}}_t) \tag{21}$$

where $\bar{\ddot{\boldsymbol{z}}}_t = \begin{pmatrix} N^{-1}\sum_{i=1}^{N}(y_{it} - \bar{y}_i) \\ N^{-1}\sum_{i=1}^{N}(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i) \end{pmatrix} = \begin{pmatrix} \bar{y}_t - \bar{y} \\ \bar{\boldsymbol{x}}_t - \bar{\boldsymbol{x}} \end{pmatrix}$ and similarly ,

$$\bar{\ddot{\boldsymbol{u}}}_t = \begin{pmatrix} 1 & \boldsymbol{\beta}' \\ 0 & I_k \end{pmatrix} \begin{pmatrix} \sum_{i=1}^{N} (\varepsilon_{it} - \bar{\varepsilon}_i) \\ \sum_{i=1}^{N} (\boldsymbol{v}_{it} - \bar{\boldsymbol{v}}_i) \end{pmatrix} = \begin{pmatrix} 1 & \boldsymbol{\beta}' \\ 0 & I_k \end{pmatrix} \begin{pmatrix} \bar{\varepsilon}_t - \bar{\varepsilon} \\ \bar{\boldsymbol{v}}_t - \bar{\boldsymbol{v}} \end{pmatrix}$$

Notice here that $\bar{y}, \bar{\boldsymbol{x}}$, $\bar{\varepsilon}$ and $\bar{\boldsymbol{v}}$ are all fixed scalars. Moreover, when $N \to \infty$, $\bar{\ddot{\boldsymbol{u}}}_t \xrightarrow{q.m} \boldsymbol{0}$ and $\bar{\ddot{\boldsymbol{C}}} \xrightarrow{p} \boldsymbol{C} = \begin{pmatrix} \boldsymbol{\gamma} & \boldsymbol{\varphi} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta} & I_k \end{pmatrix}$. These results provide that

$$(\boldsymbol{f}_t - \bar{\boldsymbol{f}}) - \left(\bar{\ddot{\boldsymbol{C}}}\bar{\ddot{\boldsymbol{C}}}'\right)^{-1} \bar{\ddot{\boldsymbol{C}}}(\bar{\ddot{\boldsymbol{z}}}_t) \xrightarrow{q.m} \boldsymbol{0} \tag{22}$$

Thus, it is valid to use $\bar{\ddot{\boldsymbol{z}}}_t$ as observable proxies for $\boldsymbol{f}_t$. An augmented panel data regression equation is to be written as

Model (C) : $\ddot{y}_{it} = \boldsymbol{\beta}'\ddot{\boldsymbol{x}}_{it} + \boldsymbol{\vartheta}'\bar{\ddot{\boldsymbol{z}}}_t + \varepsilon_{it}$ (23)

and the pooled estimator becomes

$$\tilde{\bar{\beta}}_p = \left(\sum_{i=1}^{N} \ddot{\boldsymbol{X}}_i'\ddot{\boldsymbol{M}}\ddot{\boldsymbol{X}}_i\right)^{-1}\left(\sum_{i=1}^{N} \ddot{\boldsymbol{X}}_i'\ddot{\boldsymbol{M}}\,\tilde{y}_i\right) \tag{24}$$

where $\ddot{\boldsymbol{M}} = \boldsymbol{I}_T - \bar{\ddot{\boldsymbol{z}}}_t(\bar{\ddot{\boldsymbol{z}}}'_t\bar{\ddot{\boldsymbol{z}}}_t)^{-1}\bar{\ddot{\boldsymbol{z}}}'_t$, $\ddot{\boldsymbol{X}}_i = (\ddot{\boldsymbol{x}}_{i1}, \ddot{\boldsymbol{x}}_{i2})'$ and $\ddot{y}_i = (\ddot{y}_{i1}, \ddot{y}_{i2})'$.

Those models based on unobserved factors are examined in the application part for the analysis of the growth, wealth and religious diversification relationship.

3. Empirical Findings

The purpose of this section is to capture the relationship between religious and economic development measured by income growth and government consumption as a wealth variable. The set of all variables examined in this part are summarized in Table 1.

Table 1. Definition of Variables

POLAR	*Polarization Index*
FRAC	Fractionalization Index
CONS	Private Consumption
INV	Total Investment
POP	Population in millions
GCONS	Government Consumption Expenditure
GROWTH	Change in GDP per capita
PINV	Price of Investment
PCONS	Price of Consumption
PGCONS	Price of Government Consumption
POL-F	Averages of Polarization Rates as a Factor Proxy
FRAC-F	Averages of Fractionalization Rates as a Factor Proxy
CONS-F	Averages of Consumption Amounts as a Factor Proxy
INV-F	Averages of Investment Amounts as a Factor Proxy
POP-F	Averages of Populations as a Factor Proxy
GCONS-F	Averages of Gov.Consumption Amounts as a Factor Proxy
GROWTH-F	Averages of Growth Rates as a Factor Proxy
PINV-F	Averages of Price of Investments as a Factor Proxy
PCONS-F	Averages of Price of Consumptions as a Factor Proxy
PGCONS-F	Averages of Gov.Consumption as a Factor Proxy

Notice here that one of the dependent variable GROWTH is the growth rate of GDP per capita which is calculated by taking the average of GDP growth between 1960 and 1970 for the year 1970 and taking the average of growth rate between 1971 and 2000 for the year 2000. This type of calculation is needed here for each country because the data set covers the survey on the religiosity repeated for the years only 1970 and 2000.

In order to capture the effect of religious on the GDP growth rate, fractionalization (FRAC) and polarization (POL) indices are included in the regressions. One could construct two basic measures for religious diversity to assess the importance of religious interactions and potential conflict within a country. The index of religious fractionalization can be interpreted as the probability of two randomly selected individuals in a country that will belong to different religious groups. It is calculated via the formulation such that

$$FRAC_i = 1 - \sum\nolimits_{j=1}^{J} \pi_{ij}^2$$

where π_{ij} is the proportion of people affiliated to religion j in country i. Therefore fractionalization increases when the number of groups increases.

An alternative indicator of religious diversity is the index of religious polarization of Montelvo and Reynal-Querol (2000) :

$$POL_i = 1 - \sum_{j=1}^{J} \left(\frac{0.5 - \pi_{ij}^2}{0.5} \right)^2 \pi_{ij}$$

It is opposite to the fractionalization index in a sense that polarization reaches a maximum when there are two religious groups of equal size . In this type of index, it takes care of the groups that view other groups as a potential threat for their interests. In other sense, for a given number of groups, the threat is higher if the size of the another group is larger than the size of the reference group. Thus, polarization index can reflect potential religious conflict in a society better than fractionalization index.

Moreover, as shown by Montalvo and Querol (2005), fractionalization and polarization indices are highly correlated so that this may lead to the multicollinearity problem. In order to remove this problem, regressions involved only one of the religious index are runned appropriately.

Table 2 and 3 show the results based on the Model (A). As shown in most of the columns of Table 2, it is found that the POL index of religious diversity have a statistically significant direct effect on the growth rate. However, the rest of the variables do not provide the expected results, for instance, all the coefficients are not significant in columns (7) and (8), although investment and consumption have the expected signs and both are significant in regressions (3) and (4). On the other side, Table 3 presents the religious diversification effect on the government consumption (as a proxy for the wealth) and I concluded that the only variable price of government consumption has a significant negative effect on government consumption due to usual relationship between price and consumption or demand and supply. Although a proxy variable for unobserved factors (i.e, intercept terms) are all statistically significant in Table 2, the similar result is not valid in Table 3.

Table 4 and 5 serves the results obtained through the parameter estimation from the Model (B). In regression (4) of Table 4, investment motivates to increase of the growth rate . POL index is the only variable that has an negative impact on the growth rate. The reverse results are handled from Table 5 for POL index. The parameter of POL index is statistically significant and has a positive effect on the government consumption. This implies that an increase in religious conflict is ended up with a rise in government consumption. The empirical results based on Model (C) are shown in Table 6 and 7. Many regressions have been run to determine the number of factor variable in Table 6. POL index and public consumption have significant negative signs in all regressions. Hence, growth rate may fall down due to religious conflict and higher public consumption. I conclude that if only one factor variable is used as a proxy for unobservable effects, the coefficient of this variable is to be highly significant. These results can be justified through the regressions from (7) to (16) in Table 6. However, these results are not possible when the government consumption is taken into account as a dependent variable in Table 7. Factor variables are also not significant except regression (2). On the other hand, there are strong evidence that significant negative correlation between government consumption and both price of investment and price of government consumption exist through all the regressions.

TABLE 2. Results for Model (A)

Dependent Variable→		ΔGROWTH						
Independent Variables↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.014**	-0.015**	-0.018**	-0.017**	-0.015**	-0.014**	-0.017	-0.017**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔFRAC		-0.023						
		(0.62)						
ΔPOLAR	-0.044*		-0.039*	-0.016	-0.043*	-0.045*	-0.024	-0.024
	(0.09)		(0.10)	(0.54)	(0.09)	(0.09)	(0.35)	(0.37)
ΔCONS			-0.001*				-0.001	-0.001
			(0.01)				(0.14)	(0.29)
ΔINV				0.001*			0.001	0.001
				(0.01)			(0.19)	(0.15)
ΔGCONS					-0.001			-0.001
					(0.28)			(0.37)
ΔPOP						0.000		-0.000
						(0.82)		(0.51)
R^2	0.09	0.08	0.29	0.28	0.13	0.09	0.34	0.37
#Observation	32	32	32	32	32	32	32	32

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

TABLE 3. Results for Model (A)

Dependent Variable→	ΔGCONS							
Independent Variables↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.17	0.43	0.470	0.900	0.053	0.045	0.490	0.556
	(0.86)	(0.69)	(0.55)	(0.39)	(0.96)	(0.47)	(0.54)	(0.56)
ΔFRAC	-6.39							
	(0.43)							
ΔPOLAR		2.80	0.380	-0.035	2.01	-0.094	0.089	-0.027
		(0.56)	(0.92)	(0.99)	(0.69)	(0.98)	(0.98)	(0.99)
ΔCONS			0.068				0.059	0.050
			(0.33)				(0.50)	(0.61)
ΔINV				0.000			-0.018	-0.019
				(0.99)			(0.87)	(0.88)
ΔPOP					-0.000			0.000
					(0.51)			(0.82)
ΔPCONS			0.172^{**}			0.161^{**}		0.168^{*}
			(0.00)			(0.00)		(0.01)
ΔPGCONS	-0.034^{*}	-0.036^{*}	-0.145^{**}	-0.074^{*}	-0.035^{*}	-0.150^{**}		-0.149^{**}
	(0.10)	(0.10)	(0.00)	(0.02)	(0.10)	(0.00)		(0.00)
ΔPINV				0.090		0.026		0.014
				(0.08)		(0.56)		(0.79)
R^2	0.11	0.08	0.46	0.23	0.13	0.18	0.45	0.46
#Observation	32	32	32	32	32	32	32	32

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

TABLE 4. Results for Model (B)

Dependent Variable→	GROWTH							
Independent Variables↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FRAC	-4.434 (0.19)							
POLAR		-6.616^{*} (0.05)	-6.578^{*} (0.05)	-5.452^{*} (0.10)	-6.919^{*} (0.05)	-6.507^{*} (0.07)	-6.049^{*} (0.09)	-6.087^{*} (0.10)
CONS			-0.154 (0.15)				-0.080 (0.54)	-0.082 (0.55)
INV				0.248^{*} (0.10)			0.182 (0.35)	0.181 (0.35)
GCONS					0.109 (0.69)		0.110 (0.69)	0.111 (0.69)
POP						0.000 (0.85)		0.000 (0.96)
R^2	0.06	0.07	0.09	0.10	0.11	0.06	0.11	0.07
#Observation	32	32	32	32	32	32	32	32

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

TABLE 5. Results for Model (B)

Dependent Variable→			GOVCONS					
Independent Variables↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FRAC	1.063							
	(0.49)							
POLAR		2.764*	2.955*	3.074*	2.509	2.768*	2.426	2.828*
		(0.09)	(0.09)	(0.07)	(0.14)	(0.10)	(0.17)	(0.10)
CONS						-0.003	-0.009	0.023
						(0.96)	(0.89)	(0.75)
INV					0.014		0.003	0.033
					(0.85)		(0.98)	(0.74)
POP				-0.000				-0.000
				(0.51)				(0.18)
PCONS						0.010	0.006	0.014
						(0.60)	(0.77)	(0.50)
PGCONS	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.79)	(0.99)	(0.77)	(0.74)	(0.87)	(0.81)	(0.88)	(0.75)
PINV					0.00		0.00	0.00
					(0.17)		(0.21)	(0.18)
R^2	0.04	0.05	0.09	0.10	0.11	0.06	0.11	0.07
#Observation	64	64	64	64	64	64	64	64

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

TABLE 6. Results for Model (C)

Dependent Variable→			GROWTH					
Independent Variables↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FRAC	0.002							
	(0.85)							
POLAR		-0.044*	-0.026*	-0.039*	-0.039*	-0.040*	-0.040*	-0.040*
		(0.02)	(0.10)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
CONS				-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
INV							0.00	0.00
							(0.91)	(0.76)
GCONS								-0.001
								(0.25)
POP								
GROWTH-F			-0.00					
			(0.99)					
POL-F		-0.260**	0.056	-0.309**	-0.186		-0.309**	-0.320**
		(0.00)	(0.99)	(0.00)	(0.84)		(0.00)	(0.00)
FRAC-F	-0.216**							
	(0.00)							
CONS-F					0.004	0.009**		
					(0.89)	(0.00)		
GOVCONS-F								
INV-F								
POP-F								
R^2	0.47	0.51	0.66	0.62	0.61	0.62	0.62	0.07
#Observation	64	64	64	64	64	64	64	64

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

TABLE 6 (Continued). Results for Model C

Dependent Variable→	GROWTH							
Independent Variables↓	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
FRAC								
POLAR	-0.042* (0.01)	-0.042* (0.01)	-0.042* (0.01)	-0.045** (0.00)	-0.042* (0.01)	-0.042* (0.01)	-0.041* (0.02)	-0.040* (0.01)
CONS	-0.001** (0.00)	-0.001** (0.00)	-0.001** (0.00)	-0.001** (0.00)	-0.001** (0.00)	-0.001** (0.00)	-0.001** (0.00)	-0.001** (0.00)
INV	0.00 (0.73)	0.00 (0.77)	0.00 (0.74)	0.00 (0.54)	0.00 (0.74)	0.00 (0.73)	0.00 (0.81)	
GCONS	-0.001 (0.23)	-0.001 (0.24)	-0.001 (0.23)	-0.001 (0.23)	-0.001 (0.23)	-0.001 (0.23)	-0.001 (0.26)	-0.001 (0.24)
POP	-0.00 (0.70)	-0.00 (0.87)	-0.00 (0.67)	-0.00 (0.55)	-0.00 (0.67)	-0.00 (0.67)		
GROWTH-F					1.010** (0.00)			
POL-F	-0.311** (0.00)							
FRAC-F								
CONS-F		0.009** (0.00)					0.009** (0.00)	
GOVCONS-F			0.016** (0.00)					0.016** (0.00)
INV-F				0.133** (0.00)				
POP-F						-0.00** (0.00)		
R^2	0.62	0.63	0.63	0.61	0.61	0.62	0.62	0.62
#Observation	64	64	64	64	64	64	64	64

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

TABLE 7. Results for Model (C)

Dependent Variable→	GCONS							
Independent Variables↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FRAC	-1.658							
	(0.27)							
POLAR		0.399	0.799	-0.549	-0.549	-1.49	-1.49	-1.49
		(0.91)	(0.81)	(0.87)	(0.87)	(0.65)	(0.65)	(0.65)
CONS				0.073	0.073	0.079	0.079	0.079
				(0.21)	(0.21)	(0.18)	(0.18)	(0.18)
INV				0.009	0.009	0.017	0.017	0.017
				(0.84)	(0.84)	(0.72)	(0.72)	(0.72)
POP						-0.00	-0.00	-0.00
						(0.17)	(0.18)	(0.18)
PCONS				0.065*	0.065*	0.061*	0.061*	0.061*
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
PGCONS			-0.031*	-0.055*	-0.055*	-0.050*	-0.050*	-0.050*
			(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
PINV				-0.031*	-0.031*	-0.032*	-0.032*	-0.033*
				(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
POL-F		-19.61*		-106.83				
		(0.02)		(0.62)				
FRAC-F	-5.990							
	(0.47)							
CONS-F							-13.794	
							(0.63)	
GOVCONS-F					7.844			-19.906
					(0.62)			(0.62)
INV-F						7.350		
						(0.63)		
POP-F								-0.002
								(0.62)
PGCONS-F			-0.002			0.038		
			(0.93)			(0.57)		
PINV-F				2.505	3.518			
				(0.63)	(0.62)			
PCONS-F							-1.505	
							(0.63)	
R^2	0.14	0.13	0.14	0.23	0.29	0.30	0.31	0.31
#Observation	64	64	64	64	64	64	64	64

Note: p-values are given in parenthesis. (**) implies p-value is less than 0.01. (*)implies p-value is between 0.1 and 0.01.

4. Conclusion

This work analyzes the effects of religious diversity on the income growth and the wealth. Through the empirical investigations using the survey data for both 1970 and 2000, it is shown that the explanatory power of either religious fractionalization or polarization is strong enough to argue that they influence both income growth and government consumption. However, it is diffucult to be concluded that the religious diversity has an impact on the private consumption in OECD countries.

APPENDIX

Data on Religiosity

This research uses two types of datasets, one for religiosity and one for economic growth and other possible determinants for economic growth. Our empirical research began with a previously constructed broad cross-country data set. The data include national-accounts variables and an array of other economic, political, and social indicators. The main sources of these data are Heston, Summers, and Aten (2002), World Bank(2005), Barro and Lee (2001), Freedom House, and *International Country Risk Guide*. We have expanded this data set to include measures of religiosity. The most useful sources of international data on attendance at religious services and religious beliefs are the surveys in the three waves of the World Values Survey (WVS) (1981–1984, mostly 1981; 1990–1993, mostly 1990; and 1995–1997, mostly 1995 and 1996), the two reports on religion by the International Social Survey Program (ISSP) (1990–1993, mostly 1991; and 1998–2000, mostly 1998), and the Gallup Millennium Survey (1999). Another wave of the WVS applies to 1999–2003 and has recently been made available for public use. The Data for each country is available for your request.

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