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EXPLORING THE RELATIONSHIP BETWEEN R&D AND PRODUCTIVITY: A COUNTRY-LEVEL STUDY

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Research and development (R&D) has been considered a source of growth in productivity starting from Schultz (1953). Since then, significant research has studied this relationship at the firm, industry and country level. However, at the country level, most of the empirical studies assessing the R&D-productivity relationship often fail to consider the possible simultaneity of these variables. Do more productive countries invest more on R&D or does the higher level of R&D investment lead to higher levels of productivity? Do both relationships occur at the same time? Using a 65-country panel for the time period of 1960-2000, this study provides evidence that the relationship is mainly based on investment in R&D and not the reverse. In addition, we found that per capita R&D expenditure is strongly exogenous to productivity. These results suggest that, on average, those countries making the most effort in the R&D sector will be more productive in the future. Finally, we present evidence those points out a strong relationship between R&D and productivity in terms of both magnitude and significance.

Keywords: Innovation, Growth.

JEL: O11, O33.

Exploring the Relationship between R&D and Productivity: A Country-Level Study[1]

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1. Introduction

The relationship between productivity and R&D expenditure has been a topic of inquiry since the early work of Schultz (1953) and Griliches (1958), who pioneered this area by studying this relationship within the agricultural sector. Since then, this area of research has produced a significant amount of empirical and subsequent theroretical work. While Zvi Griliches posed and approached most of the empirical questions, recent theoretical works credit a substantial role to R&D as an engine of productivity and hence economic growth.[2] In these theoretical models, the connection between economic growth and R&D is generally established through an equilibrium equation that determines the resources allocated to this sector which spurs total factor productivity (TFP) growth. Notwithstanding these research efforts, there are still very relevant questions on the nature of the relationship between productivity and R&D expenditure that remain unanswered both at the level of the firm and, even further, at the country level.

At the country level, to the best of our knowledge, there is no clear-cut answer on whether more productive countries invest more on R&D, or does the higher level of R&D investment lead to higher levels of productivity, or that both relationships occur at the same time. To answer these questions correctly has crucial relevance for developing countries, since each answer leads to a very different set of policy recommendations regarding innovation and technology policies. In this paper we try to shed light to these questions using a panel of 65 developed and developing country economies, for the period 1960-2000.

In theory, R&D expenditure could increase productivity through different channels. First, it makes it possible to produce new goods and services that bring with them more effective use of existing resources. Second, it may make it easier and faster to adapt the benefits of technological progress elsewhere in the world to local realities. Third, R&D activities elsewhere in the world may increase domestic productivity through learning embodied in new technologies and productive processes and the import of goods and services with technology incorporated (Coe and Helpman (1995)). This last channel becomes especially relevant when foreign direct investment and international trade in goods and services are considered.

[2] See for example, Romer (1990), Helpman and Grossman (1991), Rivera-Batiz and Romer (1991), Aghion and Howitt (1992)

The empirical literature generally confirms the enormous benefits of the R&D sector's development in terms of total factor productivity (TFP). However, a significant number of studies do not take into account the potential problems of simultaneity and reverse causality between R&D and TFP.[3] On one hand, more resources should make technological change more likely, which in turn should influence productivity. However, given the strong relationship between both variables and income,[4] it is likely that both spending on R&D and productivity could respond in a similar way to demand shocks without the two necessarily being related. The causal relationship could even move in the opposite direction, if R&D spending were to respond positively to expected changes in demand (Frantzen (2003)). As Zvi Griliches points out, "[...] *If research and development is chosen on the basis of economic incentives, it is unlikely to be fully independent of the shocks and errors which affect the production relations we are trying to estimate*."[5]

The limited evidence for statistical causality between spending on R&D and productivity comes from several firm- and industry-level studies. With some methodological differences, Rouvinen (2002), Frantzen (2003) and Zachariadis (2004) studied the causal relationships at the industry level in OECD countries. Lu, Chen and Wang (2006), meanwhile, analyzed the R&D-productivity link for a group of electronic firms in Taiwan. The results point to statistical causality going from R&D toward TFP. However, to the best of our knowledge, there is no evidence available that indicates whether the reverse causality problem is present at the country level.

There are at least two good reasons for studying the relationship between R&D and productivity at the country level. The first is that innovative activity generates significant externalities, which in practice could be difficult to capture using firm or industry-level data. In contrast, evaluating R&D's impact on TFP using country-level data should ensure that net externalities are considered with no additional adjustments. In this manner we will attempt to

[3] Mairesse and Sassenou (1991) and Wieser (2001) offer two complete surveys with evidence of the R&D-productivity relationship at the industry and firm levels. For country-level studies, see Coe and Helpman (1995), Van-Pottelsberghe and Lichtenberg (2001) and Bitzer and Kerekes (2005) among others.
[4] The strong procyclic nature of R&D expenditure was pointed out by Lederman and Maloney (2003)
[5] Griliches (1998), pp 273 (italics added).

give a full account of the impact of R&D within the whole economy. Secondly, given that TFP differences explain most of the differences in countries' economic growth and income,[6] clarifying the nature of the relationship between R&D and TFP could help us to identify future economic growth paths. These results are particularly relevant for developing countries as they could help to fine tune development policies.

In this paper we investigate the nature of the relationship between R&D and TFP, using the following three measures of R&D: level of R&D in constant PPP dollars, R&D as a share of GDP, and R&D per capita, also in constant PPP dollars. To study the potential simultaneity among the variables, we first study their degree of exogeneity establishing whether R&D and TFP are either weakly exogenous or endogenous. Secondly, we establish the statistical causality between R&D and productivity by means of Granger causality tests and then we conclude on weak and strong exogeneity. The main results suggest that our three measures of R&D are weakly exogenous. With respect to causality, we find that most of the relationship goes from R&D per capita to productivity and not vice versa; therefore R&D per capita is strongly exogenous to TFP. With respect to the other measures of R&D, we obtain mixed results on the Granger causality tests. Finally, we explore whether the R&D sector's impact on productivity is robust with respect to the impact of factors such as openness to trade, terms of trade, financial market development, foreign direct investment and institutional variables. The evidence suggests that the R&D expenditure per capita is an important productivity determinant of TFP even when controlling for other factors.

The paper is organized as follows: in section 2 we provide the analytical framework necessary to present our empirical strategy. Section 3 presents the data, methodology and results. Finally, section 4 concludes.

2. Analytical FrameworkA Simple Model of TFP.

[6] See Klenow and Rodríguez-Claire (1997), Hall and Jones (1999), Easterly and Levine (2002) and Bosworth and Collins (2003)

The basic model assumes that the economy is described by a Cobb-Douglas production function. As we show in (1), the stock of knowledge (K) is included in the production function as a productive factor in a similar way to physical capital (C) and labor (L):[7]

$$Q_{it} = e^{\mu} e^{\eta_i} e^{\xi_t} K_{it}^{\beta_K} C_{it}^{\beta_C} L_{it}^{\beta_L} , \qquad (1)$$

where ζ_t and η_i respectively represent fixed effects over time and among firms. In this formulation, no specific returns at the global or local scale are required and $(\beta_K + \beta_C + \beta_L)$ may have a value greater than, lesser than, or equal to 1.

By applying logarithms to equation (1), we can define a relationship between TFP and the stock of knowledge, which includes ν_{it} as an error term that varies across time and individuals:

$$ln(TFP)_{it} = \mu + \beta_K lnK_{it} + \eta_i + \zeta_t + \nu_{it} . \qquad (2)$$

The main problem for estimating a specification such as this one (2) is that the stock of knowledge is not observed. The perpetual inventory method makes it possible to construct measures for this variable using R&D expenditures (*R*). It should be noted, however, that the stocks resulting from this method are often extremely sensitive to the initial capital stock and to the assumed depreciation of the stock of knowledge. For this reason, we chose the alternative of assuming that the stock of knowledge can be expressed as a weighted average of past and current spending on R&D. Thus, we can rewrite equation (2) as:

$$ln(TFP)_{i,t} = \mu + \beta_{PTF} ln(PTF)_{i,t-1} + \sum_{k=0}^{m} \beta_{R(t-k)} ln(R)_{i,t-k} + \beta_X ln(X)_{i,t} + \eta_i + \zeta_t + \nu_{i,t} , \qquad (3)$$

[7] Much of the literature studying R&D's contribution to economic development has used similar specifications to those of (1), based on work by Griliches (1979)

where $\beta_{R(t-k)} = \beta_k \times \gamma_{R(t-k)}$, and where a lagged dependent variable has been added to allow it to adjust, with some delay, to shocks. Finally, vector X_{it} is included to consider the effect of other factors that could influence TFP.

Equation (3) shows a relationship between the TFP logarithm and the logarithm for past and present R&D investment, which is easily estimated. The advantage of this specification is that, unlike in (2), the stock of knowledge accumulates through R&D investment, without having to assume an *ex-ante* depreciation rate or weights.

It is important to note, however, that this condition assumes that R&D is exogeneous for total factor productivity. In other words, if we estimate this equation we would be assuming that R&D could be taken as given without loss of information. In addition, the estimation of equation (3) overlooks possible feedbacks from TFP to R&D spending. In presence of these feedbacks, forecasts of TFP based on R&D's values would be invalid.

Luckily, Engle, Hendry and Richards (1983) develop the concept of weak and strong exogeneity. As they suggest, different types of exogeneity will allow us to make valid inference and forecasting of the model's parameters. Given that our purpose in this paper is to determine whether we can state that those countries making the most R&D efforts will be more productive in the future, we require strong exogeneity from R&D with respect to TFP. After reviewing our data sources and descriptive statistics, we will review with more detail both concepts and the empirical test we propose for the panel data case.

3. Data, Empirical Methodology and Results.

3.1 Data

The main sources of information for R&D expenditure and TFP came from the following data bases: Lederman and Saenz (2003, referred to as LS), Heston, Summers and Aten (2002, known as the Penn World Table, and referred to as PWT), and Klenow and Rodríguez-Claire (2005, referred to as KRC), all available for the 1960-2000 period.

We used the LS dataset to obtain series for R&D expressed as percent of the GDP. Then, we used these series and PWT information to construct both aggregate and per capita R&D expenditure series, expressed in purchasing power parity (PPP) 1995 dollars.

The total factor productivity series that we used were from those constructed by KRC. These authors used a Cobb-Douglas production function, which is a function of countries' physical capital, labor force and human capital:[8]

$$\begin{aligned} ln(TPF) &= ln(Q/L) - \alpha ln(K/L) - (1-\alpha) ln(H/L) \\ \text{where } H &= hL = exp(\phi s)L \end{aligned} \tag{4}$$

where Q/L represents the capital to worker ratio, K/L represents physical capital per worker and H is the stock of real human capital. In this version, the authors assume that $\alpha = 1/3$ and a return on education ϕ equal to 0.085

We used this information to build an unbalanced panel with observations averaged over five consecutive years. We had two main reasons for using data averaged over longer periods. The first was that that there were many years for which data for R&D expenditure was missing, thus averaging over longer periods gave us more consecutive observations. This was particularly useful for estimating dynamic specifications. The second reason was that, by using longer time periods, we could avoid cyclical factors that may have influenced R&D expenditure.

The sample that resulted from crossing the information from PWT and LS data bases, consider 65 countries for which there were at least two consecutive observations for both R&D spending and TFP. The following regions were represented in the data panel: Africa (eight countries), Central America and the Caribbean (five countries), North America (three countries), South America (ten countries), Asia (15 countries), Europe (22 countries) and Oceania (two countries). The country list and total number of observations per country is provided in Appendix B.

[8] For a more detailed description of how this series was constructed, see Klenow and Rodríguez-Claire (2005).

Several other sources of information were used to obtain the series we used later to estimate TFP's determinants. First, we used information from IMF's *International Financial Statistics* to construct series for trade as percent of GDP, financial market development and macroeconomic instability. As is detailed in appendix A, this last variable is directly related to annual inflation rate, which is derived from annual IPC variation. Therefor, in using this variable we are implicity assuming the existence of a relationship between high-inflation episodes and macroeconomic instability. Secondly, we used the World Bank's *World Development Indicators* to obtain homogenous measures of terms of trade and foreign direct investment. Lastly, we obtained information for institutional variables from the ADB Institute's *International Country Risk Guide* (ICGR). From this dataset we obtain two subjetive variables: socioeconomic conditions and investment profile. While the first variable reflects dissatisfaction of the society that could in turn constrain the government action, the second variable considers the risk to invest in a particular country. This investment risk could be associated to contract viability, profits repratiation laws and/or delays in the payments. Higher values of these variables reflect a lower socioeconomic pressures and a lower investment risk respectively.

Table 1 provides descriptive statistics for the variables used in the tests and those used subsequently as controls in the section measuring R&D expenditure's impacts on TFP. The sample includes a heterogeneous group of economies. Their per capita income ranged widely from US $900 to almost US $32,000, and averaged US $11,500. Per capita R&D spending, meanwhile, averaged US $131, with a significant group of economies investing virtually nothing in this activity.

Table 2 shows unconditional correlations between the variables examined. R&D expenditure posted a stronger relationship to total factor productivity when expressed in per capita terms than when actual amounts were considered. Moreover, both openness and financial market development correlated positively with TFP, while macro instability posted a negative relationship. Foreign direct investment flows, meanwhile, did not correlate significantly with TFP. The table reveals, moreover, that macroeconomic instability correlated negatively with all other variables, showing that, historically speaking, high-inflation environments tended to coincide with less development of financial markets, less R&D expenditure and smaller flows of goods and investment from abroad.

3.2 Exogeneity and Causality.

3.2.1 Definitions.

The seminal work that presents the concepts of weak and strong exogeneity is Engle, Hendry and Richards (1983). In general terms, a variable x_t can be considered as weakly exogenous for the parameters of interest if it is determined outside of the system under study. In this case, inference of the interest parameters conditional on x_t involves no loss of information. However, in dynamic contexts weak exogeneity is not enough to avoid for feedback from the endogenous to the (weakly) exogenous variable. Engle, Hendry and Richards (1983) define the absence of feedbacks and weak exogeneity as strong exogeneity. Given that strong exogenity depends on the presence of weak exogeneity, we start by explaining that concept.

Whether a variable is defined as weakly exogenous depends on the properties of the data generation process. In fact, as Engle, Hendry and Richards state, there is weak exogeneity, when the equation defining the weakly exogenous variables, denominated marginal equation, can be ignored without loss of information for inference purposes in the equations that explain the dependent variable under study, known as the conditional equation. Therefore, weak exogeneity represents a necessary condition for satisfactory single-equation regression models.

The test for weak exogeneity that we applied follows the work of Engle (1984). As he explained, such test consists in determining whether the estimated residuals of the marginal equation are statistically correlated to the conditional equation residuals, even after controlling for the regressors of the conditional equation. If the model is well specified, the distribution of this test will converge asymptotically to the normal distribution.

In this paper, we first test whether R&D is weakly exogenous to TFP. Thus, the marginal model explains the R&D variable. In our specification we follow the main results of those empirical papers studying R&D determinants. A common finding in those studies is that R&D is a very persistent variable.[9] Additionally, as Lederman and Maloney (2003) and Garcia (2007) show -for the same dataset we are using in this paper- R&D is strongly related to countries's per capita GDP. Therefore, we will assume that both lagged R&D and per capita GDP, aside time dummies and fixed effects, capture most of the variation of R&D across time and countries. Following the test, the conditional model explains the TFP and, in our specification, includes as explanatory variables the lagged TFP, R&D, time dummies and fixed effects. This will be the baseline model we will use to estimate the R&D contribution to total factor productivity. The following expressions resume the specifications for the marginal and the conditional model respectively:

$$R\&D_{i,t} = \mu^M + \beta_1^M R\&D_{i,t-1} + \beta_2^M \ln\left(pc\ GDP\right) + time\ dumm. + \eta_i^M + \varepsilon_{i,t}^M \qquad (5)$$

$$\ln\left(TFP\right)_{i,t} = \mu^C + \beta_1^C \ln\left(TFP\right)_{i,t-1} + \beta_2^C R\&D_{i,t} + time\,dumm. + \eta_i^C + \varepsilon_{i,t}^C \qquad (6)$$

The specification of the Engle test for the panel data case we propose is similar to that of the time series case. In a first step, we estimate the marginal and the conditional models and we obtain the estimated residuals $\hat{\varepsilon}_{i,t}^M$ and $\hat{\varepsilon}_{i,t}^C$ respectively. Then we estimate the following regression:

$$\hat{\varepsilon}_{i,t}^C = \mu^C + \beta_1^C \ln\left(TFP\right)_{i,t-1} + \beta_2^C R\&D_{i,t} + \gamma\hat{\varepsilon}_{i,t}^M + time\,dumm. + \eta_i^C + \omega_{i,t} \quad (7)$$

We will conclude that the R&D variable is weakly exogenous for TFP if we can not reject the null hypothesis that $\hat{\gamma} = 0$. Considering that the size of our sample is not the large enough to ensure asymptotic normality (we have a samples for 65 countries and 40 years at maximum), we decided to compute the critical values of $\hat{\gamma}$'s t-statistic by applying bootstrap techniques for panel data.

[9] See Gullec and Van Pottelsberghe (2000), Lederman and Maloney (2003), Falk (2006), and Garcia (2007)

The bootstrap method for univariate time series is well developed. However, the developments for panel data are scarce and they are concentrated in panel unit root studies[10]. In these works, the authors applied parametrical-block bootstraps in which the estimated errors of the equation of interest are resampled, maintaining the cross-section index fixed, instead of resampling them individually. In this way they preserve the cross correlation structure of the error term.

In contrast, in this paper we applied a non-parametrical bootstrap. Because we are concerned about the correlation between the dependent and the independent variables, we applied a paired resampling for the variables of interest instead of resampling the estimated errors. We apply the stationary bootstrap of Politis and Romano (1994) which is basically a block boostrap in which the length of the block is selected according to a geometrical function. The advantage of this method over traditional block-bootstraps is that we avoid generating non-stationary artificial samples. We generated 1,000 artificial samples according to this procedure. Then, for each sample we applied the t-test for the null hypothesis that $\hat{\gamma} = 0$. This will allow us to derive the empirical distribution that in turn will provide us critical values to evaluate the null hypothesis of the Engle's exogeneity test. The critical values are selected according to Efron's confidence intervals, at the 90 percent confidence level.

Is important to note that the sample we used for the bootstrap-based weak exogeneity test corresponds to a restricted version of the whole sample. In fact, as we resample annual observations, we could just consider those countries with more than 20 years of consecutive observations of R&D and TFP. To maximize the sample size and, given that R&D intensity is a smooth variable, we apply linear interpolation for this variable in those countries in which there are few missing values. Then we constructed R&D series expressed in 1995 US PPP dollars using actual GDP. Once we obtained the resampled series, we build one unbalanced panel for each artificial sample with observations averaged over five consecutive years. In practice we used only 24 countries for the bootstrap based tests.

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[10] See Wu and Wu (2001), Maddala and Wu (1999), Chang (2004), Cerrato and Sarantis (2007) for some examples of boostrap techniques applied to panel unit root test.

Once we test for weak exogeneity, we determine whether there is feedback from TFP to R&D for our sample of countries. As defined by Engle, Hendry and Richards (1983), there is strong exogeneity when, in addition to weak exogeneity, there are absence of feedbacks. To answer the question about the direction of the R&D and TFP relationship, we use Granger's concept of precedence. According to Granger (1969), if the variable X causes or precedes variable Y, it is better to predict Y using past values of X, than without them.

In Granger's sense, causality is a concept regarding statistical precedence and does not necessarily refer to a causal relationship in the economic sense. Notwithstanding, a confirmation of the presence of this type of precedence going from R&D to TFP, together with weak exogeneity, would make it possible to state that those countries who invested the most in R&D in the past would be those with the greatest productivity growth. This result, which is consistent with existent gowth theory, will be interpreted as evidence of an economic relationship between the two variables.

The specifications used in Granger causality tests for the case in which the X and Y variables corresponding to panel data are similar to those used in time series. As per work by Holtz-Eakin, Newey and Rosen (1988), we used specifications for vector autoregression adjusted to panel data, which included individual fixed effects (h_i):

$$Y_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_{1,j} Y_{i,t-j} + \sum_{j=1}^{m} \alpha_{2,j} X_{i,t-j} + \eta_i^Y + \varepsilon_{i,t}^Y \tag{8}$$

$$X_{it} = \beta_0 + \sum_{j=1}^{m} \beta_{1,j} X_{i,t-j} + \sum_{j=1}^{m} \beta_{2,j} Y_{i,t-j} + \eta_i^X + \varepsilon_{i,t}^X \tag{9}$$

It will be concluded that, as per Granger, X(Y) causes Y(X) if $\alpha_{1,j}$ ($\beta_{2,j}$) $\forall j = 1,\ldots,m$ are statistically different from zero. If both $\alpha_{1,j}$ and $\beta_{2,j}$ $\forall j = 1,\ldots,m$ are statistically different from zero, then Granger bi-causality is present between X and Y. We applied a Wald test to determine whether the null hypotheses of no-Granger precedence can be rejected, using small sample critical values.

3.2.2 Estimation Methodology

The problem of estimating (3), (4), (5) and (6) using Ordinary Least Squares (OLS) is that the parameters estimated are inconsistent, given that the lagged dependent variable is correlated with the error term $(\eta_i + \upsilon_{it})$. Meanwhile, although the fixed effects estimator (FE) eliminates the source of inconsistency by expressing the equation in terms of deviations from time averages, the result is nonetheless inconsistent.[11]

Given that when using OLS to estimate the lagged dependent variable correlates positively with the error term the coefficients estimated will be positively biased. Meanwhile, coefficients estimated for the FE will be negatively biased, since the correlation has the opposite sign.[12] The fact that these two estimators are oppositely biased is useful to prove robustness for alternative estimators because, if the estimated coefficient for the lagged dependent variable were consistent, it would be found in the middle of the values provided by the OLS and FE estimators.[13]

One common alternative for solving the inconsistency problem is to apply the Arellano and Bond (1991) method. This involves eliminating the source of the inconsistency, fixed effects, by applying the first difference operator to the equation under consideration. The resulting equation is then estimated using the Generalized Method of Moments (GMM), using lags of the explanatory variables as instruments.[14] However, if the dependent variable is highly persistent, so that instruments correlate weakly with the variables being instrumentalized, first-difference model estimations may present substantial bias.[15] The high estimated persistence for TFP described below suggests the possibility of weak instruments in the context of our study.

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[11] Expanding terms for average deviation reveals the presence of terms with other than zero expectations. For more details, see Bond (2002).

[12] See Arellano (2003).

[13] This is explained in detail in Benavente, Galetovic, Sanhueza and Serra (2005), among other works.

[14] The need to use instruments arises from the fact that, unless the idiosyncratic error follows a random walk process, it will correlate with the lagged dependent variable.

[15] See work by Blundell and Bond (1998) and Blundell, Bond and Windmeijer (2000).

Blundell and Bond (1998) note that it is possible to substantially improve estimation efficiency by combining moment conditions. They suggest applying the Generalized Method of Moments (GMM), using as instruments the variable lags in the difference equation and the variable differences in the level equation. Estimations for (4) and (5) are performed using this estimator, known in the literature as the "*GMM system estimator*".

These estimations involve using a weighting matrix that is the inverse of the variance-covariance matrix, constructed in a two-step estimation. This yields an asymptotically efficient estimator. However, as Windmeijer (2005) shows using Montecarlo simulations, standard asymptotic errors estimated using two-step GMM can lead to extreme underestimations in small samples. Because of this, we apply the Windmeijer finite sample correction to all estimations.

One critical assumption for the validity of GMM estimations is that the instruments must be exogenous in order to meet orthogonality conditions. To test the validity of the instrument set used, we applied the Hansen (1982) test. However, increasing amounts of instruments makes the test increasingly weaker[16]. Given that the literature does not concretely define how many instruments are "too many" and, that in most of the estimations the *p-values* of the tests rise enormously when the number of instruments is greater than the number of groups (even reaching values of 1,000), as a rule of thumb we discarded all specifications for which the number of instruments was greater than the number of groups. Considering that the validity of the instrument set depends on the error structure, we also used the Arellano Bond (1991) M2 test, which allow us to detect second order autocorrelation of the error in the first-differences equation. Where the M2 test rejected the null hypothesis (no second order autocorrelation of errors), only the dependent variable lags $y_{i,t-1-i}$ ($i = 1, 2, \ldots$) were valid as instruments in the first difference equation and first differences $Dy_{i,t-i}$ ($i = 1, 2, \ldots$) in the level equation. In all the estimations we also used as instruments the independent variables' lags and first differences. In the latter's case, the rule followed to choose instruments' lag-length was identical to that used in the case of the lagged dependent variable. This was to avoid bias related to the endogeneity of any of the independent variables.

[16] In fact, Bowsher (2002) shows that the use of too many moment conditions causes the Sargan / Hansen test to be undersized and to have extremely low power.

3.2.3 Exogeneity and Causality: Estimation Results.

We will start with showing our results for the weak exogeneity test. In the estimation of the conditional and marginal models we made use of consistent dynamic panel data estimators. In particular, we estimate by mean of the System GMM estimator.

In figures 1, 2 and 3 we show the empirical distribution derived for aggregate R&D logarithm, per capita, R&D logarithm and R&D as percent of GDP respectively. For each empirical distribution we compute Efron's confidence intervals at the 90 percent level. In contrast with the normal distribution, the derived empirical distributions are asymmetrically distributed around a non-cero value. This supports our strategy of use a bootstrap based test.

As is evident in the figures, the t-stat calculated with the original sample for each of the three R&D variables is inside the interval. Therefore, we can not reject the null hypothesis that each of the R&D variables are weakly exogenous. Inference of the parameters of interest in the conditional equation can be made without loss of information.

The next step is to test whether strong exogeneity is fulfilled for R&D variables. A crucial point in the estimation of Granger's equations (8) and (9) is the choice of the number of lags m to be included. This value should reflect the productive life that R&D investment is thought to have. Assuming a depreciation rate of 0.15, 90% of R&D would disappear within 15 years.[17] Consequently, the maximum value we used for m in Granger tests for both X and Y were identical to each other and equal to two.[18] The validity of this assumption was verified using estimations with m=3 (VAR(3)) and testing the joint significance of third order lags, making it impossible to reject the null hypothesis in any case.

[17] This value is frequently cited in the literature. See Griliches (1998), and Mairesse and Sassenou (1991).

[18] Restricting the maximum number of lags would mean that some variables would appear with more lags than those really having a coefficient other than zero, but at the same time would reduce the number of specifications to which the Granger test should be applied.

Aside from the test underlying expression (3) between the logarithm of R&D expenditure and the TFP logarithm, two further groups of tests were considered, with R&D expenditure expressed in per capita terms and as a ratio of the Gross Domestic Product (GDP). This was done for two reasons. Firstly, scaling R&D expenditure provided a natural test for the robustness of results. Secondly, dividing R&D spending by variables representing economic scale also provided more rigorous indicators when it came to evaluating increases in the resources going to this sector.

Given that Granger tests are sensitive to the instrument set available, instead of choosing a single specification, we present the results for three specifications for each VAR(p) (p=1,2) instrumentalized using different variable lags.[19] Then, we discarded the specifications in which: (i) the Hansen test rejected the validity of the instrument set; (ii) the Arellano and Bond (1991) M2 test found first-order autocorrelation in the errors of the level equation and the instrument set as a whole contained both the (p+1)-nth lag and the p-nth difference of the VAR(p) dependent variable, and (iii) the sum of the autoregressive coefficients was outside the limit provided by the OLS and FE estimations.[20]

All estimations were conducted through system GMM estimators. We presented three groups of statistics. The first one shows the Granger test and its associated p-value. The second one provides information on the validity of the estimated specification and, therefore, the reported Granger test. In this group we provide the Hansen test, autocorrelation tests for second order residuals in first difference equations, and the sum of the estimated OLS, system GMM and FE autoregressive coefficients. The final statistics group provides information on the number of observations, groups, instruments and lags of the variables used as instruments.

The results in Tables 3, 4 and 5, revealed that the estimations share some characteristics. In the first place, none of the estimations revealed first order autocorrelation in level equation errors.[21] Second, the estimated coefficients were sensitive to the set of instruments used and, in some cases, their sum was outside the limit provided by OLS and FE estimations.

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[19] In practice, each VAR(p) specification is instrumentalized with variable lags of an order: (a) greater than or equal to $p+1$, (b) greater than or equal to $p+2$ and (c) greater than or equal to $p+3$

[20] For reasons of space we have not presented the underlying parameters estimated in each specification of the test.

[21] Although not reported, we also carried out tests to evaluate the presence of second order autocorrelation in level equations. In no case was it possible to reject the null for second order non-autocorrelation.

Table 3 analyzes Granger precedence between the TFP logarithm and the aggregate R&D spending logarithm. In all specifications, the Hansen test is not able to reject the validity of the instrument set and the coefficients estimated through system GMM were within the limit established by OLS and FE estimations. The M2 test, however, suggests the presence of second order autocorrelation in the errors of the difference equation of specifications (1) and (4). Although specifications (2) and (3) show second order autocorrelated errors, they are considered valid since they use as instruments lags of an order greater than three, so the null correlation assumption for instruments with the error term, both in level equations and first differences, is satisfied.

Overall, the results were not very conclusive. On one hand, the two valid VAR(1) specifications suggest one-way Granger precedence, from R&D to TFP. VAR(2) specifications, meanwhile, are less clear. In this case, the test for R&D is not statistically significant in either of the two valid specifications, while the test for TFP is significant in just one case, at 5% confidence level (column 5 in the lower panel of Table 3).

Table 4 provides results for R&D expenditure expressed in terms of per capita logarithms. Once again, for specifications (1) and (4) in Table 4, the M2 test suggests the presence of second-order autocorrelated errors in difference equations, which invalidates the tests underlying these expressions. Moreover, specifications (6) in the upper panel and (3) in the lower panel are not considered either, since the sum of the coefficients of the lagged dependent variable is outside the limit provided by the OLS and FE estimations.

Precedence results are noticeably clearer when per capita R&D expenditure is used instead of aggregate R&D. In all valid VAR (1) specifications, the per capita R&D logarithm precedes the TFP logarithm at the 1% level, and not vice versa (columns 2 and 3). This also holds true for the only valid VAR(2) specifications, in which R&D spending precedes TFP to 5%. Thus, the evidence suggests the presence of one-way Granger precedence from (per capita) R&D expenditure to TFP.

Finally, Table 5 shows the results of applying the causality test for R&D expenditure expressed as a share of Gross Domestic Product. Once invalid specifications are ruled out, only one R&D spending specification statistically precedes the TFP logarithm (column 2). Moreover, unlike the previous two cases, in this specification we can see considerable feedback from the TFP logarithm to R&D spending. In the other specifications, meanwhile, there's no evidence of statistical precedence between TFP and R&D. The available evidence therefore does not clearly establish a relationship of statistical precedence and, if one exists, it is not possible to determine if it goes from R&D spending to TFP or vice versa.

Robustness

To analyze the robustness of results, we compute Granger precedence tests for the original dataset, averaged over four-, three- and two-year periods. Tables 6, 7 and 8 provide the results for R&D logarithms, per capita R&D logarithms, and R&D as a percentage of GDP logarithms, respectively. For reasons of space, we only present the respective statistic, indicating cases where the null is rejected to 10%, 5% and 1%, along with valid specifications, according to the requirements described at the start of this section. As in the case of the five-year periods, the order of specifications (*m*) was chosen so that estimations include information for the past 15 years.

Test results for the different data sources successively confirmed the results from the five-year average data, with some results calling for further comment. First, the causality relationship appeared strong in low-order VAR(p) specifications when per capita R&D spending was considered (Tables 6 and 7), as in the five-year average dataset. Secondly, tests for R&D spending as percent of GDP were again not very conclusive (Table 8). For these cases, despite the fact that overall there seems to be stronger statistical precedence supporting an influence from R&D to TFP, the large number of invalid specifications hampers a reasonable evaluation of the precedence hypothesis.

The fact that precedence exercise results are so dependent on how the R&D variable is defined should be noted. When the variable is the R&D logarithm, the results reveal precedence, which although weak, moves from R&D to TFP. When the per capita spending ratio is used, the statistic precedence from R&D to TFP grows stronger. Finally, in test with the two previous cases, when the R&D intensity is considered, the statistical-precedence relationship between R&D and TFP fades. These results suggest as a whole that, at least from the statistical perspective, scaling R&D by population offers a more robust measure than R&D intensity or aggregate R&D. Another advantage to using this variable in empirical work is that when we scale by population we introduce less noise into changes in R&D expenditure, since the population tends to be more stable than economic product. However, we underline the need to explore more deeply the reasons behind these divergent results.

3.3. R&D's Impact on Productivity

3.3.1 Estimation Methodology

Once strong exogeneity of R&D spending has been established, it becomes necessary to evaluate the economic relationship between R&D and productivity. In practice, we estimate versions of equation (3) that differ according to the set of variables included in vector "X". This equation is estimated for both the aggregate R&D spending logarithm and the per capita R&D spending logarithm. Evaluating the impact of R&D spending as percent of GDP has been ruled out, since the results from the previous section do not ensure one-way precedence from R&D to TFP.

Choosing the factors to be included as explanatory variables for total factor productivity is not simple. A significant number of the studies that have examined country productivity determinants have used *ad hoc* approaches inspired in the growth literature led by Barro (1991). Despite the fact that this method has been particularly criticized for overfitting the data, in this study we have taken a similar approach. This is due to our main objective to test robustness in the R&D and TFP correlation, when controlling for different factors. To provide a full history of the factors determining productivity in these countries goes beyond the reach of this study.

The evidence available indicates that variables such as the terms of trade, openess, institutional variables, or financial system development, all tend to correlate positively with TFP.[22,23] Luckily, these variables are broadly available for different economies and we can incorporate them in our regressions.

Aside from the lagged productivity logarithm and the R&D spending variable, the TFP specification included an indicator for openness to trade[24], a terms of trade variable, foreign direct investment (FDI) as percent of GDP[25], an indicator for financial market development[26], institutional and socioeconomic variables, and an indicator for macroeconomic instability, measured as the inflation rate divided by one plus the inflation rate. This last variable was found to have a negative relationship with TFP by authors as Edwards (1998) and Fuentes, Larraín and Schmidt-Hebbel (2006). Regarding the financial development measure used in the regressions, our favorite measure is the credit to private sector as percent of GDP. As suggested by King and Levine (1993), this is a better measure of financial market development than the size of the financial intermediaries relative to economic activity or than the credit provided by commercial banks as percent of total credit. However, is important to stress that our results are not dependent to the financial market development variable used. Finally, to capture the quality of the institutions and the socioeconomic climate, we include high and low income dummies[27] aside two institutional variables in our regressions: a subjective indicator of the investment profile of the country, and other indicator of the socioeconomic conditions of the country. Appendix B describes data sources and the specific definition of these variables.

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[22] Fuentes, Larraín and Schmidt-Hebbel also show that misalignments in the real exchange rate correlates with TFP in Chile. However, in this study, this variable could not be considered since it was not available for a significant number of countries during the period under examination.

[23] Evidence of the link between these variables and productivity can be found in Edwards (1998), Alcala and Ciccone (2004) and Fuentes, Larraín and Schmidt-Hebbel (2006).

[24] Edwards (1998), Frankel and Romer (1999), Millar and Upadhyay (2000) and Alcala and Ciccone (2004) provide evidence of a positive relationship between openness and/or trade and productivity.

[25] Borensztein, De Gregorio and Lee (1998) provide evidence suggesting a positive relationship between FDI and TFP.

[26] Greenwood and Jovanovic (1990), Bencivenga and Smith (1991) and Greenwood and Smith (1997) develop models that show the positive relationship between financial market development and growth. Empirical evidence of the relationship with productivity can be found in Levine and Zervos (1998) and in Aghion, Howitt and Mayer-Foulkes (2005).

[27] To construct these dummy variables, we defined high and low-income thresholds equal to percentile 30 and 70 of the per capita GDP distribution. For the construction of these thresholds we considered per capita-GDP averages across the whole period.

The empirical strategy starts by estimating a baseline set of specifications which include as controls the lagged TFP, openness variables, terms of trade, private credit as percent of GDP, and institutional variables. Then, in a second and in a third set of regressions we incorporate the R&D logarithm and the per capita R&D logarithm respectively. Considering the dynamic nature of the specifications, we calculate the long-term elasticity between R&D and TFP for all specifications in which R&D variables were included. In this way we attempt to evaluate the size of the contribution from R&D expenditure in the long-run.

Finally, we use interactions terms between R&D and other variables to test some hypotheses of interest. As a first plausible hypothesis, we consider that the impact of R&D could be higher in low-income countries because they have unexploited possibilities to imitate and copy the inventions of more technologically advanced economies. However, on the other hand, one could reasonably argue that experience is important for R&D activities, thus R&D spending in low income economies could have actually a lower impact on TFP. To answer this question we interact the income dummies with the R&D variables. Another hypothesis we want to test is whether the R&D profitability is higher in macroeconomic stable environments. We try to answer this question by interacting R&D with the macro-instability variable.

All equations were estimated using system GMM. The instruments used in each specification were the second and third lag for each variable, except when estimations did not meet any of the requirements described in section 2.3. In those case specifications with more lags were sought. The arbitrariness of this choice took into consideration the trade-off between efficiency gains from including more information and the overfitting of the data due to inclusion of lagged instruments for each variable. Finally, it should be noted that, as with Granger precedence tests, we use the data expressed in five-year averages so the parameters estimated would reflect the average impact of the variable under consideration on productivity during the five-year period.

3.3.2 **R&D's Impact on Productivity: Estimation Results.**

We present our results in three tables. In the first set of regressions –Table 9– we include neither R&D variable. The second set of regressions –Table 10– provides the results when we include the R&D logarithm. Finally, in the third set of regressions –Table 11– we show our results when per capita R&D logarithm is considered.

As Tables 9, 10 and 11 make clear for all factors under consideration, the unconditional correlation with total factor productivity calculated in Section 3 held true. However, the significance of these partial correlations varied widely, according to the variable. Moreover, estimations revealed a highly persistent TFP logarithm, with values ranging from 0.75 to over 0.85. These values were always limited by the parameters estimated by OLS and FE, thereby meeting the test for robustness described in section 2.3 (not reported).

Baseline regressions of table 9 shows that lagged TFP, terms of trade and the investment profile had the expected sign and moreover, were statiscally significant in all the specifications. In contrast, openness variables, financial system development (aproximated by the domestic private credit as percent of GDP) and income dummies were not significant in most of the regressions. These results held true when we included R&D variable in tables 10 and 11. The most noticeable difference with baseline results was that the openness variable increased its significance and the high-income dummy became significant in table 11 when we considered the per capita R&D logarithm.

In table 10 we show our results for R&D logarithm. The contemporaneous R&D spending appears as statistically significant in all the specifications, even in the fourth one where we included interactions of the R&D variable with high- and low-income countries aside from macroeconomic stability. Estimations show approximately a value for the R&D elasticity of 0.02. This value implies that a 10 percent increase in the R&D spending brings 0.2% more of productivity. With regard to the interactions, none turned out to be statistically significant.

It is important to note that, given that we estimated dynamics specifications, the impact of an increase in R&D will be higher in the long-run than in the short-run. In table 12, we compute these long-run elasticities for the R&D expenditure, evaluating them in the mean value of the macroeconomic stability variable for high-, median- and low-income countries. To calculate the statistical significance of these elasticities, we used Delta method. As showed in the first column of table 12, the estimated long-run elasticity for the full sample goes from 0.125 to 0.145. However, when we try separate the long-run impact between high-, median- and low-income countries, the estimated elasticity is only significant for median income countries. This is a novel result that deserves to be considered with caution and that requires further research.

Finally, in table 11 we show our results when using the per capita R&D logarithm variable. The results suggest a stronger relationship between per capita spending on R&D and total factor productivity than in the case of the aggregate R&D. Moreover, the estimates are of a substantial magnitude. In fact, the long-term elasticities computed in the second column of table 12 reveal that a 10% increase in per capita R&D spending should generate an average between 1.6% and 2% rise in the long run total factor productivity. Again, when we compute the long run elasticity for high-, median- and low- income countries, the high-income country elasticity becomes not significant. This higher long-run impact in median- and low-income countries supports the hypothesis of unexploited possibilities of imitating and copying more technologically advanced economies. The correlations of the other variables estimated coincided with those estimated in table 9 for baseline specifications. This suggests a robust correlation for these parameters.

4. Concluding Remarks

The relationship between productivity and R&D expenditure has been a topic of inquiry since the middle of the twentieth century. Since then, this area of research has produced a significant amount of empirical and subsequent theroretical work. Notwithstanding these research efforts, there are still very relevant questions on the nature of the relationship between productivity and R&D expenditure that remain unanswered both at the level of the firm and even further at the country level.

Most of the empirical studies assessing the R&D-productivity relationship at the country level often fail to consider the possible simultaneity of these variables. Do more productive countries invest more on R&D or does the higher level of R&D investment lead to higher levels of productivity? Do both relationships occur at the same time? To answer correctly these question has crucial relevance for developing countries as it involves a very different set of policy recommendations regarding innovation and technology policies.

In this paper we investigate the nature of the relationship between R&D and TFP, using three measures of R&D: level of R&D in constant PPP dollars, R&D as a share of GDP, and R&D per capita also in constant PPP dollars. To study the potential simultaneity among the variables, we first study their degree of exogeneity, establishing whether R&D and TFP are either weakly exogenous or endogenous. Secondly, we establish the statistical causality between R&D and productivity by means of Granger causality tests and then we conclude on weak and strong exogeneity. The main results suggests that our three measures of R&D are weakly exogenous. With respect to causality, we find that most of the relationship goes from R&D per capita to productivity and not vice versa; therefore R&D per capita is strongly exogenous to TFP. With respect to the other measures of R&D, we obtain mixed results on the Granger causality tests. We also explore whether the R&D sector's impact on productivity is robust with respect to the impact of factors such as openness to trade, terms of trade, financial market development, foreign direct investment and institutional variables. The evidence suggests that the R&D expenditure per capita is an important productivity determinant of TFP even when controlling for other factors.

Thus, there are important lessons that can be derived from our results. In particular, our results deviate from the existing consensus on the relevance of R&D intensity as measured by R&D share in the GDP. Our results imply that R&D expenditure per capita is more important than the intensity or effort that an economy puts into the development of R&D activities. Our measure of R&D per capita as cause of productivity growth could be interpreted as the availability of resources devoted to improve and create goods and services on an individual (consumer) basis and not necessarily in the economy as a whole (intensity).

The evidence shows that it is possible to increase the level of the productivity of a country, measured by its TFP, by increasing its R&D per capita. This implies that in growing economies with constant population, it might be sufficient to keep the share of R&D constant to create further TFP growth. However, in economies with growing populations, our results imply that a significant effort must be carried out to increase R&D to the level where resources devoted to R&D that grows faster than population growth.

In any case, these results should be analyzed with care. The R&D spending variable used was a more aggregate measure than is desirable, so the impact found reflects the average for all types of R&D carried out in our sample. There is no reason to assume that all types of R&D spending have the same impact on productivity growth. Some types of R&D may have an even larger or smaller impact on TFP and these impacts might defer between countries and productive structures. To quantify these differences opens up an interesting area of future research.

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Appendix A: *Description of Variables*

• **Total Factor Productivity:** This definition is from Klenow and Rodriguez-Claire (2005), who calculate it as follows:

$$PTF = \frac{Y/L}{[(K/Y)*(Y/L)]^{\alpha} * exp(\phi * att)^{1-\alpha}},$$

where Y/L represents real product per worker, K/Y equals the capital to product ratio, and att are years of education of individuals over 26 years of age. Finally, it is assumed that $\alpha = 1/3$, and $\phi = 0.085$. The authors take this last value, which represents the return on education, from Psacharopoulos and Patrinos (2002). Average years of education for individuals over 25 years is from Barro and Lee (2000), while other variables come from the Penn World Table, version 6.1.

• **R&D Spending:** This variable is from Lederman and Saenz (2003). These authors collected information on R&D spending from UNESCO, World Bank, *Red de Indicadores de Ciencia y Tecnología Ibero Americana* (RICYT) and the Taiwan Statistics Data Book data bases. The definition of R&D used here includes basic and applied research, along with experimental development. The Lederman and Saenz (2003) data base includes information on R&D expenditure as percent of GDP. To build the series expressed in dollars according to parity purchasing power (PPP) and per capita PPP, the value was multiplied by real GDP expressed in PPP and the per capita GDP in PPP. These last two series were from the Penn World Table.

• **Macro instability:** $\pi/(1+\pi)$, where π represents average annual inflation for the period. Average annual inflation is constructed as a geometric average of the change in the CPI over the period (line 64 of the IFS)

• **Private credit:**[28] $(0.5)*[F_t/Pe_t + F_{t-1}/Pe_{t-1}]/[GDP_t/Pa_t]$, where F is credit provided by commercial banks and other non-financial institutions to the private sector (lines 22d + 42d in

28 This variable is constructed as per Aghion, Howitt and Mayer-Foulkes (2005), based on King and Levine (1993).

the IFS), GDP is from line 99b, Pe is CPI at period's end (line 64), and Pa is the average CPI for the year.

• **Bank:**[29] This is the ratio of commercial bank assets (lines 22a-d) over total commercial bank plus central bank assets (lines 12a-d).

• **LLY:**[30] $(0.5)*[F_t/Pe_t + F_{t-1}/Pe_{t-1}]/[GDP_t/Pa_t]$, where F is M3 (line 55 in the IFS) or M2 when this is not available (lines 34+35 in the IFS). As with private credits, GDP is from line 99b, Pe is CPI at period's end (line 64), and Pa is average CPI for the year.

• **Openness:** (X+M)/GDP, where X represents exports (line 90c) and M imports (line 98c). Source: *International Financial Statistics.*

• **Terms of trade:** Corresponds to the ratio of the export price index to the corresponding import price index measured relative to the base year 2000. Source: *World Development Indicators.*

• **Foreign Direct Investment/GDP:** Flows of foreign direct investment over GDP. Source: *World Development Indicators*.

• **Socioeconomic Environment Subjective Index:** This variable reflects socioeconomic pressures at work in society that could constrain government action or fuel social dissatisfaction. It is the sum of three sub-categories: unemployment, consumer confidence, and poverty. Source: *International Country Risk Guide.*

• **Investment Profile Subjective Index:** Corresponds to an assessment of factors reflecting the risk of specific factors to investment. It is composed by three subcomponents: contract viability / expropriations, profits repatriation, and payment delays. Source: *International Country Risk Guide.*

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29 Constructed based on King and Levine (1993).
30 Constructed according to Aghion, Howitt and Mayer-Foulkes (2005), based on King and Levine (1993).

Table: Appendix B
Sample

País	Obs.	País	Obs.	País	Obs.
Argentina	6	Hong Kong, China	1	Poland	2
Australia	5	Hungary	6	Portugal	6
Austria	6	Iceland	6	Romania	2
Belgium	6	India	6	Senegal	1
Bolivia	1	Indonesia	5	Singapore	4
Brazil	5	Ireland	6	South Africa	2
Canada	6	Israel	6	Spain	6
Chile	4	Italy	6	Sri Lanka	1
China	2	Jamaica	1	Sweden	6
Colombia	3	Japan	6	Switzerland	6
Costa Rica	5	Jordan	3	Taiwan, China	4
Cyprus	1	Korea, Rep.	6	Thailand	4
Denmark	5	Malaysia	2	Togo	1
Ecuador	4	Mauritius	2	Tunisia	1
Egypt, Arab Rep.	5	Mexico	4	Turkey	6
El Salvador	3	Netherlands	6	Uganda	1
Finland	6	New Zealand	3	United Kingdom	5
France	6	Norway	6	United States	6
Germany	2	Pakistan	4	Uruguay	3
Greece	4	Panama	2	Venezuela, RB	6
Guatemala	4	Peru	5	Zambia	1
Guyana	1	Philippines	5	**TOTAL**	**261**

Source: Authors' construction.
Note: Correspond to the number of observations in the five-year averaged data. Only countries with observations for both total factor productivity and lagged total factor productivity were considerated.

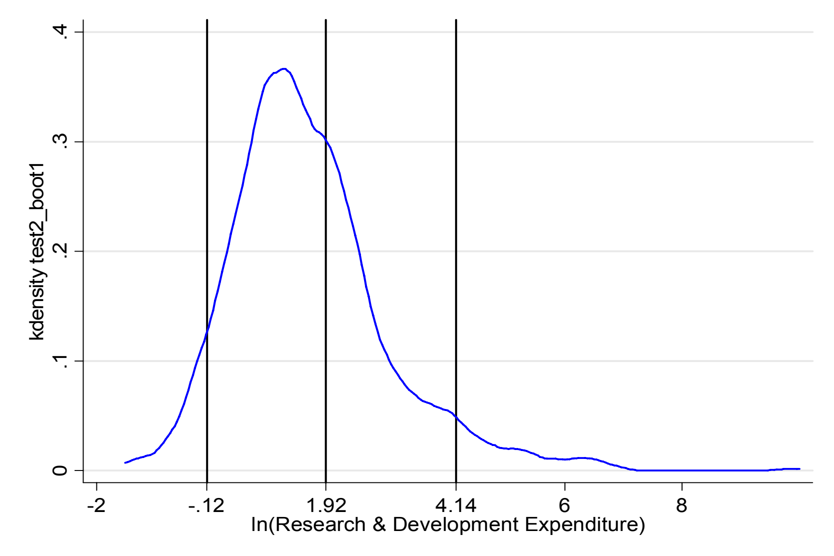
Figure 1

Empirical Distribution Engle's Weak Exogeneity Test

Variable: ln(Research and Development Expenditure)

Statistic calculated: 1.92

90% Bootstrap confidence interval calculated: [-0.12 , 4.14]



Source: Authors' computations

Note: The figure corresponds to a Epachelnikov Kernel of the Engle's weak exogeneity test emprirical density. The red line denote the value of the test for the original data.

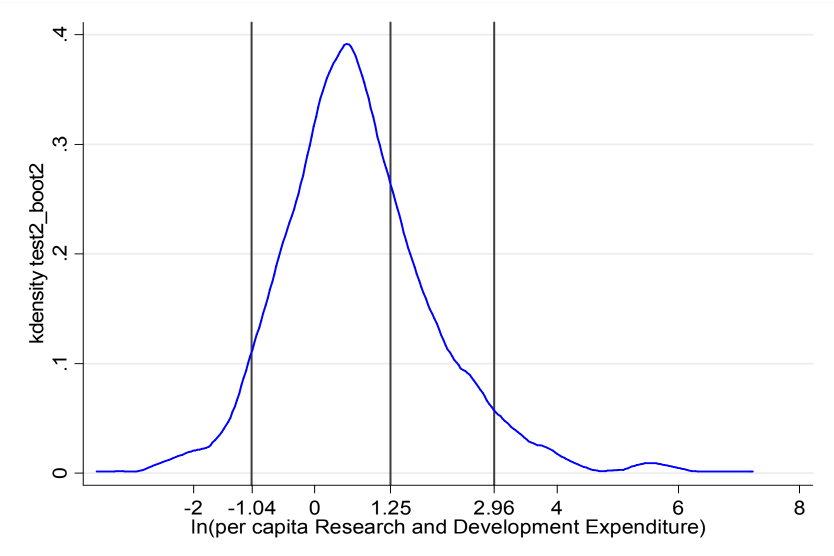
Figure 2

Empirical Distribution Engle's Weak Exogeneity Test

Variable: ln(per capita Research and Development Expenditure)

Statistic calculated: 1.25

90% Bootstrap confidence interval calculated: [-1.04 , 2.96]



Source: Authors' computations

Note: The figure corresponds to a Epachelnikov Kernel of the Engle's weak exogeneity test emprirical density. The red line denote the value of the test for the original data.

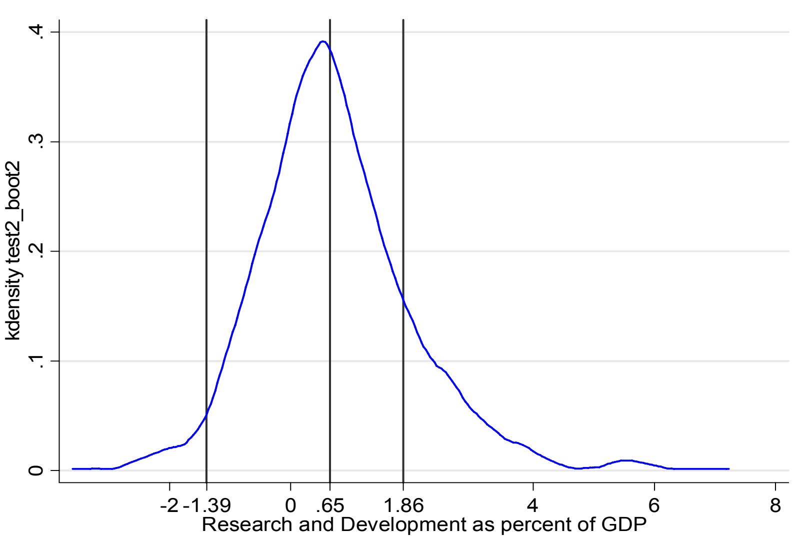
Figure 3

Empirical Distribution Engle's Weak Exogeneity Test

Variable: Research and Development as percent of GDP

Statistic calculated: 0.65

90% Bootstrap confidence interval calculated: [-1.39 , 1.86]



Source: Authors' computations

Note: The figure corresponds to a Epachelnikov Kernel of the Engle's weak exogeneity test emprirical density. The red line denote the value of the test for the original data.

Table 1
Descriptive Statistics
Sample: 1965-2000

Variable	Obs	Media	D.est.	Min	Max
id.country	---	---	---	1	65
id.period	---	---	---	1	8
TFP	261	459.1	125.34	154.74	786.08
Ln(TFP)	261	6.08	0.33	5.04	6.67
Ln(R&D)	261	20.81	2.18	14.1	26.14
R&D per capita[b]	261	167.72	190.31	0.06	822.81
GDPper capita[b]	261	11,578	7,265	903	31,179
R&D /GDP	261	0.01%	0.01%	0.001%	3.72%
Openness[c]	261	0.58	0.44	0.08	3.26
FDI/GDP[d]	252	0.02	0.03	0	0.34
Private Credit[e]	233	0.59	0.39	0.05	2.44
LLY[g]	180	0.53	0.35	0.12	2.29
Bank[f]	239	0.82	0.16	0.19	1
Macro Instability	242	0.13	0.16	0	0.89
Inflation	242	0.29	0.94	0	8.24
Terms of Trade	198	106.3	25.8	61.72	245.6
Socioeconomic Environment	259	6.88	1.88	2.58	11
Investment Profile	259	7.19	1.93	2.48	11

Source: Authors' calculations. Note: (a) Only are considered observations of tose countries with both TFP and lagged TFP available; (b) Expressed in terms of 1995 dollars, PPP adjusted; (c) Ratio of Imports plus exports to GDP; (d) Foreign direct investment; (e) Percent of GDP; (f) Ratio between comercial banks assets and comercial banks assets plus central bank assets; (g) M3 over GDP.

Table 2
Inconditional Pairwise Correlation
Sample: 1965-2000

Variable		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
ln(TFP)	**A**	1.000											
ln(R&D)	**B**	0.760*	1.000										
ln(per capita R&D)	**C**	0.708*	0.704*	1.000									
Openness (PWT)	**D**	0.127	-0.291*	0.166*	1.000								
FDI/GDP	**E**	0.137*	-0.042	0.059	0.350*	1.000							
Macro Instability	**F**	-0.416*	-0.459*	-0.598*	-0.232*	-0.299*	1.000						
Private credit	**G**	0.455*	0.555*	0.536*	0.064	-0.059	-0.483*	1.000					
Bank	**H**	0.447*	0.458*	0.479*	0.239*	0.100	-0.644*	0.562*	1.000				
LLY	**I**	0.572*	0.452*	0.382*	0.151	-0.044	-0.454*	0.648*	0.576*	1.000			
Terms of Trade	**J**	-0.130	-0.087	-0.140	-0.159	0.122	0.039	0.064	-0.074	-0.123	1.000		
Socioeconomic Environment	**K**	0.448*	0.391*	0.524*	0.130	-0.171	-0.380*	0.334*	0.422*	0.408*	-0.267*	1.000	
Investment Profile	**L**	0.326*	0.224*	0.312*	0.064	-0.003	-0.173	0.115	0.188	0.197	-0.082	0.623*	1.000

Source: Authors' calculations. Note: (a) Only are considered observations of tose countries with both TFP and lagged TFP available;

Table 3
Granger Precedence Test, logarithm of R&D
Estimation Method : System GMM
Sample: 1965-2000 (five year averages)

Null Hiphotesis: **Log of R&D does not cause to Log of TFP**

	VAR(1)			VAR(2)		
	(1)	(2)	(3)	(1)	(2)	(3)
Granger - Test Statistic	3.271 *	15.424 **	3.392 *	6.066 ***	2.411	1.044
Valid Specification?	No	Yes	Yes	No	Yes	Yes
Hansen- Test (p -value)	0.163	0.309	0.747	0.235	0.715	0.603
Arellano M2 Test (p - value)	0.028 *	0.02 **	0.017 **	0.085 *	0.127	0.145
Sum of OLS Coefficients	0.932	0.932	0.932	0.95	0.95	0.95
Sum of System GMM Coefficients	0.791	0.832	0.576	0.858	0.795	0.575
Sum of FE Coefficients	0.507	0.507	0.507	0.339	0.339	0.339
Observations	261	261	261	190	190	190
Countries	65	65	65	54	54	54
Lags used as Instruments	[3 , 5]	[4 , 6]	[5 , 7]	[2 , 4]	[3 , 5]	[4 , 6]
Instruments	40	32	24	31	23	15

Null Hiphotesis: **Log of TFP does not cause to Log of R&D**

	VAR(1)			VAR(2)		
	(1)	(2)	(3)	(1)	(2)	(3)
Granger - Test Statistic	0.004	0.067	0.029	1.527	4.143 **	0.019
Valid Specification?	Yes	Yes	Yes	Yes	Yes	Yes
Hansen- Test (p -value)	0.315	0.474	0.331	0.204	0.369	0.477
Arellano M2 Test (p - value)	0.547	0.54	0.536	0.36	0.462	0.531
Sum of OLS Coefficients	0.947	0.947	0.947	0.954	0.954	0.954
Sum of System GMM Coefficients	0.791	0.832	0.576	0.858	0.795	0.575
Sum of FE Coefficients	0.301	0.301	0.301	0.073	0.073	0.073
Observations	261	261	261	190	190	190
Countries	65 #	65	65	54	54	54
Lags used as Instruments	[3 , 5]	[4 , 6]	[5 , 7]	[2 , 4]	[3 , 5]	[4 , 6]
Instruments	40	32	24	31	23	15

Source: Authors' estimations.
*Note: The statistics has a F(r, n - k) distribution, where r is the number of restrictions, n correspond to the observations and k is the number of parameters estimated. The data is averaged for five-year period. The regressions include temporal dummies and a constant term (not reported). * Statistically significant at the 10% level; ** Statistically significant at the 5% level; *** Statistically significant at the 1% level.*

Table 4
Granger Precedence Test, logarithm of per Capita R&D

Estimation Method : System GMM

Sample: 1965-2000 (five year averages)

Null Hiphotesis: **Log of per Capita R&D does not cause to Log of TFP**

	V A R (1)			V A R (2)		
	(1)	(2)	(3)	(1)	(2)	(3)
Granger - Test Statistic	1.744	15.515 ***	27.383 ***	6.124 ***	3.106 *	0.007
Valid Specification?	No	Yes	Yes	No	Yes	No
Hansen- Test (p -value)	0.218	0.19	0.372	0.157	0.333	0.043 *
Arellano M2 Test (p - value)	0.022 **	0.019 **	0.011 **	0.071 *	0.059 *	0.048 *
Sum of OLS Coefficients	0.884	0.884	0.884	0.88	0.88	0.88
Sum of System GMM Coefficients	0.829	0.774	0.618	0.872	0.867	1.206
Sum of FE Coefficients	0.49	0.49	0.49	0.311	0.311	0.311
Observations	261	261	261	190	190	190
Countries	65	65	65	54	54	54
Lags used as Instruments	[3 , 5]	[4 , 6]	[5 , 7]	[2 , 4]	[3 , 5]	[4 , 6]
Instruments	40	32	24	31	23	15

Null Hiphotesis: **Log of TFP does not cause to Log of per Capita R&D**

	V A R (1)			V A R (2)		
	(1)	(2)	(3)	(1)	(2)	(3)
Granger - Test Statistic	0.034	0.733	0.119	14.014***	1.462	0.139
Valid Specification?	Yes	Yes	No	Yes	Yes	Yes
Hansen- Test (p -value)	0.319	0.783	0.758	0.411	0.852	0.5
Arellano M2 Test (p - value)	0.576	0.551	0.532	0.653	0.316	0.638
Sum of OLS Coefficients	0.905	0.905	0.905	1.015	1.015	1.015
Sum of System GMM Coefficients	0.905	0.902	1.015	0.915	0.977	1.004
Sum of FE Coefficients	0.311	0.311	0.311	0.073	0.073	0.073
Observations	261	261	261	190	190	190
Countries	65 #	65	65	54	54	54
Lags used as Instruments	[3 , 5]	[4 , 6]	[5 , 7]	[2 , 4]	[3 , 5]	[4 , 6]
Instruments	40	32	24	31	23	15

Source: Authors' estimations.

*Note: The statistics has a F(r, n - k) distribution, where r is the number of restrictions, n correspond to the observations and k is the number of parameters estimated. The data is averaged for five-year period. The regressions include temporal dummies and a constant term (not reported). * Statistically significant at the 10% level; ** Statistically significant at the 5% level; *** Statistically significant at the 1% level.*

Table 5

Granger Precedence Test, R&D as percent of GDP

Estimation Method : System GMM

Sample: 1965-2000 (five year averages)

Null Hiphotesis: **R&D as percent of GDP does not cause to Log of TFP**

	VAR(1)			VAR(2)		
	(1)	(2)	(3)	(1)	(2)	(3)
Granger - Test Statistic	4.331 **	3.507 *	1.411	0.331	0.217	0.049
Valid Specification?	No	Yes	Yes	No	Yes	No
Hansen- Test (p -value)	0.475	0.366	0.138	0.3	0.162	0.192
Arellano M2 Test (p - value)	0.042 **	0.055 *	0.062 *	0.076 *	0.08 *	0.063 *
Sum of OLS Coefficients	0.939	0.939	0.939	0.93	0.93	0.93
Sum of System GMM Coefficients	0.928	0.847	0.786	0.974	0.914	1.011
Sum of FE Coefficients	0.661	0.661	0.661	0.569	0.569	0.569
Observations	261	261	261	190	190	190
Countries	65	65	65	54	54	54
Lags used as Instruments	[3 , 5]	[4 , 6]	[5 , 7]	[2 , 4]	[3 , 5]	[4 , 6]
Instruments	40	32	24	31	23	15

Null Hiphotesis: **Log of TFP does not cause to R&D as percent of GDP**

	VAR(1)			VAR(2)		
	(1)	(2)	(3)	(1)	(2)	(3)
Granger - Test Statistic	2.4	5.188 **	0.118	1.565	0.245	0.147
Valid Specification?	Yes	Yes	Yes	No	No	Yes
Hansen- Test (p -value)	0.217	0.613	0.438	0.58	0.403	0.335
Arellano M2 Test (p - value)	0.573	0.516	0.557	0.085 *	0.226	0.918
Sum of OLS Coefficients	0.943	0.943	0.943	0.968	0.968	0.968
Sum of System GMM Coefficients	0.858	0.782	0.939	0.974	1.083	0.718
Sum of FE Coefficients	0.565	0.565	0.565	0.529	0.529	0.529
Observations	261	261	261	190	190	190
Countries	65 #	65	65	54	54	54
Lags used as Instruments	[3 , 5]	[4 , 6]	[5 , 7]	[2 , 4]	[3 , 5]	[4 , 6]
Instruments	40	32	24	31	23	15

Source: Authors' estimations.

*Note: The statistics has a F(r, n - k) distribution, where r is the number of restrictions, n correspond to the observations and k is the number of parameters estimated. The data is averaged for five-year period. The regressions include temporal dummies and a constant term (not reported). * Statistically significant at the 10% level; ** Statistically significant at the 5% level; *** Statistically significant at the 1% level.*

Table 6

Granger Precedence Test, Robustness I

Estimation Method: System GMM

Sample: 1965-2000 (five year averages)

Null Hypothesis:		**Logarithm of R&D does not cause to Logarithm of TFP**						**Logarithm of TFP does not cause to Logarithm of R&D**					
		Two-year		**Three year**		**Four -year**		**Two-year**		**Three year**		**Four -year**	
VAR(1)	***Set A***	6.66 A	**	5.72	***	4.28	**	4.08 A	*	0.34 A		0.25	
	Set B	4.94	**	7.21	***	14.08	***	1.26 A		0.79		1.48	
	Set C	5.59	**	19.73	***	10.55	***	1.03 A		0.43		3.11	*
VAR(2)	***Set A***	12.08	***	4.96	**	3.39	**	1.63 A		1.45 A		0.70 A	
	Set B	7.36	***	2.89	*	4.38	**	4.40 A	**	1.18		0.20	
	Set C	2.07		6.53	***	3.63	**	0.56 A		0.86 A		0.39	
VAR(3)	***Set A***	11.6	***	1.96 A		0.84		1.83 A		1.80		2.07	
	Set B	2.07		9.81	***	1.04		1.2 A		0.99 A		0.46	
	Set C	5.74	***	39.25 A	**	1.36		0.74 A		0.90 A		4.15 A	**
VAR(4)	***Set A***	1.76		1.64		--		0.44 A		3.23 A	**	--	
	Set B	2.07 A	*	2.26	*	--		0.48 A		2.83	**	--	
	Set C	0.99 A		1.27		--		0.51 A		0.26 A		--	
VAR(5)	***Set A***	0.66 A		--		--		0.44 A		--		--	
	Set B	1.44 A		--		--		0.58		--		--	
	Set C	1.86		--		--		1.29		--		--	

Source: Authors' estimations.

*Note: The statistics has a F(r,n-k) distribution, where r is the number of restrictions, n correspond to the observations and k is the number of parameters estimated. A: Not valid specification, accord to section 2.3 requirements. The data is averaged for two-, three and four- year periods. The regressions include temporal dummies and a constant term (not reported). * Statistically significant at the 10% level; ** Statistically significant at the 5% level; *** Statistically significant at the 1% level.*

Table 7

Granger Precedence Test, Robustness II

Estimation Method: System GMM

Sample: 1965-2000 (five year averages)

Null Hypothesis:		**Logarithm of per Capita R&D does not cause to Logarithm of TFP**						**Logarithm of TFP does not cause to Logarithm of per Capita R&D**					
		Two-year		**Three year**		**Four -year**		**Two-year**		**Three year**		**Four -year**	
VAR(1)	***Set A***	5.10 A	**	16.82	***	9.16	***	3.72 A	*	1.42 A		0.55	
	Set B	7.16	***	24.44	***	8.17	***	1.60 A		1.54		2.99	*
	Set C	17.02	***	21.67	***	8.25	***	1.02 A		1.38		5.27	
VAR(2)	***Set A***	8.44	***	19.75	***	8.04	***	1.37		1.88		0.49 A	
	Set B	11.63	***	11.42	***	7.05	***	0.83		1.20		0.46	
	Set C	5.70	***	22.96	***	5.24	***	0.41		1.33		0.98	
VAR(3)	***Set A***	9.41	***	5.00	***	3.97	**	0.47 A		1.53		0.86	
	Set B	3.73	**	3.90	**	4.44	***	0.50		2.24	*	1.83	
	Set C	4.38	***	7.12 A	***	1.13		0.38		6.29 A	***	1.18	
VAR(4)	***Set A***	3.06	**	1.25		--		0.61 A		1.77		--	
	Set B	0.10		4.96	***	--		0.39 A		1.07 A		--	
	Set C	0.01		1.08		--		0.24 A		1.44 A		--	
VAR(5)	***Set A***	0.36		--		--		0.03 A		--		--	
	Set B	1.11		--		--		0.19 A		--		--	
	Set C	4.66	***	--		--		0.96 A		--		--	

Source: Authors' estimations.

*Note: The statistics has a F(r,n-k) distribution, where r is the number of restrictions, n correspond to the observations and k is the number of parameters estimated. A: Not valid specification, accord to section 2.3 requirements. The data is averaged for two-, three and four- year periods. The regressions include temporal dummies and a constant term (not reported). * Statistically significant at the 10% level; ** Statistically significant at the 5% level; *** Statistically significant at the 1% level.*

Table 8

Granger Precedence Test, Robustness III

Estimation Method: System GMM

Sample: 1965-2000 (five year averages)

Null Hypothesis:		**Logarithm of per Capita R&D does not cause to Logarithm of TFP**						**Logarithm of TFP does not cause to Logarithm of per Capita R&D**					
		Two-year		**Three year**		**Four -year**		**Two-year**		**Three year**		**Four -year**	
VAR(1)	***Set A***	5.44 A	**	10.99 A	***	5.95	**	0.51 A		1.74 A		0.80 A	
	Set B	6.42	**	4.36	**	4.35 A	*	1.05 A		5.74	**	2.59 A	
	Set C	5.13	**	8.06	***	8.22	***	0.001 A		5.0 A	**	2.97	**
VAR(2)	***Set A***	2.67	*	1.82		3.36	**	0.77 A		0.81 A		0.77 A	
	Set B	1.65		4.45	**	4.27	**	0.54 A		1.48 A		1.81 A	
	Set C	2.86	*	2.76	*	1.51		0.017 A		0.13 A		0.24	
VAR(3)	***Set A***	1.89		4.19	**	1.62		0.26 A		0.8 A		0.76 A	
	Set B	0.00 A		2.64 A	*	1.00		0.82 A		0.19 A		0.40 A	
	Set C	1.1		0.75 A		-		1.82 A		2.5 A	*	-	
VAR(4)	***Set A***	1.68 A		0.56		--		1.20 A		0.62 A		--	
	Set B	1.06		0.1		--		0.45 A		0.75 A		--	
	Set C	1.07		0.24 A		--		0.72 A		0.25 A		--	
VAR(5)	***Set A***	0.65		--		--		0.43 A		--		--	
	Set B	0.58 A		--		--		0.74 A		--		--	
	Set C	0.86		--		--		0.47 A		--		--	

Source: Authors' estimations.

*Note: The statistics has a F(r,n-k) distribution, where r is the number of restrictions, n correspond to the observations and k is the number of parameters estimated. A: Not valid specification, accord to section 2.3 requirements. The data is averaged for two-, three and four- year periods. The regressions include temporal dummies and a constant term (not reported). * Statistically significant at the 10% level; ** Statistically significant at the 5% level; *** Statistically significant at the 1% level.*

Table 9
TFP Determinants, Baseline Regression
Dependent variable: ln(TFP)
Estimation: System GMM
Sample: 1965-2000 (five year averages)

	1		2		3		4	
Dynamic								
Lagged Total Factor Productivity (in logs)	0.856	***	0.851	***	0.859	***	0.865	***
	(0.086)		(0.086)		(0.084)		(0.078)	
Openness Variables								
Trade (share of GDP)	0.035		0.033		0.024		0.026	
	(0.031)		(0.033)		(0.032)		(0.028)	
Foreign Direct investment (share of GDP)	0.178		0.157		0.191		0.139	
	(0.137)		(0.144)		(0.142)		(0.129)	
Cyclical variables								
Terms of Trade	0.063	*	0.063	*	0.067	**	0.047	*
	(0.033)		(0.034)		(0.031)		(0.026)	
Structural / Institutional Variables								
High Income Country	-0.010		-0.005		-0.017		-0.022	
	(0.028)		(0.028)		(0.026)		(0.021)	
Low Income Country	-0.019		-0.024		-0.032		-0.034	
	(0.042)		(0.036)		(0.038)		(0.040)	
Socioeconomics Conditions	0.007		0.009		0.007		0.011	
	(0.008)		(0.009)		(0.008)		(0.008)	
Investment Profile	0.017	**	0.016	**	0.015	**	0.012	*
	(0.006)		(0.006)		(0.006)		(0.007)	
Private Credit to Domestic Market (% GDP)			-0.020				-0.002	
			(0.019)				(0.030)	
Macro instability					-0.065	**	-0.055	
					(0.028)		(0.046)	
Observations	178		176		177		176	
Countries	49		49		49		49	
Sargan Test	0.235		0.283		0.425		0.563	
Instrumentos	25.000		26		26		33	
Arellano - Bond AR 1 Test	0.035		0.032		0.047		0.045	
Arellano - Bond AR 2 Test	0.555		0.570		0.562		0.569	
Arellano - Bond AR 3 Test	0.956		0.589		0.577		0.618	

Note: standar deviation in parentheses
** significant at 10%; ** significant at 5%; *** significant at 1%*

Table 10
R&D Impact on Total Factor Productivity
Dependent variable: ln(TFP)
Estimation: System GMM
Sample: 1965-2000 (five year averages)

	1		2		3		4	
Dynamic								
Lagged Total Factor Productivity (in logs)	0.848	***	0.853	***	0.843	***	0.845	***
	(0.092)		(0.094)		(0.091)		(0.088)	
Openness Variables								
Trade (share of GDP)	0.062	**	0.064	**	0.059	*	0.047	
	(0.030)		(0.029)		(0.030)		(0.030)	
Foreign Direct investment (share of GDP)	0.087		0.088		0.100		0.081	
	(0.222)		(0.225)		(0.226)		(0.231)	
Cyclical variables								
Terms of Trade	0.037		0.036		0.037		0.040	
	(0.024)		(0.023)		(0.024)		(0.026)	
Structural / Institutional Variables								
High Income Country	-0.035		-0.030		-0.028		0.361	
	(0.029)		(0.024)		(0.022)		(0.236)	
Low Income Country	-0.007		-0.012		-0.018		0.226	
	(0.045)		(0.039)		(0.043)		(0.341)	
Socioeconomics Conditions	0.002		0.006		0.007		0.003	
	(0.006)		(0.007)		(0.007)		(0.009)	
Investment Profile	0.015	**	0.013	*	0.013	*	0.014	**
	(0.006)		(0.007)		(0.007)		(0.007)	
Private Credit to Domestic Market (% GDP)			-0.037	*	-0.035		-0.012	
			(0.020)		(0.031)		(0.036)	
Macro instability					-0.002		0.123	
					(0.053)		(0.179)	
R&D and Interactions								
Research & Development (in logs)	0.021	***	0.021	***	0.020	***	0.024	*
	(0.009)		(0.008)		(0.008)		(0.012)	
* High Income Country	-		-		-		-0.018	
							(0.011)	
* Low Income Country	-		-		-		-0.012	
							(0.017)	
* Macro instability	-		-		-		-0.008	
							(0.010)	
Observations	178		176		176		176	
Countries	49		49		49		49	
Sargan Test	0.573		0.341		0.388		0.459	
Instrumentos	44		31		32		35	
Arellano - Bond AR 1 Test	0.067		0.068		0.061		0.054	
Arellano - Bond AR 2 Test	0.835		0.722		0.685		0.536	
Arellano - Bond AR 3 Test	0.998		0.473		0.449		0.497	

Note: standar deviation in parentheses

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table 11
Per Capita R&D Impact on Total Factor Productivity
Dependent variable: ln(TFP)
Estimation: System GMM
Sample: 1965-2000 (five year averages)

	1		2		3		4	
Dynamic								
Lagged Total Factor Productivity (in logs)	0.815	***	0.814	***	0.757	***	0.717	***
	(0.050)		(0.056)		(0.070)		(0.123)	
Openness Variables								
Trade (share of GDP)	0.042	*	0.040	*	0.045	*	0.033	*
	(0.023)		(0.022)		(0.023)		(0.029)	
Foreign Direct investment (share of GDP)	0.076		0.087		0.076		0.128	
	(0.189)		(0.179)		(0.151)		(0.166)	
Cyclical variables								
Terms of Trade	0.039	*	0.036	*	0.060	**	0.065	*
	(0.022)		(0.021)		(0.029)		(0.038)	
Structural / Institutional Variables								
High Income Country	-0.058	**	-0.065	***	-0.070	***	0.126	***
	(0.024)		(0.023)		(0.024)		(0.164)	
Low Income Country	0.021		0.026		0.003		0.005	
	(0.029)		(0.033)		(0.038)		(0.143)	
Socioeconomics Conditions	0.003		0.004		0.005		0.002	
	(0.006)		(0.006)		(0.006)		(0.012)	
Investment Profile	0.016	***	0.018	***	0.021	***	0.015	*
	(0.006)		(0.006)		(0.007)		(0.008)	
Private Credit to Domestic Market (% GDP)			-0.012		-0.004		-0.001	
			(0.016)		(0.026)		(0.041)	
Macro instability					0.016		0.122	*
					(0.062)		(0.071)	
R&D and Interactions								
Per Capita Research & Development (in logs)	0.034	***	0.038	***	0.039	***	0.060	**
	(0.009)		(0.008)		(0.012)		(0.027)	
* High Income Country	-		-		-		-0.037	
							(0.031)	
* Low Income Country	-		-		-		0.001	
							(0.033)	
* Macro instability	-		-		-		-0.042	*
							(0.024)	
Observations	178		176		176		176	
Countries	49		49		49		49	
Sargan Test	0.607		0.556		0.688		0.712	
Instrumentos	48		49		46		34	
Arellano - Bond AR 1 Test	0.101		0.117		0.110		0.034	
Arellano - Bond AR 2 Test	0.941		0.989		0.834		0.332	
Arellano - Bond AR 3 Test	0.845		0.522		0.371		0.493	

Note: standar deviation in parentheses

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table 12
Long-run R&D elasticity
Estimation Method : System GMM
Sample: 1965-2000 (five year averages)

	Aggregate R&D		Per capita R&D	
(1), Full Sample	0.137	**	0.182	***
	(2.04)		(4.34)	
(2), Full Sample	0.145	***	0.203	***
	(2.95)		(3.54)	
(3), Full Sample	0.125	**	0.162	***
	(2.45)		(5.41)	
(4), High Income Countries	0.038		0.081	
	(0.66)		(0.76)	
(4), Median Income Countries	0.148	*	0.199	*
	(1.88)		(1.96)	
(4), Low Income Countries	0.07		0.208	*
	(1.16)		(1.93)	

Note: t-statistics in parenthesis. The standard deviation of long run coefficients was calculated according to Delta Method. Long run coefficients for R&D logarithm and per capita R&D logarithm were derived from the values estimated for the parameters in tables 10 and 11 respectively.

** significant at 10%; ** significant at 5%; *** significant at 1%*