Udvari B. (ed) 2020: Proceedings of the 4th Central European PhD Workshop on Technological Change and Development. University of Szeged, Doctoral School in Economics, Szeged, pp 131–161.

Technological Change in the System of National Accounts – the Effect of New Capitalization Rules

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The increasing role of technological advancement in a nation's economic performance is also reflected in the recent changes to the System of National Accounts. As a result of the 2008 modifications in this macroeconomic accounting system, the expenses of research and development (R&D) are accounted as accumulation of capital and capitalized on the balance sheets. In the present research paper, I compare the strength of detectable relationships between the growth in economic performance and the different measurements of R&D at the level of nation economies. R&D is taken as stock type data from newly available statistics on the one hand and computed from flow type data on the other. The computation methods are tested with a regression using data from 2009 to 2017 for 15 European countries. The analysis may highlight not only the importance of technology, but also reveal information on the accounting treatment of R&D expense

Keywords: System of National Accounts, Asset capitalization, R&D productivity

1. Introduction

The most important change in the 2008 version of the System of National Accounts (SNA) is the capitalization of research and development (R&D) costs as intangible assets on the balance sheet of a nation's economy (EC et al. 2009). This change has a twofold relevance in the advancement of economic analysis studies. First, it highlights the ever-increasing importance of and attention paid to R&D activities as the engines of growth for modern economies. The new regulation is expected to give more opportunities to analysts to find better articulated relationships in the behaviour of such activities. Second, the capitalization of R&D is part of a lengthy process of extending the asset boundary accounted for in the national accounts. In fact, it seems to be a considerable milestone, since earlier capitalized assets all have reasonably fair and justifiable evaluation methods. In the case of R&D, however, the outcome of the investment expense is very uncertain both in magnitude and occurrence, if it happens at all. Under such circumstances, the evaluation and capitalization of an intangible asset requires more sophisticated approaches and methods on the part of economists and statisticians.

Is the capitalization of R&D in the national accounts of real help to economic analysis? The main question of this study is whether estimation results can be improved using the new stock type statistical data available due to this capitalization, instead of those calculated from flow type data in the old-fashioned way. Since the most important research question in the field of R&D from a macroeconomic point of view is the productivity growth achieved by R&D investments (Hall et al. 2009), I test the estimated values of R&D assets on an equation, which aims to find an economy's elasticity of overall productivity on the change of R&D assets.

In the second chapter I outline the asset capitalization problem, and the extension of the asset boundary from both the economist's and the statistician's point of view. In the third chapter I review the literature analysing the productivity of R&D at the macroeconomic level. Emphasis will be given to the choice and calculation of the R&D input, since that is the variable, which can be changed in the models to available statistical data. In the fourth chapter I prepare R&D productivity estimations with the help of a regression of 15 European countries with available data for the period between 2009–2017. The first two estimations will be performed with newly available statistical data of R&D assets, while the third and fourth estimation is prepared with R&D stock data calculated from the flow type R&D capital formulation data from the same data set in the way specified in earlier studies. Finally, the statistical and economic relevance of the two estimations will be compared.

2. Extension of the asset boundary

Initially macroeconomic models identified two distinct resources as factors of production and economic activity, labor and capital (Lichtenberg 1992). The interpretation of these factors was rather simple in taking into account only the tangible aspect of activities, and dividing it into a human related part in the one hand (labor) and a tool and structure related part on the other (capital). Both factors are essential for economic activity, still they behave in very different ways.

As for the tool and structure part, it was regarded as useful in the long-term in activities. These resources owned and operated by individuals and organizations and used over a longer period of time have to be planned and managed in order to achieve reasonable returns. Planning and management require measurements of value on the basis of expected future performance. Such measurements are then registered in regular points of time in a document listing the resources and their value to show the wealth, that is, the potential to produce useful goods and services for every economic unit. This document is generally called the balance sheet, where the use and the changes in the value of listed resources called assets, can be followed. Including an asset into this list is consequently called capitalization, signaling that the item is regarded as capital, or physical capital in a narrower sense (Lequiller-Blades 2014). Therefore, it was inevitable from the beginning that tools and structures have to be evaluated and accounted for as economic assets on balance sheets, that is, they have to be capitalized.

The human related part of production factors, on the other hand, proved to be much more difficult to evaluate. It is hard to decide whether these resources are utilized in a longer or a shorter run, while their productivity is highly uncertain. Both evaluation and management seemed to be almost impossible at first sight, because in this case we do not know the length of the utilization period, and also the performance of future periods can vary greatly. Moreover, it is not possible to put them onto a balance sheet, because they are inseparable from human beings, which in turn cannot be owned by economic units under the laws of modern societies respecting human rights (Lequiller-Blades 2014). The behavior of a human being will always carry more uncertainties than that of tools, machines and structures, therefore it was prudent to handle resources related to them separately, while avoiding their evaluation and capitalization in a balance sheet is also understandable.

Intangible drivers of growth and development like technological change were regarded to be exogeneous to these first-generation models (Lichtenberg 1992). This means that due to difficulties of interpretation and evaluation, economic accounting did not engage in predicting their future effect and regarded them to be out of the scope of economic calculations. This approach is understandable to a certain extent, as economists may not want to base calculations on overly unpredictable phenomena. However, the need of societies changed this situation.

Economists identified certain intangible factors of production included in those termed residual or technological change, and of which it was possible to find out at least something, even if punctual calculations were not feasible (Griliches 1998). Among these, human capital was the first, defined as the knowledge and experience of working people, which can be estimated by the means of measuring education activities (Lichtenberg, 1992). The human capital theory, building on the similarities of knowledge and physical capital, started to show the way ahead to including more types of resources in macroeconomic models and including them in calculations like endogenous factors. However, uncertainty still remained in terms of measurements, utilization period and productivity, and therefore evaluation and asset capitalization did not seem to make sense.

Likewise, a wide range of other types of intangible capital were researched, however measurement problems remained, therefore including them in capital formation and their capitalization was viewed as highly problematic (Vanoli 2005). Though the preface of the 1968 SNA prompted fast development in the modification of SNA recommendations to include balance sheets in the system, and extend the boundary of the included circle of assets (UNITED NATIONS 1968), these developments came along only partially in the 1993 modification (Vanoli 2005).

The most suitable intangible assets to be included in the SNA balance sheets and capital formation were those related to technological change. These, including R&D values, were widely researched in the preceding decades. The relationship between productivity and R&D received special attention, though mainly at the micro level (Lichtenberg 1992). This focus was understandable, if we take into account that most of the growth and the events of economies cannot be explained by the use of traditional types of resources, only by the ambiguous "residual" (Griliches 1998). On the basis of research conducted by Griliches and others, R&D expenses and assets seemed to play a major role in inducing economic growth. However, the quality of data available for such research was poor in many respects, especially in the case of R&D assets, although not only in their case.

According to the above proceedings, it was expected that in the course of the 1993 modifications of the SNA, R&D expenses would be included in capital formation and capitalized on the balance sheets, which were officially incorporated into the account system. Unfortunately, this was not to happen at that time. Debates started around the evaluation accuracy of human capital and finally its capitalization was rejected. Confidence wavered in accounting for intangibles altogether (including intangible human capital, R&D and other intangibles) and finally the experts among national accountants decided not to capitalize R&D expenses, either (Vanoli 2005). Nevertheless, some progress was made as a small group of intangibles, including software, artworks and expenses on mineral exploration were adopted as capital expenses, and therefore included on the balance sheets.

This stumbling in the process of extension of the asset boundary was corrected in the next round of modifications to the SNA. In 2008, the most important change was that capitalization of R&D assets became recommended, meaning they were now regarded as long term intentional investments in future performance. This change also brought about the change in the balance sheet that complete R&D results are now accounted for as produced assets, thus fully integrated into the logical sequence of the SNA similarly to produced tangible assets. With this step it is acknowledged also in statistics that technological change is not an exogeneous factor to the economy, as it was anticipated by the early macroeconomic models, but that technological development can to a certain extent be managed through the control of the R&D expenses which fuel it. The changes were consequently recommended in ESA 2010 (European System of Accounts), the corresponding set of rules for the statistics of the European Union (EC et al 2009, EUROSTAT 2014/a).

The need for further extensions of the asset boundary, that is, including further asset types in the balance sheet and capital formation is obvious from the perspective of economists, as stock type data are consistently used in economic analyses as variables. These variables, however, have been mostly calculated from the available statistics by simplified methods according to the limited possibilities of economists using them (e.g. calculations of Guellec and van Pottelsberghe 2001). Perhaps, economic analyses would be more informative, if the calculation of the values of R&D assets is done by statisticians applying a wider information basis. If we wish to find explanations for the changes in productivity in economies, we should seize any opportunity to calculate the value of intangibles more accurately. The importance of innovations, knowledge, communication, and many other intangibles in productivity growth has been inevitable since at least the 1980's (Vanoli 2005).

However, there are fundamental problems to asset evaluation in the case of intangible assets. By general definition, the value of an asset can be calculated at best with its future contribution to economic wealth. This value can be estimated by the markets as the average evaluation of market players or can be estimated by economists applying for example net present value calculations (Lequiller-Blades 2014). Mostly, market prices are considered to be closer to the true value, though in their absence, at cost calculations are thought to be the second-best solution for asset evaluation (EUROSTAT 2014/b). At present, uncertainty is high in every aspect of asset evaluation when applied to intangibles. The problems are listed in the next three paragraphs.

First of all, we cannot be sure of what we are measuring by economic wealth or economic growth. Some assets contribute to the well-being of people, though this performance is not measurable, and if it is not paid in money, is not regarded as economic (Hall et al. 2009). On the other hand, some measurable contributions do not really serve true development of a society, therefore measured productivity may not be in line with the development of a country or region. However, these uncertainties are equally true for tangible assets, so it should not affect the extension of the asset boundary to include more intangibles.

Second, it is often cited, especially in the case of R&D, that results from such expenses occur in a random way, therefore the positive relationship between R&D investment and productivity cannot be justified (Vanoli 2005). This argument can be countered with the statistical success of such investments. At the macroeconomic level R&D expenses are very likely to produce good results even if lots of individual projects fail. It is also worth noting that positive relationship between R&D and productivity is definitely revealed even at the micro level using only poor-quality data (Griliches 1998).

Third, the measurement of consumption of R&D is uncertain, as well. Intangibles do not have depreciation as defined in the case of tangible assets. The amortization of intangibles comes from obsolescence instead of planned wearing out. Again, this is also the case with many tangible assets (Vanoli 2005), therefore this should not be an obstacle in the way of expanding the asset boundary.

Intangible assets are difficult to mobilize, many of them do not have a market at all. In the absence of market prices, asset evaluation cannot be regarded as punctual. The secondbest estimation of evaluating them at cost often results in lower values than for those assets valued by markets. In the case of R&D evaluation, this phenomenon often occurs in connection with government investments (Griliches 1998). In case of self-production or common consumption, the additional value given by the market to the asset is missing. Though this argument is valid indeed, it is a common feature with some of the tangible assets.

The problems of asset evaluation are inevitably present in the case of R&D assets. Still, they are profoundly different from human capital in that they are separable from the human being and belong to economic units. Obsolescence can be traced, and therefore their evaluation is not much more difficult than that of tangible assets. In fact, even investment in the most conventional tangible assets has always involved some risks (Vanoli 2005).

Taking the above into account, including R&D assets on the balance sheet and in capital formation seems justifiable. It had been demanded by economists researching the topic for a long time, and the need for possible explanations of changes in economic performance will necessitate more research towards extending the asset boundary even further. Still, asset evaluation problems warn us to be cautious (Räth 2016). If the value calculated for intangible assets does not represent their real value, calculations done with them may secede from reality, and economists may once again end up being unable to provide valid explanations for the events of economies. This risk, however, has always been present in economic research. The economy cannot be described by the old models of easily interpretable tangibles any more. While these models may still be valid, their explanatory strength has certainly lessened (Griliches 1998), and therefore measuring new assets and new relationships is necessary, even if the uncertainty in using them is ever increasing.

3. Analyses on the effectiveness of R&D activities at the macroeconomic level

Research on the effect of R&D on economic performance started almost simultaneously with the creation of macroeconomic models in the 1950-ies (Griliches 1998). The basic model interpreted the residual in economic growth not accounted for when calculating the effect of conventional factors of production, as the effect of technological change. Taking this as a starting point, it was simply natural to continue thinking in the direction of finding a relationship between R&D and productivity. However, this research took place mainly at the micro level.

The macro level studies were conducted either as cross-country comparisons or temporal case studies. The first combined estimation was done by Lichtenberg only in 1992 (Lichtenberg 1992, Hall et al. 2009). The basis of research in most cases was the traditional Cobb-Douglas production function augmented with research and development as an additional type of capital. In older studies, R&D was examined together with other capital types, most importantly with conventional physical capital, but sometimes with human capital, as well. However, even R&D capital was further divided into different parts already in earlier research, as their effect on productivity was expected to be different. As for the combined effect of all R&D investments it was remarked that the effect is positive and significant (Hall et al. 2009).

The positive and significant effect of R&D on productivity was measured through very different models and approaches. The dependent variable (productivity), the independent variable of interest (R&D), and the control variables were constructed in different ways. It is remarkable that in all cases the result was a statistically significant and positive coefficient (Hall et al. 2009).

The dependent variable in these equations is a performance measurement, which can be either a productivity ratio (level estimation) or its growth rate. A productivity ratio divides a performance indicator by the amount of resources used up to produce it. The performance indicator in macroeconomic studies is most often the GDP or some other aggregated income figure (sometimes called output), while the dividing amount of resource can be one or more of the factors of production accounted for in the model. The total factor productivity, for example, takes into account both capital and labor when dividing GDP or value added, but in many cases, the number of working or working-aged people, perhaps even population size, represent the amount of resources.

The independent variable of interest, which in this case represent the R&D activity, can be a stock type amount showing the accumulated value of R&D assets, or a flow type amount as expenses or investments. In many cases the independent variable of interest is a ratio itself, dividing the R&D amount by economic performance or total investments. In these cases, the variable of interest is the share of R&D within the total of activities. The growth rate of R&D amounts also can be regarded as an independent variable. Regarding the long term and uncertain nature of R&D investments, it is worth including some lags into the regression. Often the R&D figures are those of some previous years or computed as the average of earlier years compared to the dependent variable.

The distinction between stock and flow type measurements deserve special attention. Most of the studies apply a stock type R&D amount (Guellec-van Pottelsberghe 2001, Chandra et al. 2018). The rationale behind this may be that in case of long-term assets the expenditures will have an effect in more future years, therefore probably would not give a good estimation result in a regression with one dependent variable. However, stock type data is more difficult to access. In case of R&D, it is hardly observable directly. If there are no statistics available, economists can compute an R&D stock figure from flow type data for example with the help of the perpetual inventory method, which is also widely used (Lequiller-Blades 2014, Guellec-van Pottelsberghe 2001). The problem here is that for this method we need to know the amount of investment and depreciation for all the years. Investments as flow type data are mostly available, though we may have serious problems with depreciation rates. If no better estimation is available, it is possible to use a fixed depreciation rate. However, it has to be remarked that depreciation in the case of intangible assets like R&D is obsolescence and called amortization (Vanoli 2005). Amortization means devaluations, which do not happen in equal portions in a timely manner as in the case of planned depreciation of physical assets, therefore fixed depreciation rates in case of intangible assets certainly would distort the results. This is due to a fundamental difference between tangible and intangible assets, that tangible assets do lose further utilization capacity when used, while intangibles remain equally useful for an indeterminable length of time. If they lose value, it occurs as obsolescence and not as a result of utilization, therefore it would be inappropriate to relate their service to their loss in value within a time period.

Regressions of productivity and R&D may include a series of control variables. Mainly, these are country specific variables of size or economic situation. In case of panel regressions, it is also possible to include time lag variables of the dependent variable.

In the literature, relatively few studies deal with cross-country and temporal comparisons together (Hall et al. 2009). Measurement problems and the poor availability of data may have discouraged this type of research for a long time. With the 2008 modification of the SNA, comparable stock type R&D statistical data is now available for many countries, therefore panel research will perhaps be easier in the future. Anticipating this, it is worth outlining previous research done in this specific direction.

First, Lichtenberg made a comparison between data from 74 countries all over the world in 1992. He used real GDP/working age population as an overall productivity ratio for the dependent variable of the regression calculated for the year 1985. The independent variable of interest was the share of nominal R&D investments in nominal GNP in a 25-year average between 1964 and 1989. The author examined several other factors of production, among them human capital and physical capital, and controlled for the population growth rate. A fixed depreciation rate of 0.03 was applied. The estimation was done also for the growth rate dependent variable version. The results of the non-linear least squares regression showed that both R&D elasticity and production function parameters were in positive relationship with productivity over this longer period, and their significance and strength was equally high as those of physical capital (Lichtenberg 1992).

Guellec and van Pottelsberghe prepared a panel regression for 16 OECD countries for the years 1980–1998 (Guellec and van Pottelsberghe 2001). Their dependent variable was the multi factor productivity of the industrial sector. For independent variables they used R&D stock figures calculated by the perpetual inventory method with a fixed depreciation rate of 0.15. They were interested in the coefficients of the domestic business R&D stock, the foreign capital stock and the public R&D stock, but did not calculate the strength of relationship between the overall R&D stock and productivity. R&D stocks were taken into the regression equation with a two-year lag, while their growth with a one-year lag. Productivity growth was also included with one-year lag and productivity level with a two-year lag. For control variables a business cycle effect was included and a dummy variable for Germany signaling the years before and after unification. The model was estimated with 3 stage least squares and seemingly unrelated regression estimation methods. The results of regressions showed positive elasticity for all the three types of R&D stocks.

All these results reinforce the notion that the relationship of R&D and productivity in an economy is positive. Time lags in the independent variables should be included, though there are different methods of doing this. However, the use of stock type R&D data seems to be necessary (Hall et al. 2009), even if they can be calculated only with serious distortions. The main reason for this is that productivity may be boosted by research and development costs spent in many earlier years, and therefore the accumulated value of R&D seems appropriate for estimations.

4. Comparison of R&D net asset statistics with R&D stock figures calculated from flow type data

In this paper I examine the results of a regression equation, where the dependent variable is productivity at the macro level, and the independent variable of interest is R&D. My aim is primarily to compare the performance of newly available data with the results produced by more usual data processing methods. For an accurate estimation of the effect of R&D expenses on productivity growth, longer time data is needed, as it is still not possible to fully characterize their operating pattern in the few years that have elapsed since the 2008 financial crisis.

4.1. Data and Methods

I use data of the national accounts compiled according to the rules of SNA 2008 and ESA 2010. This set of data already contains R&D expenses as capital expenditures, and R&D stock data (net assets) is also provided. The same regression is done for the net assets data given in the statistics, and for net assets data calculated by the perpetual inventory method from available R&D expenses figures. The latter method is widely used in econometric papers and statistics (Lequiller-Blades 2014). My aim is to find out whether the new rules of statistical data compilation can improve the results of regressions compared to earlier calculations.

It is not usual to examine periods shorter than 12 years in a study of R&D effects. This can be especially problematic at the country level, since effects are not likely to be observable at higher levels of aggregation, where productivity is influenced by a multitude of factors. My reason for trying to estimate a regression with macroeconomic data for only 9 years is that I was curious, whether the newly available stock type R&D statistics can produce any better estimations than the previous data under these hard conditions. The regression I apply is an OLS regression as the length of the data time series is not adequate for a panel regression. I use the GDP and R&D figures of 15 European countries for the years 2009–2017. All my data are derived from the easily available national accounts statistics of Eurostat (EUROSTAT 2019).

In my present study, the dependent variable is the growth of GDP per capita directly taken from Eurostat statistics. The independent variables of interest are different aggregated R&D data given in the national account statistics. The control variables are also taken from statistics and include a time trend and controls for size and country specifics. Undoubtedly this regression is suitable to reveal less detailed information that way than panel regressions used in previous studies (e.g. Guellec and van Pottelsberghe 2001). Still, my aim does not go further than to find results for a shorter period with the help of more accurate data.

Based upon the above principles the first estimated equation with R&D net asset data taken directly from Eurostat statistics is:

$$GrGDPc = const + \alpha_1\, GrNA\_1 + \alpha_2\, GrNA\_2 + \alpha_3\, GrNA\_3 + \beta\, LNA\_2 + \gamma_i\, X_i + e \quad (1)$$

Here the dependent variable *GrGDPc* is the growth rate of GDP/capita between two subsequent years representing the change in productivity. The regressors are the following:

- *const*: constant
- *GrNA_1*, *GrNA_2*, *GrNA_3*: the growth rates of R&D net assets statistics between two subsequent years in one, two, and three-year lags, respectively (net asset data taken directly from statistics)
- *LNA_2*: the log of R&D net assets statistics in two years lag (net asset data taken directly from statistics)

- X_i: four control variables: a time trend, a country index, the log of population size and the log of GDP/capita in one-year lag.

The variables of interest are *GrNA_1*, *GrNA_2*, *GrNA_3* and *LNA_2* as they show the effects of R&D on productivity. The control variables control for the time, the size, the economic development level, and other specifics of the countries.

All of these regressions were conducted including a time trend for addressing trend stationarity. Difference stationarity, however, was not handled in the first regression. The reason for this is that in the case of the relationship between productivity and R&D, it is possible to have factors which affect productivity and the value of R&D in a different way, disturbing their co-movement, but still do not influence the underlying basic connection between them. Here, for example, I would point to those research results, which were not implemented in practice within the first years of existence. Though it is supposed that they are or would be useful, their application for the time can be delayed. In these cases, their productivity effect is not discernible. Nevertheless, they do not wear off due to this delay. Productivity may drop or stagnate while R&D values are relatively high or even rising, still at an overall scale we should not accept that this means R&D is ineffectual or not in significant relationship with productivity. Their true effect in my opinion can be grasped exactly in those non-stationary co-movements, which are eliminated by difference stationarity treatment.

Despite this concern, in the second regression all variables were tested for stationarity and treated by differencing in order to achieve difference stationarity, as well. The corresponding unit root tests are included in Appendix 1, where the names of variables contain the letter "d" for differencing. Both regressions were calculated with robust (HAC) standard errors to address heteroskedasticity and autocorrelation.

The coefficient of *LNA_2* gives the component of productivity raising effects, which is exercised by existing and accumulated stock type R&D assets. In other words, *LNA_2* represents the accumulated intellectual capital, which is assumed to be effective in a two-year lag on productivity (e.g. also in Guellec and Pottelsberghe 2001). Since effects later on are also likely as the R&D assets do not wear off with utilization, it is acceptable to make calculations using the stock type figure. Valuable assets remain on the balance sheet and continue to have effects on productivity. The coefficients of *GrNA_1, GrNA_2, GrNA_3* show the productivity effect of changes in R&D assets, that is, the flow type investments in time lags. This can be interpreted as an elasticity measurement or the effect of newly-created R&D capital on productivity. It should be noted that depreciation or utilization of R&D assets calculations were done by statisticians in this case. The applied stock type data were compiled with a very detailed version of the perpetual inventory method. This method is also used by statisticians, though they have more detailed information, and do more punctual estimations than economists can do (Lequiller-Blades 2014).

The third estimated equation works with R&D stock data calculated by the perpetual inventory method from R&D capital formation statistics by the analyst, as specified by Guellec and Pottelsberghe. This method estimates R&D stock from the actual R&D expenditures and an initial value of R&D expenses with the following formula:

$$pNA = CF/(1\text{-}1/(1+(CF/CF_0)^{1/n}\,(1\text{-}\delta))) \qquad (2)$$

In this formula *CF* is the figure of R&D capital formation in a given year, while CF_0 is the R&D capital formation of a selected initial year. The letter *n* indicates the number of years spanning the time length of calculations, finally δ is for the depreciation rate. Depreciation rate was set as 0.15 by Guellec and van Pottelsberghe in their 2001 study of R&D effect on productivity. They also concluded that their model was not sensitive to the change in the depreciation rate (Guellec-van Pottelsberghe 2001). I applied the depreciation rate given in this basis study. As data for comparison with R&D, net asset statistics is available for 7 years I set $n = 7$. CF_0 is the R&D capital formation statistic figure of 2009.

The third regression equation is put together partly from the same statistics as the first, only R&D figures are replaced by those calculated with the formula above:

$$GrGDPc=const+\alpha_1\, GrpNA\_1+\alpha_2\, GrpNA\_2+\alpha_3\, GrpNA\_3+\beta\, LpNA\_2+\gamma_i\, X_i+e \qquad (3)$$

Here the dependent variable is GrGDPc again, which is the growth rate of GDP/capita between two years. The independent variables are the followings:

- *const*: constant
- *GrpNA_1*, *GrpNA_2*, *GrpNA_3*: the growth rates of R&D stocks between two subsequent years in one, two and three-year lags respectively (net asset data calculated from flow data with the perpetual inventory method)
- *LpNA_2*: the log of R&D stock in two-year lag (net asset data calculated from flow data with the perpetual inventory method)
- X_i: four control variables: a time trend, the log of population size, the log of GDP/capita with a one-year lag and a country index.

The variables of interest were changed in this third equation to *GrpNA_1*, *GrpNA_2*, *GrpNA_3* and *LpNA_2*, as they are calculated in a different way, although their meaning and interpretation remained the same. All the other variables remained unchanged.

Depreciation rate enter into this estimation as a parameter used in calculating the variables *GrpNA_1*, *GrpNA_2*, *GrpNA_3*, and *LpNA_2*. It is set as fixed all over the period and for all countries in this calculation model, since detailed information of its true value was not available. Regarding the special features of intangible assets, among them R&D stocks, counting with fixed depreciation rates can cause serious distortions in the results, as losing value in the case of R&D assets is anything but fixed in time and space. However, in case of longer time series, the approximation provided by the perpetual inventory method may be appropriate in case of missing data on R&D assets.

The fourth regression was also done with varibales calculated by the perpetual inventory method, but this time all the variables were differenced in order to address difference stationarity, similarly to the second regression. The third and fourth regressions were estimated with robust (HAC) standard errors in order to address autocorrelation and heteroskedasticity, similarly to the first two estimations.

4.2. The effect of R&D on productivity calculating with R&D net asset statistics

The results of the first regression calculation (equation (1) without differencing treatment) are summarized in *Table 1* as follows.

Table 1 Regression result of measuring the elasticity of productivity on R&D investment with R&D net asset statistics, European countries, 2009–2017

	Coefficient	***Std. Error***	***p-value***
Dependent variable: GrGDPc			
GrNA_1	0.113	0.064	0.1002
GrNA_2	0.087	0.031	0.0151
GrNA_3	– 0.005	0.069	0.9389
LNA_2	0.058	0.025	0.0362
R^2	0.587	*Adjusted* R^2	0.537
Durbin-Watson:		1.04	

Source: own construction based on Eurostat data

In the first case, calculating with R&D net asset statistics without difference stationarity treatment, the coefficient of *LNA_2* is significant at the 5% significance level and positive. The result for *GrNA_2* is also statistically significant at the 5% level and positive. This indicates that using data directly from statistics and the usage of stock type figures for estimating the effect of R&D activity on productivity is justified. The level of accumulated R&D has a positive effect on productivity growth two years later, while the effect of additional R&D investments on productivity in the next years is also likely.

All these are largely in line with the findings of previous studies. R-squared values are also consistent with those obtained earlier (around 0.5 in Guellec-van Pottelsberghe 2001). Therefore, in spite of having shorter time series, it is possible to draw similar conclusions with the help of R&D net asset statistics to those of previous studies.

The second regression calculated with the variables adjusted for difference stationarity (equation (1) with differencing treatment) is shown in *Table 2.*

Table 2 Regression result of measuring the elasticity of productivity on R&D investment with R&D net asset statistics (treated for difference stationarity), European countries, 2009–2017

	Coefficient	**Std. Error**	**p-value**
Dependent variable: ddd GrGDPc			
dd GrNA_1	– 0.107	0.101	0.3044
d GrNA_2	– 0.362	0.471	0.4553
GrNA_3	– 0.013	0.157	0.9359
dd LNA_2	0.535	1.13	0.6431
R^2	0.806	*Adjusted* R^2	0.783
Durbin-Watson:		1.745	

Source: own construction based on Eurostat data

In this case, calculating with R&D net asset statistics, the coefficient of *ddLNA_2* is not significant after differencing. The results for the growth variables *ddGrNA_1*, *dGrNA_2*, and *GrNA_3*, are also not significant statistically.

It is apparent that if difference stationarity requirements are not applied, significant results can be achieved. On the other hand, differencing the variables according to requirement gives no significant results. This confirms that other factors have significant effects on productivity, some of them affecting R&D similarly, some of them differently. In the meantime, R^2 values and the Durbin-Watson test value improved a lot compared to the first case. Also, due to the relatively short period of time examined, it is not possible to say much about the relationship of productivity and R&D under these requirements.

4.3. The effect of R&D on productivity calculating net assets by the perpetual inventory method

Results of the third regression (equation (3) without differencing treatment) are summarized in *Table 3*.

Table 3 Regression result of measuring the elasticity of productivity on R&D investment with estimated R&D stock from R&D capital formation, European countries, 2009–2017

	Coefficient	**Std. Error**	**p-value**
Dependent variable: GrGDPc			
GrperpNA_1	0.016	0.011	0.1564
GrperpNA_2	0.003	0.007	0.6583
GrperpNA_3	– 0.025	0.044	0.5814
LperpNA_2	0.044	0.033	0.1416
R^2	0.498	*Adjusted* R^2	0.438
Durbin-Watson:		0.829	

Source: own construction based on Eurostat data

The results of the third regression show that the variables of interest – *GrperpNA_1*, *GrperpNA_2*, *GrperpNA_3,* and *LperpNA_2* – do not have statistically significant and interpretable coefficient values. Furthermore, R-squared values are worse than in the first model.

The results of the fourth regression applying variables estimated by the perpetual inventory method and treated for difference stationarity are given in *Table 4.*

Table 4 Regression result of measuring the elasticity of productivity on R&D investment with estimated R&D stock from R&D capital formation (treated for difference stationarity), European countries, 2009–2017

	Coefficient	***Std. Error***	***p-value***
Dependent variable: ddd GrGDPc			
dGrperpNA_1	– 0.017	0.017	0.3420
dGrperpNA_2	– 0.014	0.051	0.7836
GrperpNA_3	– 0.022	0.092	0.8101
dLperpNA_2	– 0.039	0.253	0.8785
R^2	0.802	*Adjusted* R^2	0.778
Durbin-Watson:		1.776	

Source: own construction based on Eurostat data

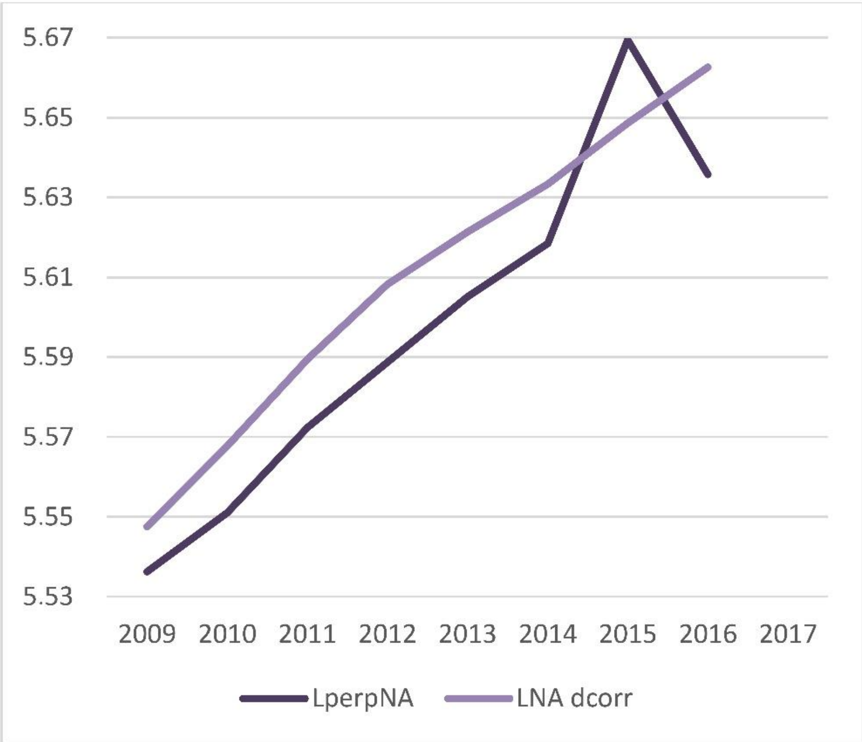
In this regression neither of the included variables have significant coefficients, again. However, due to the differencing treatment, R^2 values and the Durbin-Watson test variable are better than in the case of not controlling for difference stationarity. Differencing treatment inevitably improves the statistical features of the regression, still we cannot say anything else about the relationship of the examined phenomena other than that seemingly there is no significant co-movement at this stage.

4.4. Comparison of the R&D net assets statistics and R&D stock calculated by the perpetual inventory method

There are serious limitations in using the above calculations for evaluating the impact of R&D on productivity. The time period is too short to include the longer-term effects and also the circle of examined countries is limited. In the first years of the data series the effects of the 2008 crisis was still observable in many countries, lowering their productivity growth. All these problems imply that the model carries a high degree of uncertainty and it seems difficult to arrive at an interpretable result. For individual countries or years, it is not possible to draw relevant conclusions, no matter, which type of calculations we use.

Taking into account all these uncertainties, it seems to be a positive result for measurements using R&D net asset statistics untreated for difference stationarity, the calculated coefficient of the R&D asset level being significant and positive in relation to productivity growth. The R&D stock figures, also calculated from national accounts data with the usual perpetual inventory method, were not able to produce similar results. In order to determine the difference in their behaviour, Figure 1 shows their values aggregated for the included countries through the period examined.

Figure 1 Net asset statistics and perpetual R&D stocks in 15 European countries, in log of million euro



Source: own calculation on the basis of Eurostat data (EUROSTAT 2019). Data is shown with a shift in order to make them more comparable.

Figure 1 shows that the values of R&D net assets were more stable throughout the period than values of the calculated R&D stock. The run of *LperpNA* is much more bumpy, with an outstanding value in 2015. This is not surprising taking into account that *LperpNA* is calculated from the capital formation figures of each year, which being flow type data, show much more variability.

Also, using R&D net asset statistics treated for difference stationarity, the calculated coefficient of the R&D asset level was closer to significance than the figures calculated from flow data. This, however, does not say anything about the actual relationship of productivity and R&D, although it may be informative for the comparison of R&D data taken directly from the statistics and calculated by the perpetual inventory method by the analyst. The data of the statistics perform better than the calculated data even in the absence of interpretable results.

From the above calculations it is clear that R&D net asset statistics provide a better solution for macroeconomic estimations of the effects of R&D activities on productivity than earlier methods, which has been used in the absence of more reliable data. The difference between the two sets of estimations lies in the measurement of R&D stocks. The figures given in the statistics are compiled on the basis of more information with a more elaborate methodology than figures calculated from flow type data.

5. Conclusion

As indicated by the above analysis, R&D net asset statistics provide a better basis for future research of R&D than the previously calculated R&D stock figures. This is true not only for estimation models, which have been in use for decades, but probably, new, perhaps more simple models could also provide results, which make sense. This might well be an important step ahead in economic analysis, because research of the R&D activities at the country level has always had difficulties in obtaining statistically relevant results due to the relatively small value of R&D figures compared to GDP or total production of a country.

R&D expenses are, however, inevitably long-term investments. Their effect on productivity is observable only after a certain time lag, therefore longer time series of data will always be necessary for deeper analysis. The time span of 9 years applied here is too short to obtain an interpretable result, therefore it would be useful to conduct similar research if at least twelve-year data sets are available. It may also be useful to try more diverse estimation methods, dynamic panel regressions among others.

The case of R&D capitalization shows that extending the asset boundary is a process which is truly worthwhile. The possibility of better and faster interpretation of data is an important advantage for economists as data users, even if advancement in this field of statistics is full of difficulties. Careful consideration and innovative thinking on new methods of evaluation and possibilities of asset capitalization therefore should be welcome and continued.

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Appendix 1.

Dickey-Fuller tests were run for all the variables applied in this study. The variables were treated for difference stationarity by differencing the times the letter "d" is written before the name of the variable. The tests here show the performance of the variables after the treatment. In the case of GrNA_3 differencing treatment was not necessary, therefore its test is shown without such treatment.

1. dddGrGDPc
Dickey–Fuller test for d_d_d_GrGDPc
with constant and trend
model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
estimated value of (a – 1): –0.193648
test statistic = –0.419554 [0.8616]
Unit 2, T = 4, lag order = 0
estimated value of (a – 1): –3.27577
test statistic = –4.83507 [0.1114]
Unit 3, T = 4, lag order = 0
estimated value of (a – 1): –1.22606
test statistic = –2.07901 [0.4355]
Unit 4, T = 4, lag order = 0
estimated value of (a – 1): –1.20225
test statistic = –2.14467 [0.4169]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –1.63588
test statistic = –2.10067 [0.4344]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –1.95584
test statistic = –2.35224 [0.3662]
Unit 7, T = 4, lag order = 0
estimated value of (a – 1): –1.12362
test statistic = –1.71123 [0.6460]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): –1.63361
test statistic = –4.84013 [0.1113]
Unit 9, T = 4, lag order = 0
estimated value of (a – 1): –1.64289
test statistic = –3.9532 [0.1799]
Unit 10, T = 4, lag order = 0
estimated value of (a – 1): –0.68602
test statistic = –1.02014 [0.7988]
Unit 11, T = 4, lag order = 0
estimated value of (a – 1): –1.82295

test statistic = –9.23072 [0.0178]
Unit 12, T = 4, lag order = 0
estimated value of (a – 1): –1.17463
test statistic = –5.98687 [0.0645]
Unit 13, T = 4, lag order = 0
estimated value of (a – 1): –1.64351
test statistic = –144.701 [0.0001]
Unit 14, T = 4, lag order = 0
estimated value of (a – 1): –1.93287
test statistic = –3.317 [0.2527]
Unit 15, T = 4, lag order = 0
estimated value of (a – 1): –1.63224
test statistic = –22.6691 [0.0007]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –14.0907
Choi meta–tests:
Inverse chi–square(30) = 70.0645 [0.0000]
Inverse normal test = –3.3876 [0.0004]
Logit test: t(79) = –3.96014 [0.0001]

2. ddGrNA_1
Dickey–Fuller test for d_d_GrNA_1
with constant and trend
model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
estimated value of (a – 1): 0.610005
test statistic = 0.911672 [0.9571]
Unit 2, T = 4, lag order = 0
estimated value of (a – 1): –1.91053
test statistic = –1.86846 [0.4852]
Unit 3, T = 4, lag order = 0
estimated value of (a – 1): –1.19174
test statistic = –1.33388 [0.7418]
Unit 4, T = 4, lag order = 0
estimated value of (a – 1): –1.74239
test statistic = –6.40493 [0.0568]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –2.07273
test statistic = –6.85839 [0.0461]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –2.45508
test statistic = –38.2313 [0.0001]
Unit 7, T = 4, lag order = 0

estimated value of (a – 1): –1.69746
test statistic = –4.51511 [0.1288]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): –1.35296
test statistic = –2.34524 [0.3667]
Unit 9, T = 4, lag order = 0
estimated value of (a – 1): –3.40445
test statistic = –11.2602 [0.0094]
Unit 10, T = 4, lag order = 0
estimated value of (a – 1): –1.74276
test statistic = –2.56499 [0.3332]
Unit 11, T = 4, lag order = 0
estimated value of (a – 1): –1.63915
test statistic = –2.16774 [0.3884]
Unit 12, T = 4, lag order = 0
estimated value of (a – 1): –1.67623
test statistic = –3.59898 [0.2278]
Unit 13, T = 4, lag order = 0
estimated value of (a – 1): –1.8626
test statistic = –2.36419 [0.3654]
Unit 14, T = 4, lag order = 0
estimated value of (a – 1): –5.25995
test statistic = –21.8766 [0.0009]
Unit 15, T = 4, lag order = 0
estimated value of (a – 1): –1.6414
test statistic = –5.89222 [0.0699]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –7.35804
Choi meta–tests:
Inverse chi–square(30) = 76.3769 [0.0000]
Inverse normal test = –3.84525 [0.0001]
Logit test: t(79) = –4.41626 [0.0000]

3. dGrNA_2
Dickey–Fuller test for d_GrNA_2
with constant and trend
model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
estimated value of (a – 1): –0.854175
test statistic = –2.33852 [0.3672]
Unit 2, T = 4, lag order = 0
estimated value of (a – 1): –1.60642
test statistic = –0.99044 [0.8010]

Unit 3, T = 4, lag order = 0
estimated value of (a – 1): –1.16794
test statistic = –1.81484 [0.6044]
Unit 4, T = 4, lag order = 0
estimated value of (a – 1): –1.63114
test statistic = –2.0494 [0.4503]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –2.35358
test statistic = –196.767 [0.0001]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –2.53276
test statistic = –2.15267 [0.4161]
Unit 7, T = 4, lag order = 0
estimated value of (a – 1): –1.76964
test statistic = –3.99068 [0.1777]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): 1.14609
test statistic = 2.36076 [0.9995]
Unit 9, T = 4, lag order = 0
estimated value of (a – 1): –5.28808
test statistic = –7.25866 [0.0384]
Unit 10, T = 4, lag order = 0
estimated value of (a – 1): –2.62841
test statistic = –8.6278 [0.0222]
Unit 11, T = 4, lag order = 0
estimated value of (a – 1): –1.58793
test statistic = –2.14455 [0.4169]
Unit 12, T = 4, lag order = 0
estimated value of (a – 1): –1.73344
test statistic = –3.0914 [0.2680]
Unit 13, T = 4, lag order = 0
estimated value of (a – 1): –1.19143
test statistic = –2.69728 [0.3107]
Unit 14, T = 4, lag order = 0
estimated value of (a – 1): 1.02177
test statistic = 0.260567 [0.9314]
Unit 15, T = 4, lag order = 0
estimated value of (a – 1): –1.62597
test statistic = –1.94437 [0.4730]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –15.5498
Choi meta–tests:
Inverse chi–square(30) = 51.1795 [0.0093]

Inverse normal test = –1.19496 [0.1161]
Logit test: t(79) = –1.31793 [0.0957]

4. ddLNA_2
Dickey–Fuller test for d_d_LNA_2
with constant and trend
model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
estimated value of (a – 1): –0.864664
test statistic = –2.29519 [0.3757]
Unit 2, T = 4, lag order = 0
estimated value of (a – 1): –1.609
test statistic = –0.997231 [0.8005]
Unit 3, T = 4, lag order = 0
estimated value of (a – 1): –1.16964
test statistic = –1.81256 [0.6044]
Unit 4, T = 4, lag order = 0
estimated value of (a – 1): –1.63304
test statistic = –2.06152 [0.4491]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –2.37382
test statistic = –124.108 [0.0001]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –2.54716
test statistic = –2.16458 [0.4150]
Unit 7, T = 4, lag order = 0
estimated value of (a – 1): –1.76983
test statistic = –4.00616 [0.1767]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): 1.2207
test statistic = 1.3866 [0.9724]
Unit 9, T = 4, lag order = 0
estimated value of (a – 1): –4.94891
test statistic = –8.4206 [0.0253]
Unit 10, T = 4, lag order = 0
estimated value of (a – 1): –2.625
test statistic = –8.27543 [0.0266]
Unit 11, T = 4, lag order = 0
estimated value of (a – 1): –1.5957
test statistic = –2.14848 [0.4165]
Unit 12, T = 4, lag order = 0
estimated value of (a – 1): –1.73336
test statistic = –3.0663 [0.2705]
Unit 13, T = 4, lag order = 0

estimated value of (a – 1): –1.19002
test statistic = –2.65139 [0.3206]
Unit 14, T = 4, lag order = 0
estimated value of (a – 1): 1.54343
test statistic = 0.312558 [0.9370]
Unit 15, T = 4, lag order = 0
estimated value of (a – 1): –1.6039
test statistic = –1.82626 [0.5461]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –10.8089
Choi meta–tests:
Inverse chi–square(30) = 51.3039 [0.0090]
Inverse normal test = –1.50048 [0.0667]
Logit test: t(79) = –1.85661 [0.0335]

5. ddddLcap (log of population size)
Dickey–Fuller test for d_d_d_d_Lcap
with constant and trend
model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
estimated value of (a – 1): –1.84707
test statistic = –5.45565 [0.0790]
Unit 2, T = 4, lag order = 0
estimated value of (a – 1): –1.743
test statistic = –3.50544 [0.2347]
Unit 3, T = 4, lag order = 0
estimated value of (a – 1): –1.85375
test statistic = –2.52342 [0.3420]
Unit 4, T = 4, lag order = 0
estimated value of (a – 1): –2.47153
test statistic = –1.00244 [0.8001]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –1.72874
test statistic = –2.36393 [0.3654]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –1.48079
test statistic = –1.64201 [0.6577]
Unit 7, T = 4, lag order = 0
estimated value of (a – 1): –1.67809
test statistic = –2.29472 [0.3757]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): –1.8169
test statistic = –21.6438 [0.0009]

Unit 9, T = 4, lag order = 0
  estimated value of (a – 1): –6.31262
  test statistic = –6.74043 [0.0481]
Unit 10, T = 4, lag order = 0
  estimated value of (a – 1): –1.12536
  test statistic = –5.03574 [0.1051]
Unit 11, T = 4, lag order = 0
  estimated value of (a – 1): –2.05561
  test statistic = –7.43322 [0.0361]
Unit 12, T = 4, lag order = 0
  estimated value of (a – 1): –1.80472
  test statistic = –8.10121 [0.0282]
Unit 13, T = 4, lag order = 0
  estimated value of (a – 1): –1.32686
  test statistic = –2.10591 [0.4341]
Unit 14, T = 4, lag order = 0
  estimated value of (a – 1): –2.40826
  test statistic = –10.3771 [0.0117]
Unit 15, T = 4, lag order = 0
  estimated value of (a – 1): –1.5989
  test statistic = –1.95562 [0.4720]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –5.47871
Choi meta–tests:
  Inverse chi–square(30) = 65.8251 [0.0002]
  Inverse normal test = –3.6669 [0.0001]
  Logit test: t(79) = –3.90606 [0.0001]

6. dddLGDPcap_1
Dickey–Fuller test for d_d_d_LGDPcap_1
  with constant and trend
  model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
  estimated value of (a – 1): –0.681572
  test statistic = –3.03415 [0.2736]
Unit 2, T = 4, lag order = 0
  estimated value of (a – 1): –0.545819
  test statistic = –0.315977 [0.8712]
Unit 3, T = 4, lag order = 0
  estimated value of (a – 1): –1.39503
  test statistic = –2.68737 [0.3169]
Unit 4, T = 4, lag order = 0
  estimated value of (a – 1): –1.26804

test statistic = –2.99758 [0.2828]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –2.37594
test statistic = –15.918 [0.0037]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –1.42619
test statistic = –2.59919 [0.3303]
Unit 7, T = 4, lag order = 0
estimated value of (a – 1): –1.20477
test statistic = –2.48281 [0.3460]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): –1.69872
test statistic = –10.5959 [0.0110]
Unit 9, T = 4, lag order = 0
estimated value of (a – 1): –1.58862
test statistic = –15.2247 [0.0043]
Unit 10, T = 4, lag order = 0
estimated value of (a – 1): –0.943855
test statistic = –2.3935 [0.3583]
Unit 11, T = 4, lag order = 0
estimated value of (a – 1): –1.81523
test statistic = –3.7205 [0.2166]
Unit 12, T = 4, lag order = 0
estimated value of (a – 1): –1.4564
test statistic = –4.21902 [0.1512]
Unit 13, T = 4, lag order = 0
estimated value of (a – 1): –1.58139
test statistic = –13.1951 [0.0062]
Unit 14, T = 4, lag order = 0
estimated value of (a – 1): –2.2206
test statistic = –3.89796 [0.1878]
Unit 15, T = 4, lag order = 0
estimated value of (a – 1): –1.70416
test statistic = –10.343 [0.0118]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –6.24165
Choi meta–tests:
Inverse chi–square(30) = 74.4321 [0.0000]
Inverse normal test = –4.3328 [0.0000]
Logit test: t(79) = –4.64441 [0.0000]

7. dGrperpNA_1
Dickey–Fuller test for d_GrperpNA_1

with constant and trend
model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 5, lag order = 0
estimated value of (a – 1): –0.770249
test statistic = –0.645304 [0.8727]
Unit 2, T = 5, lag order = 0
estimated value of (a – 1): –1.27991
test statistic = –2.01106 [0.4698]
Unit 3, T = 5, lag order = 0
estimated value of (a – 1): –1.57327
test statistic = –2.94216 [0.2581]
Unit 4, T = 5, lag order = 0
estimated value of (a – 1): –1.03875
test statistic = –1.40454 [0.7386]
Unit 5, T = 5, lag order = 0
estimated value of (a – 1): –2.14108
test statistic = –6.39328 [0.0281]
Unit 6, T = 5, lag order = 0
estimated value of (a – 1): –1.9878
test statistic = –78.2446 [0.0001]
Unit 7, T = 5, lag order = 0
estimated value of (a – 1): –1.75353
test statistic = –4.43943 [0.0875]
Unit 8, T = 5, lag order = 0
estimated value of (a – 1): –1.41994
test statistic = –2.77366 [0.2882]
Unit 9, T = 5, lag order = 0
estimated value of (a – 1): –2.88608
test statistic = –13.6059 [0.0015]
Unit 10, T = 5, lag order = 0
estimated value of (a – 1): –1.03759
test statistic = –1.64361 [0.6574]
Unit 11, T = 5, lag order = 0
estimated value of (a – 1): –1.68805
test statistic = –3.47471 [0.1848]
Unit 12, T = 5, lag order = 0
estimated value of (a – 1): –1.30172
test statistic = –4.51054 [0.0833]
Unit 13, T = 5, lag order = 0
estimated value of (a – 1): –1.17955
test statistic = –1.92545 [0.4970]
Unit 14, T = 5, lag order = 0
estimated value of (a – 1): –1.99468
test statistic = –2.53306 [0.3271]

Unit 15, T = 5, lag order = 0
  estimated value of (a – 1): –1.62081
  test statistic = –2.89536 [0.2641]
H0: all groups have unit root
N,T = (15,5)
Im–Pesaran–Shin t–bar = –8.62951
                10%   5%   1%
Critical values: –3.33   –3.88   –5.72
Choi meta–tests:
  Inverse chi–square(30) = 66.4775 [0.0001]
  Inverse normal test = –3.20529 [0.0007]
  Logit test: t(79) = –3.70406 [0.0002]

8. dGrperpNA_2
Dickey–Fuller test for d_GrperpNA_2
  with constant and trend
  model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
  estimated value of (a – 1): –1.69436
  test statistic = –2.22041 [0.4034]
Unit 2, T = 4, lag order = 0
  estimated value of (a – 1): –1.20983
  test statistic = –1.2665 [0.7640]
Unit 3, T = 4, lag order = 0
  estimated value of (a – 1): –1.60902
  test statistic = –2.12509 [0.4124]
Unit 4, T = 4, lag order = 0
  estimated value of (a – 1): –1.37717
  test statistic = –1.16123 [0.7773]
Unit 5, T = 4, lag order = 0
  estimated value of (a – 1): –1.80417
  test statistic = –3.33028 [0.2487]
Unit 6, T = 4, lag order = 0
  estimated value of (a – 1): –1.97413
  test statistic = –56.6912 [0.0001]
Unit 7, T = 4, lag order = 0
  estimated value of (a – 1): –1.75339
  test statistic = –3.13981 [0.2660]
Unit 8, T = 4, lag order = 0
  estimated value of (a – 1): –1.41575
  test statistic = –1.94318 [0.4731]
Unit 9, T = 4, lag order = 0
  estimated value of (a – 1): –3.67591
  test statistic = –15.0924 [0.0044]

Unit 10, T = 4, lag order = 0
  estimated value of (a – 1): –6.25805
  test statistic = –3.72384 [0.2165]
Unit 11, T = 4, lag order = 0
  estimated value of (a – 1): –1.71039
  test statistic = –2.6094 [0.3295]
Unit 12, T = 4, lag order = 0
  estimated value of (a – 1): –1.04355
  test statistic = –9.24633 [0.0177]
Unit 13, T = 4, lag order = 0
  estimated value of (a – 1): –0.960279
  test statistic = –1.17605 [0.7752]
Unit 14, T = 4, lag order = 0
  estimated value of (a – 1): 1.09166
  test statistic = 0.695655 [0.9515]
Unit 15, T = 4, lag order = 0
  estimated value of (a – 1): –1.66903
  test statistic = –3.8058 [0.2112]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –7.12239
Choi meta–tests:
  Inverse chi–square(30) = 57.8844 [0.0016]
  Inverse normal test = –2.17048 [0.0150]
  Logit test: t(79) = –2.63711 [0.0050]

9. dLperpNA_2
Dickey–Fuller test for d_LperpNA_2
  with constant and trend
  model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 5, lag order = 0
  estimated value of (a – 1): –1.16709
  test statistic = –1.66631 [0.6488]
Unit 2, T = 5, lag order = 0
  estimated value of (a – 1): –1.30804
  test statistic = –1.96712 [0.4821]
Unit 3, T = 5, lag order = 0
  estimated value of (a – 1): –1.47471
  test statistic = –2.45089 [0.3425]
Unit 4, T = 5, lag order = 0
  estimated value of (a – 1): –0.845728
  test statistic = –1.74981 [0.6227]
Unit 5, T = 5, lag order = 0
  estimated value of (a – 1): –1.65873

test statistic = –6.26341 [0.0303]
Unit 6, T = 5, lag order = 0
estimated value of (a – 1): –2.11021
test statistic = –5.61894 [0.0446]
Unit 7, T = 5, lag order = 0
estimated value of (a – 1): –1.39012
test statistic = –2.14945 [0.4335]
Unit 8, T = 5, lag order = 0
estimated value of (a – 1): –1.3989
test statistic = –2.62117 [0.3080]
Unit 9, T = 5, lag order = 0
estimated value of (a – 1): –3.15652
test statistic = –214.542 [0.0001]
Unit 10, T = 5, lag order = 0
estimated value of (a – 1): –0.869741
test statistic = –2.1646 [0.4150]
Unit 11, T = 5, lag order = 0
estimated value of (a – 1): –1.0898
test statistic = –1.64981 [0.6566]
Unit 12, T = 5, lag order = 0
estimated value of (a – 1): –1.33528
test statistic = –6.09251 [0.0332]
Unit 13, T = 5, lag order = 0
estimated value of (a – 1): –1.04581
test statistic = –2.91129 [0.2624]
Unit 14, T = 5, lag order = 0
estimated value of (a – 1): –2.0396
test statistic = –1.22642 [0.7827]
Unit 15, T = 5, lag order = 0
estimated value of (a – 1): –1.61959
test statistic = –3.03978 [0.2461]
H0: all groups have unit root
N,T = (15,5)
Im–Pesaran–Shin t–bar = –17.0743

	10%	5%	1%
Critical values:	–3.33	–3.88	–5.72

Choi meta–tests:
Inverse chi–square(30) = 56.4579 [0.0024]
Inverse normal test = –2.55848 [0.0053]
Logit test: t(79) = –2.9365 [0.0022]

10. GrNA_3
Dickey–Fuller test for GrNA_3
with constant and trend

model: (1–L)y = b0 + b1*t + (a–1)*y(–1) + e
Unit 1, T = 4, lag order = 0
estimated value of (a – 1): –1.65695
test statistic = –2.25683 [0.4025]
Unit 2, T = 4, lag order = 0
estimated value of (a – 1): –1.58412
test statistic = –1.81368 [0.6044]
Unit 3, T = 4, lag order = 0
estimated value of (a – 1): –1.45747
test statistic = –2.41304 [0.3567]
Unit 4, T = 4, lag order = 0
estimated value of (a – 1): –0.76999
test statistic = –0.901293 [0.8132]
Unit 5, T = 4, lag order = 0
estimated value of (a – 1): –2.31685
test statistic = –2.76487 [0.3052]
Unit 6, T = 4, lag order = 0
estimated value of (a – 1): –1.32404
test statistic = –1.39272 [0.7400]
Unit 7, T = 4, lag order = 0
estimated value of (a – 1): –1.7729
test statistic = –2.91476 [0.2991]
Unit 8, T = 4, lag order = 0
estimated value of (a – 1): –0.3029
test statistic = –2.78595 [0.3048]
Unit 9, T = 4, lag order = 0
estimated value of (a – 1): –3.37744
test statistic = –28.7468 [0.0003]
Unit 10, T = 4, lag order = 0
estimated value of (a – 1): –0.16541
test statistic = –0.149364 [0.8965]
Unit 11, T = 4, lag order = 0
estimated value of (a – 1): –2.5667
test statistic = –2.03964 [0.4533]
Unit 12, T = 4, lag order = 0
estimated value of (a – 1): –1.7916
test statistic = –3.0609 [0.2708]
Unit 13, T = 4, lag order = 0
estimated value of (a – 1): –1.67302
test statistic = –2.21566 [0.3948]
Unit 14, T = 4, lag order = 0
estimated value of (a – 1): –1.195
test statistic = –41.0331 [0.0001]
Unit 15, T = 4, lag order = 0

estimated value of (a – 1): –1.6793
test statistic = –2.28829 [0.3761]
H0: all groups have unit root
N,T = (15,4)
Im–Pesaran–Shin t–bar = –6.45179
Choi meta–tests:
Inverse chi–square(30) = 55.9678 [0.0028]
Inverse normal test = –1.9536 [0.0254]
Logit test: t(79) = –2.57096 [0.0060]