JEL Classification: O16, H55, C23
Keywords: pension funds assets, output growth, common factors, heterogeneous panel, panel cointegration, panel spurious regression

Are Funding of Pensions and Economic Growth Directly Linked? New Empirical Results for Some OECD Countries*

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Abstract

We empirically test on a panel of OECD countries the hypothesis of a direct and positive link between funding of pensions and economic growth, which is based on the idea that richer pension systems can accelerate the development of the financial system and thus promote a more efficient capital allocation. We follow Davis and Hu (2008) in estimating a modified Cobb-Douglas production function where pension fund assets are treated as a shift factor, but in line with the recent econometric literature we control for common global shocks driving per capita outputs. Therefore we adopt a more general approach suitable to the presence of a multifactor error structure. The previous evidence of a long run cointegration relationship between autonomous (or total) pension fund assets and per capita output for our panel of OECD countries is not robust to our augmented specification.

1. Introduction

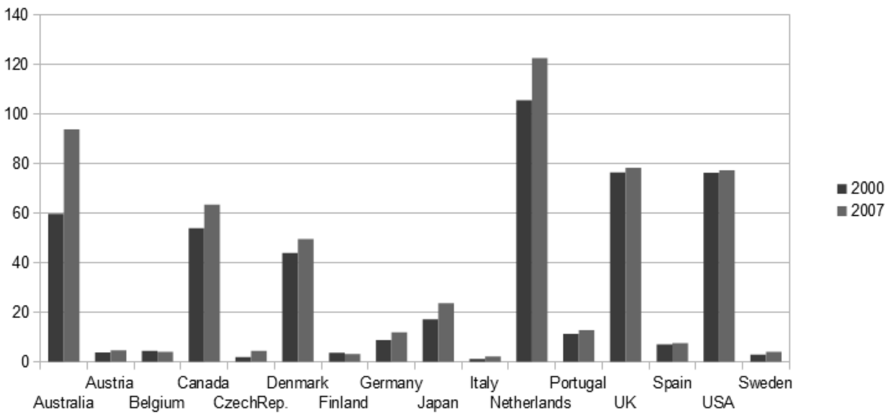
The aging of the developed world's population has attracted the attention of governments involved in social security policies. In fact it is widely accepted that, especially in developed countries, pay-as-you-go (PAYG) systems are no longer able to cope with demographic change. These systems are considered reasonably appropriate when economic growth and population growth are strong, but clearly this is not the case in many developed countries, for example those of continental Europe, where it is widely adopted (Boeri et al, 2006). Some important institutions, notably the World Bank (see Holzmann and Hinz, 2005), sponsored a shift from PAYG system to the fully funded system, also for emerging economies. The Chilean pension reform of 1981 (see Holzmann, 1997), that made the desired shift and that is considered by several as a decisive factor to make Chile the first South American member of the OECD, is famous in this respect. Anyway, the last decades have seen a growth of fund based pension systems in almost every developed economy. This

*The authors thank the editor and two anonymous referees for their valuable suggestions and comments. The views expressed by the authors are solely their own and do not necessarily reflect those of their institutions and employers.

All the computations in the paper are done inside the R open-source environment for statistical computing (R Core Team, 2020), generally using the plm add-on package for panel data econometrics (Croissant and Millo, 2008).

trend continued at least until the beginning of the economic crisis of 2008. As can be seen in Figure 1, in the period between 2000 and 2007 the Pension fund assets/GDP ratio increased in sixteen of the eighteen countries. The Netherlands are the continental European country most akin to the Anglo-Saxon systems, so it is no wonder that its figure is much higher than that of neighboring countries.

Figure 1 Pension Fund Assets as a % of GDP in 2000 and 2007 for Sample Countries



Source: OECD's Institutional Investors database

Despite the shifting trend to funded systems which undoubtedly started around the world, there are still several countries that adopt the PAYG system. In fact, although there is a general consensus about the greater sustainability of the fully funded system with respect to the PAYG system, objections and reluctances lie mainly with the social costs of the transition. A typical remark is that the shift would create a "twice paying generation", that would be required to pay for current pensioners, according to the current PAYG scheme, and also for funding their own pension plan. However, several criticisms have been made to this approach; see Feldstein and Samwick (1997). An interesting one focuses on the idea that a funded pension system would act as a stimulus to economic growth, and that this growth would thus be able to compensate for the losses incurred by the " twice paying generation"; see, e.g., Holzmann (1997). Where does this belief originate?

Since Solow (1956), economic theory has suggested a positive relationship between the saving rate of a country and its long-run output level. A correlation between the saving rate and the pension system has been widely considered and explored in the past decades, with mixed results depending on the methods used and the countries considered (see Kohl and O'Brien, 1998). But there is also a more recent approach that has caught our attention. Some authors have argued about a direct link between the presence of pension funds in the economy and its growth rate (see, among others: Holzmann, 1997; Impavido et al, 2000; Börsch-Supan et al, 2005; Hu, 2006). The origin of this link lies mainly on the idea that richer pension systems can accelerate the development of the financial system and thus promote a more efficient capital allocation, that in turn is associated to increased economic growth (Levine and Zervos, 1998; Beck and Levine, 2004).

A fully funded pension system, as mentioned above, would be more sustainable for public finances. This would result in a financial stability which, as the current European debt crisis revealed, is a very important factor for economic growth.

The establishment of a funded pension system leads to the presence of large institutional investors in the market: the pension funds. The presence of institutional investors could, according to these theories, increase the demand for financial assets, both in the stock market and in the government bond market. Moreover, compared to small investors, institutional investors could put pressure on those who organize and regulate the market, so that the presence of pension funds would better ensure the efficient functioning of markets. Finally, through the participation share of their pension funds, reaching a partial mutual control, companies could achieve a broader and more loyal shareholder base. Also workers could be most interested in the performance of the company of which they are, indirectly, shareholders (see Blake, 1992). It is worth noticing that there are also some critical aspects concerning the presence of pension funds in the capital markets: they are mainly related to the degree of risk aversion of these institutions, for their social security role. The pension funds are heavily influenced by market trends (see for example Bikker et al, 2010) , and this in turn could lead to pro-cyclical consequences, that could adversely affect subjects with a negative cycle.

In short, there is a theoretical justification, but subject to some caveats, for the existence of this direct link between the presence and value of pension funds in an economy and its growth rate and it seems to be reasonable. But what about empirical evidence?

Empirical works on this issue are not so numerous. An important contribution on this subject, besides that of Holzmann (1997), was made by E. Philip Davis (2004), through his studies on institutionalization. Especially interesting in this regard, however, is Davis and Hu (2008)'s paper. In this paper the authors specifically investigated the existence of the direct link between pension fund assets and economic growth through a modified Cobb-Douglas production function, considering pension fund assets as a shift factor. They found evidence of this relationship for both OECD countries and emerging economies using panel as well as country-by-country cointegration analysis. However, as they recognized, the relatively small number of observations casts some doubt on the robustness of their conclusions based on the dynamic heterogeneous panel model as well as on Johansen-cointegration tests. Moreover and most importantly, the Dynamic OLS (DOLS) results that Davis and Hu (2008) argue to be less affected by data limitations, are based on the critical assumption that the error terms are independently distributed across countries, so that the regression residuals shouldn't show any systematic pattern of correlation across countries. The problems arising from such correlation are well-known in the econometric literature on panel time series (Phillips and Sul, 2003; Andrews, 2005; Pesaran, 2006; Bai, 2009). Furthermore, in recent applied work it has been shown that cross-sectional correlation has a significant bearing on estimation (see e. g. Holly et al, 2010) and the results obtained in the empirical literature considering these issues have often eroded the significance of previous results (see e.g. Eberhardt et al, 2013). For this reason and given the relevance of Davis and Hu (2008)'s result for its policy implications, it is interesting even with regard to this topic to revisit the previous empirical findings in a more modern and robust econometric perspective. In particular, we investigate the adequacy of the implicit assumption on which their panel data analyses were based, taking into account the alternative hypothesis of error cross-sectional dependence.

The latter would suggest the presence of common latent factors, that affect all countries albeit to a different extent. As emphasized above, testing for cross-sectional independence is crucial for the validity of the results obtained by Davis and Hu (2008), since both the DOLS and Mean Group estimator they applied turn out to be inconsistent under the alternative hypothesis. We find a highly significant level of correlation in the residuals across countries. Therefore, in order to account for it we estimate the long-run relationship between pension funds and output per capita, considered by Davis and Hu (2008), in the presence of a multifactor error structure. We use the common correlated effects mean groups and common correlated effects pooled estimators advanced by Pesaran (2006) and Kapetanios et al (2011). Moreover, we test for the possibility of a panel spurious regression using the procedure reported in Holly et al (2010) that, more recently, Banerjee and Carrion-i Silvestre (2017) have shown to be consistent also under the null hypothesis of a unit root in the idiosyncratic errors.

Also Zandberg et al (2013) have criticized the conclusions drawn by Davis and Hu (2008), but on different grounds. One of their criticisms concerns the formulation of the pension fund assets variable. In fact, Davis and Hu (2008) considered only the autonomous pension fund assets, while Zandberg et al (2013) consider as more appropriate variable the total pension fund assets[1]. They argue that the beneficial effect on economic growth of investments in the capital market should not depend on the type of institution is entitled to manage pension fund assets, whether autonomous pension funds or insurance companies, banks and investment companies. To verify possible differences in the results, we will also take account of Zandberg et al (2013)'s suggestion reestimating the model using their variable.

2. Model Specification

As mentioned in the previous section, our empirical analysis is based on the model specification adopted by Davis and Hu (2008). They considered the following standard Cobb-Douglas production function, normalized by labor force, with the addition of the pension fund assets as a shift factor:

$$Q_{it} = e^{\alpha_i + \gamma_i t + e_{it}} K_{it}^{\beta_{i,1}} P_{it}^{\beta_{i,2}} \tag{1}$$

where Q is output per unit of labor, K is capital per unit of labor and P denotes the pension fund assets.

[1] In the following, when we refer to P we consider pension assets of autonomous pension funds, when we refer to TP we consider also pension assets of funds managed by other institutions such as insurance companies, banks, investment companies, etc.

Expressing the model in log terms we obtain:

$$lQ_{it} = \alpha_i + \gamma_i t + \beta_{i,1} lK_{it} + \beta_{i,2} lP_{it} + e_{it} \tag{2}$$

where $\alpha_i + \gamma_i t$ represents the technology level with α_i the individual intercept term and t the time trend, and e_{it} is an error term.

The Davis and Hu (2008) specification is one of many possible alternatives from the literature. Our analysis being an extension of their work, their original specification is a natural starting point; but the estimation of their model will also provide an implicit validation of their specification choice.

In fact, Davis and Hu (2008) set their model in a cointegration framework: a statistical setting which provides both a check and, if cointegration is found, also an empirical validation of the specification choice. In particular, cointegration estimators are robust under cointegration to the omitted variables problem (see the discussion in Herzer et al, 2012). In fact, if a cointegrating relationship exists among a set of nonstationary variables, as established by finding stationarity in the residuals of the model, the same cointegrating relationship also exists in an extended variable space (Johansen, 2000, p.263). In the words of Pedroni (2007, p.3), "[a] nonstationary panel approach [permits] to examine the distribution of key slope coefficients across countries which will be invariant to a broad class of [...] omitted variables"; although these may be potentially relevant in a broader sense for explaining the dependent variable. See also the discussion in Herzer and Nunnenkamp (2012).

2.1 Cross-Sectional Correlation

As noted above, Davis and Hu (2008) estimated the heterogeneous long-run relationship in eq. (2) by employing the dynamic panel data model proposed by Pesaran and Smith (1995) and their Mean-Group (MG) estimator, under the assumption that the long-run elasticities were random coefficients with common mean and that the error terms were independently distributed across countries. It is worth noticing that the assumption of cross-sectional independence of the error terms is critical for the consistency of the average long-run estimates obtained by the MG estimator (see Pesaran, 2006; Kapetanios et al, 2011). So, it is of vital importance to test for residual cross-sectional independence if misleading conclusions are to be avoided. In the following we will analyze this critical issue in more depth.

Moreover, before estimating the long-run relationship of interest, Davis and Hu (2008) performed three types of panel unit root test on the variables involved: the LLC test (Levin et al, 2002), the IPS test (Im et al, 2003) and the Hadri (2000) panel stationarity test. Also in this case, the adoption of the above tests implicitly suggests the assumption of errors cross-sectional independence, because otherwise their results would be misleading.

Therefore, in the following we firstly apply the IPS panel unit root test to *lK*, *lP* and *lQ* and then check for residuals cross-sectional dependence using Pesaran (2004)'s CD test.

If present, cross-sectional dependence will have to be addressed. We will do so in an unobserved multifactor setting.

2.2 Multifactor Error Structure

To take account of error cross-sectional dependence, Pesaran (2006), Kapetanios et al (2011) and Pesaran and Tosetti (2011), among others, have proposed the following multifactor error structure for the disturbances of eq. (2):

$$e_{it} = \lambda_i^{'}\mathbf{f}_t + \varepsilon_{it} \tag{3}$$

where $\mathbf{f}_t$ is the vector of unobserved common factors and λ_i represents its corresponding vector of factor loadings. The factor loadings are assumed to be heterogeneous across countries which means that each single common factor may have a different impact on the per capita outputs. The remainder idiosyncratic error, ε_{it}, is allowed to be a general stationary process[2], as well as being weakly cross-sectionally dependent (see Pesaran and Tosetti, 2011). Notice that in eq. (3) the common factors take account of the strong (i.e. global) forms of cross-sectional dependence, whereas the idiosyncratic errors take account of the residual weak (i.e. local) forms of dependence across countries.

Moreover, the unobserved common factors could be correlated with the regressors of eq. (2) and, given the results of the panel unit root tests reported in the following, they may be also I(1). Therefore, the following general specification is proposed for the regressors:

$$\mathbf{x}_{it} = a_i + b_i t + A_i\mathbf{f}_t + \mathbf{u}_{it} \tag{4}$$

where $\mathbf{x}_{it} = \left(lK_{it}, lP_{it}\right)^{'}$, a_i and b_i are two 2×1 vectors of individual specific intercepts and trend coefficients respectively, and A_i is the matrix of factor loadings. Finally, the vector of disturbances, $\mathbf{u}_{it}$, is assumed to be a general stationary process. Kapetanios et al (2011) have shown that the common correlated effects (CCE) estimators proposed by Pesaran (2006) are still valid[3], when the unobserved common factors contain unit root processes. It is worth noticing that in such case $y_{it} = lQ_{it}$, $\mathbf{x}_{it}$, and $\mathbf{f}_t$ must be cointegrated. Moreover, they have shown that both the common correlated effects mean group (CCEMG) and the common correlated effects pooled (CCEP) estimators turn out to be consistent and asymptotically Normally distributed[4] for the mean of the individual specific slope coefficients in eq. (2).

[2] So that in general it will be autocorrelated.

[3] Pesaran (2006) noted that linear combinations of the unobserved factors can be well approximated by cross-section averages of both the dependent variable and the observed regressors and proposed a new set of estimators, referred to as CCE estimators which are computed by running standard panel regressions augmented with these cross-section averages.

[4] Under the assumption of random slope coefficients.

3. The Common Correlated Effects Principle

In this section we describe the estimators and unit root tests employed in the following applications, which, as mentioned above, turn out to be robust to cross-sectional dependence.

3.1 CCE Estimators

The common correlated effects (CCE) estimators work by augmenting the basic model with cross-sectional averages of both the response ($\bar{y}_t$) and regressors ($\bar{\mathbf{x}}_t$) which pick up the effect of the common factors (see Pesaran, 2006) so that the individual slope parameters β_i can be consistently estimated by applying least squares to the augmented regression

$$y_{it} = \alpha_i + d_i t + \beta_i' \mathbf{x}_{it} + g_i' \bar{\mathbf{z}}_t + e_{it} \tag{5}$$

where $\bar{\mathbf{z}}_t = \left(\bar{y}_t, \bar{\mathbf{x}}_t\right)'$. The OLS estimator for each individual slope β_i coefficients can then be written compactly as

$$\hat{\beta}_{CCE,i} = \left(\bar{\mathbf{x}}_i' \bar{\mathbf{M}} \bar{\mathbf{x}}_i\right)^{-1} \bar{\mathbf{x}}_i' \bar{\mathbf{M}} \mathbf{y}_i \tag{6}$$

with $\bar{\mathbf{M}} = \mathbf{I}_T - \bar{\mathbf{H}}\left(\bar{\mathbf{H}}'\bar{\mathbf{H}}\right)^{-1}\bar{\mathbf{H}}'$, where $\mathbf{I}_T$ is an identity matrix of dimension T and the matrix $\bar{\mathbf{H}}$ contains: the columns of observations of the cross-sectional averages $\bar{\mathbf{z}}_t$, t=1,…T; and the deterministic components, comprising individual intercept and time trend (Pesaran, 2006, p.974). Finally, $\mathbf{x}_i$ and $\mathbf{y}_i$ contain the observations for, respectively, the individual regressors and dependent variable. Cross-sectional averages are employed as N-consistent estimators of the unobserved common factors; in a partitioned regression perspective, each individual regression (6) controls for the common deterministic component (1,t)' and for the estimated common factors $\bar{\mathbf{z}}_t$ through the residual operator $\bar{\mathbf{M}}$.

CCE estimation can be performed either imposing parameter homogeneity (but maintaining heterogeneity in intercepts, factor loadings and time trends) which leads to the common correlated effects pooled (CCEP) estimator

$$\hat{\beta}_{CCEP} = \left(\sum_{i=1}^{N} \bar{\mathbf{x}}_i' \bar{\mathbf{M}} \bar{\mathbf{x}}_i\right)^{-1} \sum_{i=1}^{N} \bar{\mathbf{x}}_i' \bar{\mathbf{M}} \mathbf{y}_i \tag{7}$$

and is to be preferred on efficiency grounds when the underlying assumption that $\beta_i = \beta$ is reasonable; or parameters β_i can be left free to vary, and the average $E\left[\beta_i\right]$ is estimated by the Mean Groups (MG) method,

$$\hat{\beta}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{CCE,i} \tag{8}$$

the latter estimator being known as CCEMG.

It shall be noted that some common estimators can be seen as special cases of this more general formulation, where augmentation is eliminated or reduced: pooled OLS as CCEP with $\bar{\mathbf{M}} = \mathbf{I}_T$, individual fixed effects as CCEP with $\bar{\mathbf{H}}$ containing only individual dummies. The Mean Groups (MG) estimator (see Hsiao and Pesaran, 2008, 6.4) can in turn be seen as CCEMG where $\bar{\mathbf{M}} = \mathbf{I}_T$.

Another observation that shall be made is that by its own nature, and analogously to what happens with the more popular fixed effects estimator, the CCEP estimator will not produce an overall intercept, because the latter is individual-specific; and individual intercepts will have been absorbed by the first step of the estimation procedure anyway. On the contrary, heterogeneous (CCE)MG estimators will produce an intercept, which is the mean of the estimated individual intercepts.

We will employ both the CCEP and CCEMG estimators. One last note of caution is in order regarding sample sizes: in fact, the samples at our disposal are of rather modest size. While it is true that the CCE approach was born in a context of "large" panels, witness the title of the original paper (Pesaran, 2006), still the properties of CCE, both in the MG and in the CCEP version, turn out to be quite good in small samples as well. In their simulations, Pesaran and Tosetti (2011) consider T=10, N=20 as their minimal starting point; the estimator proves to behave quite well with this sample size too (Pesaran and Tosetti, 2011, Tables 1 to 4). See also Chudik et al (2011, Tables 3 to 6), where the minimal dimensions are T=20, N=20. Among empirical applications, see e.g. Banerjee and Carrion-i Silvestre (2017) on N=19 countries.

3.2 Cross-Sectionally Augmented Unit Root Tests

Unit root tests in the spirit of Dickey and Fuller, like the ADF in time series and the IPS in the present context, are based on auxiliary panel regressions. As such, cross-sectional dependence potentially disrupting the consistency of the estimates is a serious issue. This consideration has led to the development of the so-called "second generation" panel unit root tests, which are those that control for cross-sectional dependence.

In this line of research, Pesaran (2007) proposes a panel unit root test robust to cross-sectional dependence, based on applying the same factor augmentation principle discussed above to an Augmented Dickey-Fuller regression:

$$\Delta y_{it} = \alpha_i + \delta_i t + b_i y_{i,t-1} + \sum_{j=1}^{p} d_{ij}\Delta y_{i,t-j} + g_i^{'}\bar{\mathbf{z}}_t + e_{it} \tag{9}$$

where $\overline{\mathbf{z}}_t = \left(\overline{y}_{t-1}, \Delta\overline{y}_t, \Delta\overline{y}_{t-1}, ..., \Delta\overline{y}_{t-p}\right)'$ is the vector of cross-section averages of response and regressors, as above. Pesaran's CIPS test for a unit root in N_1 of the N time series y_{it} (with N_1 / N tending to a fixed nonzero constant as N diverges) is based on the cross-sectional average of the t-ratios of the OLS estimates of the coefficients b_i in (9).

4. Data Description

Unfortunately, we do not have access to the data-set used by Davis and Hu (2008), but we use the same sources as regards both the pension data and output per capita. We analyze 16 OECD countries, listed in the following Table 1 together with the time span of the variables.

Table 1 Autonomous Pension Fund Assets Data

	Country	***Begin***	***End***
1	Australia	1988	2009
2	Austria	1991	2010
3	Belgium	1980	2010
4	Canada	1980	2010
5	Czech Republic	1995	2010
6	Denmark	1994	2010
7	Finland	2000	2010
8	Germany	1995	2010
9	Italy	1999	2009
10	Japan	1980	2010
11	Netherlands	1980	2010
12	Portugal	1989	2010
13	Spain	1989	2010
14	Sweden	1990	2010
15	United Kingdom	1980	2010
16	United States	1980	2010

Source: Pension data are taken from OECD's Institutional Investors database. Capital stock data are taken from the Annual Macro-economic Database of the European Commission's Directorate General for Economic and Financial Affairs. Data on per capita output come from the World Development Indicators of the World Bank.

5. Estimation and Cointegration Analysis

We will start with an analysis of stationarity of the variables under study. First, we will apply first-generation unit root tests, but only for the sake of comparison, as we expect cross-sectional dependence in the data, and therefore this type of test to deliver misleading results. Then a cross-sectional dependence test will assess whether the residuals of eq. (9) are independent. In case of rejection we will proceed to testing for stationarity, but this time employing the second-generation CIPS test.

5.1 Unit Root and Cross-Sectional Dependence Tests

We start the empirical analysis applying the IPS unit root test to the three variables under scrutiny[5]. The results are reported in Table 2. For the variables in levels, the IPS test is performed with a constant and a linear trend as deterministic components, whereas only a constant term is added to the equation specification for the first differences of the variables. Moreover, the test statistics are reported for both models with one or two lags of the dependent variable as regressors.

Table 2 IPS Test

Intercept and trend	***Lags: 1***	***P-value***	***Lags: 2***	***P-value***
lP	0.93	0.8244	0.65	0.7407
lK	-0.39	0.3478	1.94	0.9738
lQ	-0.50	0.3102	1.04	0.8513
Intercept only				
ΔlP	4.55	0	3.87	0.0001
ΔlK	-2.92	0.0018	-2.09	0.0184
ΔlQ	-6.26	0	-3.47	0.0003

Notes: For the variables in levels, the IPS test is performed with a constant and a linear trend as deterministic components. Only a constant term is added to the equation specification for the first differences.

As we can see from Table 2, all the three variables appear to be I(1). However, the results of the CD test reported in Table 3 strongly reject the null hypothesis of cross-sectional independence of the residuals, casting doubt on the reliability of the conclusions reached by the IPS test.

Table 3 P-values of the CD Test on the Residuals of the Individual ADF Regressions in the IPS Test

Intercept and trend	***P.value***	***P.value***
Lags	1	2
lP	0.00	0.00
lK	0.00	0.00
lQ	0.00	0.00

Therefore, in Table 4 we report the results of the CIPS test which Pesaran (2007) has shown to be robust to the presence of cross-sectionally correlated errors. In order to take account of error cross-sectional dependence, as possibly deriving from either an omitted factor structure or from spatial spillovers, Pesaran (2007) proposed to augment the regressors of the IPS test with cross section averages of both the regressors and the dependent variable. From Table 4 we can see that the null hypothesis of a unit root is not rejected for all the three variables also in this case.

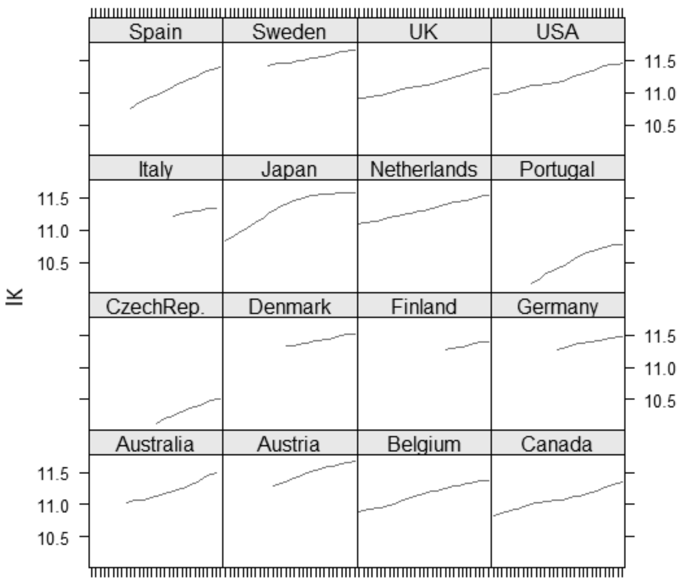
[5] Like Davis and Hu (2008), per capita output and capital are used as proxies for respectively output and capital per units of labor. The ratio of autonomous pension fund assets to GDP proxies the value of the pension fund assets in the economy.

Table 4 CIPS Unit Root Test for the Three Variables of the Model

Intercept and trend		
Lags	1	2
lP	-2.37	-1.21
lK	-1.47	-0.76
lQ	-1.76	-0.91
Critical values (5%)	-2.76	-2.76
Critical values (10%)	-2.66	-2.66
Intercept only		
Lags	1	2
Δ lP	-2.34**	-1.55
Δ lK	-1.98	-0.99
Δ lQ	-3.12**	-1.85
Critical values (5%)	-2.25	-2.25
Critical values (10%)	-2.14	-2.14

Notes: Significance stars: '*' indicates significance at the 10% level; '**' 5%.

Figure 2 Log of Real Capital per Capita for 16 OECD Countries, 1980-2010



The CIPS test results for the differenced variables are instead mixed. The presence of a unit root is rejected for ΔlP and ΔlQ but only for the model specification with one lag. However, this might depend on a loss of power when adding further lags: given the short sample and the fact that we are testing for a unit root the variables in first differences, we consider the test results with one single lag the most reliable. As far as lK is concerned, CIPS tests conclude for the presence of at least two unit roots, which both for theoretical considerations and on inspection of the variable graphs (see Figure 2) seems to be unrealistic. Therefore, all three variables will be treated as I(1) in the subsequent analyses.

5.2 Model Estimation

In Table 5 we report the MG estimates of the long-run elasticity obtained by directly estimating separately the long-run static eq. (2) for each country by OLS and averaging the coefficients estimates across countries. This way to proceed is different from Davis and Hu (2008) that obtained their long-run elasticity MG estimates starting from a dynamic model specification: the estimated long-run effect was computed for each country from the OLS estimates of the dynamic model, and then the MG estimates were obtained as cross-sectional averages of the countries long-run effects. Especially for short time-series, our approach is preferable as the country OLS estimates of the static models result to be less biased.

As we can see from Table 5, both estimated MG elasticities are positive but only the capital elasticity is significantly different from zero in both model formulations. In Table 5, also the Common Correlated Mean Group (CCEMG) and the Common Correlated Effects Pooled (CCEP) estimates are reported. As noted by Pesaran (2006) and Kapetanios et al (2011), the assumption of cross-sectional independence of the error terms in eq. (2) is critical for the consistency of the average long-run coefficient estimates obtained by the MG estimator[6].

Table 5 Model Estimates

Intercept and trend	α	β_1	β_2
Mean Group	-8.11* (4.79)	1.61*** (0.42)	0.009 (0.027)
CCEMG	5.29 (3.86)	0.62** (0.30)	0.03* (0.018)
CCEP		0.38 (0.32)	0.06 (0.041)
Intercept only			
Mean Group	-2.14** (1.06)	1.07*** (0.10)	0.009 (0.027)
CCEMG	0.38 (1.19)	1.09*** (0.23)	0.076*** (0.021)
CCEP		0.73 (0.59)	0.06 (0.062)

Notes: α is the (average) model intercept, when meaningful. β_1 and β_2 are the (average) long-run elasticities of output to, respectively, capital and pension fund assets. Standard errors in parentheses. Significance stars: '*' indicates significance at the 10% level; '**' 5%; '***' 1%.

Therefore in Table 6 we report the results of the CD test applied to the OLS residuals of eq. (2) estimated both with and without the linear trend.

[6] However, the MG estimator turns out to be consistent in case of residuals autocorrelation and/or heteroskedasticity.

Table 6 Cross-Sectional Dependence Test (Pesaran's CD) for the Model Residuals

Test for the residuals of the models		
	CD Statistic	P-value
OLS Intercept and trend	5.23	0.00
CCEMG intercept only	15.4811	0.00
CCEMG intercept and trend	18.4492	0.00
CCEP intercept only	8.1021	0.00
CCEP intercept and trend	27.0135	0.00

As can be seen from Table 6 we are in presence of cross-sectional dependence in both cases. A result this one that suggests the existence of common latent factors which drive the per capita outputs of the OECD countries under analysis.

Therefore, as anticipated, we proceed by calculating the CCEMG and CCEP estimates of the model. Given that the dependent variable was found to be I(1), we consider more reliable the estimation results reported in Table 5 of the model without deterministic trends. In Table 5 we can see that the calculated elasticities, although both positive, vary widely for the two estimators. Moreover, as far as the pension fund assets long-run elasticity is concerned, only the CCEMG estimate of the mean of β_{2i}, named β_2, appears to be significantly different from zero in the model without trend. For this model, we find that also the average long-run capital elasticity is positive and significantly different from zero when the slope coefficients are assumed to be heterogeneous but random across countries, instead of the same as assumed by the CCEP estimator.

In order to avoid estimating a panel spurious regression (Phillips and Moon, 1999), it is crucial also in this context to test for cointegration. Therefore in Table 7 we report the results of the CIPS test for the presence of a unit root in the idiosyncratic residuals[7], $\hat{\varepsilon}_{it}$. In addition to the standard procedure, a test of panel cointegration is also performed using the test procedure proposed by Banerjee and Carrion-i Silvestre (2017), named BC test in Table 7, and their critical values[8].

It is worthwhile to notice that, according to the CD test results reported in Table 6, the IPS test would be inconsistent[9], when applied to the model residuals computed gross of potential common factors.

[7] Therefore the variables result to be not cointegrated under the null hypothesis of a unit root in the residuals.
[8] Such a procedure generalizes that used by Holly et al. (2010) for testing for panel cointegration. More importantly, Banerjee and Carrion-i-Silvestre (2011) show that the CCEP estimator is still consistent for the long-run average coefficient regression in the presence of a panel spurious regression. The BC test has been performed assuming one common factor.
[9] As such, it might lead to misleading conclusions about the existence of a cointegration relationship.

Table 7 CIPS and Banerjee and Carrion-i Silvestre (2017) (BC) Tests for the Different Models' Residuals

Intercept only		
Lags	1	2
CCEMG residuals	-0.61	-0.44
CCEP residuals	-1.21	-1.69
Critical values (5%)	-2.25	-2.25
Critical values (10%)	-2.14	-2.14
BC test statistic	-0.21	0.06
Critical values (5%)	-2.36	-2.31
Critical values (10%)	-2.26	-2.20
Intercept and trend		
Lags	1	2
CCEMG residuals	-0.83	-1.18
CCEP residuals	-0.54	-0.29
Critical values (5%)	-2.76	-2.76
Critical values (10%)	-2.66	-2.66
BC test statistic	-0.23	-0.09
Critical values (5%)	-2.97	-2.87
Critical values (10%)	-2.87	-2.79

Looking at the cointegration test results reported in Table 7, we can see that the null hypothesis of no cointegration is never rejected. As such, the CCEMG and CCEP estimates reported in Table 5 have to be interpreted as panel spurious regressions, instead of long-run relationships among *lK*, *lP* and *lQ*. In the case of a panel spurious regression the CCEMG estimator is no more consistent, but as shown by Banerjee and Carrion-i Silvestre (2017) the CCEP estimator is still consistent for the long-run average coefficient regression. Therefore, the CCEP results reported in Table 5 are still useful to shed light about the existence of a direct and positive long-run link between funding of pensions and the output of the economy. However, also from this point of view conclusions remain unchanged, given that the long-run average elasticity of output with regard to pension fund assets is positive but not significant in both specifications of the deterministic regressors.

5.3 Results for the Alternative Sample on Total Pension Fund Assets

As noted in the Introduction, also Zandberg et al (2013) have criticized the conclusions drawn by Davis and Hu (2008), but on different grounds. One of their criticisms concerns the formulation of the pension fund assets variable. In fact, Davis and Hu (2008) considered only the autonomous pension fund assets, while Zandberg and Spierdijk (2013) consider the total pension fund assets (TP) as more suitable for the analysis. They argue that the beneficial effect of the investment is present in the economy also in the case the investment is carried out by another type of institution, such as insurance companies, banks, or investment companies, instead of a pension fund. Therefore, we check the robustness of the conclusions reached so far by estimating the model above with the variable proposed by Zandberg and Spierdijk (2013).

Data on total pension assets are provided by Zandberg et al (2013), and were taken from several OECD collections. In this case, due to a different time coverage of the variable, the sample is restricted to 12 OECD countries; see Table 8 for the list of countries included and time span of variables.

Table 8 Total Pension Fund Assets Data

	Country	*Begin*	*End*
1	Austria	2001	2010
2	Belgium	2001	2010
3	Canada	2001	2010
4	Czech Republic	2001	2010
5	Denmark	2001	2010
6	Finland	2001	2010
7	Germany	2001	2010
8	Netherlands	2001	2010
9	Portugal	2001	2010
10	Spain	2001	2010
11	Sweden	2001	2010
12	United States	2001	2010

Source: Zandberg et al (2013), from various OECD collections.

The MG, CCEMG and CCEP estimates and IPS/CIPS statistics are shown in Table 9, for the model with intercept and trend/only intercept.[10]

Table 9 Model Estimates; Alternative Sample from Zandberg et al (2013)

Intercept and trend	***A***	***β₁***	***β₂***	***IPS/CIPS***
Mean Group	-26.09*** (8.47)	3.22*** (0.75)	0.08 (0.05)	3.355***
CCEMG	-1.55 (6.17)	0.90 (0.93)	0.006 (0.15)	-0.67
CCEP		-0.23 (0.97)	0.007 (0.015)	-2.81
Intercept only				
Mean Group	0.78 (2.60)	0.81 (0.22)	0.005 (0.04)	-1.875*
CCEMG	-2.37 (2.86)	0.31 (0.70)	0.02 (0.02)	-1.39
CCEP		-0.20 (0.58)	0.001 (0.015)	-3.24

Notes: α is the (average) model intercept, when meaningful. β_1 and β_2 are the (average) long-run elasticities of output to, respectively, capital and pension fund assets. Standard errors in parentheses. Significance stars: '*' indicates significance at the 10% level; '**' 5%; '***' 1%.

Even in this case, when properly accounting for cross-sectional correlation we do not find evidence of a long-term relationship between pension assets value and economic growth. This leads us to stress once again the importance of considering cross-sectional correlation of errors when it is present. Secondly we conclude that, although the observations of Zandberg and Spierdijk (2013) about the specification of the pension variable seem well-founded, the results obtained taking them into

[10] Considering the short sample, IPS/CIPS tests were performed using only one lag.

account lead us to the same conclusions. However, it is important to stress that the brevity of the sample makes it very difficult to draw definitive responses.

Table 10 Cross-Sectional Dependence Test (Pesaran's CD) for the Model Residuals, Alternative Sample from Zandberg et al (2013)

Test for the residuals of the models	*CD*	*P.value*
OLS Intercept and trend	5.23	0
OLS Intercept only	13.38	0
CCEMG intercept only	15.4811	0
CCEMG intercept and trend	18.4492	0
CCEP intercept only	8.1021	0
CCEP intercept and trend	27.0135	0

6. Conclusions

The significance of the previous empirical results obtained in the literature, using panel time series models under the assumption of errors cross-sectional independence, has been often eroded by subsequent analyses, where the presence of cross-sectional correlation was tested and properly accounted for. A similar situation has been encountered in our context, since we have found that cointegration between pension fund assets and per capita output has not been rejected for our panel of OECD countries, but only under the false hypothesis of independence of residuals across countries. On the contrary, taking into account errors cross-sectional dependence we excluded the existence of a positive and direct relationship between the value of pension fund assets and output, at least regarding OECD countries.

We cannot exclude the possibility that the negative effects on growth of pension funds' risk aversion offset the positive ones discussed by Davis and Hu (2008), and reviewed in the Introduction. In fact, also some advocates of the positive effect on growth of pension funds recommend a different way of allocating investments (see Hu, 2006).

However, the small sample size issue due to the scarcity of data has to be emphasized. In fact, the analyses we carried out were based on an unbalanced panel, where – in the case of autonomous fund assets – only ten out of sixteen developed countries cover a full thirty-years time period. In the other case, when we considered total pension assets, we had a balanced panel of twelve countries, only ten-years long.

We believe that a longer sample is a necessary condition in order to draw more significant and definitive conclusions on the long run relationship between pension fund assets and growth. Therefore, although the results we obtained with the data currently available have not found evidence of such a relationship, we hope that in the coming years a greater amount of pension data will be recorded, in order to get more comprehensive answers to the questions we posed.

REFERENCES

Andrews DWK (2005): Cross-Section Regression with Common Shocks. *Econometrica* 73(5):1551-1585

Bai J (2009): Panel Data Models with Interactive Fixed Effects. *Econometrica* 77(4):1229–1279

Banerjee A, Carrion-i Silvestre JL (2017): Testing for Panel Cointegration Using Common Correlated Effects Estimators. *Journal of Time Series Analysis* 38:610–636

Beck T, Levine R (2004): Stock Markets, Banks, and Growth: Panel Evidence. *Journal of Banking & Finance* 28(3):423–442

Bikker JA, Broeders DW, De Dreu J (2010): Stock Market Performance and Pension Fund Investment Policy: Rebalancing, Free Float, or Market Timing. *International Journal of Central Banking* 6(2)

Blake D (1992): *Issues in Pension Funding*. Routledge

Boeri T, Bovenberg AL, Coeuré B, Roberts A (2006): Dealing with the New Giants: Rethinking the Role of Pension Funds. *Geneva Reports on the World Economy* (8)

Börsch-Supan A, Köke FJ, Winter J (2005): Pension Reform, Savings Behavior and Capital Market Performance. *Journal of Pension Economics & Finance* 4(1):87–107

Chudik A, Pesaran MH, Tosetti E (2011): Weak and Strong Cross-Section Dependence and Estimation of Large Panels. *Econometrics Journal* 14(1)

Croissant Y, Millo G (2008): Panel Data Econometrics in R: the plm Package. *Journal of Statistical Software* 27(2), URL http://www.jstatsoft.org/v27/i02/

Davis EP (2004): Financial Development, Institutional Investors and Economic Performance. In: Goodhart CAE (ed) *Financial Development and Economic Growth*, Springer, pp 149–182

Davis EP, Hu YW (2008): Does Funding of Pensions Stimulate Economic Growth? *Journal of Pension Economics & Finance* 7(2):221–249

Eberhardt M, Helmers C, Strauss H (2013): Do Spillovers Matter when Estimating Private Returns to R&D? *Review of Economics and Statistics* 95(2):436–448

Feldstein M, Samwick A (1997): The Economics of Prefunding Social Security and Medicare Benefits. *NBER macroeconomics annual* 12:115–148

Hadri K (2000): Testing for Stationarity in Heterogeneous Panel Data. *The Econometrics Journal* 3(2):148–161

Herzer D, Nunnenkamp P (2012): The Effect of Foreign Aid on Income Inequality: Evidence from Panel Cointegration. *Structural Change and Economic Dynamics* 23(3):245–255

Herzer D, Strulik H, Vollmer S (2012): The Long-Run Determinants of Fertility: One Century of Demographic Change 1900-1999. *Journal of Economic Growth* 17:357–385

Holly S, Pesaran M, Yamagata T (2010): A Spatio-Temporal Model of House Prices in the USA. *Journal of Econometrics* 158(1):160–173

Holzmann R (1997): Pension Reform, Financial Market Development, and Economic Growth: Preliminary Evidence from Chile. *Staff Papers* 44(2):149–178

Holzmann R, Hinz R (2005): *Old-age income support in the 21st century: An international perspective on pension systems and reform*. The World Bank

Hsiao C, Pesaran MH (2008): Random Coefficient Models. In: Matyas L, Sevestre M (eds) *The Econometrics of Panel Data*, 3rd Ed., Springer Netherlands, chap 6, pp 185–213

Hu YW (2006): Pension Reform in China – a Case Study. *Economic and financial discussion papers, Economics and Finance Section, School of Social Sciences* 06-05

Im KS, Pesaran MH, Shin Y (2003): Testing for Unit Roots in Heterogeneous Panels. *Journal of econometrics* 115(1):53–74

Impavido G, Musalem AR, Catalan M (2000): Contractual Savings or Stock Market Development Which Leads? *Policy research working papers, The World Bank*, August 2000

Johansen S (2000): Modelling of Cointegration in the Vector Autoregressive Model. *Economic Modelling* 17(3):359–373

Kapetanios G, Pesaran M, Yamagata T (2011): Panels with Non-Stationary Multifactor Error Structures. *Journal of Econometrics* 160(2):326–348

Kohl R, O'Brien P (1998): The Macroeconomics of Ageing, Pensions and Savings: a Survey. *OECD Economics Dept Working Paper* 200

Levin A, Lin CF, Chu CSJ (2002): Unit root tests in panel data: asymptotic and Finite-Sample Properties. *Journal of econometrics* 108(1):1–24

Levine R, Zervos S (1998): Stock Markets, Banks, and Economic Growth. *American economic review* 88(3):537–558

Pedroni P (2007): Social Capital, Barriers to Production and Capital Shares: Implications for the Importance of Parameter Heterogeneity from a Nonstationary Panel Approach. *Journal of Applied Econometrics* 22(2):429–451

Pesaran MH (2004): General Diagnostic Tests for Cross Section Dependence in Panels. *Working Paper* 1229, *CESifo*

Pesaran MH (2006): Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica* 74(4):967–1012

Pesaran MH (2007): A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence. *Journal of Applied Econometrics* 22(2):265–312

Pesaran MH, Smith R (1995): Estimating Long-Run Relationships from Dynamic Heterogeneous Panels. *Journal of econometrics* 68(1):79–113

Pesaran MH, Tosetti E (2011): Large Panels with Common Factors and Spatial Correlation. *Journal of Econometrics* 161(2):182–202

Phillips P, Moon H (1999): Linear Regression Limit Theory for Nonstationary Panel Data. *Econometrica* 67(5):1057–1111

Phillips P, Sul D (2003): Dynamic Panel Estimation and Homogeneity Testing under Cross Section Dependence. *The Econometrics Journal* 6:217–259

R Core Team (2020): *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria

Solow RM (1956): A Contribution to the Theory of Economic Growth. *The quarterly journal of economics* 70(1):65–94

Zandberg E, Spierdijk L, et al (2013): Funding of Pensions and Economic Growth: are They Really Related? *Journal of Pension Economics and Finance* 12(2):151–167