ISSN: 2279-7807

**Quaderni di Dipartimento**

# And Yet they Co-Move! Public Capital and Productivity in OECD: A Panel Cointegration Analysis with Cross-Section Dependence

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# 154 (11-11)

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Novembre 2011

# And Yet they Co-Move! Public Capital and Productivity in OECD: A Panel Cointegration Analysis with Cross-Section Dependence

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This version: November 9, 2011

**Abstract**

In this paper we add to the debate on the public capital - productivity link by exploiting very recent developments in the panel time series literature that take into account cross sectional correlation in non-stationary panels. In particular we evaluate the productive effect of public capital by estimating various production functions for a panel of 21 OECD countries over the period 1975-2002. We find strong evidence of common factors that drive the cointegration relationship among variables; moreover, our results suggest a public capital elasticity of GDP in the range 0.05-0.15, depending on model specification. Results are robust to the evidence of spillovers from public capital investments in other countries and to controlling for other productivity determinants like human capital, the stock of patents and R&D capital.

**KeyWords:** Public capital; Productivity; Panel Cointegration; Cross-section Dependence.

**JEL - Classification**:C33, C15, H54, O47

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# 1 Introduction

The role of public expenditure as a countercyclical economic policy instrument has been the object of a lively debate among both academics and policymakers, at least since the burst of the 2008-9 recession and the announcement of the fiscal package stimulus by the Obama's administration. In particular, the U.S. Congress approved in 2009 the $787 billion American Recovery and Reinvestment Act, on top of the $125 billion provided by the Economic Stimulus Act of 2008, whereof approximately two-thirds amounted to direct government expenditure and transfers. Most of the recent theoretical and applied macroeconomic literature focuses on quantifying the economic impact of the fiscal stimulus(Leeper, Walker, and Yang, 2010) and, more generally, on estimating the magnitude of the fiscal multiplier (Hall (2009), Christiano, Eichenbaum, and Rebelo (2009) among the others).

However, a large fraction of the Obama's fiscal package (approximately $130 billion) has been devoted to infrastructure expenditure (mainly water, transportation, housing, energy and federal buildings), which not only may be used as a countercyclical tool, but it also might have a more lasting long run effect on the productive potential of an economy: this is the issue we focus on in this study.

Since the Aschauer (1989)'s seminal paper, several contributions have highlighted that public infrastructures are important inputs that contribute to economic growth. Improvements in public infrastructures (e.g. better and more extensive transport networks) might impact total factor productivity in a number of ways, e.g. by increasing the productivity of private inputs like physical capital and R&D or by reducing production and transport costs, thereby fostering greater specialization, more intensive competition and in general by providing those public goods that are crucial for economic growth.[1]

The empirical literature that has sought to estimate the economic impact of public capital has developed along a number of strands according to differences in the type of sample, theoretical approach and econometric methodology (Afraz, Aquilina, Conti, and Lilico, 2006).

Most studies estimated production functions with public capital entering as a TFP driver, while others relied on the estimation of cost functions where public capital is assumed to be a quasi-fixed input (Cohen and Morrison, 2004); in turn, some authors included public investment as an additional explanatory variable in growth convergence equations derived from the Solow growth model (Esfahani and Ramirez, 2003). As far as the sample choice is concerned, most contributions are based on aggregate data at either country (Kamps, 2005) or regional level (Bronzini and Piselli, 2009), with a minority focusing on industry level data (e.g. Fernald (1999); Bottasso and Conti (2010)) or cross country data (Canning and Pedroni (2008) or Demetriades and Mamuneas (2000)). Turning to the econometric methodology, recent studies on aggregate (single) country data adopted VAR techniques, which investigate the relationship

[1]For a survey on the theoretical literature on the links between public infrastructure and economic growth, see Irmen and Kuehnel (2009).

between public capital, GDP and private inputs without imposing a theoretical structure, and generally found positive effects of public capital on GDP, although with non-negligible differences across countries (Kamps, 2005); however, purely time series studies are often plagued by small sample problems linked to the short time span of the data. For this reason, many authors have turned to conducting studies based on cross country or regional level data: while "first generation" panel studies simply estimated either fixed or random effects models, thus neglecting likely simultaneity issues, "second generation" studies tackled the endogeneity problems that plague the estimation of production functions more seriously by using instrumental variable techniques, such as the Arellano-Bond GMM estimator (Holtz-Eakin, 1994). Only recently issues stemming from the non-stationarity nature of panel data have been addressed by some authors in order to avoid possible biases associated to the presence of unit roots (e.g Calderon, Moral-Benito, and Serven (2011) , Bronzini and Piselli (2009) among the others).

However, these studies do not account for unobservable time varying heterogeneity associated to unobserved common shocks which might affect each country or region to a different extent, thus generating cross sectional correlation: this is likely to be the case when analyzing macro panel data, where cross section dependence can be due to a variety of factors, such as omitted unobserved common factors, spatial spillover effects, trade linkages, global economic cycles, etc. Indeed some authors (e.g. Calderon, Moral-Benito, and Serven (2011)) have addressed cross sectional correlation by removing unobserved common factors through a demeaning of the variables: this procedure works insofar as unobserved common factors have the same impact on individual countries. Such assumption is however quite restrictive, as it amounts to assume that, for example, a global economic shock (e.g. a financial crisis) has the same impact in each country.

The presence of cross-sectional dependence may affect the validity of commonly used panel unit root and cointegration tests, since stationarity and no-cointegration tests that assume independence might have substantial size distortions when this assumption does not hold. In particular, Banerjee, Marcellino, and Osbat (2004) show that neglecting the cross-section dependence arising from a common factor structure may have quite drastic effects on cointegration testing, while Coakley, Fuertes, and Smith (2006) and Urbain and Westerlund (2008) find that the presence of cross-sectional dependence is likely to lead to substantial bias for various pooled estimators.

To date, only few studies apply cointegration analysis techniques which account for cross sectional dependence[2] and there does not yet seem to exist a consensus about successful modeling strategies in such framework.

In this paper we make use of some recent developments in the panel time-series literature and we assume that cross sectional dependence can be successfully modeled within the framework proposed by

[2]See, for example, Costantini and Destefanis (2009) and Eberhardt and Teal (2008) who highlights the importance of cross-section dependence in macro productivity analysis.

the PANIC representation of Bai and Ng (2004) who adopt a common factor structure for the series investigated. This assumption is maintained both in the analysis of the statistical properties of the data and in the cointegration analysis which is based on Gengenbach, Palm, and Urbain (2006). This kind of analysis has never been conducted before and adds to the literature on the productive impact of public capital by providing more accurate and robust estimates of the long run elasticity of GDP with respect to public capital for the most important OECD countries.

In particular we consider a panel of 21 OECD countries observed over the period 1975-2002 and we estimate different production function models in order to investigate the short and long run relationship between public capital and GDP, also taking into account the role played by other important productivity determinants suggested in the literature on endogenous growth, like human capital and the innovation potential, captured by either the R&D or the patents capital stock. We focus on a large sample of the richest OECD countries for two reasons: first, we want to understand the productive effect of public capital investment in the case of high income countries, given the revival of interest in public infrastructure investments among policymakers in both the US and the EU; secondly, by considering countries with similar institutions and levels of development, we should alleviate concerns of parameter heterogeneity in the production function, although still allowing for heterogeneity in productivity levels and growth rates as well as in the effects of unobserved common shocks.

Integration and cointegration analysis show that the non-stationarity of the variables entering our production function is entirely due to unobserved common components and that our series are cointegrated along the cross-sectional dimension. In order to tackle estimation and inference issues we apply the Continuously Updated Estimator suggested by Bai, Kao, and Ng (2009), which is an extension of the two stage fully modified estimator proposed by Bai and Kao (2006) for the case of non-stationarity of the unobserved common components and in presence of cross-member cointegration.

Overall results suggest that the long run elasticity of GDP with respect to public capital ranges between 0.05 and 0.15, depending on model specification: this result is in line with the past literature which found average public capital elasticities of about 0.1-0.2, as shown in the meta-analysis conducted by Bom and Ligthart (2009). Secondly, we provide some weak evidence of the existence of possible spillovers effects associated to public capital stocks in neighboring countries. Moreover, we also find evidence of a positive impact on GDP of R&D capital and the stock of patents, with elasticities of about 0.10 and 0.05, respectively, again quite in line with previous evidence. Another interesting result is provided by Granger causality tests which suggest that public capital and the stock of patents might Granger cause GDP while the opposite does not seem to occur. Finally, as a further robustness check, we have also estimated a TFP regression that confirms our main results.

The remainder of the paper is organized as follows. In section 2 we discuss our empirical model, while section 3 describes the data. The statistical properties of time series as well as the cointegration analysis can be found in section 4; section 5 describes long run analysis, while section 6 is devoted to analyzing short run dynamics. Finally, section 7 concludes.

## 2 The empirical model

In this paper we estimate the impact of public capital on productivity adopting a production function framework. In particular, we assume that GDP is produced according to the following Cobb-Douglas technology:

$$Y_{it} = TFP_{it} K_{it}^{\alpha} (HL)_{it}^{\beta} \tag{1}$$

where $Y_{it}$ is the GDP in country $i$ at time $t$; $K_{it}$ and $HL_{it}$ are the associated private capital stock and human capital augmented labour (Bils and Klenow, 2001) and $TFP_{it}$ represents total factor productivity in country $i$ at time $t$ while $\alpha$ and $\beta$ are the output elasticity of private capital and labour, respectively. The economic literature has identified many possible determinants of TFP, with the firms' innovative activity being as one of the most important (Aghion and Howitt, 2006). Hence, total factor productivity can be represented by the following equation:

$$TFP_{it} = G_{it}^{v} P_{it}^{\eta} \exp(u_{it}) \tag{2}$$

where $G_{it}$ and $P_{it}$ represent the public capital stock and the stock of patents, respectively, for country $i$ at time $t$ and $u_{it}$ is an error term accounting for other determinants of productivity like cyclical shocks, etc. (see below). In particular, we use the stock of patents instead of the stock of R&D as a TFP determinant because the latter represents the input of the innovative activity, while patent counts are the main output of the research process and, therefore, should better capture its impact on a country productivity.[3]

It should be noted that controlling for human capital and patents can be important if we remember the role played by knowledge in new growth theories. Moreover, our data suggest that countries with a high public capital to output ratio tend also to have a highly educated population and a large stock of patents. While many studies that have sought to estimate the impact of public capital on production have neglected the role played by innovation and human capital in driving economic growth and productivity (a recent exception being Bronzini and Piselli (2009)), a failure to control for their effect could potentially

[3]The use of the stock of patents as a proxy for the intensity of the innovation process may have some drawbacks. In particular, not all innovations are patented, and different sectors may be characterized by significant differences in their patenting propensity. Therefore, differences in the sectoral mix across countries might lead to differences in their stock of patents, for a given level of innovative activity. However, in all regression specifications we also include country fixed effects and time trends that should capture major differences in the sectoral composition of each country and therefore in their patent propensity. Furthermore, Bottazzi and Peri (2007) found empirical evidence consistent with the existence of a strong and significant cointegrating relationship between R&D and the stock of patents. In the results section we will also show that our main results are not affected by the inclusion of R&D capital as a proxy for a firm innovative activity.

bias the estimate of the impact of public capital on production.

Substituting equation 2 into 1 and taking logs, we get (where lower case variables denote natural logs):

$$y_{it} = \alpha k_{it} + \beta hl_{it} + \upsilon g_{it} + \eta p_{it} + u_{it} \tag{3}$$

Turning to the error term $u_{it}$, we can decompose it as follows:

$$u_{it} = e_i + a_i trend_t + \lambda_i F_t \tag{4}$$

where $e_i$ is a country fixed effect accounting for persistent differences in TFP levels across countries (for instance associated to institutions, barriers to entry, etc.); $trend_t$ is a set of country specific trends (with associated parameters $a_i$) which account for unobserved shocks that drive the evolution of each country's TFP linearly and, finally, $\lambda_i F_t$ is a vector of (possibly non-stationary) unobserved common factors with country specific factor loadings $\lambda_i$ that proxy for global macroeconomic shocks to TFP, like global changes in economic policy, oil shocks, financial crisis or spatial spillovers (e.g. due to public infrastructure or innovation activity) that might induce cross sectional correlation in the data.[4] It is important to highlight that the assumption of country specific factor loadings allows for a differential impact of the same global shock on TFP across countries.

As explained in more depth in the next sections, the possible existence of a set of unobserved common factors in the evolution of TFP has important econometric implications because it creates cross sectional dependence in the error term. In turn, the latter does not only invalidate inference, but, if not dealt with properly in the estimation, might preclude the identification of the impact of variables that might generate important spillover effects, like patents and public capital[5] as noted by Eberhardt, Helmers, and Strauss (2011) for the case of R&D expenditure. In fact, if there were important spillovers effects, conventional estimators that neglect cross sectional dependence in the data might not be able to identify the effect of, say, own public capital stock on GDP as they might just be capturing the effect of other countries' public capital stock, or a mix of the two. Furthermore, even if one tries to control for spillovers by including, say, the stock of other countries' public capital, she might still not be capturing them properly, given the inherent arbitrariness of most weighting schemes that a researcher is forced to adopt and the possibility that cross sectional correlation does not arise only from spatial spillovers. In any case, for robustness checks, but also in order to analyze the existence of spatial spillover effects associated to public capital within an econometric framework that duly takes into account spatial dependence, in some regression specifications we augment equation 3 with the stock of public capital in other countries ($goth_{it}$).

[4]The CD test statistics by Pesaran (2004) strongly suggests the presence of cross sectional correlation in our sample.

[5]See Coe, Helpman, and Hoffmaister (2009) and Bottasso and Conti (2010) for findings of spillovers associated to innovation and public infrastructure, respectively.

We can note that in equation 3 we are not imposing constant returns to scale neither for private nor for all inputs and we do not make any assumption of perfect competition. However, for robustness check, we have also estimated a version of equation 3 after imposing constant returns to scale in private inputs ($\alpha + \beta = 1$): this assumption in turn, together with that of perfect competition in input and output markets, allows us to use income shares as proxies for private inputs' elasticities and therefore to reformulate equation 3 as:

$$tfp_{it} = \upsilon g_{it} + \eta p_{it} + v_{it} \tag{5}$$

where $tfp_{it}$ was computed residually as $y_{it} - \alpha k_{it} + (1 - \alpha) l_{it}$ assuming a constant capital share of one third. The estimation of equations 3-5 raises a set of significant econometric challenges, such as the analysis of non stationarity and possible cointegration of the variables, as well as concerns of cross-section dependence which we address in the following sections.

# 3 Data

The data employed in this study are derived from different sources and are referred to 21 OECD countries, namely Austria, Belgium, Denmark, Spain, France, Italy, UK, Netherlands, Sweden, Finland, Germany, Austria, Greece, Canada, Japan, New Zealand, Norway, USA, Switzerland, Portugal and Ireland observed over the period 1975-2002.

Output $Y$ is taken from the OECD Analytical Database and is defined as GDP at 1995 constant prices, converted in purchasing power parities using OECD PPP exchange rates. The labour input $L$ is defined as the total annual hours worked and it is sourced from the total Economy Database of the University of Groningen. Private (K) and public (G) capital stocks are taken from Kamps (2004) to whom we refer for a detailed explanations of the sources and methodologies adopted in their computations; in particular, both capital stocks are valued at constant 1995 prices and converted into a common currency using OECD PPP exchange rates. Summary statistics reported in Table 1 suggest that there is more variation in the public capital to output ratio than in the case of the private capital to output ratio. In particular, in both 1975 and 2002 the countries with the highest public capital to output ratio were New Zealand, Japan and the Netherlands; in turn, Portugal, Belgium and Spain were the countries with the lowest ratio in 1975 and Ireland, Belgium and Canada those with the lowest ratio in 2002. In general, the cross country average slightly fell over time from about 0.56 to about 0.51[6] possibly because of a decline in government investment or because of the privatization process that reduced the scope of government intervention in some areas of the economy especially after 1995.

Table 1 reports summary statistics for human capital stock, which is proxied by the average number

[6]This trend can be contrasted with that of the private capital to output ratio which was essentially constant.

of schooling years for the population aged 25 or more ($S$) and it is taken from Cohen and Soto (2007) to whom we refer for a detailed explanation of the main differences with other popular human capital stock series.[7] As the Cohen and Soto (2007) data have only been computed at ten year intervals since 1960 to 2010, we have derived information for the missing years by linear interpolation.[8] We then have followed Bils and Klenow (2001) in order to build a human capital augmented labour input as $HL_{it} = L_{it} * \exp[f(mq_i) * S_{it}]$, where $f(mq_i)$ represents a country specific piecewise concave function of the mincerian return to education of one additional schooling year corrected for the quality of the educational system in each country, taken from Cohen and Soto (2007).

The stock of patents $P$ has been computed as in Bottazzi and Peri (2007) by accumulating past patents using the perpetual inventory method. In particular, we have taken information on the number of patents from the University of Groningen Patent Database which covers the period 1970-2002.[9] Following Bottazzi and Peri (2007), the stock of patents for country $i$ in 1970 was computed as $P_{i,1970} = NP_{i,1970}/(g_i + \delta)$, where $NP_{i,1970}$ is the number of patents granted by the USPTO to country $i$ in 1970, $g_i$ is the rate of growth of the number of patents in the period 1970-1974 and the depreciation rate $\delta$ was set to 0.1. For the following years, the stock of patents was computed as $P_{it} = (1 - \delta)P_{it-1} + NP_{it}$. [10] Data reported in Table 1 confirm both the substantial differences in the stock of patents even between countries with similar levels of GDP, but also the surge in the stock of patents granted by the USPTO that occurred between 1975 and 1999, with the exceptions of the US and the UK.

In some model specifications we will need an estimate of the stock of public infrastructure of the other countries in the sample in order to capture the spatial spillovers associated to the infrastructure and innovative activity carried out in the rest of the world. The stock of public capital of the rest of the world for country $i$ in year $t$ is defined as $GOTH_{it} = \sum_{j \neq i} G_{jt} W_{ij}$, where the row standardized weight matrix $W_{ij}$ is based on the distance between the capital of country $i$ and that of each of the other 20 countries in the sample.[11]

As a robustness check we have used physical indicators as proxies for the stock of public infrastructure, namely the Km of motorways and railways lines taken from the Database of World Infrastructure compiled by Canning (2007), Eurostat and country level sources.

Finally, in some specifications we need the stock of R&D capital. The latter is taken by the EUKLEMS database, which reports data for the period after 1980. We have reconstructed the stock up to 1975 applying the perpetual inventory method backwards (with a depreciation rate of 12%) using OECD data.

[7] In particular, the main difference with other series such as the Barro and Lee one is the use of surveys based on an uniform classification system of education over time and a more extensive use of information by age groups.

[8] We used the *ipolate* function in STATA.

[9] In particular, the Patent database is an update of the NBER database which contains information on the number of patents granted to residents of country $i$ in year $t$. The choice of using only patents granted in the US is a way to focus only on the most important innovations in each country.

[10] For this variable, we lose information on New Zealand and Switzerland. Moreover, the period covered is 1975-1999.

[11] In particular, we have assumed that the weights are proportional to the inverse of the distance between the capital cities.

Table 1: Descriptive statistics

| | *Year* | |
|---|---|---|
| *variable* | 1975 | 2002 |
| $GDP$ | 522.6 (883) | 1092 (2030) |
| $K$ | 1171.6 (1807) | 2582 (4303.8) |
| $G$ | 324.4 (613) | 633 (1237.4) |
| $H$ | 8.76 (1.88) | 11.06 (1.70) |
| $P$ | 49676 (164613) | 65477 (168793) |
| $G/Y$ | 0.55 (0.21) | 0.50 (0.20) |
| $L$ | 27258 (40161) | 32789 (56399) |

*Note: St. dev in parenth. Y, K, G billions of \$; H number of years; P number of patents (in 1975 and 1999); L million of hours.*

For Austria, Belgium, Switzerland, New Zealand, Portugal and Greece the EUKLEMS database does not report data on the R&D capital stock: for these countries we have constructed it using a similar procedure to that employed in the EUKLEMS database, applying the perpetual inventory method using OECD data on R&D expenditure. In particular, we have constructed the benchmark R&D capital in 1973 (the first year for which we have data) as $\mathrm{R\&D}_{73}/(\delta + g)$, where $\delta$ is the depreciation rate equal to 0.12, $g$ is the average rate of growth of R&D expenditure over the period 1973-1985. Data have been converted in US$ using OECD GDP PPPs exchange rates.

# 4 Statistical properties of time series

## 4.1 Integration analysis

In this section we conduct a through investigation of stationarity properties of our data by applying recent panel data unit root tests.[12] The most commonly used panel unit roots tests are those proposed by Levin, Lin, and Chu (2002) and Im, Pesaran, and Shin (2003), which however have been found to poorly perform in the presence of cross sectional dependence and when the number of cross section increases (Larsson and Lyhagen, 2000b). For this reason we prefer to employ the PANIC unit root tests proposed by Bai and Ng (2004) which take into account the presence of cross sectional dependence in the data.[13] In

[12]It is well known in the literature that panel based unit root tests have higher power than unit root tests based on individual time series and panel data techniques are also preferable because of their high degree of flexibility.

[13]Nevertheless, we have performed the Levin, Lin, and Chu (2002) and Im, Pesaran, and Shin (2003) tests and we have found that for our variables in no case we can reject the null of non-stationarity at standard levels of significance; in turn first differences of time series resulted to be stationary.

particular, the PANIC framework assumes the following factor structure for observed panel data:

$$Y_{it} = \lambda_i^{'} F_t + e_{it} \tag{6}$$

where $F_t$ is a $(k \times 1)$ vector of common factors, $\lambda_i$ is a vector of factor loadings and $e_{it}$ is an idiosyncratic error component. The series may be nonstationary if either $F_t$ or $e_{it}$ (or both) are non-stationary and each hypothesis can be separately tested.[14] In order to test for individual unit roots on the idiosyncratic component, $e_{it}$, the authors propose pooled tests ($Z_e$) for the hypothesis that all $e_{it}$ are non-stationary, which are based on Fisher-type statistics and converge to a standard normal distribution for $(N, T) \to \infty$. As far as the presence of unit roots in the common component is concerned, Bai and Ng (2004) suggest the following strategy: if a single common factor is estimated, it can be applied an ADF test ($ADF$) whose limiting distribution coincides with the Dickey-Fuller distribution; if more than one common factor is estimated, authors provide an iterative procedure to select the number of independent stochastic trends, which is similar to the Johansen trace test for cointegration. They suggest two modified statistics, $MQ_d$ and $MQ_f$, where the former uses a non-parametric correction to account for additional serial correlation, while the latter employs a parametric correction.[15] In table 2 below we present the results for the $MQ_f$ statistic only, but the results are robust to the application of the $MQ_d$ test whose results are not reported for reasons of space.

Table 2: Bai Ng (2004) unit root tests

| variable$^{\S}$ | # of factors | $Z_e^{\tau}$ | $ADF^{\tau}$ | $MQ_f^{\tau}$ | # of factors |
|---|---|---|---|---|---|
| GDP | 1 | 5.96 | -2.81 | | |
| LHC | 1 | 6.2 | -3.15 | | |
| K | 1 | 8.19 | -3.72 | | |
| G | 1 | 6.89 | -1.97 | | |
| P | 2 | 7.91 | | -8.96 | 2 |

*Note: the suffices $^{\tau}$ for the statistics $Z$, $ADF$ and $MQ_f$ indicate the intercept and linear trend case. $^{\S}$The abbreviations for the variables used are presented in Section 2. $^{*}$The PC3 criterion of Bai and Ng (2002) was used to estimate the number of unobserved common factors. $^{**}$Number of factors estimated by the $MQ_f$ statistics.*

The $Z_e$ tests reject the null of unit root for the estimated idiosyncratic components for all the analyzed variables so that it becomes important to verify if possible non stationarity of the series rest in the unobserved common components, i.e. if the nonstationarity in the observed data is due to a pervasive source. When estimating a single common factor for Human capital augmented labour, Public capital,

[14] If the series may be represented by (6), testing for the presence of unit root in $Y_{it}$ could provide misleading results. If, for instance, one component is $I(0)$ and one is $I(1)$ unit root tests on $Y_{it}$ are oversized while stationarity tests have low power. See Ng and Perron (2001).

[15] Both statistics have a non standard limiting distribution whose critical values are provided by Bai and Ng (2004). The two statistics are modified variants of the statistics $Q_c$ and $M_f$ proposed by Stock and Watson (1988).

Private capital and GDP, the $ADF$ tests does not reject the unit root hypothesis except for the Private capital (the critical value $ADF^{\tau}$ is -3.41); estimating 2 common factors for Patents, both $MQ_f^c$ and $MQ_f^{\tau}$ cannot reject the null hypothesis that there are 2 independent stochastic trends.[16] The critical values for the statistic is -31.356 (Bai and Ng (2004), Table I). The remainder of our analysis proceeds on the assumption, supported by the tests performed above, that most log level variables are I(1) processes, while all log differenced variables follow stationary, I(0), processes.[17]

### 4.2 Cointegration analysis

In this section we describe the cointegration analysis conducted through different econometric approaches. First, we apply the panel cointegration tests derived by Pedroni (1999) and Pedroni (2004), who proposed seven different statistics for testing the presence of a single cointegration relationship under the assumption of cross-sectional independence.

Results support the hypothesis of a cointegration relationship between our variables, since four out of seven tests reject the null hypothesis of no cointegration at the 10% significance level. The statistics that fail to reject the no cointegration hypothesis are however undersized in small panels (Pedroni, 2004)[18].

As an additional test for cointegration, we apply the LR-bar and the PC-bar tests proposed by Larsson, Lyhagen, and Lothgren (2001) and Larsson and Lyhagen (2000a), respectively. The LR-bar statistic suggests that it does exist a common cointegration rank in the panel, or at least a common largest rank of 2, while the PC-bar test rejects a minimum cointegrating rank of 2: hence we cannot infer that there is a common cointegrating rank for all countries in the panel.[19]

However the panel multivariate cointegration methods proposed by Larsson and Lyhagen (2000a), Larsson, Lyhagen, and Lothgren (2001) and by Pedroni (1999) do not take into account the presence of cross sectional dependence; in particular Gengenbach, Palm, and Urbain (2006) demonstrates that the panel cointegration tests proposed by Pedroni (1999) are inconsistent when the data present a common factor structure and show a consistent size distortion which increases with the cross-sectional dimension $N$.

In the presence of cross sectional dependence, cross-unit cointegration might arise.[20] In the case of cross sectional cointegration, standard panel multivariate cointegration analysis might provide misleading results and might fail to detect any cointegration relationship among data. In order to take into account

[16] We use the BIC3 criterion of Bai and Ng (2002) to estimate the number of unobserved common factors and we allow for at most 6 factors. Since the cross section and time series dimensions of the panel are approximately of the same magnitude, the BIC3 criterion tends to be superior over the alternatives. However, the results shown are robust to using other selecting criterions and selecting a different maximum numbers of allowed common factors.

[17] As a robustness check we have also performed the Pesaran (2007) panel unit root test, which is robust to the presence of cross sectional dependence, and our results are confirmed.

[18] Results are available upon request.

[19] To correct for finite sample bias, the trace statistic is multiplied by the scale factor $(T-pL)/T$, where $T$ is the number of the observations, $L$ the lag order of the underlying VAR model and $p$ the number of the variables, see Reimers (1992).

[20] For a formal definition of cross-unit cointegration, see Wagner and Hlouskova (2010).

the possible existence of cross sectional cointegration, we follow the approach proposed by Gengenbach, Palm, and Urbain (2006) which focus on testing for no-cointegration when the cross-sectional dependence in the panel is modeled with the PANIC approach of Bai and Ng (2004).

In particular, Gengenbach, Palm, and Urbain (2006) addresses the issue of no-cointegration within three different possible frameworks: 1) testing for idiosyncratic components no-cointegration when the observed non-stationarity in the series originates from idiosyncratic stochastic trends only, 2) testing for common factors no-cointegration when the non-stationarity is due to cross-sectional common trends only, 3) testing for panel no cointegration when there are both cross-sectional common and idiosyncratic stochastic trends.

As discussed in section 4.1, the integration analysis has shown that the non-stationarity in our panel is entirely due to a reduced numbers of common stochastic trends: in this case cointegration between the dependent variable and the regressors can only occur if the common factors for $Y_{it}$ cointegrate with those of $X_{it}$. Hence, we have to test for common factor no-cointegration (case 2 listed above). In this case Gengenbach, Palm, and Urbain (2006) suggests to test the null of no-cointegration between the factors using the Johansen likelihood ratio test.

Table 3: Gengenbach, Palm, and Urbain (2006) cointegration test

| trace test statistic | critical value | cointegration rank |
|---|---|---|
| 102.77 | 94.15 | 0 |
| 55.36** | 68.52 | 1 |
| 34.93 | 47.21 | 2 |
| 23.03 | 29.68 | 3 |
| 11.64 | 15.41 | 4 |
| 4.73 | 3.76 | 5 |

Table 3 presents the results of the Johansen trace test for cointegration between the six estimated common factors. Results suggest the existence of a single cointegrating relationship, which in turn allows us to interpret the long run relation in equation 3 as a conventional production function. To the best of our knowledge this is the first paper seeking to estimate the productive effect of public capital in a panel non-stationary environment that tests for the number of cointegrating vectors, as previous studies simply assumed the existence of a unique contegrating relationship.

# 5 Long run analysis

In the previous analysis we have found evidence that the variables entering the production function are non-stationary and cointegrated. In this section we discuss parameter estimates of the augmented production function presented in equation (3). It is well known that estimating it by OLS is not appropriate if regressors are endogenous and residuals are serially correlated: in such a case the estimator is inefficient and the bias in the cointegration parameters is of order T. As a matter of fact, the estimation of production functions is plagued by the risk of bias due to endogeneity because inputs and outputs are jointly determined; moreover, the presence of cross sectional dependence needs to be properly taken into account.

In order to tackle the econometric issues raised by simultaneity and cross sectional dependence we apply two different techniques, namely the Dynamic OLS (DOLS) proposed by Mark and Sul (2001), which corrects for the possible endogeneity of the non-stationary regressors but does not take into account the cross-equation dependence in the equilibrium errors, and the Continuously Updated (CUP) estimator introduced by Bai, Kao, and Ng (2009), which accounts for the presence of cross sectional dependence in the data.

## 5.1 Econometric issues

The estimation of the equation (3) by DOLS involves adding past and future values of the first differences of the explanatory variables as additional regressors, so that all nuisance parameters, which represent short run dynamics, are I(0) and uncorrelated with the error term (by construction). This procedure corrects for the possible endogeneity of the non-stationary regressors;[21] however, this estimator sacrifices asymptotic efficiency because it does not take into account the cross-section dependence; furthermore, it may fail to precisely identify parameter estimates in the presence of important spillover effects. Nevertheless we apply DOLS technique for robustness results.

Given the presence of cross sectional dependence in our data we also apply the estimator proposed by Bai, Kao, and Ng (2009) who consider the problem of estimating the cointegrating vector for a panel with unobserved non stationary common factors. The authors consider the following model,

$$y_{it} = x_{it}^{'}\beta + \lambda_i^{'}F_t + \epsilon_{it} \tag{7}$$

when $F_t$ is a $(r \times 1)$ vector of non-stationary unobserved common factors and $x$ is a vector of regressors possibly including country trends and country specific fixed effects.

Bai, Kao, and Ng (2009) propose the CupBC (continuously-updated and bias-corrected) and the CupFM (continuously-updated and fully-modified) estimators for $\beta$. Both estimators are asymptotically unbiased and normally distributed and are valid when there are mixed stationary and non-stationary factors, as well as when the factors are all stationary. Bai, Kao, and Ng (2009) propose an iterative solution in the same line of that proposed by Bai (2009) and Bai and Kao (2006).[22] The CUP estimators

[21] Kao and Chiang (2000) showed that in finite samples DOLS outperforms both the OLS and the Fully Modified OLS estimator suggested by Pedroni (2004).

[22] Bai and Kao (2006) considered a two-step fully modified estimator (2sFM) in the case of nonstationary series which

of Bai, Kao, and Ng (2009) minimize the following concentrated least square function:

$$CLS(\beta, F) = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{NT^2}(y_{it} - x_{it}^{'}\beta + \lambda_i^{'}F_t)^2$$

where the function has been already minimized over $\lambda_i$ and $F_t$, treated as parameters. $\lambda_i$ and $F_t$ are subject to the following identification constraints: $T^{-2}\sum_{t=1}^{T} F_t F_t^{'} = I$ and $\Lambda'\Lambda$ is positive definite where $\Lambda = (\lambda_1^{'}, \cdots, \lambda_N^{'})^{'}$. The continuous updated estimator (Cup) for $(\beta, F)$ is defined as

$$(\hat{\beta}, \hat{F}) = argmin_{\beta,F} CLS(\beta, F) = \sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - x_{it}^{'}\beta + \lambda_i^{'}F_t)^2$$

in particular $(\hat{\beta_{CUP}}, \hat{F_{CUP}})$ is the solution to the following two nonlinear equations

$$\hat{\beta} = (\sum_{i=1}^{N} x_i^{'} M_{\hat{F}} x_i^{'})^{-1}\sum_{i=1}^{N}(x_i^{'} M_{\hat{F}} y_i) \tag{8}$$

$$\hat{F}V_{NT} = [\frac{1}{NT^2}\sum_{i=1}^{N}(y_i - x_i\hat{\beta})(y_i - x_i\hat{\beta})^{'}]\hat{F} \tag{9}$$

where $x_i$ is a $(T \times k)$ matrix of regressors, $y_i$ is a $(T \times 1)$ vector of dependent variables and $V_{NT}$ is the diagonal matrix of the $r$ largest eigenvalues of the matrix inside the brackets, arranged in decreasing order. The estimator is obtained by iteratively solving for $\hat{\beta}$ and $\hat{F}$ using (8) and (9). An estimate of $\Lambda$ can be obtained as:

$$\hat{\Lambda} = T^{-2}\hat{F}^{'}(Y - X\hat{\beta})$$

While the CUP estimator of $\beta$ is consistent, there is an asymptotic bias arising from endogeneity and serial correlation, and thus the limiting distribution is not centered around zero. Bai, Kao, and Ng (2009) consider two fully-modified estimators, along the lines of Philipps and Hansen (1990), which correct the asymptotic bias. The first one, the CupBC estimator, does the bias correction only once, at the final stage of the iteration while the second one, the CupFM estimator, corrects the bias at every iteration. While the CupFM estimator is computationally more costly it may have better finite sample properties.

The procedure outlined above requires the number of common factors, $r$, to be known. In general that is not the case and $r$ has to be estimated. We make use of the BIC3 information criteria of Bai and Ng (2002) which performs well in empirical studies where the cross size and the time series dimensions are similar, to obtain consistent estimates of the number of common components.

are cointegrated in the case of error cross section dependence given by $e_{it} = \lambda_i^{'}F_t + \epsilon_{it}$. The 2-stage fully modified (FM) estimator proposed by Bai and Kao (2006) is inconsistent when the unobserved factors are nonstationary.

## 5.2 Estimation results

In Table 4 we report empirical estimates of equation 3 obtained with both DOLS[23] and the CUP-FM estimator of Bai, Kao, and Ng (2009). In both cases, we allow for country-specific fixed effects and time trends while, in the case of the CUP-FM estimator, we also allow for a set of unrestricted common factors with heterogenous factor loadings. Estimates reported in Table 4 show that all parameters are statistically significant at the 1% level, with very similar values across estimation methods, with the notable exception of private capital elasticity. The latter in fact is about 0.25 when the model is estimated with the CUP-FM estimator, not too far from the share of capital in national income (which is roughly 1/3) but it rises to 0.75 in the DOLS case, perhaps reflecting the impact of neglecting cross sectional correlation. In turn, both estimators find a somewhat low elasticity for human capital augmented labour, a not uncommon finding in the empirical macroeconometric literature though.

Moreover, estimates of the elasticity of public capital is similar across the two methods with a value of about 0.13, well in line with previous empirical evidence and in particular with the recent studies that have employed panel data time series techniques within a production function framework. For instance, Calderon, Moral-Benito, and Serven (2011) employed the Pesaran et al (1999)'s pooled mean group estimator to a large panel of countries and obtained output elasticities of infrastructure in the range 0.07-0.10; [24] Bronzini and Piselli (2009) report an output elasticity of about 0.2 from a production function estimated on a sample of Italian regions with the FMOLS estimator; finally, Canning and Bennathan (2000) find output elasticities of paved roads in the range 0.05-0.08 for a panel of world countries.[25]

Finally, the elasticity of GDP with respect to patents turns out to be about 0.10, i.e. in the lower range identified by Madsen (2007) who estimated with DOLS the long run cointegrating relationship between TFP and the domestic stock of patents (as well as foreign patents) for a sample of 16 OECD countries observed over the period 1870-2004; moreover, they are fully in line with the results of Coe, Helpman, and Hoffmaister (2009) who in fact found an elasticity of about 0.10 between a country's TFP and the stock of domestic R&D capital for a panel of OECD countries observed over the period 1970-2004.[26]

In Table 5 we probe the results of our baseline specification reported in Table 4 along a number of ways. First, we believe it is worthwhile to assess the impact of public capital (as well as the patent stock) on Total Factor Productivity, given that such approach is very common in the previous literature. In order

[23] In the DOLS case standard errors are computed by means of an HAC estimator of the long run variance.

[24] We should bear in mind that, strictly speaking, our estimates are not directly comparable to those of Calderon, Moral-Benito, and Serven (2011) because in their production function they include total capital stock, rather than the private sector capital stock, as in our case, and therefore their infrastructure variable appears twice in the production function. The total elasticity of infrastructure capital is likely to be increased by 0.33*0.08=0.026, where 0.33 is the elasticity of output with respect to private capital found in their paper and 0.08 is the share of infrastructure in total capital, which would yield a total elasticity of infrastructures of about 0.095-0.125, remarkably similar to ours.

[25] See also Haemaelaeinen and Malinen (2011) for a study conducted on a sample of Finnish regions.

[26] We should recall that, unlike in the case of the public capital elasticity, in the patents case the elasticty should be interpreted in terms of the additional effects on output brought about by patents, on top of that already accounted for by private inputs, assuming that researchers and facilities used in carrying out R&D activity had been paid their marginal products.

Table 4: **Estimates of the long-run cointegration relation.**

| | CupFM | DOLS |
|---|---|---|
| LH | 0.168*** | 0.188*** |
| | (0.019) | (0.057) |
| K | 0.246*** | 0.748*** |
| | (0.038) | (0.036) |
| G | 0.129*** | 0.127*** |
| | (0.036) | (0.032) |
| P | 0.092*** | 0.108*** |
| | (0.023) | (0.024) |
| Country trends | X | X |
| Country fixed effects | X | X |

*Note: Panel Data using 19 countries for the period 1975-2000. Methods of Estimation: CupFM of Bai, Kao, and Ng (2009) and DOLS . standard errors in parenthesis.* $***p < 0.01$, $**p < 0.05$, $*p < 0.10$.

to estimate a TFP model as specified in equation 5, we impose constant returns to scale in the production function, assume perfect competition in input and output markets and adopt private input elasticities measures deduced from national accounting data. Empirical results displayed in column 1 show that both public capital and the stock of patents are positive and statistically significant at 1%. In particular, the elasticity of public capital is barely altered with respect to that reported in Table 4, while the elasticity of the stock of patents about doubles, although remaining within the range of estimates one can find in Madsen (2007), Coe, Helpman, and Hoffmaister (2009) and in the short literature review contained in Eberhardt and Teal (2011) who report, for studies conducted on panel of countries, elasticities of TFP with respect to R&D capital between 0.05 and 0.23.

In column 2 we use the stock of R&D instead of the stock of patents as a measure of a country knowledge capital. As we can see, there are no major changes with respect to our baseline specification in Table 4: in particular, the public capital elasticity goes up to 0.15, while R&D enters significantly in the production function, with a somewhat small coefficient of 0.05, which is however statistically significant, although notably smaller than the results reported in Coe, Helpman, and Hoffmaister (2009).

Given the possibility that public infrastructures can generate important spillovers related to network effects mainly associated to transport infrastructures (e.g. motorways, airports, etc.) in column 3 we include in our regression specification the stock of public capital in other countries (and we drop the stock of R&D): to the best of our knowledge, this is the first paper to shed some light on this issue within a proper econometric framework that duly takes into account cross sectional correlation. Parameter estimates show that the elasticity of own public capital is barely affected by the inclusion of the stock of public capital in other countries, suggesting that an econometric framework that takes into account unobserved common factors is robust to the omission of the public capital stock in other countries and the associated spillover effect. In turn, the stock of public capital in other countries enters significantly

Table 5: Estimates of the long-run cointegration relation. CupFM estimator of Bai, Kao, and Ng (2009)

| dep.var. | TFP | GDP | GDP | GDP | GDP | GDP | GDP |
|---|---|---|---|---|---|---|---|
| *LH* | - | 0.199*** | 0.09*** | 0.17*** | - | - | - |
| | | (0.017) | (0.015) | (0.02) | | | |
| *L* | - | - | - | - | 0.57*** | 0.58*** | 0.40*** |
| | | | | | (0.029) | (0.027) | (0.029) |
| *G* | 0.12*** | 0.15*** | 0.15*** | - | 0.06*** | 0.09*** | 0.13*** |
| | (0.028) | (0.029) | (0.028) | | (0.024) | (0.026) | (0.029) |
| *K* | - | 0.38*** | 0.34*** | 0.71*** | 0.62*** | 0.34*** | 0.63*** |
| | | (0.032) | (0.037) | (0.029) | (0.029) | (0.027) | (0.03) |
| *P* | 0.21*** | - | - | - | - | - | 0.05*** |
| | (0.017) | | | | | | (0.015) |
| *R&D* | - | 0.05*** | - | 0.03*** | - | 0.09*** | - |
| | | (0.011) | | (0.011) | | (0.009) | |
| *GOTH* | - | - | 0.40*** | - | - | - | - |
| | | | (0.064) | | | | |
| *CONGPOP* | - | - | - | 0.05* | - | - | - |
| | | | | (0.029) | | | |
| Country fixed effects | X | X | X | X | X | X | X |
| Country trends | X | X | X | | X | X | |

*Note: Panel Data using 19 countries for the period 1975-2000.*
*Method of Estimation: CupFM of Bai, Kao, and Ng (2009) standard errors in parenthesis.*

in the production function with an elasticity of about 0.4. This effect is larger than that reported by (Bottasso and Conti, 2010) for a panel of EU industries, or by Cohen and Morrison (2004), who in turn estimated a cost function on manufacturing data for a panel of US states. However, it is also notably smaller than that estimated by Bronzini and Piselli (2009) for a sample of Italian regions. Our findings of a large spillover effect for public capital however appears to be quite sensitive to the specification of the production function. In fact, if we include in equation 3 the stock of R&D, the stock of public capital in other countries becomes marginally insignificant.[27]

There is evidence (Fernald (1999) and (Bottasso and Conti, 2010)), that congestion might significantly reduce the productive effects of public infrastructures; therefore, in column 4 we include the public capital stock after dividing it by country population (CONGPOP) in order to take into account possible congestion effects, even if admittedly in an approximate way.[28] Empirical results confirm that public capital still enters significantly in the production function, but with a smaller coefficient of about 0.05, statistically significant at 10% level, thus confirming the importance of controlling for congestion effects when seeking to analyze the impact of public capital on production.

A possible pitfall of the specifications estimated so far is the possibility that human capital corrected labour has been estimated with error (see data section); for this reason we have run some versions of equation 3 with raw labour not corrected for human capital. In column 5 we estimate a production function with raw labour augmented only by the stock of public capital: we note an increase in private input elasticities, with respect to previous specifications and a somewhat low elasticity of public capital of about 0.06, statistically significant at 1%.

In column 6 we instead augment the previous regression with the stock of R&D capital and we find a slightly higher public capital elasticity of about 0.09 and an elasticity of R&D capital of 0.09, somewhat larger than that reported in column 2. Finally, in column 7 we estimate our baseline specification by including the stock of patents rather than the stock of R&D and main results are again broadly confirmed: in particular, the elasticity of public capital goes up to 0.13, while that of patents drops to 0.05.

As we mentioned in the data section, the public capital stock in monetary terms used in this study, although theoretically the correct proxy for the services provided to the economy by public investments, might be criticized on a number of grounds, namely the differences across countries in building project costs associated to both government efficiency and corruption; differences in timing of privatization of government assets; etc. Although the use of country fixed effects and trends should take this concern somewhat into consideration, we decided to assess the robustness of our results by running a series of

[27] We have also included in our baseline equation the stock of patents in other countries, but surprisingly the results have always been largely insignificant.

[28] Similar ways of addressing the fact that public capital is not a pure public good are those of Barro (1990) and Shioji (2001), who modelled congestion dividing the public capital stock by a measure of the size of the economy, such as GDP and employment. See, for a different approach, Fisher and Turnovsky (1998).

regressions using alternatively railways and motorways kms instead of the public capital stock. We generally found that both motorways and railways have a positive and statistically significant impact on GDP, with elasticities of 0.02 and 0.17, respectively.

On average, the econometric estimates displayed in Table 4 and 5 suggest an elasticity of GDP with respect to public capital in the range of 0.05-0.15, with an average of 0.11, pretty much in line with our baseline specification. Considering the public capital stock to GDP ratio in 2002 (the last year of our panel), this yields a gross rates of return of public capital of about 0.23, with most countries in the range 0.15-0.25, with the true exceptions being Japan and Finland on the lower and upper tails of the returns distribution, respectively. Such rates of return are quite large, although notably smaller than the 100% value implied by Aschauer (1989) empirical estimates. If we instead take the most conservative value for the public capital stock elasticity, namely 0.05, these gross rates of return would be about halved, with most countries following in the range 0.08-0.15 (broadly comparable to these reported for OECD countries by Canning and Bennathan (2000) for the case of paved roads).

It might be interesting to compare these gross rates of return of public capital to the user cost of public infrastructure in order to compute net rates of return (as of 2002). Keeping in mind the difficulties than one faces in computing the user cost of public capital, we find, for an elasticity of 0.11, that all countries in our sample might have a positive net rate of return of public investment, perhaps with the exception of Japan, which has a return very close to zero.[29] However, if we take the most conservative figure for the public capital stock elasticity (0.05), then we find rates or return very close to zero or even negative for a few countries, namely Japan, Austria, New Zealand, Germany and France, with Ireland and Finland being the countries with the highest net returns.

# 6 Short run dynamics

Given our finding that the production function in equation (3) represents a long run cointegrating relationship, we re-parametrize it in the Error Correction Form (ECM) in order to analyze short term dynamics and to formally test for Granger Causality between GDP and the explanatory variables in equation (3), both in the short and in the long run. In particular, we consider the following panel ECM:

[29] The computation of the user cost of public capital is fraught with difficulties. In this study we have computed it using the Jorgenson approach, as suggested by Bosca, Escriba, and Murgui (2002), i.e. as $ucpc = \frac{p_I}{p}(\delta - \widehat{p_g} + r)$, where $p$ is the gdp deflator, $p_I$ is the deflator of investment (as a proxy for the deflator of public investment: results are robust to using of the deflator of government consumption), $r$ is the long run real interest rate on ten year government bonds, $\widehat{p_I}$ is the rate of change of the deflator of investment (averaged over the period 1997-02) and $\delta$ is the depreciation rate, assumed to be 4.5%. It is important to remember that in this empirical analysis we do not include in the user cost of public capital the distortions arising from non-lump sum taxation that a government incurs in order to finance public investment. On the other hand we do not consider the benefits of public capital accruing to households, e.g. in terms of lower travel time. Data for real interest rates are taken from the EU AMECO database, while the GDP and investment deflators are from the Penn World Tables, version 7.0.

$$\Delta y_{it} = \varphi_{1i} + \eta_1 \widehat{e}_{it} + \delta_{11}\Delta y_{it-1} + \delta_{12}\Delta lh_{it-1} + \delta_{13}\Delta k_{it-1} + \delta_{14}\Delta g_{it-1} + \delta_{15}\Delta p_{it-1} + u_{1it} \quad (10)$$

$$\Delta lh_{it} = \varphi_{2i} + \eta_2 \widehat{e}_{it} + \delta_{21}\Delta y_{it-1} + \delta_{22}\Delta lh_{it-1} + \delta_{23}\Delta k_{it-1} + \delta_{24}\Delta g_{it-1} + \delta_{25}\Delta p_{it-1} + u_{2it} \quad (11)$$

$$\Delta k_{it} = \varphi_{3i} + \eta_3 \widehat{e}_{it} + \delta_{31}\Delta y_{it-1} + \delta_{32}\Delta lh_{it-1} + \delta_{33}\Delta k_{it-1} + \delta_{34}\Delta g_{it-1} + \delta_{35}\Delta p_{it-1} + u_{3it} \quad (12)$$

$$\Delta g_{it} = \varphi_{4i} + \eta_4 \widehat{e}_{it} + \delta_{41}\Delta y_{it-1} + \delta_{42}\Delta lh_{it-1} + \delta_{43}\Delta k_{it-1} + \delta_{44}\Delta g_{it-1} + \delta_{45}\Delta p_{it-1} + u_{4it} \quad (13)$$

$$\Delta p_{it} = \varphi_{5i} + \eta_5 \widehat{e}_{it} + \delta_{51}\Delta y_{it-1} + \delta_{52}\Delta lh_{it-1} + \delta_{53}\Delta k_{it-1} + \delta_{54}\Delta g_{it-1} + \delta_{55}\Delta p_{it-1} + u_{5it} \quad (14)$$

where $\Delta$ represents the first difference operator, $\widehat{e}_{it}$ is the residual of the production function in equation (3) estimated with the CUP-FM estimator and $\eta$ measures the speed of adjustment to the equilibrium in the above model, while $u$ is an error term and the $\varphi_i$s are a set of country fixed effects.[30] For the variables in equation (10)-(14) to represent a long run cointegrating relationship, the Engle-Granger representation theorem requires at least one of the $\eta$s to be significantly different from zero. Moreover, the sign of the $\eta$s, as well as that of the $\delta$ coefficients, can be used to test for the existence of short and long run Granger causality. For instance, if $\eta_4$ in the equation for public capital is not significantly different from zero, then one might say that public capital is not Granger-caused in the long run by the other variables in the system and can therefore be considered as weakly exogenous; in turn, if also the coefficients of the lagged differentiated variables ($\Delta y_{it-1}$, $\Delta lh_{it-1}$, $\Delta p_{it-1}$ and $\Delta k_{it-1}$) are jointly equal to zero, then public capital could be considered strongly exogenous.

As far as the estimation strategy is concerned, the stationarity of the variables included in the above system might allow us to estimate it equation by equation with OLS. However, the presence of the lagged dependent variables, as well as simultaneity concerns associated to production function inputs, are likely to make both the OLS and fixed effects estimators biased and inconsistent. A preferable estimation strategy might be that of first differencing the above equations to get rid of the fixed effects and then using appropriate lags of the endogenous variables (in levels) as instruments using the Arellano and Bond (1991) GMM-Difference estimator. However, the Arellano and Bond estimator might suffer of lack of power of the internal instruments when variables are very persistent; for these reasons we prefer to estimate each equation of the above system with the GMM-System estimator of Arellano and Bover (1995), that exploits more informative moment conditions by using lagged first differences as instruments for the equations in levels (e.g. the equations in the system (10-14)) on top of the usual lagged levels for the equation in differences.[31]

[30] The inclusion of country fixed effects in the system of equations (10-14) is due to the existence of a set of country trends in the cointegrating relationship (3)

[31] However, the GMM-SYS estimator is based on the assumption of stationary initial conditions and on the hypothesis that country fixed effects are uncorrelated with the first difference of variables in equation (10-14). As a robustness check we have also estimated the panel ECM by OLS, fixed effects and GMM-DIFF (as well as by the GMM-SYS with different lags for the instruments) and we have found broadly similar results. Estimates are available from the authors upon request.

Table 6: Estimates of the ECM

| dep.var. | $\Delta \ln Y$ | $\Delta \ln LHC$ | $\Delta \ln K$ | $\Delta \ln G$ | $\Delta \ln P$ |
|---|---|---|---|---|---|
| $\Delta \ln Y_{t-1}$ | 0.745*** | 0.961 | 0.124*** | 0.027 | 0.036 |
| | (0.238) | (0.615) | (0.589) | (0.072) | (0.297) |
| $\Delta \ln LH_{t-1}$ | -0.114 | -0.533 | 0.034 | 0.002 | 0.329 |
| | (0.126) | (0.254)** | (0.027) | 0.013 | (0.312) |
| $\Delta \ln K_{t-1}$ | 0.100 | -0.372 | 0.769*** | -0.008 | 0.069 |
| | (0.269) | (0.597) | (0.079) | (0.069) | (0.349) |
| $\Delta \ln G_{t-1}$ | -0.121 | 0.213 | 0.013 | 0.889*** | -0.156 |
| | (0.145) | (0.227) | (0.031) | (0.038) | (0.18) |
| $\Delta \ln P_{t-1}$ | 0.091 | -0.239 | -0.0154 | 0.023 | 0.869*** |
| | (0.11) | (0.209) | (0.011) | (0.019) | (0.131) |
| $\widehat{e}_{t-1}$ | -0.674* | -0.238 | 0.019 | -0.047 | -0.688 |
| | (0.363) | (0.209) | (0.098) | (0.106) | (0.663) |
| Country fixed effects | X | X | X | X | X |
| M1 (p value) | 0.038 | 0.40 | 0.23 | 0.25 | 0.11 |
| M2 (p value) | 0.38 | 0.07 | 0.35 | 0.65 | 0.39 |
| Hansen (p value) | 0.50 | 0.64 | 0.57 | 0.25 | 0.72 |
| Diff in Hansen (p value) | 0.96 | 0.60 | 0.73 | 0.59 | 0.93 |

*GMM-SYS estimates. Standard errors are two-step robust with the Windmeijer correction. M1 and M2 are Arellano-Bond tests for first and second order serial correlation. Hansen J is an overidentification test statistics; Diff-Hansen is a test for the validity of the extra moment conditions for the level equation. Instruments: y, lh, k, g, and p all dated T-5, T-6, T-7 for the level equation and* $\Delta lh, \Delta k, \Delta g, \Delta gdp, \Delta p$ *dated T-4, T-5 and T-6 for the level equation. Instruments have been collapsed (Roodman, 2009) to avoid the overfitting problems associated to the proliferation of instruments when T is large.*

Parameter estimates in Table 6 show that in all equations there is no evidence of second order serial correlation and both Hansen and Difference in Hansen test statistics suggest that we do not fail to reject the null hypothesis that instruments are uncorrelated with the error terms. Turning to parameter estimates, the coefficient of the error correction term ($\eta_1$) in the GDP equation is negative, as required for the system to be stable, and statistically significant at 10% level,[32] confirming that output is caused in the long run by the variables in equation (3); however, an F test on the joint significance of lagged variables fails to reject the hypothesis that they are jointly equal to zero, implying that there is not short run impact of the regressors on GDP. This result suggests that public capital investments might not be an effective countercyclical instrument, while it might be a valid tool for increasing GDP in the long run. Moreover, we can not reject the hypothesis that the coefficients of the error correction terms are equal to zero in all the other equations; this, together with the fact that a series of F tests suggest that lagged differenced variables are jointly statistically significant in the case of the private capital equation only, leads us to conclude that public capital, the stock of patents and human capital-augmented labour are strongly exogenous, while private capital is only weakly exogenous.

# 7 Conclusions

Public infrastructures have long been considered important inputs to economic and productivity growth. The basic intuition behind this is that improvements in public infrastructures are expected to raise the productivity of private inputs, to reduce the costs of production and raise total factor productivity.

Several empirical studies have tried to shed some light on this issue by adopting different approaches in term of sample choice, empirical models and econometric techniques: most works find that public capital has a positive impact on GDP, but the relative elasticity has been found to vary across studies.

In this paper we consider a panel of 21 OECD countries observed over the period 1975-2002 and we estimate different production function models in order to investigate the short and long run relationships between public capital and GDP; moreover, we investigate the role played by human capital and the innovation potential, captured by either the R&D or the patents capital stocks.

The novelty of our study rests in the adoption of the most recent econometric methodologies which control for the presence of cross sectional dependence and cross sectional cointegration in a panel time series framework. In particular, we assume that data are characterized by a common factor structure and we investigate both integration and cointegration analysis within the framework of the PANIC approach suggested by Bai and Ng (2004). This approach allows us to better identify the impact of our variables on GDP since, by treating cross sectional dependence, we account for possible bias stemming from spillover effects linked to spatial issues or trade linkages.

[32]The coefficient of 0.6 implies that the system returns to its log run equilibrium following a shock in less than two years.

Main results show that our series are not stationary and that cross sectional cointegration does exist among estimated common factors. We estimate the long run relationship among GDP and explicative variables with appropriate estimation techniques (Bai, Kao, and Ng, 2009) which account for such data characteristics.

On average, the econometric estimates suggest a long run elasticity of GDP with respect to public capital in the range of 0.05-0.15, while the average elasticity of GDP with respect to patents turns out to be about 0.10. Both results are in line with those suggested by most previous international evidence. Overall result are confirmed when we estimate the impact of public capital (as well as the patent stock) on TFP and when we augment the baseline model in order to account for possible effects of congestion and for the presence of spill-over effects stemming form infrastructure investments from neighboring countries. Short run analysis does not confirm the existence of a significative impact of public capital on GDP, thus suggesting that public capital investments might not be an effective countercyclical instrument, while it might have significant productive effects in the long run.

We believe that the empirical approach we have adopted in this study is particularly appropriate in the case of our sample that includes countries which are tied by different links deriving from geographical, historical, institutional and economic factors. Such characteristics deserve a specific treatment and might generate misleading results when not properly accounted for.

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