On the Empirics *of* R&D Creation

a contribution

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1. Introduction & Purpose

Why are we so rich and they so poor? This question has for centuries fascinated historians, geographers, and economists alike. David Landes chose it as the title of his address at the annual meeting of the American Economic Association in 1989. He emphasised that, regardless of whether it was because we are so good or so bad, we all want to bridge the gap between the rich and the poor. Since then, economic disparity between nations has proved itself to be a challenging chimera to slay and, so far, only growth theory has come close to understand it.

This thesis investigates the determinants of *research and development* (R&D) at the country level, with a focus on previously unexplored demographic and government spending components. It benefits from strong internal validity provided by sturdy theoretical models and by long-run cointegration methods. Differently from other studies on this topic, the rationale of this piece is not to explain the exact relationship between R&D and one determinant, but rather to establish a holistic view of innovation development across countries and determine the relative magnitude with which certain variables affect R&D levels. If successful, the cliometric framework of this research could be of great academic and governmental interest as it tests three theorised hypotheses. First, Romer's 1990 endogenous growth model and Acemoglu's 1998 study, both of which link the difference in technological levels of countries to differences in skills level (human capital) hold in the long-term. Second, a specification of the model could help determine whether demographic variables such as aging and birth rate can explain the secular stagnation, also known as the *Japanification* malaise, of the developed world through a slowdown of technological development channel. A third, but equally relevant, result would be to ascertain that the already established relationships in industrial economics between technological opportunity, appropriability, demand-pull, and R&D propagate at the aggregate country-level too.

Discovering what gears can be twisted and turned to affect the future levels of R&D would be of great usefulness considering that markets currently induce socially suboptimal levels of R&D. In fact, in both the Romer and Schumpeterian models the share of researchers is lower than optimal due to 2 main distortions: researchers cannot internalise that current research will affect the productivity of their future counterparts (standing on the shoulders of giants effect) and that entrepreneurs only take into consideration the private returns and not the social returns to their efforts (Zvi Griliches and Edwin Mansfield among others). While a more practical use of a coherent framework would be found in the context of forecasting for monetary policy within central banks and other international institutions. A consistent model with a strong predictive power could be introduced as an extra stochastic equation to complement existing ones within the “core” and the so-called “small forward-looking” models to increase precision and consistency of the forecast produced by said models, especially for long-term predictions.

Finally, the usefulness that identifying hidden paths for human development can have on people’s wellbeing is beyond words. Alleviating the soulcrushing experience that is poverty has been possibly the defining goal every generation of economists. Findings from this research could help policy makers take decisions that would have direct effects on the lives of billions for years to come. Thus, it is compelling to ask: what determines R&D at the country level?

This thesis begins to address the question with an account of what has been theorised and discovered so far regarding the classification of the determinants of research and development. In a second part, the author constructs a theoretical model by adapting pre-existing ones to fit the purposes of this paper. The focus then shifts on the data and econometric equations used by the author to analyse the advancement of research across developed countries, with precise explanations of the theory behind the instruments utilised. The following section illustrates the results of the regressions of various specifications of the models. Lastly, these results are discussed and from them, conclusions are drawn.

2. Literature Background

The first answer to the question of why we are so rich and they so poor posed by Landes came through the progress made on the Solow model, most notably thanks to the papers by Mankiw, Romer, and Weil (1990) and Barro & Sala-i-Martin (1990). Countries that are far below their steady state[1], they argue, will grow faster than those above it: output per worker is determined by the growth rate of the labour force, the rate of *investment in private inputs*, and the *productivity* of these inputs.

This discovery led, however, to more questions; what then determines investment in private inputs and their productivity? The solution, again, came from the Solow model: the engine of growth halts unless the technology of production improves over time. Entrepreneurs drawn by the prospects of riches and fame create the new ideas that foster technological advancement. Through the same model, differences in countries' productivity can be explained practically: the Dutch agricultural sector employs high-tech machinery, while the Indian one is labour-intensive, because individuals in developed nations have learned over the years to use and develop very advanced capital goods, while people in developing countries could not (Jones and Vollrath, 2013). As a never-ending Russian doll, the latter findings lead to an even deeper question: what determines *technological development*? Answering to this question is an empirical matter; the ambitious aspiration of this thesis.

Taking a step back, quite some research on finding an empirical relationship between productivity and technological advancement has been carried out at the macro-level. Coe & Helpman (1993), later confirmed by Engelbrecht (1997) and Coe et Al (2008), explain that growth in total factor productivity[2] closely follows R&D investment. Their findings suggest that not only there indeed exist tight links between productivity and R&D at the national level, but that both domestic and foreign R&Ds are the drivers of GDP per capita growth. Similarly, Coccia

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[1] In this context the point where GDP per capita remains constant.

[2] TFP: the component of output growth that is not attributable to the accumulation of inputs.

(2008) demonstrated that more than 65% of productivity growth variance is determined by Gross Domestic Expenditure on R&D, while Bronzino & Piselli (2016) discovered a long-run relationship between total factor productivity and R&D[3] between 1980 and 2001 across Italian regions and showed that a long-run equilibrium between productivity level and research capital exists. Sterlacchini (1989) derives a cross-sectional study for the United Kingdom, in which he finds that inter-industry total factor productivity (TFP) growth is associated with R&D expenditure and a number of significant innovations, therefore confirming the relationship between TFP and R&D also at the aggregate industry level.

Furthermore, there is a separate, quasi self-standing, branch of industrial economics that for decades has been trying to establish what factors drive R&D investment at the firm level. It was first Joseph Schumpeter, in 1934, who observed that it was the largest firms in the market that produced the vast majority of technological progress, coming to the conclusion that large monopolistic firms offered decisive welfare advantages. Today, the consensus is that when controlling for industry effects in aggregate samples, R&D increases proportionately with firm size. This close positive monotonic relationship between research and firm size points to a cost-spreading advantage to larger firm size in R&D, which most probably reinforces itself over time (Kleppler and Simon, 2005). Firm size falls into the *appropriability* explanation for higher research efforts: "[…] the extent that new knowledge is transmitted at relatively low cost from its creator to prospective competitors, and particularly to the extent that such knowledge is embodied in new processes and products that may be copied or imitated at relatively low cost, appropriable rewards (must be) sufficient to justify innovative effort" (Cohen, 2010). Appropriability is, together with *demand-pull* (or product market demand) and *technological opportunity*, the triad of channels Pakes & Schankerman (1984) developed to classify the independent variables affecting innovative activity and that is widely recognisable across this branch of economics.

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[3] And human capital and public infrastructure.

Cohen (2010) defines technological opportunity as "the set of production possibilities for translating research resources into new techniques of production that employ conventional inputs". This channel therefore includes all variables that represent the availability of resources that can be deemed useful for research purposes or that indirectly free these type resources in other departments of the firm. Schmookler (1962) developed a parallel explanation to that of technological opportunity whereby it is the profit-seeking behaviour of firms that explains technological change, this concept has become known as *demand-pull*. Barge-Gil & Lopez (2013) delve into the Schumpeterian hypothesis and discover that appropriability and demand-pull have a decisive effect on development, while technological opportunity is the main driver for research. In fact, Stoneman (1979) already showed that the cost of, as well as the demand for inventions conditioned the level of innovative effort.

It has been established that firms carry out R&D to assimilate outside knowledge among other aims, however different economists[4] have argued that research spillovers diminish companies' incentives to invest in R&D by undermining the appropriability of returns to inventive activity; what effects dominate is uncertain and a matter of empirical research. Higher foreign stock of R&D attained through exports and the access to a wider market could therefore function as catalysts for R&D as they increase the domestic firms' need to exploit this pool of knowledge by carrying out research[5], or as a retardant, by reducing the incentives of being the first entrant. Whatever direction it takes, this effect would then be tempered by the countries' ease of access to foreign research; the characteristics of outside knowledge that make R&D more or less critical to the maintenance and development of absorptive capacity. Recently, Chen & Miller (2007) have taken a different approach by focusing on proximity to bankruptcy and *slack* in firms, shifting the discourse on institutionalised internal mechanisms of carrying out R&D.

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[4] e.g. Nelson 1959 and Arrow, 1962.

[5] As established by Coe & Helpman, 1995.

Notwithstanding the above-mentioned stock of literature, and quite surprisingly, cross-country empirical studies on what determines technological advancement[6] at the country level are sparse and do not follow a single theoretical thread. Moreover, many other papers that explore the determinants of R&D behaviour lie out the scope of this research, as they look at specific or bundles of government policies; a type of literature which does not straightforwardly reconcile neither with long-term effects nor with datasets that include a wide variety of countries. Wang (2009) first explored the question within a similar context by using human capital accumulation, scientific researches, patent right protection, technology transfer through trade and FDI, and income growth as main explanatory variables. Wang's research, regrettably however, holds an array of technical shortcomings such as a timeframe of only 10 years and the use of income growth as a determinant. A more befitting study was later carried out by Brown et Al. (2016), who discovered that strengthening contract enforcement and improving accounting standards have a positive differential relation with high tech R&D, while more generous R&D tax credits, surprisingly, lead to less R&D being carried out. Eirle & Wencki (2015) find that private enterprises seem to be driven mainly by incentives that help improve bottom lines in case of low profitability and debt contracting. Furthermore, they find that once the effects of tax and dividend incentives are removed, the determinants for capitalising development in private and public firms are analogous. All in all, due to the lack of a comparable research framework at the macro-level, the author uses the three already strongly established industrial economics channels: appropriability, technological opportunity, and demand-pull to analyse the long-term behaviour of research and development.

2.1 Appropriability

Sustaining R&D relies heavily on companies being able to benefit from discoveries of others as well as easily accessing foreign markets. Falvey et Al (2004) using a panel of 21 countries and 25 years of data claim that knowledge produced in more productive countries can spillover through both exports and

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[6] R&D in particular.

imports. Furthermore, Wagner (2006) finds that German firms that carry out R&D and export their products/services abroad tend to have a higher productivity than those that only carry out R&D which confirms the findings of the model in Hirsch & Bijaoui (1985) in which exports are a direct vector for research. Moreover, economies that are more competitive internally tend also to have higher exports as more competition ensures lower input costs.

Ginarte & Park (1997) claim that one of the main factors which influences patent protection level is research and development, while Kanwar & Evenson (2003) found that patent rights for developed countries were associated with higher R&D intensity. Even though research papers have extensively used various measures of patents as an explanatory variable R&D, the exact direction of causality has not been determined. A fascinating paper by Branstetter & Kwon (2019) demonstrates how there have been instances of external (from another economy) demand surges causing increases in R&D expenditure through an exchange rate devaluation mechanism. Indeed, the relationship between investment and exchange rate movements in developed countries has been known for some time (Campa & Goldberg, 1999), with an especially strong effect in high-mark-up sectors. Other variables such as foreign direct investment have been found not to have a direct effect on R&D expenditure (Boon-Yee & Azman-Saini 2017).

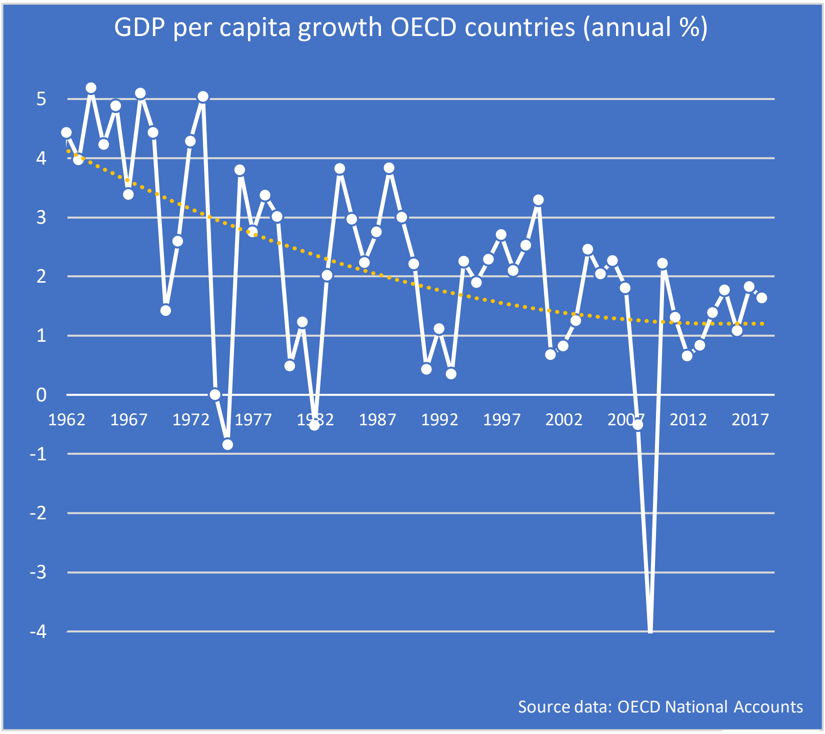
2.2 Technological opportunity

Technological opportunity encloses all major variables that affect the costs a company experiences (such as wages and energy prices) as well as both the quality and availability of inputs necessary for research (such as educated workforce and access to a wide arrange of suppliers). The effect of labour costs on R&D was examined by Raghupathi & Raghupathi (2017), who find that higher wages actually spur research investment. In this regard, human capital owns a critical role in the R&D process (Romer, 1990) and, indeed, countries with a highly educated workforce tend to invest more resources in education (Rossberger & Krause 2015 and Neagu 2013). Human capital investment is higher where better institutions (measured by ease of doing business) are present, however, it is yet to be determined whether countries with relatively worse institutions can benefit more from higher levels of human capital (Dawson, 1998). In turn, a managerial class with an academic mind will tend to see more clearly the benefits of R&D and how to reap its benefits.

Raghupathi finds a negative association between taxes and research. The nature of the latter phenomenon remains ambiguous as it might mean that higher taxes leave less financial room for firms to entertain secondary endeavours, such as research, as well as entrepreneurs’ failure to internalise social returns, which leads them to foresee relatively lower returns to investment. A latter variable that falls into the technological opportunity category is slack, a factor already widely utilised as a determinant of imports and exports (Carnot et al, 2011). Economic slack, more specifically capacity utilisation, comprises excess inputs such as underutilised physical capital, financial capital, and labour force, following Chen & Miller’s (2007) analysis slack would grant managers room for greater experimentation regardless of its uncertain outcomes.

2.3 Demography

A number of other previously unexplored demographic components might be driving long-term technological progress as well. The two main ones fall in the appropriability and technological opportunity channels, so are worth examining in this separate section. Demography has been central in productivity theory and it is of particular interest today as the growth slowdown that the developed world has been experiencing for the last half a century (*Fig. 1*) unwound concurrently with two important demographic changes. The first is a continuous birth rates drop and the second is an increase in the percentage of elderly workers

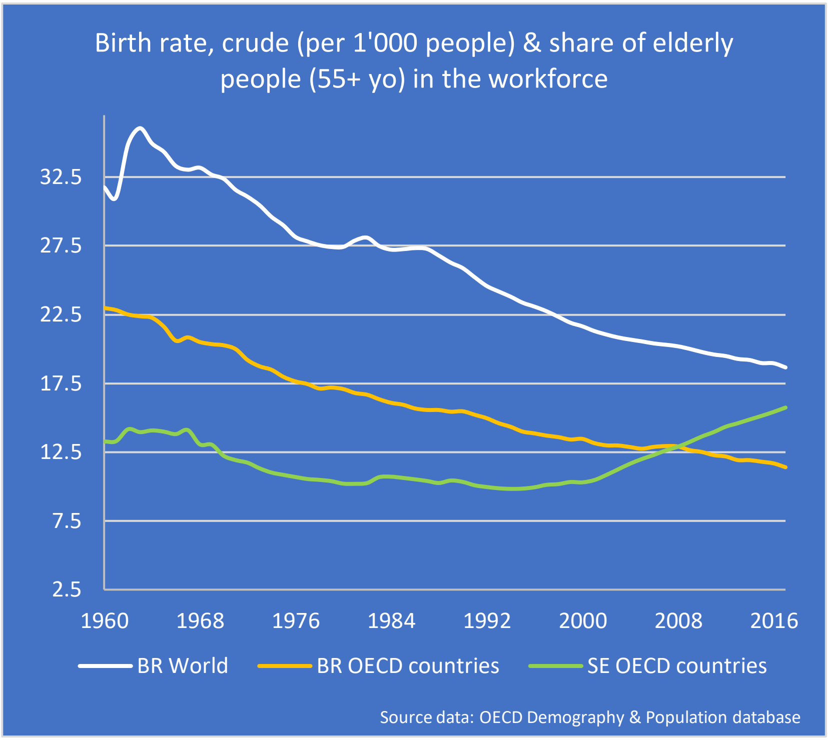

GDP per capita growth OECD countries (annual %)

Source data: OECD National Accounts

Figure 1

(55+ years old) in the workforce. Including these two variables brings a greater level of sophistication to standard growth theory, which only looks at absolute population.

Within the scope of appropriability, birth rates have been decreasing virtually monotonically across the world since the mid-1960s; more than halving within the timeframe presented in *Fig. 2*. In a complete overturn of the Malthusian Trap, the author hypothesises that decreasing birth rates are detrimental to R&D, and therefore growth, as they provide a disincentive for entrepreneurs to engage in R&D: the prospects of long-term profits shrink due to an ever-diminishing market (or at least a non-expanding one). However, the sparse existing literature points to a negative effect of fertility rate on absolute GDP growth. They are indeed the findings of Sokolov-Mladenović et Al (2016) using a panel of EU28 countries and of Li & Zhang (2007) investigating Chinese provinces.



Source data: OECD Demography & Population database

Figure 2

The author further notes there are possible negative effects stemming from the fairly recent increase in the number of senior citizens throughout the developed world (*Fig. 2*). It has been already established that an older workforce tends to utilise older physical capital and, therefore, is less productive (particularly after reaching 60 years of age) than their younger counterparts, reducing the necessity for investment in more novel forms of capital (Goebel & Zwick, 2009 and 2011). The latter mechanism can possibly work at the decisional level too, as older leaders and decision-makers would not be able to reap the returns of long-term risky investments (Albert & Duffy, 2012). More complex relationships that describe the effect of aging on technological development can be seen within the context endogenous growth theory. Mainly, people live, work, and retire for many more years, however, the percentage of their life spent accumulating skills is shorter, therefore reducing the exponent (u) in the numerator in Romer's equation.

2.4 Demand-pull

Schmookler (1962 & 1966) explains that both the demand and the size of the market affect the incentives of firms to invest in innovation. The reasoning is that the returns to a certain investment that reduces the cost of a process or increases sales are proportional to the size of the of the market and the overall demand in which the firm operates, however, the loss incurred by pursuing such invention is fixed. Thus, *ceteris paribus*, a larger market would attract more innovation activity. Empirically, to capture demand, sales has been used at the aggregate micro-level using Say's law to justify employing a variable that captures the supply side of the Marshallian scissors as well; making aggregate consumption a reasonable equivalent at the macro-level. Two notable papers that investigate the demand channel, Acemoglu & Linn (2004) and Cerda (2007), investigate R&D in the pharmaceutical industry and find substantial evidence in favour of market size on the introduction of new products to be significant.

2.5 Research and Development

Before moving forward, it is necessary to define what is meant here by research and development. The empirical analysis uses a single R&D measure, *Business Expenditure on R&D* (BERD), for three reasons. The first is that the vast majority of past endogenous growth studies (e.g. Coe & Helpman 2008 and Coccia 2008) that link R&D to TFP use BERD, which captures all spending on R&D carried out within each economy each year (MSTI OECD, 2019); this measure does not include neither research carried out by the government nor higher education institutions, but focuses instead on research carried out by businesses. The second reason is that all literature (see Cohen 2010) that investigates the determinants of R&D considers solely R&D carried out by the private sector. Finally, using BERD instead of GERD or GBARD[7] is quite straightforward: much

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[7] Gross domestic expenditure on R&D and Government budget allocation for R&D respectively.

like government spending in most macroeconomic research, the choice for government expenditure on R&D is plausibly set exogenously (Becker et Al 2014, Eierle & Wencki 2015, and Guellec et Al 2001). Indeed, the long-term behaviour of government R&D seems not to be dictated by market forces, but rather tends to evolve independently from them in the long term. One practical example of this is the 3% objective of the Lisbon Strategy set by the European Council. A more straightforward reason is that for neither GERD or GBARD there exist long-term datasets, and if they do, they do not cover nearly as many economies as those in this dataset.

It is also worth noting that all regressions use total R&D capital instead of R&D capital per capita. The reason for this choice is twofold: first, population is not a strong enough component to considerably affect the intrinsic relationships and thus the results of the regressions remain unaltered when using R&D per capita as a dependent variables[8]. Second, the main papers that this piece references use total and not per capita values, making cross-referencing inaccurate and at times outright wrong.

Fig. 3 shows the development of R&D throughout the past 47 years in selected countries. The most apparent difference is in scale; if the US or Japan were included, they would completely lie outside of the frame. However, it is important to notice that these differences do not reflect 1:1 the differences in total gross domestic products, as can be seen when comparing states with similar total GDPs, such as the UK and France. While for most nations the year-on-year development would appear to follow a predetermined long-term trend, fairly unperturbed by the succession of major geopolitical events that have shaken the world economy in the past half century, a couple of examples stand out. The first is Israel, which in a bit more than a decade bridged and then surpassed the wide gap in R&D that separated it from the Netherlands despite having half its population; a feat which is also reflected in its outstanding GDP per capita levels. The second, and most iconic, is the case of South Korea, which thanks to a series of governmental programmes was able to surpass most of the world's great

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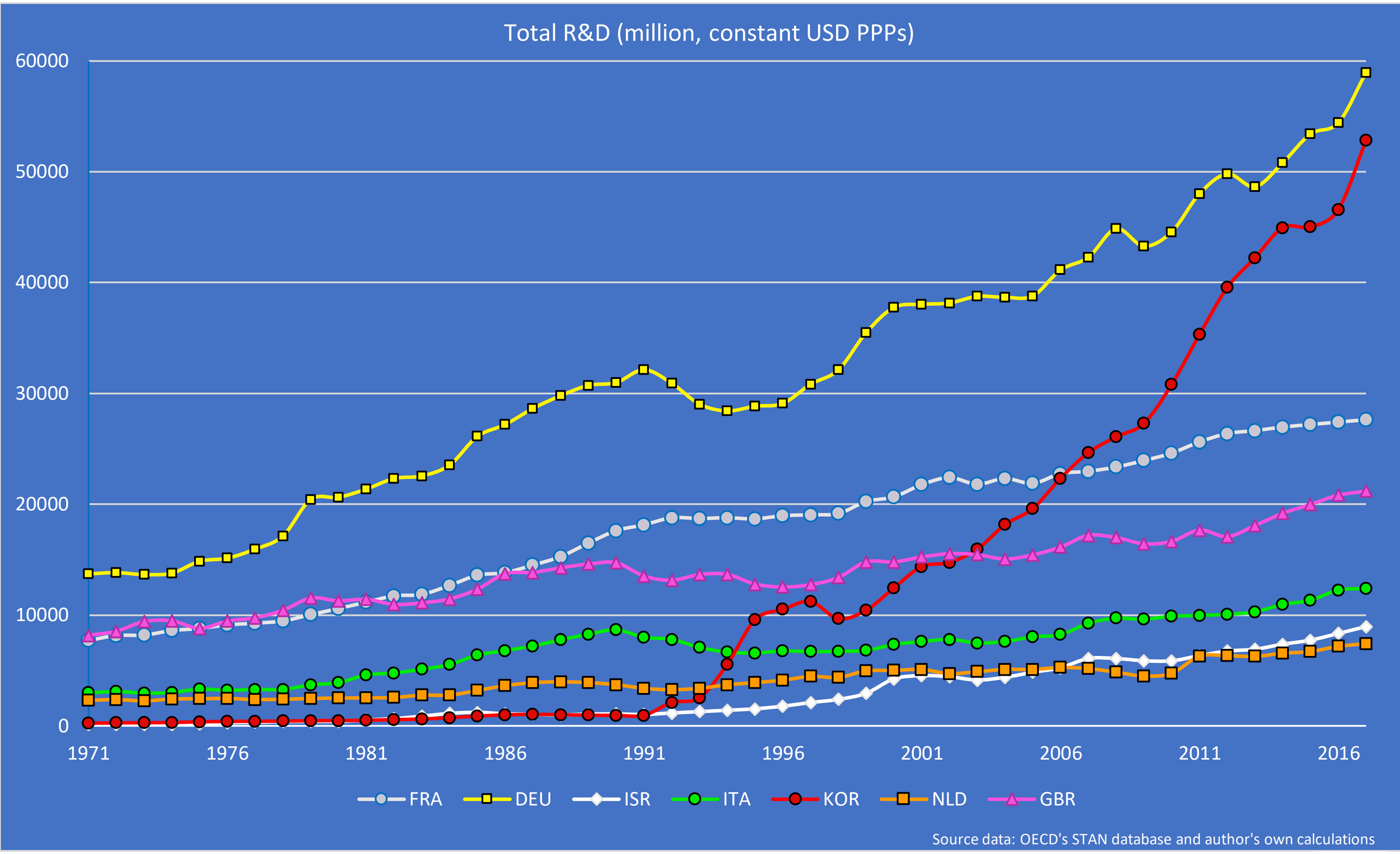
[8] See the appendix for two example comparisons of PDOLS of total R&D and R&D per capita

economies. This latter fact stands out as reminder of what societies can achieve when opportunity is matched with sound economic policy.



Total R&D (million, constant USD PPPs)

Source data: OECD's STAN database and author's own calculations

Figure 3

3. Theoretical Framework

The model takes a new and experimental approach by attempting to reconcile two strands of economics that have attempted to explore the question of R&D determinants: growth theory and industrial organisation. The former links R&D with variables such as market size/population (Acemoglu & Linn 2004 and Cerda 2007), human capital (Romer 1990, Acemoglu 1998, and Cameron et Al 2005) as well as institutional variables (Coe et Al 2008 and Nelson 1993). While the latter branch draws the connection between R&D and firm size (Schumpeter 1934 and

Mason 1951), economic slack (Chen & Miller, 2007), government R&D (Flamm, 1988, Levy & Terleckyj 1983, Levin & Reiss 1984, and Lichtenberg 1987, 1988), foreign R&D (Nadiri & Kim 1996 and Cameron et Al 2005), energy prices (Griliches, 1988), countries' ease of access to foreign research (represented by trade), and competitiveness/exports (Lee, 2009).

The main theoretical model is a fully-endogenous growth model, chosen as it presupposes proportionality of productivity growth to R&D at the firm level, which in turn affect the long-run level of growth. It is based on a modified version of Minniti & Venturini (2016) and Jones & Vollrath's (2013) semi-endogenous models for technological development, which are then integrated with microfoundations from Cohen and Levinthal's (1989) model of determination of a firm's stock of knowledge. The models were chosen as they capture most explicitly the direction of the vector from demographic and government inputs to R&D creation. For a formal derivation of model *(1.2)* please see Jones & Vollrath's (2013) and for model *(1.1)*, Minniti & Venturini (2016).

$$A_c = \int_0^F \frac{A_i}{F} di \qquad (1.1)$$

$$A_i = h\left(\frac{g}{\mu} e^{\psi u}\right)^{\gamma} \qquad (1.2)$$

The first line *(1.1)* follows Howitt's (1999) approach having A_c on the left side representing the pool of knowledge created in a year (R&D capital at the country level) and F represents the number of firms (number of varieties available at date t). The subscript i refers to the firm's laboratory i where the research is carried out and the products developed. Magnifying, the second line (*1.2*) shows production function of R&D capital, whose interpretation is similar to that of Jones'. A is the stock of knowledge created in a period of time, here simplified as R&D carried out in the laboratory, and g is the expansion rate of the technological frontier: a function of the parameters of the production function for R&D which is explored below in more detail. The interpretation of h differs slightly from Romer's 1990 paper as it does not capture the number of researchers, but instead human capital in country c. The author assumes that this modification does not alter the interpretation of the underlying relationships, because the two variables qualify as proxies of each other, and because the forces that bring people to choose to acquire the human capital necessary to become researchers (of all sorts) are essentially the same that to push people to pursue the acquisition of greater human capital in general. The term μ represents easiness of technological transfer between economies, exemplified by imports. Finally, u denotes the fraction of an individual's time spent learning skills. The remaining factors, which are assumed to be constant, are γ, that is the amount that productivity rises when an innovation occurs, and ψ, which represents the returns to education; the latter being the same Mincerian formulation of Bils and Klenow (2000) applied in the context of economic growth.

Magnifying further and following the extensive literature on industrial R&D creation, a lemma based on a modified version of Cohen and Levinthal's microfoundations enters Jones' equation substituting g, in which firms deliberately invest in R&D with two purposes: to generate new *profitable* knowledge and to develop *absorptive capacity*[9]; this is the point where growth theory is bridged. In this framework R&D spending depends on technological opportunity, demand, and appropriability conditions. Each firm chooses its level of R&D to maximise profits, taking the R&D levels of the other firms as given.

$$\begin{aligned} g = \quad & \theta p(exp_i, pop_i, eld_i\ )^{\alpha} \\ & + f(taxprofind_i, taxprofcorp_i, birthr_i, leg,\ eodb_i, compan_i) \\ & + d(con_i, market) \end{aligned} \tag{2.3}$$

g is a function of sum of the production function for R&D of all firms in a country. It depends on $p(.)$, a function of the average volume of returns if R&D is carried out (representing technological opportunity), $f(.)$, a function of the factors

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[9] The ability to assimilate and exploit outside knowledge for profit.

affecting of appropriating said profits (appropriability), and $d(.)$, a function of the demand-pull that affect the firms in a country; the variables affecting this equation are assumed to be constant across firms in a country. The binary relationship of technological opportunity and appropriability follows that identified and confirmed by Barge-Gil & Lopez (2013) complemented with Chen & Miller's (2007) discovery of the effect of slack on research. Drawing from behavioural theory, $p(.)$ is multiplied by the risk aversion coefficient θ, as carrying out R&D is a risky prospect which can be interpreted as such in this instance given the dynamics of loss-aversion have already been proved to propagate at the aggregate level (Foellmi et Al, 2018). $p(.)$ is a function of trade, size of the firm, energy, and labour costs, population, and the percentage of old workers. $f(.)$ is a non-linear function of corporate and individual profit tax rates, birth rate, and institutional variables such as ease of doing business and the type of legal system. $d(.)$ is a linear function of only domestic consumption or total accessible consumption of the market. Regarding the latter, the author decided not to follow Wang's approach of including income growth for demand-pull, given that the underlying growth theory and a wide array empirical studies have already established that the causal vector goes from R&D to total factor productivity, and not the opposite. Finally, it is important to notice that while Equation (1.2) captures macro-movements at the aggregate level, equation (1.3) describes the, aggregated, characteristics of firms and those of their environment. These two equations are then reconciled in equation (1.1), which is the basis of the econometric model shown below.

4. Data & Descriptive Statistics

The data is arranged in panel form, the combination of time-series data provides more precise asymptotic approximations to the real distribution by having more degrees of freedom and more variation, therefore generating more accurate point estimates for the cointegrating vector. Furthermore, choice of using data organised as panels instead of single time series comes as limiting distributions are standard normal[10], contrary to the non-limiting distribution of time series data, hence they can be implemented even with shorter timeframes. The latter would allow future research the grand benefit of including a greater variety of aggregate firm-related variables (which usually have fewer observations), thus further helping to bridge the gap between industrial organisation and endogenous growth theories.

The main dependent variable, R&D capital stock (rdk), draws from the dataset constructed by Coe et Al (2009) of 22 OECD countries[11], as of 2017 the combined GDPs of these nations account for 58.13% of world's GDP (World Bank). The variable's values are adjourned by the thesis' author by including an extra 14 years of data (2003-2017). It is calculated using the perpetual inventory procedure:

$$rdk_t = (1 - \delta_t)rdk_{t-1} + RD_t \tag{3.4}$$

Where δ is the country-specific depreciation rate in that year (obtained from Penn World Tables' database) and RD is real R&D expenditure in the business sector, defined as end of year. To calculate the first observation the following equation was used:

$$rdk_0 = \frac{RD_0}{(\delta_0 + g)} \tag{4.5}$$

Where g is the annual average logarithmic growth rate from 1969 to 1985 and from 1971 for non-G7 countries. The demographic variables (total population, percentage of elderly population, birth rate crude per 1000 people, total dependency ratio[12] etc.), taxes regressors (total taxes levied in a country, taxes on

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[10] The behaviour of the t statistic is standard as $n \rightarrow \infty$

[11] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States.

[12] Age dependency ratio is the ratio of dependents (people younger than 15 or older than 64) to the working-age population (those ages 15-64) (World Bank).

profits of corporations, and taxes on profits of individuals) and percentage of energy imports are found in the OECD's statistics website, while the risk aversion variables are taken from the dataset estimated by Gandelman and Hernández-Murillo (2015). Total human capital is taken from Penn World Tables' database of the University of Groningen. Finally, exports and imports of goods and services, number of listed domestic companies, household final consumption, military spending, institutional variables (such as ease of doing business) are taken from the World Bank's database. The variable "market" was constructed by the author by combining the consumption of countries the individual nation has a comprehensive free-trade agreement with, from the moment the FTA was enforced, thus also including consumption from countries not individually included in the dataset.

Table 1 presents the summary statistics of the 14 main variables used in the regressions. The author prioritised constructing a wide dataset over including a greater range of variables given the asymptotic properties of cointegrated equations having a large balanced panel dataset is of crucial importance. Nevertheless, this has been a prohibitive endeavour: all countries have missing observations for at least one variable of interest. Several methods for 'filling up the holes' such as interpolation have been be used, while other variables have been excluded completely. For the variable total number of listed companies practically all countries had missing observations for the first four years, while for taxes on profits of corporations and taxes on profits of individuals Portugal, Iceland, and Israel had some missing observations each. In order to maintain a balanced dataset these were extrapolated and interpolated using cubic splines, a valid solution given the large number of real observations already present. Graphical backtesting showed that for the periods where the observations were replaced the movements mirrored those of similar economies despite not using OLS. For four economies (Australia, Iceland, New Zealand, and Switzerland) there are missing observations for R&D for recent years. Luckily, the OECD's Structural Analysis (STAN) publishes data on total industry R&D (TI), the latter differing from the R&D data in the other database only marginally, in fact the to two have stable ratios and an average correlation of 0.99. These aspects lead the author to speculate that TI is used as the only external component of BERD for these countries, making them mutually replaceable in this context once the 1% constant differences are accounted for.

Table I. Summary of main variables
(1971-2017, 24 countries, 1128 observations)

	Mean	SD	Minimum	Maximum
R&D capital[a] (rdk)	160503.6	431679.3	.2179797	3579736
Human capital[b] (hk)	3.02e+17	4.38e+16	1.41e+17	3.81e+17
Consumption[a] (con)	8.59e+22	1.87e+23	2.51e+20	1.48e+24
Exports[c] (exp)	33.23252	17.24219	5.405245	121.965
Imports[c] (imp)	32.72873	14.60597	5.351934	105.2261
Population[d] (pop)	3.63e+07	5.67e+07	206099	3.25e+08
Birth rates[e] (birthr)	13.30603	3.624818	7	31.2
Elderly[f] (eld)	.1871779	.0431781	.0517525	.3390225
Total dependency[f] (depdend)	.7204605	.1094381	.485	1.258
Listed companies[d] (compan)	821.5377	1309.818	1	8090
Market size[a] (market)	3.61e+12	4.06e+12	6865016	1.33e+13
Taxes on individuals' profits[c] (taxprofind)	9.754002	4.630793	1.184	26.247
Taxes on corporations' profits[c] (taxprofcorp)	2.647675	1.378078	.261	12.594
Military spending[c] (milit)	2.58087	2.922741	.3	30.4638

[a] measured in constant dollars
[b] index of human capital per person, based on years of schooling and returns to education
[c] percentage of total GDP
[d] total
[e] crude, per 1000 people
[f] ratios on total population

With much regret, a number of variables could not be included. Data for slack (capacity utilisation rate) from Business Tendency Surveys for Manufacturing (St. Louis FED) is available for only 7 out of the 24 countries in the dataset. Not including it is likely to lead to a slight burgeoning of the coefficients of exports, given their close relationships between the two. Moreover, even proxies for proximity to bankruptcy have only a handful of years of observations and therefore are not featured in this piece. These two shortcomings make testing Chen & Miller's (2007) hypothesis unfeasible. All measures of wages tend to miss a quite large number of observations and had to be left out; it is probable that the absence of this variable would increase the perceived role of both consumption and human capital in regressions, the former is driven by salary and as countries that have a highly educated workforce also tend also have higher wages. Finally, total emigration numbers, the percentage of women in the workforce, and the number of female entrepreneurs could not be included in the demography theorisation due to only very recent data being available for certain variables. Relatively to institutional variables, language barriers/proximity, risk premium on loans, patent applications, quality of the banking sector, homicide rate, and inequality also have scattered observations. The most important missing variable, solely due to lack of data, is certainly government R&D given how governments that invest heavily in public R&D create resources that are useful to private R&D in the form of researchers, discoveries, and specific physical capital, therefore falling into the technological channel. Indeed, a wide arrange of papers across different branches point to a sustained relationship private and public research. The great statistical significance of taxation variables and, to a lesser degree, human capital might, in part, reflect the absence of the latter.

As previously touched upon, the empirical analysis focuses solely on developed economies. This decision stems from two pragmatic considerations. The first one is the fact that non-OECD countries' data is lacking for the vast majority of variables that are analysed; making it often impossible to include them in the dataset. The second reason is that there is a clear divide in the nature of R&D in developing nations and in developed ones. In the latter ones, innovation in products comes to directly maintain or improve market shares, while for developing countries it is driven primely by the necessity of adapting and assimilating foreign technologies (Lall, 1982). The latter phenomenon is reflected insomuch as there is no direct link between R&D investment and economic growth in lower income countries (Gittleman & Wolff 2001).

5. Econometric Estimation

The structural model is the following:

$$log\ rdk_{it} = \beta_0 + \beta_{it} \log hk_{it} + \beta_{it} \log exp_{it} + \beta_{it} \log imp_{it} + \beta_{it} \log con_{it} + \gamma X_{it} + \varepsilon_{it} \qquad (5.6)$$

Where i and t are, respectively, a country and a time indexes, $log\ rdk$ is the is the natural logarithm of R&D capital, $\log hk$ is the natural log of human capital, $\log exp$ is the natural log of exports, $\log imp$ is the natural log of imports, $\log con$ is the natural log of consumption, and γX_{it} is a vector of remaining k controls[13] at time t. The model represents equation *(1.1)* whereby certain variables have been highlighted and other factors are grouped in the error term[14]. The main explanatory variables have been chosen following the most established vectors found in the literature and the availability of data, these turn out to also be the most statistically significant variables. All regressions, as shown in the following section, have a fixed structural body composed of the same dependent variable (R&D capital), 4 explanatory variables (human capital, exports, imports, and consumption), and 1 or 2 explanatory variables. The reason for restricting the number of independent variables to 6 for each regression is due to the limitation of the *-xtpedroni-* command in STATA used to carry out said regressions[15]. Notwithstanding this shortcoming, the existence and magnitude of the relationships can be inferred without including all possible regressors at the same time and even more so as granger causality is stronger with fewer variables.

Stationary panel data have time-invariant means and variances, while non-stationary panel data have time-varying mean, time-varying variance, or both. When the first difference of a non-stationary process is stationary, it is said to be

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[13] Population, birth rate and percentage of elderly in the population, total dependency ratio, total number of listed companies, taxes on profit of individuals and corporate taxes, and military spending.

[14] Please see below and *section 7* for discussions on the issue of endogeneity.

[15] When asked about it, the author (Timothy Neal) told me that the issue is simply that Professor Peter Pedroni never provided the critical values for the cointegration test with more than 6 independent variables.

integrated of order one, $I(1)$, and when a linear combination of several order one series is stationary, the series is said to be cointegrated. Cointegration implies that the series moves together in long-run equilibrium, although a group of them can wander arbitrarily (Woolridge, 2016). The immense advantage of cointegration lies exactly in this: a long-run relationship between variables may exist (and be modelled) even if they deviate temporarily due to conditions that cannot be modelled or measured. Furthermore, cointegrated equations have the asymptotic property that, as the number of observations increases, OLS estimates of the cointegrating equation converge on the true parameter values much faster than in the case where the variables are stationary, i.e., they are 'super consistent' (C&H, 1995). This property implies that even if $E(x, \varepsilon_{it}) \neq 0$ through the standard deviation of the error, there is no asymptotic endogeneity bias (Mills, 2012): superconsistency implies that that estimates are robust to problems such as simultaneity, omitted variables, and endogeneity (Baltagi & Kao 2000, Coe et Al 2009). This innovative aspect of cointegration is particularly present in the panel dynamic ordinary least squares (PDOLS) method, which, differently from other specialised estimation procedures, yields an optimal estimator for the cointegrating coefficient in Gaussian cointegration models; thereby eliminating endogeneity (for a more detailed description of the process please see Pedroni 1996 and Phillips & Moon, 2000). Superconsistency is ever stronger in this thesis given the extremely large T and N of the dataset.

For the most part, productivity papers use a change specification because differencing is necessary to avoid the spurious correlation problem when estimating a relationship between trended variables (e.g. Miller & Upadhyay 2000, Aiyar & Feyrer 2002, and Kim 2016). However, this creates a disadvantage, in the sense that a in a change specification the information embodied in the long-run relationship between the levels of the variables is eliminated by differencing. In view of this, the advantage of the cointegrating approach, in which the relationship is estimated in level terms, is that it exploits, rather than discard, the relevant information about shared trends that is embodied in the levels data (Coe & Helpman, 1994).

Following the causal inference method developed by Stock & Watson (1993) and notions of cointegration in dynamic panel data presented in Baltagi & Kao (2000), the author bases causal inference on finding long-run cointegration specifications. While demonstrating strong causality is not an objective of this thesis, it has been long established in Engle & Granger (1987) that to demonstrate the existence of a cointegrating relationship means to demonstrate that there is error correction and therefore Granger causality[16]; either from x to y or y to x. The latter fact coupled with the elimination of feedback effects that comes by using PDOLS implies that if a strong relationship can be estimated it must have a clear causal direction.

The variables are tested for unit roots by using the second-generation panel unit root tests, equivalent to time-series augmented Dickey–Fuller tests (Im et al, 2003). Subsequently, different combinations of non-stationary variables are tested for cointegration using the four Westerlund panel cointegration tests developed by Westerlund (2007) to ensure that a cointegrating relationship exists. For the combinations where a cointegrating relationship is determined the author estimates Pedroni's PDOLS. It has been the preferred method among many researchers as it provides an efficient and fully parametric method of estimating the cointegrating vector while being flexible enough to allow for individual heterogeneous fixed effects and trend terms (Pedroni, 2004).

6. Results

Two main generations of unit root tests have been developed for panel data. The first has as its main exponents the Im, Pesaran, and Shin (2003) and the Levin, Lin, and Chu (2002) tests. The former tests the null hypothesis that *all* panels contain unit roots vs the alternative hypothesis that some panels are stationary,

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[16] It is important to note that Granger causality is a limited notion of causality where past values of one series of independent variables can predict future values of another series of a dependent variable after past values of y have been accounted for (Woolridge, 2016)

while the latter tests the null hypothesis that *some* panels contain unit roots vs the alternative hypothesis that some panels are stationary (Kunst & Franses, 2011). The IPS test is therefore less restrictive as it allows for heterogeneous coefficients and for an intermediate case in-between all vs no panels are stationary, but it has little power when deterministic terms are included in the analysis. Both tests performance increases with larger *T* and *N*. The results for both tests are found in Appendix B[17]; the results are mixed but overall one can reject the null hypothesis of stationarity.

The second generation of tests distinguishes itself insomuch as the cross-sectional independence hypothesis is rejected; they allow for some dependence among countries. Between them, Pesaran's cross-section augmented Dickey-Fuller (CADF) test is widely used across the literature and has the easiest procedure, making also the interpretation of the results straightforward: cross dependence is eliminated by augmenting the standard ADF regressions with cross section averages of lagged levels. *Table 2* reports the results of Pesaran's *cross-sectional dependence* (CD) test. Even in the mildest cases, the test overwhelmingly rejects the null hypothesis of cross-section independence; not a surprising outcome given the wide assortment of countries in the panel. It for this reason, that the author decides to consider only the results from the CADF test[18], which are presented in *Table 3*. Out of all the available variables in the dataset the null of stationarity is not rejected only for transportation infrastructure index variable and the total number of plane passengers[19].

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[17] All regressions, tests, and data transformations in this thesis have been carried out using STATA.

[18] The appropriate number of lags was chosen following Schwartz Criterion (SC). The test includes a potential time trend.

[19] Both proxies for infrastructure levels.

Table II. Pesaran’s Cross-Sectional Dependence
(1971-2017, 24 countries)

	CD
lnrdk	111.30
	(0.00)
lnhk	110.13
	(0.00)
lncon	111.50
	(0.00)
lnexp	105.03
	(0.00)
lnimp	62.24
	(0.00)
lnpop	105.03
	(0.00)
lnpopden	104.91
	(0.00)
lnbirthr	81.70
	(0.00)
lneld	100.78
	(0.00)
lntotdepend	82.33
	(0.00)
lnoldepend	85.89
	(0.00)
lncompan	26.56
	(0.00)
lnmarket	90.56
	(0.00)
lntaxprofind	12.71
	(0.00)
lntaxprofcorp	37.08
	(0.00)
lnpropertytax	13.86
	(0.00)
lnrent	111.38
	(0.00)
lntottax	45.43
	(0.00)
lntaxprof	20.01
	(0.00)
lnmilit	75.45
	(0.00)
lntransinfra	92.28
	(0.00)
lnurb	67.27
	(0.00)
lnairt	92.28
	(0.00)
lnexpect	112.11
	(0.00)

Note: the values in parenthesis specify the p-values.

Table III. Pesaran’s CADF
(1971-2017, 24 countries)

	CADF
lnrdk	-2.33
	(0.51)
lnhk	-2.57
	(0.10)
lncon	-1.99
	(0.98)
lnexp	-2.41
	(0.34)
lnimp	-2.49
	(0.20)
lnpop	-2.33
	(0.52)
lnpopden	-2.30
	(0.59)
lnbirthr	-2.39
	(0.39)
lneld	-2.25
	(0.70)
lntotdepend	-2.46
	(0.25)
lnoldepend	-2.20
	(0.78)
lncompan	-2.34
	(0.51)
lnmarket	-2.48
	(0.23)
lntaxprofind	-2.66
	(0.40)
lntaxprofcorp	-2.40
	(0.38)
lnpropertytax	-2.30
	(0.59)
lnrent	-2.27
	(0.65)
lntottax	-2.57
	(0.10)
lntaxprof	-2.51
	(0.17)
lnmilit	-2.42
	(0.34)
lntransinfra X	-2.75
	(0.01)
lnurb	-2.02
	(0.96)
lnairt X	-2.75
	(0.01)
lnexpect	-1.88
	(1.00)

Note: the values in parenthesis specify the p-values.

Now that the majority of variables have been confirmed to be non-stationary, PDOLS can be applied to extract coefficient and t-stats for each variable and specification. PDOLS, firstly developed by Pedroni (2001) share a number of characteristics with other DOLS methods that make it a an especially suitable tool for estimating unbiased long-term relationships: they are consistent even with most types of endogeneity in the regressors, such as feedback effects, and they are robust to slope heterogeneity in the single panel units (Neal, 2015). What distinguishes them, however, is that they are more efficient[20]. Moreover, test statistics have standard asymptotic distributions provide precise estimates in environments with low T which make further research with more recent data a possibility (Mark & Sul, 2003).

To test the robustness of the cointegrating relationships determined in the previous part, the specifications are subjected to Westerlund's (2007) four panel error correction-based cointegration tests. Joakim Westerlund developed them as a solution to the common problem that most cointegration tests impose that the short-run parameters must be equal to the long-run ones for the differenced variables, moreover, the tests can accommodate individual-specific dynamics such as non-strictly exogenous independent variables and serially correlated error terms. They do not impose any common-factor restriction as they are based on structural instead of residual dynamics, meaning that the tests allow for almost completely heterogeneous specifications of both long and short-run parts (Persyn & Westerlund, 2008). The logic behind the tests can be understood by examining a generalised error correction model:

$$\begin{aligned} Dy_{it} = c_i + a_{i1}Dy_{it-1} + a_{i2}Dy_{it-2} + \cdots a_{ik}Dy_{it-k} + b_{i0}Dx_{it-1} + a_{i1}Dx_{it-1} \\ + \cdots a_{ik}Dx_{it-k} + a_i(y_{it-1} - b_i x_{it-1}) + u_{it} \end{aligned}$$

The Ga and Gt tests test the null hypothesis that the speed of error correction towards the long-run equilibrium (a_1) is $=0$ for all i versus the alternative hypothesis $a_1 < 0$ for at least one i:

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[20] They have the smallest sampling error than all other mean group estimators (CCE-MG, Pooled OLS, and PDOLS with time dummies among others).

$$G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\hat{a}_i}{\hat{a}_i(1)}$$

$$G_t = \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{SE(\hat{a}_i)}$$

Rejecting H0 is evidence of cointegration for at least one country. The Pa and Pt test statistics pool information over all countries to test H0: $a_1 = 0$ for all i against H1: $a_1 < 0$ for i:

$$P_a = T\hat{a}$$

$$P_t = \frac{\hat{a}}{SE(\hat{a})}$$

Rejecting H0 is evidence of cointegration for the whole panel. For a formal derivation of a, $SE(a)$[21], $\hat{a}$, and $SE(\hat{a})$ please refer to Persyn & Westelund (2008).

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[21] Here "*SE*" is the conventional Standard Error for *a*.

6.1 Structural model and demography

Presented in Table 4 are the results from Pedroni's test for the structural model (A) and 3 specifications: the one in column B includes population, a second one (C) that has birth rates and percentage of elderlies in the population, and a third one (D) with total dependency ratio as regressor. Regression estimates using either of the three specifications are very similar, pointing to one major driver of research: human capital, and three secondary ones: exports, imports, and consumption. These are strongly supported by Westerlund's tests[22], which indicate that there is substantial evidence that domestic R&D capital, exports, imports, and consumption are cointegrated. The coefficients are positive for all variables but imports, which appear to have a significantly negative long-run effect on R&D. The coefficients and t-stats fluctuate substantially, but always proportionally for the main explanatory variables and mainly due to multicollinearity.

Table IV.
(1971-2017, 24 countries)

Pedroni's PDOLS	A	B	C	D
lnhk	7.47	4.48	4.92	11.17
	(54.34)	(40.72)	(31.58)	(60.57)
lnexp	0.32	0.75	0.82	0.46
	(-0.51)	(12.2)	(45.5)	(31.47)
lnimp	-0.51	-0.36	-1.42	-0.77
	(-11.61)	(-6.55)	(-43.79)	(-24.25)
lnncon	0.64	0.44	0.68	0.80
	(13.16)	(12.1)	(17.32)	(21.34)
lnpop		3.98		
		(16.92)		
lnbirthr			-0.72	
			(-8.71)	
lneld			-1.34	
			(-36.07)	
lntotdepend				2.06
				(-16.83)
Westerlund				
Gt	-1.47	-1.74	-1.39	-1.43
	(0.98)	(0.94)	(1.00)	(0.99)
Ga	-4.07	-2.86	-1.71	-1.71
	(1.00)	(1.00)	(1.00)	(1.00)
Pt	-11.51	-11.97	-10.50	-4.99
	(0.27)	(0.18)	(0.36)	(0.64)
Pa	-13.19	-13.39	-4.49	-0.78
	(0.07)	(0.03)	(0.78)	(0.89)

Note: the values in parenthesis for Pedroni's test specify the t-stat, while for Westerlund's they specify the p-value.For the precise definition of each variable please refer to *section 4*.

With a framework in place for modelling the behaviour R&D, ancillary effects can be tested. Starting with demography, in *Table 4* Pedroni's test finds that both birth rate and the percentage of elderly in the population negatively affect R&D, with the latter having a much higher significance. However, when testing for total dependency[23] it appears to have a positive effect on the dependent variable. This fact highlights how the dynamics of population age and research are not as straightforward as imagined, with shares of different age groups weighting

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[22] For all the tests a constant and trend are added. Due to overwhelming cross-sectional-dependence the p-values are bootstrapped with a number of replications ≥ 200.

[23] The total number of elderly and young people divided by the number of prime age population

favourably or negatively on the path of the dependent variable. Nevertheless, the variables have a significant stable effects and need be accounted for.

6.2 Ancillary variables

The results for the remaining variables are reported in *Table 5*, to facilitate comparisons the first regression (A) is the same as in *Table 4*, while adjacent specifications include respectively: total market size, taxes on profits of individuals and taxes on profits of corporations, and military spending. When including market size, the positive coefficient indicates that a larger market positively affects R&D in the long-run, albeit the effect is not particularly substantial. Differently from what Arrow and Nelson theorised then, it appears that accessing larger markets does increase domestic firms' need to exploit the pool of knowledge by investing more in research, instead of deterring it.

Table V.

(1971-2017, 24 countries)

Pedroni's PDOLS	A	B	C	D	E
lnhk	7.47	1.87	6.98	8.75	9.94
	(54.34)	(29.72)	(54.18)	(59.01)	(93.52)
lnexp	0.32	0.31	0.70	0.25	0.68
	(11.92)	(13.02)	(38.34)	(12.43)	(10.54)
lnimp	-0.51	-0.41	-0.48	-0.36	-0.28
	(-11.61)	(-8.22)	(-24.74)	(-10.23)	(-7.52)
lnncon	0.64		0.40	0.29	0.05
	(13.16)		(42.44)	(13.96)	(2.57)
lncompan				0.07	
				(2.94)	
lnmarket		0.01			
		(2.07)			
lntaxprofind			-0.17		
			(11.62)		
lntaxprofcorp			0.02		
			(21.57)		
lnmilit					-0.21
					(14.64)
Westerlund					
Gt	-1.47	-1.40	-1.48	-1.62	-1.27
	(0.98)	(1.00)	(0.98)	(0.97)	(1.00)
Ga	-3.19	-2.71	-2.07	-2.35	-1.56
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Pt	-5.34	-9.59	-7.09	-3.75	-4.82
	(0.93)	(0.45)	(0.64)	(0.96)	(0.91)
Pa	-1.56	-8.58	-3.48	-1.26	-1.39
	(0.99)	(0.19)	(0.76)	(0.99)	(0.98)

Note: the values in parenthesis for Pedroni's test specify the t-stat, while for Westerlund's they specify the p-value. For the precise definition of each variable please refer to *section 4*.

Looking at tax rates, one can notice that the effect of higher taxes on individuals' profits negatively affects R&D, while taxing corporate profits has the opposite effect; thereby only partially confirming Raghupathi's results. The model also provides evidence in favour of the Schumpeterian hypothesis of firm size affecting the amount of R&D it carries out. More specifically, it shows that a greater number of large companies can push a nation's technological development to higher levels in the long-term, albeit the variable also partially describes the size of the financial market of country, thereby capturing its effect. The latter interpretation would be in line with Masino's (2015) who finds that more financial development and trade openness have a positive effect on R&D. Finally, countries that spend a larger share of their budget on the military will see their R&D levels partially dwindle. The latter result is quite extraordinary given how large portions of military spending go directly into private R&D, which also implies that the detrimental effect of a larger military-industrial complex might be underestimated in the model.

6.3 Time-invariant variables

In this section the author attempts to account for heterogeneity based on country-specific characteristics by testing how the coefficients estimated in the above sections vary among nations when interacting them with specific dummy variables. The aim is to achieve a greater level of sophistication by capturing the effects of variables which, mostly due to their nature, are time-invariant and could not otherwise be included in cointegrating estimations. While some of these variables are expected to change little over time, they are unlikely to stay perfectly constant. For this reason, and similarly to the method carried out in Coe et Al (2009), two *types* of dummy variables are created for ease of doing business and risk avoidance each: high (hi) and low (lo). The hi variable is equal to 1 if the country has values higher than average for that specific factor and 0 otherwise; *vice versa* for the lo variable. These are then interacted with the determinants of R&D to capture their broad-based effects following theoretical understanding of the behaviour of the different variables explained in the literature review.

The focus is on the following variables:

- Ease of doing business (eodb), which is an aggregate of 11 factors: starting a business, dealing with construction permits, getting electricity, registering property, getting credit, protecting minority investors, paying

- taxes, trading across borders, enforcing contracts, and resolving insolvency (World Bank, 2017).
- Risk avoidance (riskav) at the country level, it is calculated using the method first theorised by Layard et Al. (2008) of estimating the speed with which marginal utility of income declines as income increases using data on self-reports of personal well-being carried out by the 2006 Gallup World Poll (Gándelman, N., & Hernández-Murillo, R., 2015).
- Origins of legal system (leg_sc/fr/en), in either Scandinavian, French, German, or English law (Porta et al., 1999, 2008).

Table VI.
(1971-2017, 24 countries)

Pedroni's PDOLS	A	B	C	D	E
lnhk	7.47		2.84		2.88
	(54.34)		(23.38)		(61.64)
lnexp	0.32	0.61			
	(11.92)	(32.28)			
lnimp	-0.51	-0.72	-0.46	0.19	-3.29
	(-11.61)	(-42.83)	(-24.25)	(16.72)	(-14.46)
lncon	0.64	0.67	0.42	-0.24	0.70
	(13.16)	(2.81)	(10.22)	(-31.29)	(36.14)
lnhk*eodbhi		4.43		0.05	
		(35.18)		(11.31)	
lnhk*eodblo		12.92			
		(55.84)			
lnexp*riskavhi			-0.47		
			(14.05)		
lnexp*riskavlo			0.42		
			(10.22)		
lnhk*leg_en				47.84	
				(37.10)	
lnhk*leg_sc				33.94	
				(35.36)	
lnhk*leg_fr				-39.16	
				(-21.94)	
lnexp*leg_en					-3.21
					(4.11)
lnexp*leg_sc					2.38
					(2.60)
lnexp*leg_fr					0.23
					(10.76)
Westerlund					
Gt	-1.47	-1.53	-1.46	-1.36	-1.44
	(0.98)	(0.99)	(0.99)	(1.00)	(1.00)
Ga	-3.19	-3.56	-2.63	-2.34	-2.09
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Pt	-5.34	-7.72	-4.85	-2.95	-5.43
	(0.93)	(0.61)	(0.92)	(0.97)	(0.82)
Pa	-1.56	-8.58	-1.29	-3.28	-1.38
	(0.99)	(0.96)	(0.97)	(0.77)	(0.99)

Note: the values in parenthesis for Pedroni's test specify the t-stat, while for Westerlund's they specify the p-value. For the precise definition of each variable please refer to *section 4*.

The results suggest that country differences in the ease of doing business and risk avoidance imply substantial heterogeneity in the estimated coefficients. Specifically, two findings emerge: firstly, and as visible in column B in *Table 6*, countries with lower ease of doing business have significantly higher coefficients for human capital, meaning they can benefit more from higher levels of it. Secondly, in column C countries with the highest risk aversion levels are also those whose exports benefit them the least in attaining higher levels of research. Both modifications strongly reject the hypothesis of no cointegration. Furthermore, the findings in column D indicate that countries which have an English or, to a lesser degree, a Scandinavian legal system derive greater use from higher levels of human capital. At the same time, the French-based legal system nations benefit much less from a given level of human capital than other nations as shown in column E. This does not come as a surprise given that countries with a French legal system tend also to have lower ease of doing business levels. Conversely, countries with an English-based legal system do not enjoy as much the benefits of higher exports if compared to nations with Scandinavian- or French-based legal systems, although the former is not very statistically significant. The above results remain strong when other combinations of variables are used in the equation.

7. Discussion

While unrefined, the estimation lays an econometrically-solid stepping stone for future research. By far the strongest theorised channel is technological opportunity, with costs playing a smaller role; at least when looking at the effects of single variables. Demand-pull in both total consumption and market size seems to positively drive R&D, further supporting the theoretical conjecture. The effect of trade on R&D indirectly signifies that access to foreign research and greater domestic competitiveness can determine the course of a country's economy.

Furthermore, given the essential role that human capital appears to play in carrying R&D, future research should focus on determining what specific relationship exists with education and research. One main suspect and a practical variable from a policy perspective is education expenditure; missing in this thesis due to lack of consistent data across countries. On this note, and as briefly explained in section 6.3, a majorly significant finding is that the positive effect of higher levels of human capital is strongest in countries with lower institutional quality, meaning that the least developed nations of the OECD have the most to gain more from investing in their people's skills. It is important to note, however, that wages have not been included as a separate variable, as previously mentioned its absence would probably magnify the role of human capital in regressions, as countries that have a highly educated workforce also tend also have higher wages.

While the positive effect of exports on research was to be expected to an extent, to discover imports as a negative driver comes as a surprise. Countries that are more open tend to both export and import more, and there can be positive technological spillovers in imports, but the model suggests that the former is not strong enough to counterbalance the effect of being a technological follower. Nevertheless, both variables' coefficients need to be examined knowing that slack was not accounted for when testing the models, as including it would probably lower both effects.

Another important finding is that higher taxes on individuals' profits disincentivise technological advancement, while taxes on corporate profits spur it. It can be argued that the latter dichotomy emerges as, in one hand, people will have a lower incentive to invest in increasing productivity if a larger share of the fruits of said improvements is taken away, since there is a wedge between social costs/benefits and private costs/benefits in production (and consumption) as implied by most market failures (Pigou 1947 & Jacobs 2017). On the other hand, taxing corporate profits might work as an implicit incentive to R&D given that, across all developed countries, companies have tax advantages when carrying out research and development while they do not on profits. It is interesting to note that societies in which individuals are on average more risk avoidant tend to be less prone to capture the fruits of trade, therefore negatively impacting R&D and growth. Like most endeavours, expanding to foreign markets and carrying out research are gambles where the odds are unknown, making them palatable to individuals, entrepreneurs in this case, who are risk-takers. It is these modern adventurers who help excavate new paths for human development. This negative effect of risk avoidance is bound to worsen as the percentage of elderly in the population increases due to older adults being more risk averse than younger people (Albert, 2012).

From a technical perspective, the issue of unobserved common factors in the panel, leading to correlation in the residuals across panel units, as well as correlation between the residuals and the regressors themselves, remains a looming spectre even when bootstrapping the residuals. This issue as, also known as common factors or common shocks, can be theoretically solved with more novel methods, such as Neil's Augmented Panel Dynamic OLS (AP-DOLS), which regrettably however, at the time of writing, are not available for statistical software.

A number of candidate variables were rejected even though data was available. In the technological opportunity channel: percentage energy imported, a proxy for energy prices, which only has a negligible, barely significant, and surprisingly, positive effect on R&D. Both urbanisation and population density also have an insignificant, negative, effect on the dependent variable. Rent prices, which represents housing and land costs, and total taxes as a percentage of GDP while statistically significant, would switch the direction of the effect every time the model was tweaked, therefore it was decided against including them in the results. Including fewer predictors might limit the forecasting power of the model (Stock & Watson, 2002).

8. Conclusions

Why are we rich and they are poor? Seemingly, due to more education, more exports, weaker imports, and thanks to stronger overall demand. While the precise extent with which this is the case is yet to be established, this work sheds light on the direction and relative magnitude that specific variables have on research and development, one the chief driver of growth.

The author analyses and compares decades of literature on research and development to construct a theorical framework that would reflect the discoveries made at the micro-level with current growth theory. Three separate channels are identified: appropriability, technological opportunity, and demand-pull which determine the expansion rate of the technological frontier. Within this framework various variables are tested to determine what have been the drivers of R&D in throughout the past half a century using modern econometric instruments. It can be now claimed that disruptions in trade today have long-term effects on R&D, conveying a cautionary tale against the perturbation of the fragile trade equilibria of the world economy. Moreover, confirming Romer’s 1990 endogenous growth model and Acemoglu’s (1998) research, promoting education and skills cannot be downplayed as a secondary concern but should be instead be the focal point of any government that aims at improving technological development. One could go as far as calling it a rope, from which the developed economies’ productivities hang from and one that can be climbed if our differences in productivity are to be ever bridged. Additionally, technological opportunity presents itself in various forms. While there is currently much fear of the grip that corporations have on consumers and governments alike, the role of these giants as innovators is significant. This is not the case, however, for the military complex which acts as a burden to innovation. In this vein, improving relationships between nations through free trade and fostering competitiveness and consumption is of crucial importance.

The various specifications appear to maintain coherent relationships despite the especially long-time horizon. Even though backtesting should be carried out before the models can be implemented, it is safe to say that they can be utilised for both short- and medium-term forecasting purposes of policy mix analyses. A first step would be testing on auxiliary models such as the SDS-FPS ones for the moving on to more complex ones.

Landes’ 1989 speech included several references and concerns relatively to population growth and so did most productivity theory that followed it thanks to Solow, Mankiw, Sala-i-Martin amongst many others. However, even these harbingers could not anticipate the population shift brought about by the slowdown of birth rates in the developed world. This piece failed to find evidences in favour of higher birth rates bringing about more technological development; quite the opposite in fact. Nonetheless, it did discover that a higher share of elderly people could be acting as a drag on R&D. This fact will need to be addressed with real policy measures, as it does not only pose a risk to complex balances of healthcare and retirement in the short- and medium-term but also to economic development in the long-term.

The author experimented with all available variables that fell into the model's theoretical framework and was able to obtain enough data to compile a strongly balanced panel. Indeed, while the lack of data has been a serious impediment throughout the research period, it is due to imposing strict high T and N, together with the properties of cointegration methods utilised, that the relationships here discovered are strongly believed to be empirically sound. It is with such bedrocks that future research will be able to make the most of the extraordinary instrument that is PDOLS by delving into undiscovered relationships with government R&D, firms, and demographic aggregates of variables with shorter timeframes to, perhaps, finally find another piece of the intricate yet wonderful puzzle that is technological development.

Appendix

Appendix A.

PDDOLS (1971-2017, 24 countries)				
Pedroni’s PDOLS	lnrdk	lnrdkpc	lnrdk	lnrdkpc
lnhk	7.47	7.34	4.92	4.45
	(54.34)	(49.63)	(31.58)	(31.38)
lnexp	0.32	0.28	0.82	0.82
	(11.92)	(7.68)	(45.5)	(40.89)
lnimp	-0.51	-0.47	-1.42	-1.41
	(-11.61)	(-4.70)	(-43.79)	(-39.00)
lnncon	0.64	0.44	0.68	0.56
	(13.16)	(7.11)	(17.32)	(10.64)
lnbirthr			-0.72	-0.65
			(-8.71)	(-8.40)
lneld			-1.34	-1.18
			(-36.07)	(-25.76)
lntaxprofind				
lntaxprofcorp				
Westerlund				
Gt	-1.47	-1.71	-1.43	
	(0.98)	(0.93)	(0.99)	
Ga	-3.19	-2.00	-1.71	
	(1.00)	(1.00)	(1.00)	
Pt	-5.34	-4.92	-4.99	
	(0.93)	(0.93)	(0.64)	
Pa	-1.56	-1.46	-0.78	
	(0.99)	(0.99)	(0.89)	

Note:the values in parenthesis for Pedroni’s test specify the t-stat, while for Westerlund’s they specify the p-value. For the precise definition of each variable please refer to *section 4*.

Appendix B.

Panel Unit Root
(1971-2017, 24 countries)

	LLC	IPS
lnrdk	4.17	4.63
	(1.00)	(1.00)
lnhk	3.98	0.27
	(1.00)	(0.61)
lncon	13.99	0.77
	(1.00)	(0.78)
lnexp	5.93	-1.53*
	(1.00)	(0.48)
Lnimp	5.18	-1.80*
	(1.00)	(0.06)
lnpop	3.29	1.80
	(0.99)	(0.96)
lnpopden	4.16	2.11
	(1.00)	(0.98)
lnbirthr XX	-8.01	-3.4
	(0.00)	(0.00)
lneld XX	-6.27	-1.86
	(0.00)	(0.03)
lntotdepend XX	-2.56	-3.83
	(0.01)	(0.00)
lncompan	2.04	-0.33
	(0.98)	(0.37)
lnmarket	5.64	-0.57
	(1.00)	(0.29)
lntaxprofind X	-1.19	-2.16
	(0.88)	(0.00)
Lntaxprofcorp X	-0.32	-1.95*
	(0.37)	(0.01)
lnpropertytax	-0.11	1.73*
	(0.46)	(0.04)
lntottax	4.63	-2.64
	(1.00)	(0.00)
lnmilit	-10.99*	-1.10
	(0.13)	(0.13)
lntransinfra	7.53	-0.94
	(1.00)	(0.99)

Note: the values in parenthesis for the test specify the t-stat.For the precise definition of each variable please refer to *section 4*. The LLC was run without constant. Different specifications are used following Dickey-Fuller indications.

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