Essays on Innovation, Human Capital, and Economic Instability

A thesis submitted to the University of Manchester for the degree of PhD in Economics in the Faculty of Humanities

2014

Serena Masino

School of Social sciences, Economics

List of Contents

The University of Manchester

Serena Masino

PhD in Economics

ESSAYS ON INNOVATION, HUMAN CAPITAL, AND ECONOMIC INSTABILITY

1st December 2013

This thesis represents a contribution to the empirical literature on the relation between technological progress and development. In its first chapter, the functional form properties of the relationship between national aggregate R&D expenditure and innovation outputs are investigated. A non-parametric estimation of such relationship demonstrates the existence of important non-linearities. Firstly, a critical mass effect is represented by a delayed onset of positive returns to R&D spending. Secondly, diminishing returns to the accumulation of R&D are uncovered. A disaggregation of R&D by funding source reveals that it is the privately funded R&D component the driving force behind such pattern.

The second chapter investigates the channels through which institutional and macroeconomic instability hinder innovative investment undertakings financed by the domestic private sector. The analysis is based on a sample of 44 countries representing all levels of development and considers a number of instability dimensions. The results suggest a negative impact of real, monetary and political instability on the aggregate level of national R&D financed by the business sector. Thus, they highlight the desirability of stable macro-institutional environments in preventing avoidance or abandonment of private innovation undertakings.

The third chapter investigates the impact of institutional and macroeconomic instability on the skill premium, in a 69-country panel. The results suggest a negative effect of both types of instability on the skill premium, defined as the ratio of unskilled to skilled wages. An interpretation of such findings in light of the results of chapter two indicates that low skilled wages are associated with lagging R&D investment, as a result of reduced skilled labour productivity and less demand for skilled workers. These findings stress again the importance of stable environments, as a way of preventing the shrinkage of the skill premium, and, thereby, sub-optimal human capital accumulation or brain drain.

Overall, the thesis provides empirical evidence regarding the accumulation path of technological development, and how such accumulation may be disrupted in the presence of economic instability.

Declaration

No Portion of the work referred to in the thesis has been submitted in support of an application to another degree of qualification of this or any other university or other institute of learning.

COPYRIGHT STATEMENT

INTRODUCTION

The importance of innovation, human capital, and of their interaction, for growth is widely studied and recognised in the literature (Romer, 1990; Grossman and Helpman, 1991a, Aghion and Howitt, 1992; Grossmann, 2007). This thesis takes a step forward in the study of technological progress and development by, firstly, modelling the functional form of an input-output innovation equation. And, secondly, by bringing economic instability into the picture, and analysing how innovative investment and human capital formation are affected in situations where the path of technological progress is disrupted.

In the first chapter of this thesis, the relationship between innovation inputs (R&D spending) and outputs (patent applications) is investigated, using both total R&D and its disaggregated public and private components. This is done in an attempt to uncover the underlying functional form of the innovation process, and any critical mass, composition, or threshold effects intrinsic to it. Marked non-linearities are revealed, which describe the aggregate national innovation process. In particular, the study finds that national R&D investment translates into patent applications only after a certain threshold expenditure level; and that it incurs diminishing returns to its accumulation. The pattern is shown to be driven by the business funded R&D component, whereas public R&D is found to contribute positively and linearly to national innovation activity. The implications presented in Chapter 1 are in terms of the potential for interaction and complementarity of the public and private R&D investment components in less technologically advanced economies.

The second chapter looks at the impact economic instability has on the incentive of the business sector to invest in R&D. R&D investment is characterized by long maturity horizons and high-budget requirements, which make it an intrinsically riskier type of investment. Given these considerations, we hypothesis that unstable macroeconomic environments may undermine the private sector's incentives to undertake risky innovative investment. To investigate such hypothesis, instability is disaggregated in a number of components: institutional, real, monetary, international, and financial. The findings show that only the first three elements are negatively related to business-funded R&D, and that non-linearities exist in their impact. An explanation of these results is offered.

The third chapter investigates the impact of economic instability on the second 'driver of growth': human capital formation. In particular, it focuses once again on the incentive channel, which is, this time, the incentive to acquire human capital. The skill premium, defined as the wage differential between skilled and unskilled occupations, is taken to represent such incentive. The findings indicate that both political and real volatility decrease the wage premium skilled workers can aspire to. When interpreting such findings in light of the results presented in chapter two, we can link the consequences of low levels of innovative investment to the skill premium formation pattern. In fact, after having shown that instability hinders R&D spending, it can be shown that a shrinkage of the skill premium follows. This is the result of a reduction in both determinants of skilled wage, that is, both demand for and productivity of skilled labour, which accompany lower R&D spending levels.

Overall, the thesis contributes to the empirical literature on the relation between technological progress and development; with chapter one focusing on the accumulation path of innovation and its functional form properties. Whereas, the implications of the findings presented in chapter two and three are in terms of the importance of macroeconomic stability for development. By showing that the accumulation of both so called 'engines of growth' is hampered by instability, the importance of sound macroeconomic and institutional environments is highlighted.

The rest of the thesis is divided into the three chapters summarized above, followed by some conclusions presented in the last section. Appendices containing data descriptions, results tables, and technical notes are presented at the end of each chapter.

Chapter 1: R&D Expenditure and Innovation: Threshold and Composition Effects

1. Introduction

A number of seminal papers has introduced and developed the idea that technical progress and innovation are important drivers of economic growth (Romer, 1990; Grossman and Helpman, 1991a; Aghion and Howitt, 1992). A related debate concerns whether the accumulation of knowledge through technical progress incurs diminishing or increasing returns, with opposing views claiming a 'standing on shoulders' versus a 'fishing out' effect (see Romer, 1990; Jones, 1995; Furman, Porter and Stern, 2002). Such debate, however, is limited to the stock of knowledge and its accumulation pattern. It is surprising that a similar analysis has not been attempted with regards to the flow of knowledge. Such flow is determined by the relationship between innovation inputs, in the form of research and development expenditure (R&D), and innovation outputs, in the form of annual patent applications. The present study aims to fill that gap by providing an in-depth investigation of the functional form properties linking R&D expenditure to innovation.

The applied literature on the R&D spending - patenting relationship is mainly microeconomic in nature, reflecting a firm-focused perspective (see Pakes and Griliches, 1980; Bound et al., 1984; Hausman et al., 1984; Hall et al., 1986; Blundell et al., 1995; Montalvo, 1997; Guo and Trivedi, 2002; Gurmu and Perez-Sebastián, 2008). These studies reach different conclusions as to the functional form properties of said relationship. On the one hand, Bound et al. (1984) and Lewbel (1997) showed that different estimation techniques could lead to decreasing or constant returns to scale. While on the other, both Guo and Trivedi (2002) and Gurmu and Pérez-Sebastián (2008) find evidence of decreasing returns to scale for private R&D. Instead, a pattern of increasing returns to scale does not seem to find any support in the literature.

Neglecting general equilibrium effects may, however, explain the co-existence of such contradictory findings. As argued by Griliches (1979), a firm's increase in R&D expenditure often results in the outcompeting of another. Ultimately, the emerging national innovation performance will be the result of composite inter-firm effects, thus limiting the investigation focus to the firm-level may overlook net aggregate effects. Moreover, neglecting the interplay between private and public R&D spending may also lead to different general equilibrium conclusions than focusing on the private sector exclusively. In this sense, a country-level analysis, capable of measuring the overall innovative performance is needed, which is what we propose to do in this study.

A number of studies exists which takes up a macroeconomic approach to examine the interplay of different innovation funding sources. In particular, Hu and Mathews (2005a), in an empirical analysis of the determinants of innovation in East Asia, stress the crucial role that public R&D plays at the early stages of development by providing infrastructure, and, subsequently, by guaranteeing a permanent linkage between such innovation infrastructure and private R&D investment. The pattern suggested is that of a delayed onset of private innovation, which builds upon the foundations laid by public innovation. The same result is also confirmed by Hu and Mathews (2005b) for the case of China. In the same line of thought, Rodriguez-Pose and Bilbao-Osorio (2004) demonstrate that the contribution of various R&D funding sources to aggregate innovation varies with the level of development. They show that public research complements private R&D in less technologically advanced economies, while private R&D contributes the most to patent applications in more advanced countries.

A perspective which combines the literature presented above - both that on the interplay of public and private R&D and that on firm innovation dynamics - is proposed by Cohen and Levintal (1989) and Griffith et al. (1999). In these studies, the importance of absorptive capabilities is highlighted as crucial to the private sector's innovative potential. While absorptive capacity always increases with the amount of knowledge circulating in the economy as well as internationally, firms are required to autonomously and continuously invest in R&D, in order to be able to select, process and absorb the existing external knowledge. Therefore a certain amount of business R&D is necessary before firms are able to incorporate existing knowledge into patentable output.

Cohen and Levintal (1989) identify in basic research the most important component in the generation of such pool of common knowledge. In principle, basic research can be funded and performed by either the public or the private sector. However, as argued in Arrow (1962), basic research suffers from imperfect appropriability. In fact, its output has a pronounced tendency to spill over, something which makes it a perfect candidate for private underinvestment and thus translates into a market failure scenario. In this case, it also seems likely that the business sector may initially refrain from innovating. Subsequently, only after a pool of common knowledge has been created by public research activity, will the business sector exploit such resources by incorporating them into patentable and marketable innovation outputs.

In this respect, Hall et al. (2010) point out a flaw in the literature maintaining lower overall rates of return for public R&D when compared to private R&D. They argue that such findings overlook the specific nature of public innovation, for which returns are not as easily quantifiable as those of business innovation. In fact, a big proportion of public R&D goes into basic research, or into sectors of social interests such as national defence, environment and health (OECD, 2010). Because these sectors have high social impact but low short-term returns, they typically suffer from private sector underinvestment and low 'patentability'. However, the contribution in terms of knowledge generation of such public innovation investment is hardly questionable.

This study contributes to the literature in two ways: first, by explaining the presence of a non-monotonic effect of total R&D expenditure on innovation, and, second, by considering the contribution of the various components of R&D spending to such a non-monotonic relationship. As pointed out in Blundell et al. (1995), however, technological innovation is an inherently dynamic and non-linear process, and empirical studies need to take this into account. This is the reason why, in our study, all functional form restrictions are lifted, and the innovation production function is estimated via non-parametric techniques. We find that non-linearities exist only in the patent response function to national aggregate R&D and to private R&D; whereas the contribution of public R&D is positive and linear throughout the observed period. Both of the mentioned non-linear relationship are characterised by a delayed onset of positive returns to R&D spending and diminishing returns to

R&D accumulation. We conclude that the non-linearities in the aggregate innovation production function are driven by the private R&D component, while the public R&D contribution to patenting is not strong enough to alter such pattern.

The rest of the paper is divided as follows: the method and the data are presented in section 2; while the results, together with the sensitivity analysis are described in sections 3 and 4. Finally, section 5 concludes.

2. Method and Data

Our empirical analysis aims to estimate non-parametrically the functional form of the innovation process. However, while non-parametric approaches offer the advantage of being robust to any error in the model specification, this comes at the price of much less precise estimation. In other words, as explained in Ahamada and Flachaire (2010), the performance of a correctly specified parametric model is always superior to that of a nonparametric model. In line with these considerations, we use the non-parametric techniques to reveal the correct fitting parametric relationship between variables, and apply specification tests to determine a suitable polynomial approximation. Once the latter is found, the rest of the robustness analysis is carried out using parametric specifications, in which R&D variables are represented by their correct polynomial approximations. The robustness analysis is also where endogeneity concerns will be addressed.

Kernel Weighted Local Polynomial Regression

To investigate the underlying data generation process and the response function of patent applications to R&D investment, we are going to refrain from imposing any kind of functional form assumptions.[1] We estimate a semi-parametric model where all covariates enter the model parametrically, apart from the R&D variables (see Robinson, 1988). The estimator uses a kernel weighted local polynomial fit, whereby a low-order weighted least squares regression is fit at each point of interest, using data from some neighbourhood around the point. A local polynomial fit is to be preferred to a local linear fit, as it considerably reduces the bias in the estimation at the extremities of the distribution (Ahamada and Flachaire, 2010),

[1] Given the focus of our analysis on the R&D spending – patent nexus, we are going to limit the scope of the non-parametric analysis to that relationship.

and the chosen polynomial degree p is (p)=3. This degree choice is justified under a number of respects: Fan and Gijbels (1995) show that the data approximation process is best approximated by odd-order degrees. However, because the fits are local, low-order polynomials can be used (see Wand and Jones, 1995, or Fan and Gijbel,s 1996). In fact, while higher polynomial degrees render the fitting more precise and lower the bias, this comes at a cost of higher variance. Thus, when, as in our case, the dataset is not very large, instability can be prevented by avoiding high-order fits.

Our choice of kernel is the epanechnikov and the optimal bandwidth minimises the conditional weighted mean integrated squared error (see Ruppert et al. 1995).[2] Imposing trimming restrictions may be useful to check the robustness of semi-parametric specifications. This is because observations lying in sparsely populated boundary regions of the probability distribution can be assigned too much weight. Thus, the robustness of all presented specifications has been verified with a trimming of approximately 1% of the sample lying at the boundaries of the probability distribution. Lastly, note that, in all specifications, heteroskedasticity-robust standard errors are presented, and that we always include both time-invariant country fixed effects and common time-varying effects.

Together with the results obtained via the semi-parametric local polynomial regression, we also present the Härdle and Mammen's (1993) specification test, which allows to assess whether the non-parametric component of the model specification may be approximated by a polynomial functional form. The statistic developed by Härdle and Mammen (1993) essentially compares the non-parametric and parametric regression fits using squared deviations. Because the normal distribution of the test statistics is not a good approximation to the true distribution in finite samples, wild bootstrapping is used to obtain critical values for the test, with 399 bootstrap replications in each instance.

[2] The bandwidth is defined as the width of the kernel function used for the smoothing. While, on one hand, bandwidths which are too narrow may capture spurious fluctuations, bandwidths which are too large may lead to over-smoothing and to overlooking structural features. In this sense, the choice of the bandwidth is much more important than the choice of kernel type.

System GMM Estimation

When the variables entering the model semi-parametrically are endogenous, a control function approach could be adopted to correct for such concern. Following this method, the residuals from a reduced form equation, in which the endogenous variable is regressed on all exogenous variables and excluded instruments, are plugged into the semi-parametric specification. In this way, the residuals control for the unobserved part of the error, which is thus prevented from influencing the other covariates' estimates (see Newey et al., 1999). Unfortunately, however, the applicability of such an approach is limited, in our case. In fact, in a macroeconomic sample like ours, all right hand side variables would need to be replaced by exogenous excluded instruments in the reduced form equations estimated to retrieve the residuals. As it is well known, instruments for macroeconomic variables are hard to come by, especially when several ones are needed at the same time for which the exclusion restrictions should be jointly valid. We, therefore, turn to the System GMM estimator, which allows the use of internal instruments in lag and difference form.

In particular, the System GMM estimator developed by Arellano and Bover (1995) solves contemporaneously for a number of issues arising in the data: the presence of country fixed effects, the endogeneity of the right hand side regressors, and the existence of simultaneity bias. It achieves this by combining an equation in first-differences with one in levels. In the former, the first-differences of the endogenous variables are instrumented by their own lagged levels. In the latter, lagged values of the first-differences are used as instruments, under the assumption that the regressors' first-differences are orthogonal to the individual fixed effects (Blundell and Bond, 1998). In our case, this amounts to assuming that there is no systematic relationship between a country's fixed effect and its distance from the conditional long-run mean of all the right hand side instrumenting variables. Such assumption is less restrictive than one of mean stationarity, and, while there is no a priori reason to believe it does not hold in our analysis, we follow Roodman (2009)'s recommendation and test for the quality of the instrument subset used for the equation in levels via a difference-in-Hansen test.

The instrumenting variables include all those which are not strictly exogenous, that is, all the right hand side variables. However, while it is true that more instruments convey additional useful information, too many instruments can result in the over-fitting of the instrumented variables, thereby biasing the results towards those obtained by OLS. As a consequence, we follow Roodman (2009) and present results with a collapsed instrument matrix.[3] In addition, each regression is estimated with the instrument lag interval that maximises the trade-off between the total number of instruments and the resulting degree of overidentification. Finally, two specification tests are used to confirm the validity of the instrumentation strategy. These are the Hansen (1982) J-test of overidentifying restrictions, assessing the exogeneity of the excluded instruments; and the Arellano Bond (1991) test, which is informative of the presence of serial correlation in the error term.

Data and Model

The data sample used in the model benchmark specification covers 70 countries. These countries represent all levels of development and are observed across 30 years, from 1981 to 2011. A list of all countries and data sources is presented in Appendix A below, while Appendix B describes the choice of countries and time period covered in the analysis. The non-parametric model specifications are as follows:

$$(1) \qquad \mathrm{y_{it}} = \mathrm{a_i} + \delta_\mathrm{t} + \mathrm{X'_{it}}\beta + \mathrm{f}(\mathrm{R\&}D_\mathrm{it}) + \varepsilon_\mathrm{it}$$

$$(2) \qquad \mathrm{y_{it}} = \mathrm{a_i} + \delta_\mathrm{t} + \mathrm{X'_{it}}\beta + \mathrm{f}(\mathrm{PrivateR\&}D_\mathrm{it}) + \varepsilon_\mathrm{it}$$

$$(3) \qquad \mathrm{y_{it}} = \mathrm{a_i} + \delta_\mathrm{t} + \mathrm{X'_{it}}\beta + \mathrm{f}(\mathrm{PublicR\&}D_\mathrm{it}) + \varepsilon_\mathrm{it}$$

where all covariates in the vector $\mathrm{X'_{it}}$ enter linearly and parametrically, whereas the R&D variables enter non-linearly according to a non-binding function f. Instead, the System GMM benchmark specifications, where the R&D variables enter with the appropriate polynomial approximation are as follows:

$$(4) \qquad \mathrm{y_{it}} = \mathrm{a_i} + \delta_\mathrm{t} + \mathrm{X'_{it}}\beta + \gamma\mathrm{R\&}D_\mathrm{it} + \vartheta\mathrm{R\&}D^2{}_\mathrm{it} + \pi\mathrm{R\&}D^3{}_\mathrm{it} + \varepsilon_\mathrm{it}$$

$$(5) \qquad \mathrm{y_{it}} = \mathrm{a_i} + \delta_\mathrm{t} + \mathrm{X'_{it}}\beta + \gamma\mathrm{PrivR\&}D_\mathrm{it} + \vartheta\mathrm{PrivR\&}D^2{}_\mathrm{it} + \pi\mathrm{PrivR\&}D^3{}_\mathrm{it} + \varepsilon_\mathrm{it}$$

$$(6) \qquad \mathrm{y_{it}} = \mathrm{a_i} + \delta_\mathrm{t} + \mathrm{X'_{it}}\beta + \gamma\mathrm{PublR\&}D_\mathrm{it} + \varepsilon_\mathrm{it}$$

[3] Collapsing the instrument matrix amounts to creating only one instrument for each variable and lag distance, rather than one for each time period, variable, and lag distance. This allows to contain instruments proliferation.

In both specification sets, a_i is a vector of time-invariant country fixed effects, δ_t is a vector of common time-varying effects. The set of variables in $X'_{it}\beta$ includes: 1) GDP per capita (in log form) to control for countries' level of overall development; 2) the stock of patent applications, calculated according to the formula presented in Appendix A below. The coefficient sign for this measure indicates whether the accumulation of patents generates a 'standing on shoulder' or 'fishing out effect' in this sample. It also contains: 3) the share of students enrolled in tertiary education, an indicator of the overall education level of a country which is a key determinant and input in the innovation process; 4) Foreign direct investment (FDI) inflows, expressed as a percentage of GDP, which capture the impact of knowledge transfers taking place via a direct investment channel; 5) a measure of trade openness used to control for the knowledge exchange taking place (less directly) via the trading channel; and, finally, 6) a measure of stock market capitalization, included to account for the level of alternative funds available to innovating firms.

The coefficients of interests are those associated with total R&D expenditure and its subcomponents, private, public, residual R&D expenditure the R&D measures. All of the R&D measures are expressed as a share of GDP. Total R&D spending is given by the sum of the R&D shares funded by the private, public, higher education, non-for-profit and foreign sectors. Private R&D spending is the innovation expenditure funded by the business sector, while public R&D spending is the innovation investment funded by the government sector. A residual R&D variable is also included, which corresponds to the aggregate GDP share of the three remaining R&D funding sources. The reasons for choosing to focus on the public and private R&D components only, in the core analysis, is due to the fact that, as shown in the summary statistics table (Table A1 in Appendix A), these two make up for over 85% of total R&D spending; and represent by far the largest sources of national innovation. Figures A1-A3 (in Appendix A) show scatterplots of public, private, and total R&D against the dependent variable.

The dependent variable, y_{it}, represents the total number of annual patent applications per 10,000 inhabitants filed to the European Patent Office (EPO), according to the inventor's country of residence. The reference date of the application is the priority date, which is the date of the first international filing of a patent and therefore the closest to the invention date. The choice of using patent applications rather than grants is not secondary, and it has been made in order to broaden as much as possible the notion of innovation so as to include all innovation effort in the analysis.

In particular, this is because, in spite of patents being the best available indicator of innovation output, problems remain which may at best be partially addressed with the information available. In fact, not all R&D is patentable or patented (see Pakes and Griliches, 1980); for example, basic science, by definition, lacks commercial value, thus it is much less suited for patenting. In other words, its applications are suitable for property rights protection, but basic research discoveries do not go through the patenting process despite their extremely high knowledge generation content.

Similarly, incremental innovation does not find its way to the main international patent offices, and may, at best, be granted protection at local patent offices. This leads to hypothesise that developing countries' innovation may be also mis-represented by patent applications, due to the fact that it more often tends to be of incremental rather than break-through nature. An additional concern is raised by the very nature of the application process, with geographical and institutional biases introduced by the location of the patenting office.

These concerns, however, are present in all empirical analyses of innovation. They should not, therefore, be seen as undermining neither the validity of our finding, nor their comparability with the rest of the literature. Nevertheless, we take a number of steps in order to bridge the gap described above. We consider patent applications rather than grants, as these go some way in incorporating potentially patentable knowledge into the picture, regardless of whether the patent office granted the protection at the end of the evaluation process or not. The rationale here is that, at least with regards to the main international patent avenues such as the EPO or the Patent Cooperation Treaty (PCT), most actors would not go through the application process if the value and innovative content of the patent did not justify taking such a step.[4] In this way, we minimise the proportion of innovation discarded because of reasons unrelated to the innovation content itself.

[4] We do not consider USPTO patents because the data available for the latter represents patent grants, rather than applications.

In an additional step, we test the robustness of our model's prediction to a change in the patent indicator. To be more specific, the USPTO and the EPO are the two main worldwide patenting avenues, where most patent applications seeking international protection accrue (see Ulku, 2007, and Agénor and Neanidis, 2010 on this point). However, the data collected by these patenting offices suffer from a geographical bias in favour of the US and European countries, respectively. A third international patenting procedure goes through the PCT, which usually gives protection to inventions with very high commercial value. PCT patent applications are, therefore, used as an alternative measure of innovation, as they do not suffer from any geographical bias. Nonetheless, PCT patents can still be thought as embedding an institutional bias as these fairly high-stake and high-budget projects are almost never funded by low-income non-emerging economies. Thus, a further step to test the robustness of our results turns to a new patent indicator, the worldwide count (WWC) patent index.

The WWC methodology was developed by de Rassenfosse et al. (2013) to overcome the geographical and institutional bias by capturing the incremental nature of developing countries' innovation, or, in other words, the innovation that is new-to-the-country although not new-to-the-world. This is achieved by including in the total count of a country's patents all resident inventors' applications, regardless of the patent office the applications are filed to. Therefore, in this count, patents filed to national offices are considered too. De Rassenfosse et al. (2013) show that, thanks to the absence of a patent value filter, this indicator improves the measurement of inventive activity for small and/or developing countries.

It may, therefore, seem that the WWC methodology represents a useful alternative to the main patent office indicators. However, unfortunately, its usefulness in our analysis is limited by the amount of information provided in the WWC dataset. In particular, the WWC data only considers a few emerging developing economies, while it has not been calculated for the rest of the developing countries. As evident in Table 1, when patent applications are normalised by population, only 128 observations represent developing countries' WWC patents. Whereas more than double non-OECD observations are available for both EPO and PCT patents.[5]

[5] A similar point is discussed in Agénor and Neanidis (2010), who show that normalisation

Table 1. Patent Indicators Statistics

Variable	Mean	St Dev	Min	Max	Obs	Share of zeros
EPO_PatApp (OECD)	0.743	0.744	0	3.79	499	3
PCT_PatApp (OECD)	0.278	0.571	0	3.11	490	46
WWC_PatApp (OECD)	2.902	5.269	0.071	26.26	475	0
EPO_PatApp (non OECD)	0.007	0.009	0	0.049	292	34
PCT_PatApp (non OECD)	0.000	0.005	0	0.054	285	155
WWC_PatApp (non OECD)	0.302	0.434	0.006	1.932	128	0
Private R&D (OECD)	0.927	0.684	0.0078	2.71	365	
Private R&D (non-OECD)	0.18	0.193	0.0002	1.26	208	
Public R&D (OECD)	0.568	0.205	0.121	0.996	365	
Public R&D (non-OECD)	0.279	0.178	0.015	0.823	208	

Notes: statistics based on the benchmark specification sample of column (2) in Table 4.

On the other hand, however, as anticipated, PCT applications tend to be concentrated in OECD countries. This is evident in Table 1, where the share of zeros in the non-OECD PCT patent count represents more than half of the total sample. For all these reasons, EPO patent applications are chosen as the benchmark indicator, as they provide a good compromise between innovation content and geographical coverage. In other words, the applications filed at the EPO are the biggest proportion of worldwide applications, represent average value innovations when compared to high-stake PCT applications, and provide the largest coverage for developing countries.

3. Results

In this section, we, first, present the results obtained from the semi-parametric estimation of the aggregate innovation process. Once the correct polynomial approximation for total R&D spending is found, we use the functional form suggested by this approximation to estimate a parametric model. This two-step procedure is repeated once again on the disaggregated components of total R&D. Recall that the focus is on public and private R&D exclusively, for the reasons explained above. Further, as a first step towards addressing the issue of simultaneous causation in the estimation, we replace both the R&D variables and

by population brings the EPO patent count representation in their sample ahead of even USPTO patent grants.

the other covariates with their first lag. An additional step to correct the endogeneity bias is taken with the use of System GMM estimation, presented in the sensitivity analysis section.[6]

Starting with Table 2, column (1) presents the results of a linear two-way fixed effect model in which total R&D spending enters parametrically. It appears, in this case, that a 1% point increase in the GDP share of R&D expenditure increases annual patent applications per 10,000 inhabitants by approximately 0.11. This effect is not trivial if one considers that the mean of patent applications in this sample is equal to 0.471 (see Table A1 in Appendix A).[7] In the same specification, both the overall level of development and trade openness are positively related to patent applications.

The former result is in line with Perez and Soete (1988), while the latter is confirmed by a number of theoretical (Porter, 1990; Lundvall, 1992; Nelson, 1993) and empirical (Smolny, 2003; Sameti et al., 2010; Wang, 2010) studies. These show how international openness positively impacts technological progress, due to increased external exposure and interaction. A complementary interpretation could be that trade proxies for overall openness, which, by itself, raises the incentive to patent abroad. Disentangling the two interpretations is not, however, easy. The stock of pre-existing patents also contributes positively to the flow of patents, which suggests a 'standing on shoulder' effect, whereby the stock of previously accumulated innovation increases the rate of new innovation creation (see Romer, 1990; Blundell et al., 1995; Jones, 1995; Furman, Porter and Stern, 2002).

As previously pointed out, technological innovation is an inherently dynamic and nonlinear process. Blundell et al. (1995) stress the fact that empirical studies should take such features into account. For this reason, in column (2) we re-estimate the model specification by lifting all functional form restrictions from total

[6] All regressions appearing in Table 2 and 3 have been re-estimated excluding both country and time effects (one at a time, and then both at the same time), however, no difference appeared in the R2 coefficients when doing so. The stock of patent applications is what appears to be driving the very high R2 statistics.

[7] Note that the reason why our patent indicator takes up non-integer values is the fractional count methodology used by the OECD in order to eliminate multiple counting. Fractional counts are applied to patents with multiple inventors/applicants, when the latter come from different countries. For example, a patent co-invented by one French, one US and two German residents will be counted as: 0.25 of a patent for France and the US, and 0.5 for Germany.

R&D; while all other variables still enter parametrically. Both trade openness and the patent stock retain their positive impact. Instead, the level of development loses explanatory power while stock market capitalisation turns significant in this specification. In line with our findings, Greenwood and Smith (1997) argue that stock markets development facilitates technology-intensive investment, such as R&D, by lowering the cost of mobilising savings.

Table 2. Contemporaneous Semi-Parametric and Parametric Polynomial Analysis

EPO_Patents	TotR&D FE (1)	TotR&D SemiPar (2)	ToTR&D Polyn FE (3)	Disag R&D FE (4)	DisagR&D Semipar (5)	DisagR&D Semipar (6)	DisagR&D Polyn FE (7)
LogGDPpercapita	0.015**	0.076	0.014*	0.013	0.11	0.153	0.145
	(0.007)	(0.05)	(0.008)	(0.008)	(0.093)	(0.114)	(0.132)
PatentStock	0.118***	0.1***	0.115***	0.122***	0.091***	0.089***	0.087***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.014)	(0.013)	(0.013)
Education	-0.0001	-0.001	0.000	-0.0001	-0.002	-0.001	-0.002
	(0.119)	(0.148)	(0.107)	(0.135)	(0.291)	(0.313)	(0.325)
FDI	0.001	0.0004	0.001	0.001	0.001	0.001	0.0003
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Trade	0.0005**	0.0008***	0.0005***	0.0002	0.001*	0.001*	0.0009*
	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.001)	(0.001)	(0.0005)
StockMarket	0.0007	0.012***	0.0007	0.0005	0.001	0.002	0.0014
	(0.0006)	(0.0004)	(0.0005)	(0.0006)	(0.001)	(0.001)	(0.001)
TotalR&D	0.114***	-	-0.039				
	(0.014)		(0.054)				
TotalR&D^2			0.105**				
			(0.043)				
TotalR&D^3			-0.017**				
			(0.008)				
ResidualR&D				0.025	0.024	-0.018	-0.042
				(0.09)	(0.076)	(0.115)	(0.091)
PublicR&D				0.115**	0.166*	-	0.187***
				(0.05)	(0.095)		(0.067)
PrivateR&D				0.129***	-	0.208***	-0.124
				(0.033)		(0.074)	(0.121)
PrivateR&D^2							0.401***
							(0.126)
PrivateR&D^3							-0.105***
							(0.029)
Country-d	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-d	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	813	813	813	587	587	587	587
Countries	70	70	70	61	61	61	61
R^2	0.98	0.94	0.98	0.97	0.95	0.97	0.98
SP Test		24***			23.7***	9.9***	
HM Test							
crit. Value		1.96			1.96	1.96	
T-st (cub poly)		3.91***			5.12***	0.15	
T-st (quad poly)						0.12	
Boots. Reps.		399			399	399	

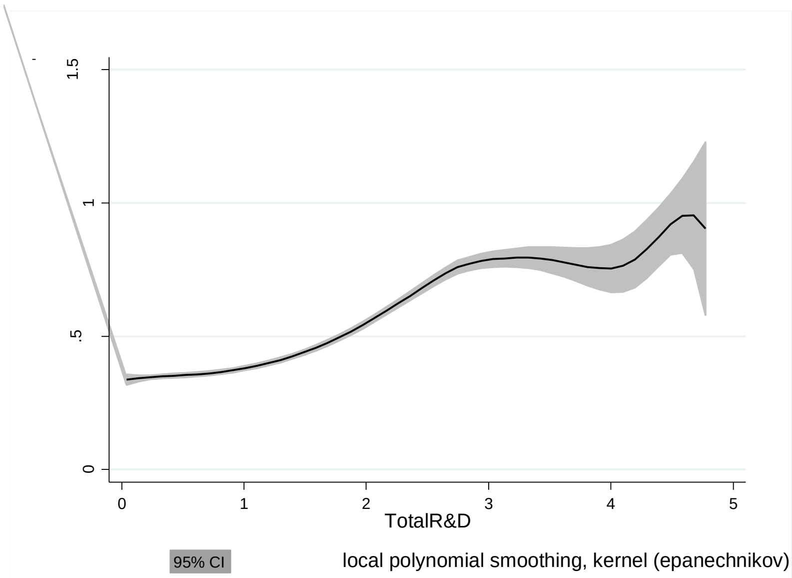
Notes: heteroskedasticity-robust standard errors are reported in parenthesis. *** p<0.01 ** p<0.05 * p<0.1

The semi-parametric response function of patent applications to R&D spending appears markedly non-linear in Figure 1, where a flat initial segment is followed by a positive relationship, exhibiting diminishing marginal returns. Finally, the semi-parametric significance test (SP) reported in Table 1 indicates that total R&D has strong explanatory power in this model. Nonetheless, as explained in Ahamada and Flachaire (2010), a correctly specified parametric model is always preferable to a non-parametric model, thanks to its superior estimation and inference properties. Therefore, we rely on the Härdle and Mammen (HM) model specification test to assess whether a polynomial approximation exists which can approximate the non-parametric fitting. The HM test compares the squared deviations of the parametric and non-parametric fits to assess which polynomial approximation best represents the non-parametric response function (Hardle and Mammen, 1993). A polynomial approximation is considered good enough to approximate the response function when it is bigger than the critical value. As visible in the post-estimation panel of column (2), the HM statistic indicates that a polynomial of degree three is a suitable approximation for the non-parametric patent response function to total R&D expenditure.

Thus, in column (3), we re-estimate the specification parametrically, with total R&D entering the model as a polynomial of degree three. In this specification, GDP per capita, trade openness, and the stock of patents enter positively. In addition, consistent with the response function plotted in Figure 1, we find that no explanatory power exists for initial values of total R&D. Only after a certain threshold, positive returns to R&D expenditure set in, as indicated by the positive coefficient of the squared R&D term; while for higher R&D levels evidence of diminishing marginal returns is found, as indicated by the negative cubic term.

In columns (4) to (6), we disaggregate total R&D in three funding components, and focus on private and public R&D, in an attempt to shed more light on the non-linearity exhibited by the aggregate innovation process. Evidence of decreasing marginal returns to the accumulation of private R&D expenditure has been found in the literature (Griliches, 1980; Guo and Trivedi, 2002; Gurmu and Pérez-Sebastián, 2008), which remains, however, rather inconclusive regarding public R&D spending. Starting with column (4), a linear two-way fixed effect model is presented, where the stock of knowledge retains its positive impact and both public and private R&D enter positively and significantly with a coefficient of 0.115 and 0.13, respectively.

Figure 1. Semi-parametric kernel weighted local linear regression (Total R&D)



When a semi-parametric specification is estimated for each of the two R&D components, column (5) indicates that a 1% point increase in the GDP share of R&D funded by the public sector leads to a 0.166 increase in the number of annual patent applications per 10,000 inhabitants. Whereas column (6) indicates that a 1% point increase in the GDP share of business funded R&D leads to a 0.21 increase in application filings. The residual R&D spending never appears to significantly affect the patenting rate.[8] In both specifications, the pre-existing patent stock once again retains explanatory power and, in addition, the coefficient on trade turns significant. The SP test in the post-estimation panel of column (5) and (6) suggests that, in both cases, the two R&D components have strong explanatory power in the model.

Moreover, the HM statistic indicates that a third degree polynomial represents a correct parametric approximation for private R&D expenditure; whereas for public R&D expenditure non-linearities are not detectable in the response function of patent application to government-funded R&D expenditure. These findings are confirmed by Figure 2 and Figure 3. In particular, marked non-linearities are visible in the private R&D spending - patent response function in Figure 2, with, once again a flat first segment followed by a positive relationship with decreasing

8 Note that the semi-parametric estimation and polynomial specification tests confirm the lack of significance of both R&D and its polynomial terms.

marginal returns. On the contrary, the patent response function to public R&D spending depicted in Figure 3 appears linear and positive throughout.

Figure 2. Semi-parametric kernel weighted local linear regression (PrivateR&D)

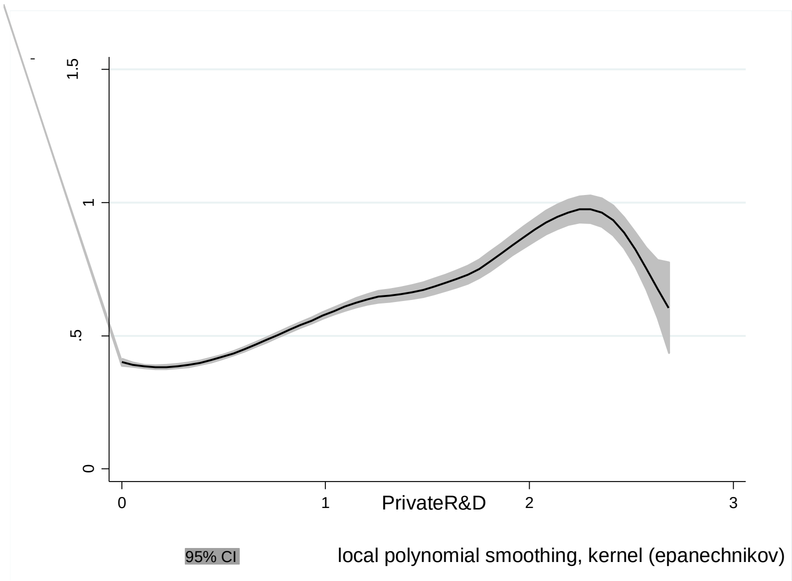
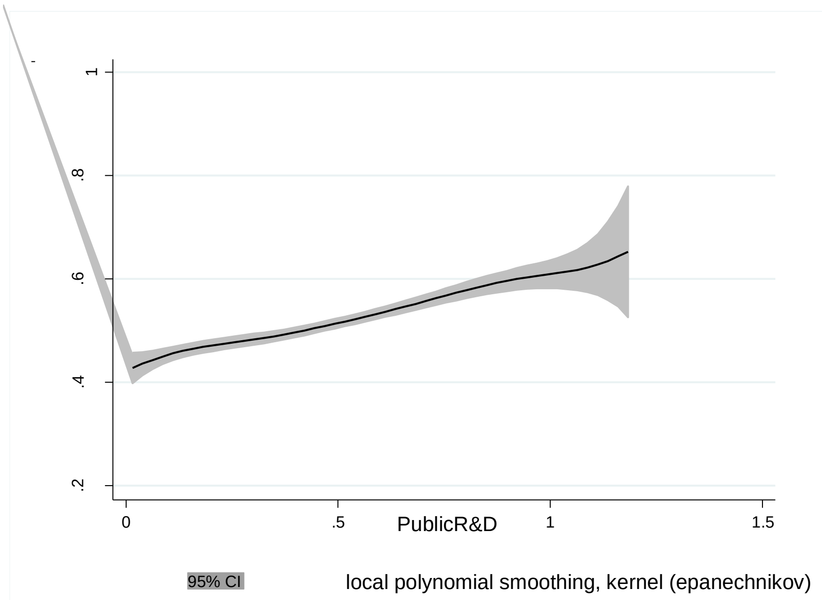


Figure 3. Semi-parametric kernel weighted local linear regression (PublicR&D)



In line with the HM test, we re-estimate (5) and (6) in a model specification where private R&D spending enters as polynomial of degree three, whereas public R&D spending enters linearly. These results are presented in column (7), where previous results carry over, while the polynomial approximation of private R&D confirms the response pattern of Figure 2 and also resembles that of total R&D in column

(3). Indeed, it is only after a certain threshold that business R&D starts having a positive impact on patent applications. Subsequently, however, it incurs diminishing marginal returns, as indicated by the negative cubic term.

These findings are in line with those of Griliches (1980), Guo and Trivedi (2002), Gurmu and Pérez-Sebastián (2008). The overall impact magnitude of an additional percentage point of private R&D spending is 0.3. This is estimated at the mean of patent applications per 10,000 inhabitants, which is 0.471, as reported in Table A1. On the other hand, the linearly positive response function in Figure 3 is confirmed by the public R&D coefficient in column (7), which indicates that a 1% increase in public R&D spending leads to an increase of 0.187 in application filings. This result is in line with Sanyal (2003), who also finds a positive impact of government spending on national innovation activity.

The difference existing in the patent response function of business and government funded innovation should not be seen as surprising. In fact, the two funding sectors have different objective functions to maximise; this divergence is reflected both in the innovation content and on the investment planning horizon (see Hu and Mathews, 2005a, and Hu and Mathews, 2005b). More specifically, R&D funds can be devoted predominantly to either research or development activities. In this sense, the distinction between basic and applied research determines the profitability and marketability of product and process innovations. When public R&D focuses on basic research, its marketability and consequently its potential to generate patents will often be limited, despite its crucial contribution to knowledge creation (see Cohen and Levintal, 1989, Hall et al., 2010, and OECD, 2010). Moreover, basic research has a marked tendency to spillover and is characterised by imperfect appropriability (Arrow, 1962). Thus, there will likely be private underinvestment in this type of research, as the business sector tends to concentrate on more applied R&D, capable of guaranteeing commercial pay-offs.

These considerations may explain why we find a high impact magnitude of private R&D, concentrated after an initial threshold; while, instead the impact of public R&D is linear and positive, albeit of smaller magnitude. Since patents are devised to protect innovations with commercial value content, private R&D naturally tends to contribute more than government R&D to national patenting. The latter, however, does not exhibit threshold behaviours nor does it suffer from decreasing marginal returns, suggesting a steady underlying contribution to the overall patenting rate. It is likely that an initial level of basic research and common innovation infrastructure is needed before private R&D can profitably translate into patent applications (see Cohen and Levintal, 1989; Griffith et al., 1999; Hu and Mathews, 2005a; Hu and Mathews, 2005b). As reflected in our findings, this may translate in a delayed onset of positive returns to investment, followed by a positive relationship with diminishing returns to private R&D accumulation.

These results allow us to qualify the non-linear relationship between total aggregate R&D and patents. More specifically, as also argued in Rodriguez-Pose and Bilbao-Osorio (2004), the predominant innovation funding source is either public or private at different stages of development. Table A1 (see Appendix A) confirms such pattern in the case of our sample, where the minimum value of public R&D spending is higher than the minimum value of private R&D spending. This is the case both when public R&D is expressed as a share of total R&D spending and when it is expressed as a share of GDP.

On the contrary, private R&D predominates when we look at maximum values of R&D spending. The fact that the patents response function to total R&D spending exhibits an initial threshold behaviour and diminishing returns for higher R&D levels may suggest that the positive and linear contribution of public R&D is not strong enough to counteract the initial delayed onset of positive returns. Whereas, because business funded R&D prevails at the other end of the spectrum, its diminishing returns pattern translates onto the overall R&D function too.

The results presented thus far are likely to suffer from simultaneity bias if any of the right hand side covariates are co-determined with patent applications. In a macroeconomic setting this is often the case, thus, in Table 3 below, we substitute all variables in our model with their first lag. Starting with column (1), the findings are very much in line with those obtained in the contemporaneous specification. In column (2), when total R&D is estimated in non-parametric form, the explanatory power of GDP per capita and trade openness once again fluctuates and disappears, while patent stock retains its positive impact and the stock market capitalisation measure gains significance. The SP test indicates that total R&D has strong explanatory power, and Figures 4 plots the patent response function to the first lag of total R&D.

Table 3. Lagged Semi-Parametric and Parametric Polynomial Analysis

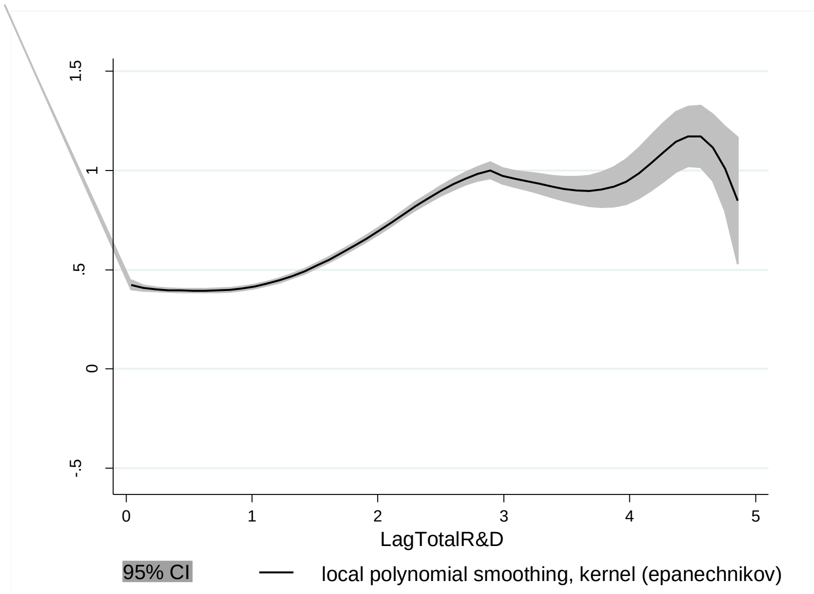
EPO_Patents	TotR&D FE (1)	TotR&D SemiPar (2)	TotR&D Polyn FE (3)	DisagR&D FE (4)	DisagR&D Semipar (5)	DisagR&D Semipar (6)	Disag R&D Polyn FE (7)
LogGDPpercapita	0.036***	0.063	0.028**	0.191**	0.207***	0.157**	0.035**
	(0.013)	(0.07)	(0.012)	(0.079)	(0.055)	(0.072)	(0.015)
PatentStock	0.11***	0.086***	0.106***	0.055***	0.061***	0.055***	0.113***
	(0.008)	(0.007)	(0.01)	(0.012)	(0.012	(0.011)	(0.01)
Education	0.0006	-0.0006	0.002	-0.001	-0.002	-0.001	-0.0001
	(0.154)	(0.215)	(0.142)	(0.25)	(0.238)	(0.247)	(0.184)
FDI	-0.0003	-0.002	-0.0005	0.0008	0.0007	0.0008	-0.0003
	(0.002)	(0.002)	(0.003)	(0.001)	(0.0009)	(0.0009)	(0.003)
Trade	0.0006**	0.0006	0.0007***	0.001**	0.0003	0.0009*	0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
StockMarket	0.0008	0.0014**	0.0007	0.0012***	0.0012**	0.002***	0.0004
	(0.0008)	(0.0005)	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.001)
TotalR&D	0.136***	-	-0.039				
	(0.023)		(0.068)				
TotalR&D^2			0.143***				
			(0.046)				
TotalR&D^3			-0.025***				
			(0.008)				
ResidualR&D				-0.041	0.079	-0.057	-0.108
				(0.083)	(0.066)	(0.092)	(0.109)
PublicR&D				0.351***	0.272***	-	0.245***
				(0.082)	(0.07)		(0.093)
PrivateR&D				0.272***	-	0.258***	-0.219
				(0.054)		(0.057)	(0.186)
PrivateR&D^2							0.436**
							(0.196)
PrivateR&D^3							-0.121**
							(0.053)
Country-d	yes	yes	Yes	yes	Yes	Yes	Yes
Year-d	yes	yes	Yes	yes	Yes	Yes	Yes
Obs.	693	693	693	479	479	489	479
Countries	62	62	62	52	52	52	52
R^2	0.95	0.91	0.95	0.98	0.93	0.95	0.98
SP Test		23.43***			21.02***	11.32***	
HM Test							
crit. Value		1.96			1.96	1.96	
T-st (cub poly)		7.58***			8.16***	1.2	
T-st (quad poly)						0.85	
Boots. Reps.		399			399	399	

Notes: heteroskedasticity-robust standard errors are reported in parenthesis. *** p<0.01 **p<0.05 * p<0.1.

Once again, the pattern is markedly non-linear, similarly to Figure 1, with a delayed onset of positive returns to innovation spending, followed by a positive relationship with decreasing marginal returns to accumulation. The HM statistic in columns (2) confirms this pattern, and suggests that a cubic polynomial approximation is appropriate, just like in the contemporaneous specification of

Table1. Thus, in column (3), we re-estimate the lagged model according to the specification suggested by the HM test. Here, GDP per capita, patent stock, and trade openness appear once again to be positively related to the national innovation flow. Moreover, estimated at the mean of patent applications in our sample, a 1% point increase in total R&D expenditure increases patent applications by 0.66.

Figure 4. Semi-parametric kernel weighted local linear regression (LagTotalR&D)



In columns (4) to (7), once again we disaggregate total R&D in its public and private components and estimate a lagged model, first in linear form, then semi-parametrically and, finally, according to the polynomial approximation indicated by the HM statistic. Starting with column (4), a number of covariates gain significance with respect to the contemporaneous specification reported in Table 1. More specifically, while patent stock retains its positive impact, now GDP per capita, trade openness and stock market capitalisation all appear with a positive and significant coefficient. Both public and private R&D also enter positively, while the impact of residual R&D is, again, not significantly different from zero.

In column (5), we estimate a semi-parametric specification where the non-parametric variable is private R&D lagged one year. The SP tests indicates that private R&D is a significant covariate in the model, while the HM test indicates once again that the patent response function to private R&D can be approximated parametrically by a cubic polynomial. This is confirmed by the plot in Figure 5, which is similar to Figure 2.

Figure 5. Semi-parametric kernel weighted local linear regression (LagPrivateR&D)

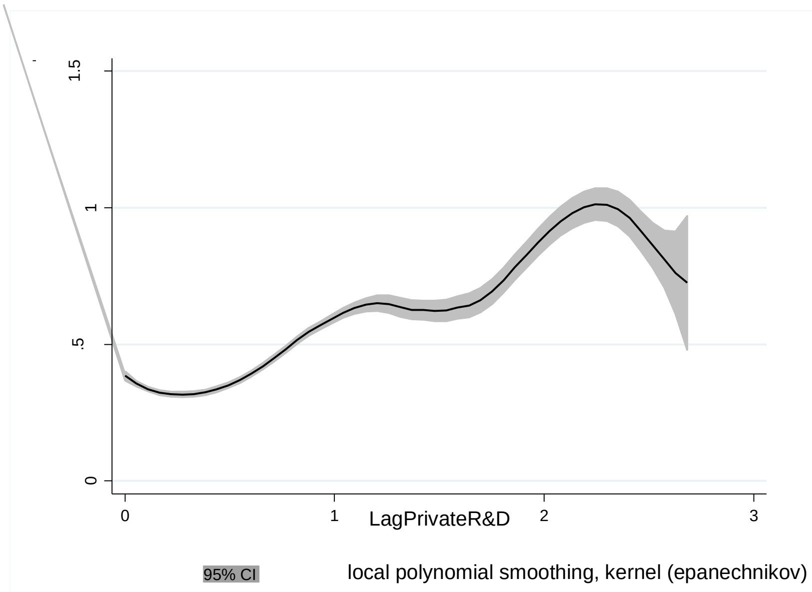
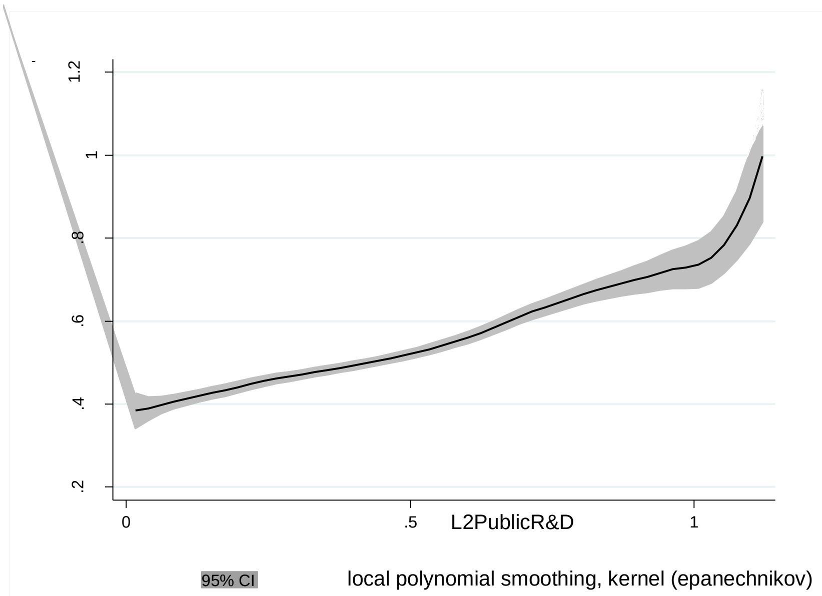


Figure 6. Semi-parametric kernel weighted local linear regression (L2PublicR&D)



In column (6), public R&D lagged by one year enters now non-parametrically. All other results carry over, and private R&D exhibits a positive relationship. The SP and HM statistics confirm the findings of the contemporaneous model specification. In fact, public R&D is a significant covariate, with its parametric approximation being simply linear, as confirmed by Figure 6. Finally, in column (7), we combine these findings in a parametric specification that follows the HM statistic indications. We find that the patent impact of both public and private R&D expenditure remains broadly similar to the results of the contemporaneous specification presented in Table 1, with only a slight increase in the coefficient magnitude.

4. Robustness Analysis

In this section, we carry out a number of sensitivity checks on the aggregate innovation production function, in order to test the robustness of the findings presented above. These tests include the identification of inflection points, the addition of new covariates, the restriction of the estimation sample to OECD economies, and the use of alternative measures for the dependent variable. All estimations are bases on the System GMM approach in order to address all remaining concerns related to the endogeneity of the right hand side variables. For the R&D variables, in particular, Stoneman (in Hall et al. 1986), explains that only part of the R&D investment is done before applying for patent protection. The continuation of R&D projects is, instead, conditional on the acceptance of patent applications. This means, as explained in Montalvo, 1997, that a great part of the R&D investment we measure is pre-determined with respect to patent applications.

Before moving to the detailed description of the result, note that the post-estimation panel at the bottom of each of the tables to follow presents the Hansen (1982) *J*-test of overidentifying restrictions, the Arellano Bond (1991) test for the presence of serial correlation in the error term, and the difference-in-Hansen statistic, referred to as *C* statistic by Hayashi (2000). Finally, in the notes appearing below each table, we report the lag structure used in each column. In all estimated specifications, no evidence of serial correlation is found. Moreover, the Hansen-*J* test indicates the validity of the instrumental set used in all instances, and, regarding the difference-in-Hansen test, in all models the null hypothesis that the instruments used for the level equation are adequate cannot be rejected.

To facilitate comparison, in columns (1) and (2) of Table 4, we replicate the polynomial approximations identified in the non-parametric analysis for both total R&D and its disaggregated components. However, in line with the main focus of

Table 4. Sensitivity Analysis

EPO_Patents	(1) DisagR&D Polyn	(2) TotR&D Polyn	(3) Threshold Polyn	(4) Addit Var	(5) Addit Var	(6) Addit Var	(7) Addit Var
LogGDPpercapita	0.087*	-0.02	-0.137***	0.04	-0.025	-0.028	-0.058
	(0.046)	(0.047)	(0.047)	(0.15)	(0.125)	(0.134)	(0.107)
PatentStock	0.105***	0.1***	0.09***	0.084***	0.095***	0.094***	0.1***
	(0.006)	(0.006)	(0.006)	(0.015)	(0.008)	(0.01)	(0.009)
Education	0.008**	0.013***	0.018**	0.008	0.013*	0.015**	0.014**
	(0.366)	(0.367)	(0.51)	(1.12)	(0.682)	(0.743)	(0.608)
FDI	0.006***	0.0007	0.002*	0.002	0.003	0.003	0.002
	(0.002)	(0.0009)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Trade	-0.001	0.002**	0.002*	-0.001	-0.0006	0.003**	0.0008
	(0.0007)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
StockMarket	0.003***	0.004***	0.002***	0.003***	0.002	0.002***	0.001
	(0.001)	(0.0005)	(0.0006)	(0.001)	(0.001)	(0.001)	(0.001)
ResidualR&D	-0.218**						
	(0.095)						
PublicR&D	0.263**						
	(0.123)						
PrivateR&D	-0.345						
	(0.283)						
PrivateR&D^2	0.351**						
	(0.178)						
PrivateR&D^3	-0.076**						
	(0.038)						
TotalR&D		-0.379		-0.55	-0.532	-0.435	-0.182
		(0.232)		(0.6)	(0.61)	(0.42)	(0.292)
TotalR&D^2		0.36***		0.426*	0.489**	0.46**	0.345**
		(0.011)		(0.28)	(0.238)	(0.205)	(0.15)
TotalR&D^3		-0.063***		-0.08*	-0.085**	-0.081**	-0.066***
		(0.016)		(0.041)	(0.036)	(0.032)	(0.024)
TotalR&D_thr1			0.042				
			(1.21)				
TotalR&D_thr2			0.451***				
			(0.057)				
TotalR&D_thr3			-0.168***				
			(0.059)				
GBC_netexpense				0.02	0.013	-0.006	0.003
				(0.015)	(0.01)	(0.01)	(0.001)
GBC_balance				0.014	0.008	-0.002	0.008
				(0.013)	(0.009)	(0.008)	(0.009)
GBC_nontaxrevenue				-0.011	0.002	0.006	-0.0001
				(0.014)	(0.008)	(0.007)	(0.008)
HighTechExports					-0.0008	-0.006	-0.004
					(0.004)	(0.004)	(0.004)
MobileSubscriptions						0.003**	0.002
						(0.001)	(0.001)
Population65+							-0.01
							(0.014)
Obs.	572	802	802	597	588	588	588
Countries	60	70	70	58	58	58	58
Num. Instrum.	65	63	63	48	52	56	60
Hansen-*J* (p val)	0.7	0.48	0.91	0.89	0.23	0.36	0.42
***C* Stat (p val)**	0.29	0.54	0.62	0.81	0.18	0.26	0.36
AR (2) (p val)	0.29	0.16	0.34	0.93	0.88	0.63	0.64

Notes: significance level as follows: *** p<0.01, ** p<0.05, * p<0.1. Lags 2-6 are used in (1); lags 2-7 are used in (2) and (3), lags 2-4 are used in (4), (5), (6), and (7).

this study, from column (3) onwards, we concentrate our attention on the functional specification of total R&D only. Because the incorporation of additional right hand side variables considerably reduces the observations availability, focusing on total R&D only will also allow us to work with a larger sample size.

Column (1) confirms a cubic polynomial relationship between patent applications and private R&D. The specification indicates a 0.28 mean overall impact of a 1% point increase in business funded R&D on annual patent applications per 10,000 inhabitants. This magnitude is comparable to the one found previously with the two-way fixed effect model, that is, approximately 0.3. The impact magnitude for the public component stands at 0.265, which is also comparable to the two-way fixed effect estimate of 0.19-0.26. Most of the other results carry over from previous specifications, while now also the share of tertiary educated students and the level of FDI turn significant with expected positive signs.

Finally, in this specification, the residual R&D component appears, for the first time, to bear explanatory power, with a negative sign. This sign may be a reflection of the type of innovative activity carried out by the sectors aggregated in this residual R&D category. In fact, if profit is not the primary objective of innovation, as it is the case for the higher education and non-profit sectors, some sort of substitution effect may occur, whereby R&D spending simply translates in knowledge that is freely available, which reduces the patenting rate. When total R&D is included in aggregate form in the model specification of column (2), its impact magnitude is higher than the one found in the fixed effect model. This coefficient indicates that a 1% increase in total R&D expenditure leads to an overall mean increase of 0.61 in patent applications.

Next, in column (3), we attempt to identify the inflection points where non-linerities occur along the total R&D function. A simple way of modelling such non-linearities would be the splitting of our sample into segments, followed by the estimation of a linear relationship for each of those. However, as explained in Ahamada and Flachaire (2010), such piecewise regression does not guarantee differentiability at the junction points. Instead, a spline regression estimator does, by estimating polynomials rather than straight lines at each segment. Therefore, following this methodology, we identify inflection points for the innovation production function presented in column (2), using Harrell (2001)'s percentile indications.

The onset of positive returns to aggregate national innovative investment is identified around the R&D intensity value of 0.23 % (expressed as a share of GDP); while the onset of diminishing returns is identified at around 2.65%. These thresholds are close enough to the inflection areas depicted in Figure 1 and 4 above. Once again, the polynomial coefficient set in column (3) confirms the existence of a delayed onset of positive returns to national R&D spending, with diminishing marginal returns to accumulation. All other covariates enter the regression with the expected sign; except for GDP per capita, which, surprisingly, takes up a negative sign. In columns (4) to (7), we test the robustness of our model to the addition of new covariates: the government budget constraint, the high-tech share of overall manufacturing exports, the mobile phone subscriptions per 100 people, and the share of over-64 population.[9]

The government budget constraint is represented by a set of three variables: overall government expenditure, from which we subtract the R&D component, government balance, and government non-tax revenue. This is done because government R&D is a public spending component, and, as argued in Adam and Bevan (2005) and Agénor and Neanidis (2010), the elements of the government budget constraint are bound together by an identity. In order to estimate the impact of public expenditure in a consistent way and to control for the source of financing, all elements of the budget constraints but one need to be included in the model specification. This avoids perfect multi-collinearity, and the impact of each of the included elements is measured as its impact net of the marginal impact of the excluded element. In our case, the excluded element is government tax revenue. The results indicate, however, that none of three government budget components influences patent applications.

Though high-tech exports represent an indication of engagement in productivity enhancing activities and, as such, may lead to the patenting of new knowledge, we do not find a significant impact of this variable. This may be due to the contemporaneous presence, in the regression, of a measure of trade openness. Similarly, mobile phone subscriptions can be seen as an indicator of the level of infrastructure. Only in column (6), however, its positive impact is significant. The demographic composition of a country's population could be seen as a determinant

[9] Note that, following the addition of these variables, the sample size drops by more than 25%.

of the existing level of demand for innovation. For example, Pereze and Soete (1988), Cohen and Levintal (1989), and Porter (1990) identify demand sophistication as a key determinant of innovative performance. To proxy for the overall level of demand for and consumption of new technologies, we consider the over-64 share of the population, expecting it to be negatively associated with national innovation output. Once again, however, the additional variable does not have explanatory power.

Moving to Table 5, we repeat, in column (1), the total R&D benchmark when estimated via System GMM, in order to facilitate comparison. In columns (2) and (3), we restrict our sample to OECD economies only. The results, however, indicate that in this sample of developed countries, total R&D is not significant when modelled as a cubic polynomial. Only the squared approximation in column (3) yields significant results. According to this specification, a 1% point increase in total R&D results in an average 1.02 additional patent applications.[10] Such results suggest that the flat segment in the full sample is driven by non-OECD countries. In Table 1 above, it is evident that the average number of annual EPO patent applications in non-OECD countries is nearly zero, while even the maximum value is not larger than 0.05. This may account for why non-OECD countries drive, in our analysis, the initial flat segment where R&D expenditure does not translate (yet) in tangible patent output.

In columns (4) and (5), we return to the original sample size, and consider alternative patent indicators, in an attempt to overcome the limitations that each indicator inevitably carries. As anticipated, instead of patent applications to the EPO, we consider, first, patent applications filed through the PCT, and second, a patent application indicator constructed with the worldwide count methodology proposed by de Rassenfosse et al. (2013). In column (4) of Table 5, where PCT patents are used. the aggregate innovation process follows a quadratic pattern, resembling the one found in column (3), where only OECD countries are considered. This may be explained by the substantial underrepresentation of developing countries when using this indicator (see Table 1 above). Instead, in column (5), where the WWC data is used, the functional form of total R&D

[10] Estimation results for the non-OECD sample are not reported due to the size of sample we are left with when considering only developing countries. Due to the large number of instruments, despite collapsing, such model does not achieve enough explanatory power

expenditure reverts back to a cubic polynomial function. Finally, note that, in the WWC specification, the magnitude of the second polynomial term's coefficient is much higher than in the EPO benchmark specification. This may suggests that returns to R&D are considerable for patents applications representing incremental innovation.

Table 5. Sensitivity Analysis

EPO_Patents PCT_Patents WWC_Patents	**TotR&D Polyn (1)**	**Cubic Polyn OECD (2)**	**Quadratic Polyn OECD (3)**	**PCT PatApp (4)**	**WWC PatApp (5)**
LogGDPpercapita	-0.02	-0.062	-0.44	0.005	-0.39
	(0.047)	(0.452)	(0.41)	(0.024)	(0.43)
PatentStock	0.1***	0.111***	0.108***	0.15***	-0.027**
	(0.006)	(0.023)	(0.018)	(0.003)	(0.012)
Eduction	0.013***	0.024	-0.009	0.007***	0.13***
	(0.367)	(3.254)	(1.64)	(0.145)	(3.5)
FDI	0.0007	0.018*	0.016*	0.0001	-0.01
	(0.0009)	(0.011)	(0.009)	(0.0007)	(0.021)
Trade	0.002**	-0.001	-0.002	0.001*	-0.003
	(0.001)	(0.003)	(0.002)	(0.005)	(0.008)
StockMarket	0.004***	-0.0004	0.002*	0.002***	-0.009*
	(0.0005)	(0.003)	(0.001)	(0.0003)	(0.005)
TotalR&D	-0.379	1.657	1.234**	0.29***	-1.452
	(0.232)	(1.187)	(0.387)	(0.053)	(1.312)
TotalR&D^2	0.036***	-0.59	-0.199**	-0.066***	1.74**
	(0.011)	(0.443)	(0.1)	(0.008)	(0.706)
TotalR&D^3	-0.063***	0.067			-0.257***
	(0.016)	(0.05)			(0.096)
Obs.	802	512	512	792	575
Countries	70	38	38	70	42
Num. Instrum.	63	35	40	72	45
Hansen-*J* (p val)	0.48	0.74	0.9	0.83	0.92
***C* Stat (p val)**	0.54	0.89	0.8	0.24	0.85
AR (2) (p val)	0.16	0.68	0.93	0.4	0.81

Notes: significance level: *** p<0.01, ** p<0.05, * p<0.1. Lags 2-7 are used in (1), lags 2-4 are used in (2), lags 2-5 are used in (3) and (5), lags 2-9 are used in (4).

5. Conclusions

This study investigates the functional form properties of the innovation process, where R&D spending represents the input and patent applications the output. A non-parametric analysis uncovers significant non-linearities in the patent response function of total R&D spending. Disaggregating the latter in its two main funding components reveals that business funded R&D drives the non-linearities. Specifically, private R&D exhibits both delayed onset of positive returns to innovation spending and diminishing marginal returns to accumulation. In contrast, the contribution of publicly funded R&D spending to the patent flow is smaller in magnitude, though it is not subject to any type of non-linearity. It is, in fact, related in a positive and linear fashion to the patent application flow.

In turn, the non-linearities exhibited by the aggregate innovation process replicate very closely the ones uncovered with respect to private R&D funding. In fact, in this case too, we find both an initial threshold effect and subsequent diminishing returns. We explore such results in more depth, by, first, identifying the approximate values around which inflection points occur. In addition, by considering a sub-sample of OECD economies, and by substituting the EPO patent count with alternative indicators, we further qualify the polynomial specifications. In particular, it appears that when developed economies only are considered, the initial threshold effect disappears.

The policy implications deriving from our analysis point in the direction of a fundamental role played by public innovation investment outlays. More specifically, apart from its direct contribution to the patenting flow, public innovation spending may also have an additional compensating role to play with respect to private R&D. In fact, our results indicate that low private R&D spending levels lack impact on the aggregate patenting rate. This opens up the possibility, in less technologically advanced economies, for additional public R&D investment to alleviate or counteract such delayed onset of positive returns. On the other hand, in technologically advanced economies, shifting part of the R&D spending from the private to the public sector could counteract diminishing returns at the margin. Further research is, however, needed surrounding the interplay of public and private R&D spending, in order to determine in what way this interaction can influence the existence of threshold effects.

Appendix A: Country and Data Summary Tables

Table A1. Summary Statistics

	Obs.	Mean	St. Dev.	Min	Max
EPOPat_App	813	0.481	0.694	0	3.793
PCTPat_App	792	0.17	0.457	0	3.11
WWCPat_App	575	2.261	4.652	0.006	26.265
LogGDPpercap	813	8.971	1.16	5.96	10.643
PrivateR&D (%TotR&D)	587	42.24	17.86	0.1	84.5
PublicR&D (%TotR&D)	587	43.93	15.58	2.4	93.2
ResidualR&D (%TotR&D)	587	9	10.5	0	76.8
TotalR&D	813	1.266	0.99	0.04	4.775
PrivateR&D (%GDP)	587	0.67	0.665	0.0002	2.684
PublicR&D (%GDP)	587	0.48	0.257	0.015	1.183
ResidualR&D (%GDP)	587	0.102	0.13	0	1.05
PatentStock	813	3.043	4.678	0	27.702
FDI	813	4.023	4.746	0	36.43
Education	813	17	6.5	2	38.94
Trade	813	79.61	38.06	16.01	199.3
StockMarket	813	44.63	39.61	0.01	275.7
GBC_netexpense	597	31.16	9.44	11.04	62.3
GBC_balance	597	-1.783	4	-30.2	18.5
GBC_nontaxrevenue	597	12.35	5.6	0.752	43.8
HighTechExports	588	13.28	9.95	0.083	48
MobileSubscriptions	588	53.34	46.08	0	160.8
Population65+	588	12.94	4	2.6	22.68

Figure A1. Scatter plot of Public R&D against EPO patent applications

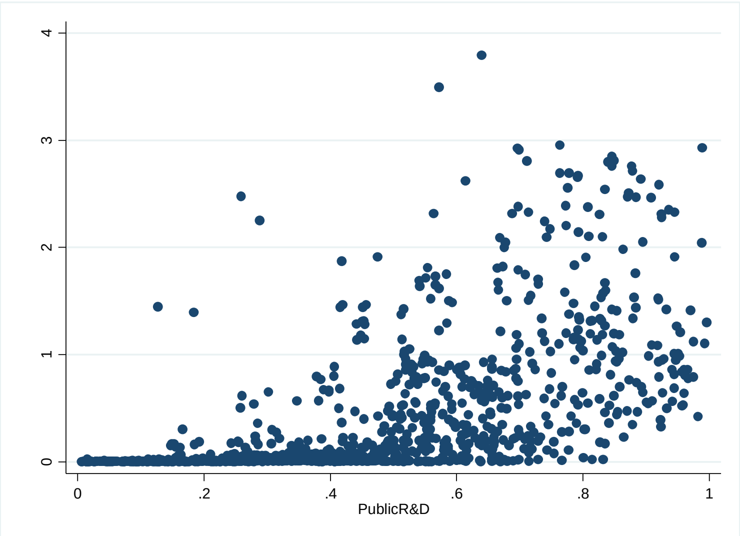


Figure A2. Scatter plot of Private R&D against EPO patent applications

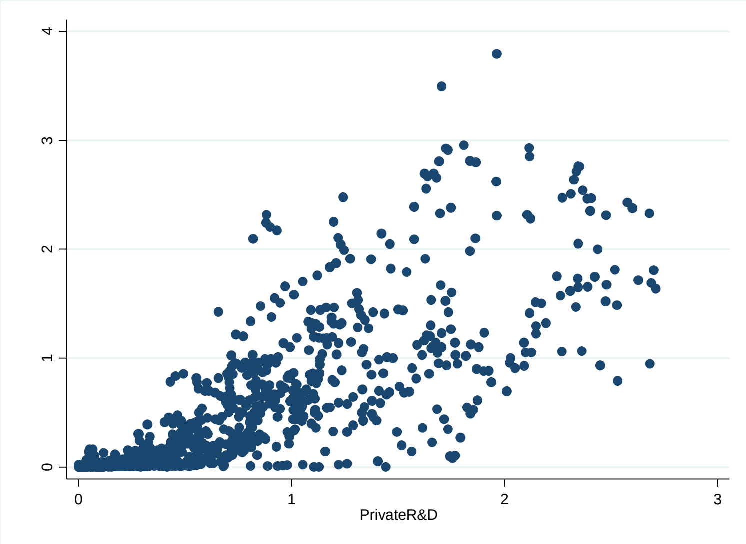


Figure A3. Scatter plot of Total R&D against EPO patent applications

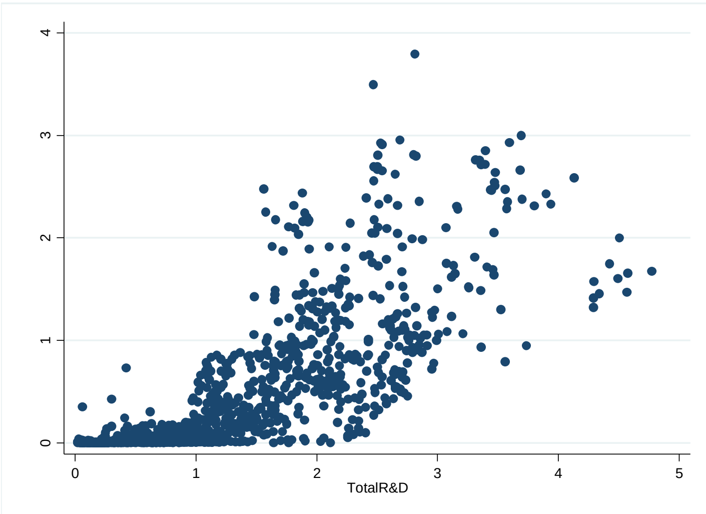


Table A2. Data Sources

Variable	Definition	Source
EPOPatent_App	Total number of patent applications per 10,000 inhabitants filed to the European Patent Office, by year of filing, according to the inventor's country of residence. The reference date of the application is the priority date, which is the date of the first international filing of a patent and therefore the closest to the invention date.	OECD, *Main Science and Technology Indicators*
PCTPatent_App	Total number of patent applications per 10,000 inhabitants filed via the international Patent Cooperation Treaty; by	OECD, *Main Science and Technology*

	year of filing, according to the inventor's country of residence. The reference date of the application is the priority date, which is the date of the first international filing of a patent and therefore the closest to the invention date.	*Indicators*
WWCPatent_App	Total number of patent applications per 10,000 inhabitants filed by all inventors residing in a specific country, regardless of the patent office, by year of filing. The reference date of the application is the priority date, which is the date of the first international filing of a patent and therefore the closest to the invention date.	*de Rassenfosse et al. (2013) http://gder.phpnet.org/ rassenfosse//data.html*
Total R&D	Total Research & Development expenditure (% of GDP).	*OECD, Main Science and Technology Indicators RICYT.org UNESCO*
PrivateR&D	Research & Development expenditure funded by the business sector (% of GDP).	*OECD, Main Science and Technology Indicators RICYT.org UNESCO*
PublicR&D	Research & Development expenditure funded by the public sector (% of GDP).	*OECD, Main Science and Technology Indicators RICYT.org UNESCO*
ResidualR&D	Sum of the Research & Development expenditure funded by the higher education, non-for-profit, and foreign sectors (% of GDP).	*OECD, Main Science and Technology Indicators RICYT.org UNESCO*
LogGDPpercap	GDP per capita in constant 2000 US$ in log form.	*World Bank, WDI*
PatentStock	The stock of patents for country i is calculated using the perpetual inventory procedure in line with Bottazzi and Peri (2005) and Coe et al. (2009): $PatStock_{it} = EPOPat\_App_{it-1} + (1-\delta)PatStock_{it-1}$	

	where the depreciation rate, δ, is assumed to be 0.1 The initial value of the patent stock at time t_o is calculated as $$PatStock_{it_0} = EPOPat\_App_{it_0}/(\delta + g_i)$$ where g_i is the annual average logarithmic growth rate of patenting in country I from the earliest date data on patents are available (t_0) to 1995. For most countries t_0 = 1977.	
FDI	Net inflows of Foreign Direct Investment (% of GDP).	*World Bank, WDI*
Education	Share of tertiary level students in the total number of all students, according to the International Standard Classification of Education 1976 and 1997 (ISCED-76, ISCED-97). For years 1981 to 1995 tertiary education includes ISCED-76 levels 5, 6 and 7. For years 1998 and after, tertiary education includes ISCED-97 levels 4, 5 and 6. The first level of each of the classifications covers programs that generally do not lead to a university degree but usually require successful completion of a program at the upper secondary level. The second level covers programs that lead to an award of a first university degree, and the third level covers programs that lead to an award of a second or further degree.	*UNESCO*
Trade	Sum of a country's exports and imports (% of GDP).	*World Bank, WDI*
StockMarket	Value of listed shares to GDP, calculated using the deflation: $$\left\{(0.5) * \left({}^{F_t}/_{P_{et}} + {}^{F_{t-1}}/_{P_{et-1}}\right)\right\}/(GDP_t/P_{at})$$ where F is stock market capitalization, P_e is end-of period Consumer Price Index, and P_a is average annual Consumer Price Index .	*Database on Financial Development and Structure (Beck et al. 2000)*
GBC_netexpense	Total expenditure of consolidated central government net of R&D expenditure (% of GDP).	*International Monetary Fund, GFS*
GBC_balance	Overall budget balance of consolidated central government (% of GDP)-	*International Monetary Fund, GFS*
GBC_nontaxrevenue	Non-tax revenue of consolidated central government (% of GDP).	*International Monetary Fund,*

		GFS
HighTechExports	High-Tech Exports as a share of total manufacturing exports.	*World Bank, WDI*
MobileSubscriptions	Mobile phone subscription per 100 people	*World Bank, WDI*
Population65+	Over 64 population (% total population).	*World Bank, WDI*

Table A3. Country List

Argentina, Armenia, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czech Rep., Denmark, Egypt, El Salvador, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, South Korea, Kuwait, Lithuania, Macedonia, Malaysia, Malta, Mexico, Mongolia, Morocco, Netherlands, New Zealand, Norway, Pakistan, Panama, Perù, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Slovak Rep., Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay.

Appendix B: Technical Notes

Notes on the Constructions of the R&D Dataset

Data availability. Three sources of R&D data were used to compile the R&D dataset used in this study. One is the OECD's Main Science and Technology Indicators (MSTI) dataset. These data covers the years 1981 to 2011, and all OECD economies. The second source is the UNESCO. These data cover a much wider number of countries, including many developing ones, but has a shorter time span. The two datasets have been merged, after verifying the content correspondence of the overlapping data sections. For all OECD countries, the MSTI dataset is the preferred data source, only missing values were replaced with available UNESCO data. On the other hand, the R&D information on the countries not covered by the MSTI has been created using the UNESCO dataset exclusively. Finally, a third source of R&D data is RICYT (Red de Indicadores Científicos y Tecnológicos) which covers Latin American countries. This source was used to fill in the gaps of the two previous databases, whenever the information provided by RICYT was missing from either the UNESCO or the OECD databases.

Unit of Measurement. Apart from data availability, another compatibility issue regards unit of measurement. In a few instances, the currency and denomination of R&D data provided by the three databases did not coincide, which led to discrepancies in the calculation of the R&D component shares of GDP. To overcome this problem, the R&D shares of GDP have been re-calculated by multiplying the R&D intensity (as % of GDP) by the respective shares of the private and public R&D components:

$$\frac{GovernmentR\&D}{GDP} = \frac{TotalR\&D}{GDP} * \frac{GovernemntR\&D}{TotalR\&D}$$

Definitions and Categories. A final source of discrepancy arises because RICYT reported, in some instances, the sum of both public and higher education R&D expressed as one single category, labelled 'public R&D'. Comparability was ensured on a case by case basis, by applying the share proportions used by either UNESCO or OECD for the same country in previous years.

CHAPTER 2: MACROECONOMIC VOLATILITY, INSTITUTIONAL INSTABILITY, AND THE INCENTIVE TO INNOVATE

1. Introduction

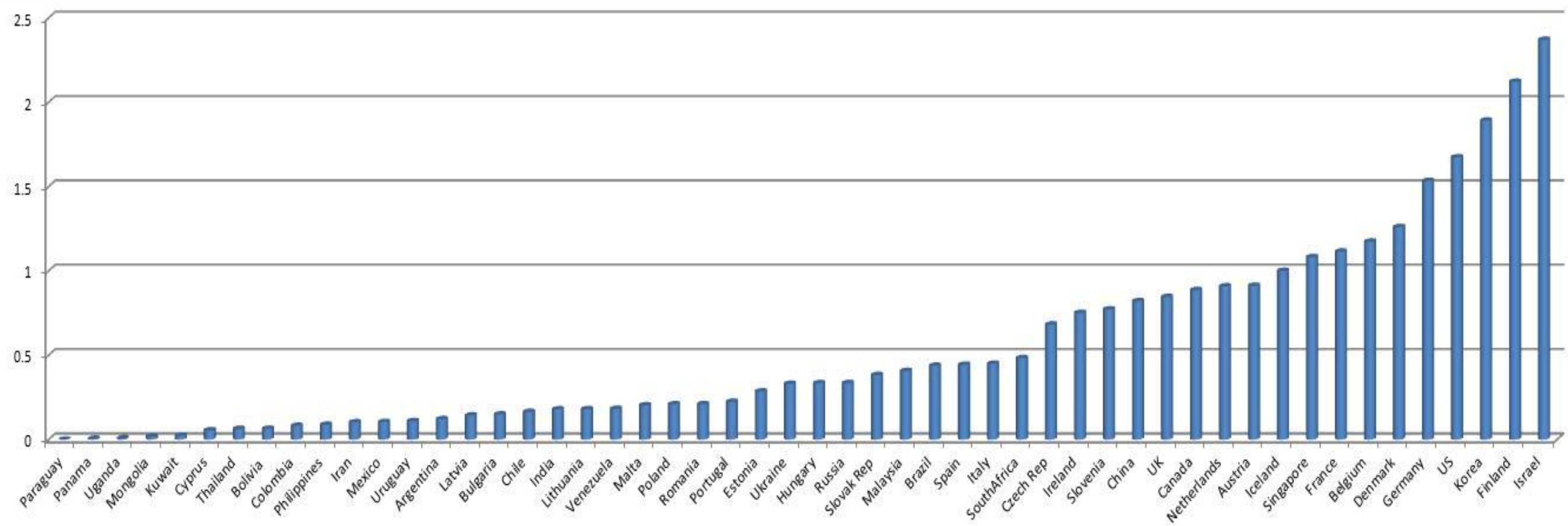
The importance of private sector's innovation is widely recognised in the economic growth literature (Romer, 1990; Grossman and Helpman, 1991b). However, pronounced disparities persist in the shares of private R&D investment across countries. Figure 1 below may help gauge the extent of the cross-country disparity existing in private sectors' R&D engagement, within the panel of economies used in this study. A number of structural factors have been investigated at length and proposed by the literature to explain the variation in countries' levels of private R&D spending.

This paper seeks to analyse such issue by focusing specifically on the impact that macroeconomic and political instability has on the level of aggregate private innovative investment. The reason for considering such perspective is related to the inherently high risk content of R&D investment, which is due to both its longer than average maturity horizon and to its high budget requirements (Katz, 1987). Based on these elements, we hypothesised that firms' plans to spend on costly and risky innovative projects may be subject to revision in uncertain environments and that, as a result, aggregate private innovation spending may remain low. In what follows, we will show that such hypothesis is supported by the findings of our empirical analysis.[11]

A number of microeconomic studies have attributed firms' abandonment or avoidance of innovative investment undertakings to the existence of a cash-flow effect, which financially constrains them and hinders their innovative spending during downturns (Rafferty, 2003; Rafferty and Funk, 2008; Aghion et al, 2008; Bohva-Padilla et al, 2009, Aghion et al, 2010). However, following the

[11] Note that we decided to focus on private R&D investment because it is viewed as being much more sensitive to volatility in the surrounding economic environment than public R&D (see Katz, 1987, or Aghion et al., 2010 – among others). Further, total R&D expenditure by containing various R&D funding components may mask differences in component responses when estimating the impact of volatility. In other words, the various R&D components may react in different ways to volatility. The aim of the study is, precisely, to uncover how the most sensitive component of R&D investment is affected by volatility, assuming that entrepreneurial incentives may quickly fade in the presence of unstable economic environments.

Figure 1. Business R&D (%GDP)



The values represent the ratio of Business Funded R&D to GDP, and they are calculated as a national average over the time span 1994-2008 (Raw data is from the OECD, Main Science&Technology Database, UNESCO UIS and RICYT

Schumpeterian analysis of the business cycle and Hall's reorganizational capital theory (1991), Saint-Paul (1993) had argued against such 'cash-flow' effect. Saint-Paul maintained that, during recessions, the opportunity cost faced by innovating firms in terms of foregone profits is lower as the value of expected sales decreases. This will provide an incentive for firms to allocate resources to R&D during recessionary phases.

Subsequently, however, Aghion and Saint-Paul (1998) revised this hypothesis and proved that it only holds as long as innovation costs are not so high as to represent a financial constraint. Along the same line of argument, Aghion *et al.* (2008) and Rafferty and Funk (2008) have shown that the existence of an asymmetry in binding constraints causes cash-flow effects to bind more during recessions than expansions. The result is that during recessions firms disinvest more than what they invest during expansions. Likewise, the 'opportunity-cost' effect is shown to bind more during booms than slumps. As a result, firms tend to relocate resources away from R&D and towards sales when positive demand shocks occur, but the opposite is unlikely to happen to the same extent during negative demand shocks. In addition, Bohva-Padilla *et al.* (2009) show that counter-cyclicality in R&D spending is more likely in small and medium-sized firms, which tend to experience binding credit constraints the most; whereas, pro-cyclicality is more likely for non-credit constrained firms, such as MNCs or subsidised firms.

This paper represents a contribution to the existing literature on volatility and innovation in a few respects. Firstly, the literature described above concentrates on the first moment of the business cycle and in particular on the relationship between uncertainty surrounding recession expectations and firms' innovative behavior. This study, instead, extends the focus to the second moment of aggregate economies' fluctuations, that is, to overall volatility. Secondly, all the previously cited studies take up a microeconometric empirical approach and use firm-level data, most often on OECD-based firms only. This is typically due to the scarcity of developing countries' aggregate data on innovation (Goel and Ram, 1999; Aghion et al., 2010; Agénor and Neanidis, 2011). The present study adopts, instead, a macroeconometric approach and analyses cross-country variations in the level of national private R&D. This is done in an attempt to uncover aggregate response patterns to macro-institutional instability which go beyond individual productive sectors' reactions.

A final contribution is represented by the estimation of separate impacts for various sub-components forming aggregate volatility. This allows to disentangle a number of contemporaneous yet different dimensions co-existing in unstable macro-institutional environments. Specifically, my econometric findings suggest three ways in which instability negatively affects business R&D spending, that is, political, real and monetary volatility. Such impacts will be shown to exhibit non-linearities and to be larger for higher values of the real and monetary volatility dimensions. In addition, the negative effect of monetary instability appears to be mitigated during expansionary phases of the cycle, in the sample considered. Finally, the evidence surrounding both financial and international volatility is inconclusive. The remaining of the paper is structured in this way: the following section describes the model and the data used in the empirical analysis. The results, along with the sensitivity analysis, are presented in section 3 and 4. Section 5 summarise the main findings and concludes. Finally, all data sources, the list of countries included in my sample and some methodological considerations appear in Appendix A and B.

2. Data and Model

The panel used for this analysis covers 15 years, from 1994 to 2008, while the baseline sample includes 956 observations. Due to missing data, however, the actual estimated panel size is reduced to 44 countries and 281 observations. Unfortunately, as it has been mentioned above, the limitations of aggregate innovation data is its scarcity. Sub-Saharan African countries, for example, with the exclusion of Uganda and South Africa, do not publish secondary data on industrial R&D. Therefore, the panel suffers from an underrepresentation of African countries that needs to be acknowledged.[12] To maximize the amount of data on public and private R&D in the dataset, three databases have been merged which report measures of business and government R&D spending for different countries. [13]

12 Furthermore, note that, because most of the grassroots, small-scale, incremental or non-industrial innovation is not measured by official R&D statistics, we fail to capture this vital component of national innovative activity

13 See Appendix B, at the end of Chapter 1, for further technical details regarding the construction of the dataset.

The choice of regressors included in the model specification has taken into account and sought comparison with a variety of stability/instability indicators used in the literature, and it includes various control variables which have been used by the literature on the determinants of innovative investment. The benchmark econometric specification is as follows:

$$(1) \qquad y_{it} = a_i + \sum_{j=1}^{m} \beta_j X_{j,it} + \sum_{k=1}^{n} \gamma_k Z_{k,it} + \sum_{l=1}^{q} \theta_l V_{l,it} + \varepsilon_{it}$$

where the dependent variable, y_{it}, is *BusinessR&D*: the share of investment in R&D financed by the domestic business sector, calculated as a % of GDP. The right hand side of the regression includes three variable vectors, alongside a vector of time-invariant country fixed effects, a_i.[14] The set $\{X_{j,it}\}_{j=1}^{m}$ and $\{Z_{k,it}\}_{k=1}^{n}$ contain, respectively, endogenous and exogenous control variables commonly used in the literature surrounding the determinants of R&D investment.

Specifically, the following variables enter $\{X_{j,it}\}_{j=1}^{m}$: GDP per capita (in log-form) controls for the overall level of development of the countries in the panel. [15] To capture a potential non-linearity in the relationship between level of development and private innovative spending, an interaction of GDP per capita with a dummy variable (*HighIncome*) has also been included. The dummy takes the value of 1 for countries classified as middle to high income economies by the World Bank's Atlas classification system and zero otherwise.[16] The share of publicly financed R&D is used to capture the

[14] A vector of time-varying common effects is also included in the benchmark specification (column 11, Table 1), though this is dropped from subsequent estimations as it never enters the estimation significantly.

[15] The relevance of human capital availability for the innovation process has been highlighted by both theory (Lucas, 1988; Mankiw, Romer and Weil, 1992; Acemoglu and Zilibotti, 2001) and empirics (Wang, 2010). The reason why such variable is excluded from this analysis is because of its very high correlation with GDP.

[16] The non-linearity hypothesis appeared an interesting aspect to test after visual inspection of the scatterplot of GDP per capita against business R&D. In the plot, a positive relationship between overall level of development and business R&D sets in only after a certain income threshold is passed. Such threshold corresponds to the level of income classified as 'high' by the World Bank's Atlas classification (see Appendix A for a list of all high-income countries appearing in the sample).

role of public investment tangible and intangible infrastructure, which may have a complementary or crowding out effect on private innovative investment (see David et al., 2000, for a review of the contrasting literature on this). Finally, this vector also contains a measure of trade openness calculated as the sum of exports and imports to GDP. Trade openness has been used by the literature (Smolny, 2003; Sameti *et al.*, 2010) to capture the contribution that international exchange is likely to have on the ease and pace of innovation and technological progress.

The real interest rate appears among the exogenous control set $\{Z_{k,it}\}_{k=1}^{n}$, alongside, a measure of stock market capitalization. The latter has been used in a number of studies to proxy for financial development; but it also captures the effect of higher levels of both credit availability and risk diversification accessible to the business sector (see David et al., 200 and Levine and Zervos, 1996, for a review). In addition, a measure of property rights protection is also included to reflect the importance this variable is believed to play in explaining the pace of innovation ((Yang and Maskus, 2001; Varsakelis; 2001; Lin et al., 2010). This is a composite index with values ranging from 0 to 10, where 10 indicates the highest degree of rule of law enforcement. The impact measured by this variable is not limited to that of property right security, but it encompasses a more composite dimension of fairness and effectiveness in justice administration.

Finally, as a component of government expenditure appears in the model (public R&D) a measure of overall government's deficit/surplus to GDP is also included. This is done in order to achieve a consistent specification of the public budget constraint (see Bose et al., 2007; Katsimi and Sarantides, 2012, for details). At the same time, though, this variable proxies for the quality of public account management. While, strictly speaking the latter is not a standard indicator of instability, it does provide a measure of fiscal reliability, and it has been used by other studies in the same way (Fisher, 1993; Burnside and Dollar, 2000). Thus, its coefficient may partly capture the effect of more stable environments on private innovation.

The third vector $\{V_{l,it}\}_{l=1}^{q}$ is composed by the indicators of instability, which impact is the object of this analysis. The Polity IV 'State Fragility Index' is used as an indicator of political and institutional stability. The index rates countries according to the fragility of their effectiveness and legitimacy, in four performance dimensions: security, policy, economics, and social cohesion. A country's fragility is measured by this Index as a state's capacity to manage conflict, make and implement public policy, deliver essential services, maintain system cohesion and quality of life. Institutional uncertainty affects many elements of the macroeconomic business environment: via, for example, failing policy commitments; switching tax and incentive regimes; or revised economic targets and priorities (Fosu, 1992; Alesina et al., 1996). Thereby, institutional instability can bring about a more or less abrupt alteration in investment profitability expectations.

Real, financial and monetary volatility is represented, respectively, by the coefficient of variation of (log) GDP per capita, stock market capitalisation, and real interest rate.[17] Recurrent fluctuations in output proxy for the instability in the overall level of savings and aggregate demand; whereas variability in stock market capitalisation rates or in lending interest rates influence the cost of capital. In view of the long-term maturity horizon characterizing innovative investment and of its high-budget, risky nature; the present analysis seeks to test whether aggregate levels of private spending in R&D decline as a consequence of excessive variability in expected return rates resulting from fluctuations in any of the aforementioned dimensions.

The model is, first, estimated using a simple within-group estimator, which takes care of time-invariant country specific fixed effects. Subsequently, to evaluate the model's dynamics of adjustment and to address any potential simultaneity bias, the same estimation is applied to a specification where the lags of all endogenous variables are used instead of their levels. The application of standard within-group panel techniques is, however, not free of problems. It may, in fact, exacerbate measurement errors by removing a significant portion of the variation in the explanatory variables. In addition, it does not deal with cross-sectional dependence concerns.

Following Pesaran (2004) and Baltagi (2005), if such cross-sectional dependence is caused by unobserved common factors which are uncorrelated with the included

[17] Technical details on the construction of the volatility indicators can be found in Appendix B.

regressors the standard within-group estimator will still be consistent. However, if the unobserved factors are correlated with the included regressors, the within-group estimator will no longer provide unbiased and consistent results. A solution is the estimation of fixed-effect IVs, provided weak identification of the instruments is not an issue (De Hoyos and Sarafidis, 2006). Therefore, a within-group Two Stage Least Squares (2SLS) model is estimated last, with a varying set of instruments. First, internal instruments are used: in this case, first and second lags of all endogenous variables. Because private innovative investment is likely to exhibit lagged adjustment and response patterns to changes in the variables appearing on the RHS of the regression, the use of time-lagged internal instruments allows for the evaluation of such 'adjustment dynamics' effect. While this is in general a second-best strategy, as ideally one would want to use excluded variables that are highly correlated with the endogenous controls but do not belong to the model specification, the difficulty of finding variables meeting such requirements in macroeconomic setting is well-known. In addition, it will be shown that lags of the endogenous variables can represent a less of a concern and more of a suitable instrument when the dependent variable exhibits no serial correlation. Nevertheless, to test the robustness of the model where internal instruments appear, a set of external instruments is selected which best conforms to the exclusion restriction requirement and this specification is presented in section 5.

3. Results

The benchmark regression in equation (1) is estimated in *Table 1* in its basic, more parsimonious, form first. Subsequently, all volatility indicators are progressively included in columns (2)-(6). Columns (1)-(7) are within-group estimates, while column (8)-(10) are 2SLS-FE estimates. The most basic regression specification in column (1) only includes (log) GDP per capita and its HI interaction, the lending interest rate, the stock market capitalization measure, public balance, trade openness and public R&D spending. Both GDP per capita and its interaction term are significant, albeit of opposite sign. This suggests the existence, in my sample, of a threshold level of GDP per capita after which Business R&D and the level of a development are positively related. Such threshold value of average national GDP per capita occurs, in my sample, at about $3000 per year.[18] The lending interest rate enters with a negative coefficient, as expected. The coefficient of stock market capitalisation indicates that more developed financial markets positively relate to the share of privately funded R&D. The latter result is in line with the findings of Levine and Zervos (1996) in that it enhances capital stock accumulation and its productivity. It is also in line with the finding of Greenwood and Smith (1997) according to which it facilitates technology-intensive investment by lowering the cost of mobilising savings. For the sample considered, all other covariates enter the basic within-group specification with coefficient insignificantly different from zero.

Successively, moving from left to right in columns (2)-(5), the instability measures are added, one at a time and each one separately, and, all enter the regression with a negative sign. This indicates that excessive fluctuations in stock market capitalization rates, in aggregate output, in lending real interest rates and in the political environment all negatively affect private innovative investment. As argued above, such instability is likely to produce a change in firms' incentives and a revision of expected return rates. These findings are in line with those of Barro (1991), Alesina et al. (1996), Fosu (2003) and confirmed by the previously cited microeconometric body of evidence surrounding the impact of volatility on R&D investment (Rafferty, 2003; Aghion *et al.*, 2008; Rafferty and Funk, 2008; Bohva-Padilla *et al.*, 2009).

In column (6), all volatility measures are included in the benchmark specification at the same time. Two relevant changes take place with respect to the previous set of regressions: the change in significance of government balance now indicates that improved fiscal performance is positively related to private innovation spending. In addition, the impact of financial volatility is no longer significant when the other measures of real, monetary and political instability are included in the regression at the same time. This may indicate that when financial volatility appeared on its own its

[18] Note that the World Bank Atlas Classification System defines as lower middle income countries all countries in which average GNI per capita is comprised between the annual value of $1026-4035.

Table 1. Benchmark Results

	FE							2SLS-FE		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
LogGDPpercapita	-0.262***	-0.261***	-0.231**	-0.175*	-0.321**	-0.246*	-0.224	-0.232**	-0.423***	**-0.226***
	(0.088)	(0.089)	(0.092)	(0.098)	(0.139)	(0.135)	(0.138)	(0.111)	(0.144)	(0.126)
LogGDPpercapita* HighIncome	0.635***	0.623***	0.547***	0.619***	0.671***	0.49***	0.579***	0.56***	0.616***	**0.532***
	(0.165)	(0.166)	(0.142)	(0.193)	(0.19)	(0.162)	(0.206)	(0.098)	(0.119)	(0.113)
InterestRate	-0.003*	-0.003*	-0.003*	-0.004**	-0.004**	-0.005***	-0.002*	-0.001	-0.005***	**-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
StockMarket	0.151***	0.154***	0.152***	0.124***	0.133***	0.144***	0.12**	0.118***	0.113***	**0.088***
	(0.036)	(0.036)	(0.034)	(0.035)	(0.035)	(0.036)	(0.053)	(0.034)	(0.038)	(0.029)
Balance	0.004	0.004	0.005	0.003	0.003	0.006*	0.004	0.005*	0.010***	**0.005***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PropertyRights	0.002	0.002	-0.002	0.009	0.009	0.005	0.017	0.013	0.007	**0.019***
	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.013)	(0.008)	(0.011)	(0.009)
GovernmentR&D	0.215	0.213	0.261	0.204	0.179	0.169	0.103	0.283	0.466*	**0.159**
	(0.189)	(0.190)	(0.181)	(0.222)	(0.21)	(0.188)	(0.124)	(0.175)	(0.246)	(0.180)
TradeOpenness	0.057	0.059	0.086	0.018	0.029	0.092	0.035	0.059	0.143	**0.030**
	(0.069)	(0.069)	(0.069)	(0.065)	(0.066)	(0.067)	(0.077)	(0.096)	(0.166)	(0.098)
StockMarketCoV		-0.080*				-0.040	-0.037	-0.011	-0.011	**-0.026**
		(0.048)				(0.039)	(0.038)	(0.041)	(0.050)	(0.046)
LogGDPpercapCoV			-0.133**			-0.205***	-0.111**	-0.14***	-0.226***	**-0.142***
			(0.054)			(0.053)	(0.05)	(0.037)	(0.055)	(0.040)
InterestRateCoV				-0.005**		-0.009***	-0.009**	-0.008***	-0.010***	**-0.010***
				(0.002)		(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
StateFragility					-0.020*	-0.022*	-0.016	-0.017*	-0.028**	**-0.023***
					(0.011)	(0.012)	(0.012)	(0.009)	(0.011)	(0.009)
Obs.	398	396	393	343	340	338	294	295	305	284
R^2	0.37	0.38	0.39	0.36	0.3	0.3	0.31	0.41	0.4	0.38
N. country	59	59	59	58	57	57	52	46	50	44
Wald F	.	.	.	.	.	.	.	2.8	3	10
Hansen-J	.	.	.	.	.	.	.	.	.	0.13

Heteroskedasticity-robust standard errors reported in brackets. Significance level: p<0.1***p<0.01 **p<0.05 *p<0.1. Columns (1)-(7) report within-estimator results. In (7), all endogenous regressors are lagged. Columns (8)-(10) report the 2SLS-FE results. In (8) and (9), respectively, only the first lag and second lag, in (10), first and second lags are combined. The results in (10) appear in bold to indicate this is the benchmark specification.

positive coefficient might have been capturing the effect of the other three components of aggregate volatility. One possible drawback of the results presented thus far is that they may be biased by reverse causation between the dependent variable and the endogenous covariates.To address the source of this simultaneity bias, the specification in column (6) is improved upon in column (7), where all endogenous variables are replaced by their first lag. While all results are substantially very similar to the ones previously presented, something to note is the fact that the level of GDP per capita turns insignificant, as does State Fragility.

A further concern, as anticipated above, is that related to the potential presence of cross-sectional dependence. To address that, as well as to improve upon the treatment of endogeneity in the model, a within-group 2SLS model is estimated in columns (8)-(10). In column (8), only the first lag is used in the internal instrument set, and in column (9) only the second lag. Both the interest rate and the index of property right protection lose significance in (8), while government balance gains it. All other results carry over from (7). In column (9), again the core results regarding the instability measures only slightly vary in magnitude. The interest rate is once again significant, as is government R&D expenditure albeit only at the 10% level.19 Neither the results of (8) nor those of (9) can, however, be trusted as the Kleibergen-Paap F statistics is considerably below 10, indicating that the identification of these models is weak. A Hansen-J statistics for the overidentification test is not reported for either because the equations are exactly identified.

To improve upon such shortcomings, in column (10) both sets of lags are combined in the instrumentation strategy. Once again, results carry over from previous specifications in that the impact of the level of development is overall positive, but the result is driven, in this sample, by middle to high income countries only. In fact, low income levels appear to be marginally detrimental to private innovative investment. As expected, higher interest rate levels discourage business R&D, while more developed stock markets, and improved

[19] Note that, due to the structure of the dataset, using the second rather than the first lag to instrument the endogenous variable results in a higher number of observations. This is due to the fact that some countries only provide innovation spending data, every two years

fiscal performance. Neither public R&D spending nor trade openness have an impact which is significantly different from zero (see David et al., 2000 and Varsakelis, 2001 for similar evidence). Note that, in this specification, the measure of property rights protection enters the model with a positive sign, indicating that improved rule of law enforcement leads to higher aggregate innovation spending. The result is in line with Yang and Maskus (2001), Varsakelis (2001) and Lin et al. (2010). It should not, however, be seen as a contradiction of the argument that strict IPRs protection might slow the pace of innovation (Helpman, 1993; Higino Schneider, 2005), because the index of property rights protection used here proxies for a broader spectrum of rule of law enforcement dimensions, such as judiciary fairness and effectiveness With regard to the volatility measures, the coefficient of variation of stock market capitalization once again is not significant when other instability measures are included at the same time. Because this variable has never entered the regression with a non-zero impact, except when estimated on its own, it will dropped from all subsequent robustness tests. Real, monetary and political instability confirm their negative relationship with private R&D investment.

These results are qualitatively similar to the ones attained by the previously cited microeconometric literature (Rafferty, 2003; Aghion et al., 2008; Rafferty and Funk, 2008; Bohva-Padilla et al., 2009) with respects to the impacts of real and monetary volatility. In this literature, aggregate demand volatility is proxied by sales, while monetary volatility is proxied by firms' financial constraints. The qualitative impact estimated is, however, broadly comparable. Similarly, with respects to the institutional dimension, my results are in line with Barro (1991), Alesina et al. (1996), Fosu (2003), and Rodrik (1989). In particular, Rodrik shows that investors' expectations are based on the subjective probability attached to policy reversal and on the magnitude of investment irreversibility.[20] It follows that when both are high, aggregate private R&D declines. In order to provide a quantitative interpretation of the coefficient magnitude for the instability indicators, it may be useful to refer to the summary statistics table (below).

[20] Goel and Ram (1999) show that, due of its high irreversibility, the impact of uncertainty is larger on R&D investment. Such high irreversibility is due to the large R&D investment shares going into project-specific personnel and equipment.

The real volatility coefficient reported in column (10) of Table 1, can be interpreted in percentage change terms (see Appendix B for details). It indicates that, in this sample, a 0.1 percentage point increase in the coefficient of variation of (log) GDP per capita, leads to a 0.014% point decrease in private R&D spending. As for monetary volatility: in this sample, half a standard deviation increase in the coefficient of variation of the interest rate results approximately in a 0.05% point decrease in private R&D. Finally, a 2 point increase in the 'State Fragility' Index (which ranges from 0 to 25) leads to a 0.046% point decrease in aggregate Business R&D spending.[21]

Table 2. Summary Statistics

Variable	Mean	St. Dev.	Min	Max
BusinessR&D	0.709	0.714	0.0007	3.402
GovernmentR&D	0.465	0.238	0.02	1.054
LogGDPpercapita	9.016	1.109	5.645	10.55
LogGDPpercapita* HighIncome	9.562	0.662	7.973	10.55
InterestRate	6.082	6.433	0	43.8
StockMarket	0.624	0.58	0.006	3.084
PropertyRights	6.79	1.565	1.599	10
Balance	-1.34	3.101	-12.67	11.37
TradeOpenness	0.97	0.626	0.234	4.381
StateFragility	3.214	4.058	0	16
LogGDPpercapCoV	0.324	0.241	0.009	1.271
InterestRateCoV	0.531	1.148	0.0005	11.74
StockMarketCoV	0.14	0.12	0.0007	0.813
ExchangeRate	189.7	746.3	0.298	9170
ExchangeRateCoV	0.082	0.186	0	1.38
LogGDPpercap_StDev	0.029	0.019	0.0009	0.094
InterestRate_StDev	2.689	4.014	0.374	41.84
PoliticalConstraints	0.447	0.142	0	0.718
Democracy	8.641	3.116	-7	10
HighTechExports	16.61	14.7	0.513	73.59
TaxRevenue	18.07	6.033	0.957	33.19
FinancialDevelopment	0.929	0.381	0.229	2.024
FinancialDevelopmentCoV	0.345	0.386	0	0.266

[21] In calculating such impacts, I standardise by considering a change of half of the observed standard deviation, reported in Table 2 (i.e. 0.1 for the coefficient of variation of (log) GDP per capita, around 0.5 for the standard deviation of the interest rate, 2 for State Fragility).

Considering that the minimum sample value of Business R&D as a share of GDP is equal to 0.0007% and its mean is 0.71% (see Table 2), it can be seen that such impacts are non-trivial. The instrumentation validity for the benchmark specification is confirmed by the F and Hansen-J statistics of (10), which indicate that the regression is correctly identified.

4. Robustness Analysis

In the following section, I investigate the robustness of the findings reported so far, by re-estimating the benchmark regression under various modifications. These include alternative instrumentation sets, the inclusion of time effects, alternative measurements of instability, variations in the regression specification, and the inclusion of non-linear effects. It will be shown, however, that the basic findings are not affected by such robustness tests.

To start with, the benchmark regression specification is repeated in column (1) to make comparison easier. In columns (2) and (3), such benchmark is re-estimated using an alternative technique, namely the System GMM estimator, developed by Arellano and Bover (1995). This technique solves contemporaneously for a number of issues arising in the data, namely, the presence of country fixed effects, endogeneity of the right hand side regressors and reverse causality.[22] Furthermore, because the system combines an equation in first-differences with one in levels, it is possible to retain non-varying time-fixed variables. In fact, after re-estimating the benchmark specification in column (2) with our time-varying measures of volatility, in column (3) the coefficient of variation measures are substituted by non-varying coefficients of variation, which are calculated using the entire time series available for each country. In changing estimation technique in column (2), some of the covariates lose significance, while others turn significant.

[22] By estimating System GMM, I am able to retain a quarter more observation as visible in Table 3 below. This is due, specifically, to the way the dataset is built. In particular, for a few countries, R&D spending data is not available with yearly frequency as it is only collected every two years. As I use up to the third lag to instrument the endogenous variables in the system, fewer observations are lost than when using up to the second lag as in the 2SLS strategy. This allows to bypass the frequency gap in data recording for a few countries and to use more of the information available.

With regard to the variables of interest, financial volatility now gains significance, entering with a negative sign, while monetary volatility turns insignificant. On the other hand, when the time-fixed coefficients of variation are used in column (3), financial volatility turns positive, while political instability loses significance.

Table 3. Changing Coefficient of Variation Measurement of Instability Indicators

	2SLS-FE Benchmark	SYS-GMM Benchmark	SYS-GMM Fixed CoV	2SLS-FE 15year CoV	2SLS-FE 10year CoV
	(1)	(2)	(3)	(4)	(5)
LogGDPpercapita	-0.226*	0.027	0.063***	1.429**	0.007
	(0.126)	(0.024)	(0.019)	(0.562)	(0.145)
LogGDPpercapita* HighIncome	0.532***	-0.003	0.045***	0.337***	0.545***
	(0.113)	(0.02)	(0.01)	(0.088)	(0.095)
InterestRate	-0.004***	-0.003	0.003***	0.0003	-0.001
	(0.001)	(0.003)	(0.0002)	(0.001)	(0.001)
StockMarket	0.088***	0.143***	0.054***	0.047*	0.048*
	(0.029)	(0.051)	(0.014)	(0.028)	(0.029)
Balance	0.005*	-0.002	0.012***	0.003	0.005*
	(0.003)	(0.006)	(0.001)	(0.003)	(0.003)
PropertyRights	0.019**	-0.01	-0.034***	0.013**	0.011
	(0.009)	(0.027)	(0.004)	(0.006)	(0.007)
GovernmentR&D	0.159	0.98***	0.158	0.174	0.193
	(0.180)	(0.03)	(0.124)	(0.159)	(0.17)
TradeOpenness	0.030	0.139*	0.13***	-0.043	0.017
	(0.098)	(0.082)	(0.036)	(0.103)	(0.083)
StockMarketCoV	-0.026	-0.234***	0.531***	0.078*	0.062*
	(0.046)	(0.082)	(0.161)	(0.046)	(0.037)
LogGDPpercapCoV	-0.142***	-0.205***	-0.182***	-0.417***	-0.111***
	(0.040)	(0.069)	(0.051)	(0.133)	(0.037)
InterestRateCoV	-0.010***	0.0001	-0.023*	-0.018*	-0.011*
	(0.003)	(0.007)	(0.014)	(0.009)	(0.006)
StateFragility	-0.023**	-0.03**	-0.004	-0.016*	-0.027***
	(0.009)	(0.015)	(0.003)	(0.009)	(0.009)
Obs.	284	354	372	296	296
R^2	0.38			0.3	0.36
N. country	44	57	53	50	50
Wald F	10			14.4	22.3
Hansen-J	0.13	0.94	0.64	5.53	4.15
AR(2)		0.8	0.38		

Heteroskedasticity-robust standard errors in brackets. Significance levels: ***p<0.01 **p<0.05 *p<0.1. Column (1) corresponds to the benchmark model in column (10) of Table 1. In (2), the benchmark is estimated with System GMM. In (3), System GMM is used again and time-fixed coefficient of variation measures are substituted. In (4) and (5), coefficient of variation measures calculated over a fifteen and ten year rolling window, respectively, are used.

In columns (4) and (5), I substitute the coefficient of variation instability indicators with two new time-varying measures, calculated using fifteen and ten year rolling windows.[23] This allows me to go back to the benchmark 2SLS-FE estimator. While the results for real, monetary and political instability carry over from the benchmark specification, financial volatility once again appears with a positive sign, although only marginally significant at the 10% level. This positive sign could be given a joint interpretation that takes into account the negative sign of monetary volatility in the regression. More specifically, once the instability in signals coming from the monetary side of the economy is taken into account, the remaining instability in financial markets could be proxying for more dynamic financial environments. In other words, what discourages investment in innovation could be the instability in expected rates of return, as proxied by the interest rate. Instead, if the stock market is only one of the sources of funding available to firms, instability in the financial environment could be proxying for turn-over rates and dynamicity in financial markets. The regression could be picking up this effect, which may explain why the coefficient of variation of the stock market capitalisation rate appears with a positive sign. Finally, note that, apart from the increased magnitude of real volatility in column (4), the volatility estimates remain fairly stable when passing from the benchmark to the new specifications.

Moving to Table 4, column (1) repeats the benchmark specification to facilitate comparison. As already mentioned, using internal instruments may not be a viable option if lags of the endogenous variables belong themselves to the model, which could be the case if the dependent variable exhibited temporal persistence. To address this concern, in column (2), external instruments are substituted to the internal ones. Recall that the endogenous variables are (log) GDP per capita and its interaction term, government R&D expenditure, and trade openness. The external instruments are the infant mortality rate, adjusted life expectancy, total tax revenue (% GDP),[24] and a trade openness indicator calculated as the aggregate regional average of the trade openness measure used in the rest of the analysis. The core results are not altered, except for the

[23] Note that, as my time series includes 15 years of data (from 1994 to 2008), there is a drawback of this approach in that it implies that the latest values of volatility are constructed using a longer time window.

[24] Tax Revenue is also included directly in the model in (9), where it enters with an insignificant coefficient.

Table 4. Additional Robustness Checks

	2SLS-FE									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
LogGDPpercapita	**-0.226***	-0.983***	-0.359**	-0.42***	-0.243	-0.407***	-0.24**	-0.247**	-0.354**	0.635***
	(0.126)	(0.332)	(0.179)	(0.148)	(0.290)	(0.127)	(0.111)	(0.119)	(0.152)	(0.245)
LogGDPpercapita* HighIncome	**0.532***	0.822***	0.61***	0.659***	0.54***	0.678***	0.428***	0.529***	0.604***	
	(0.113)	(0.238)	(0.134)	(0.133)	(0.152)	(0.108)	(0.108)	(0.112)	(0.172)	
InterestRate	**-0.004***	-0.002*	-0.004***	-0.004**	-0.003**	-0.002**	-0.004***	-0.004***	-0.003*	0.011
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.009)
StockMarket	**0.088***	0.101**	0.09***	0.098***	0.092**	0.1***	0.091***	0.089***	0.075**	
	(0.029)	(0.043)	(0.033)	(0.031)	(0.037)	(0.03)	(0.031)	(0.031)	(0.032)	
Balance	**0.005***	0.011**	0.009***	0.006*	0.004	0.003	0.004	0.004	0.004	-0.01
	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.006)
PropertyRights	**0.019***	0.011	0.019**	0.023**	0.02**	0.012*	0.019*	0.018**	0.021*	-0.028*
	(0.009)	(0.013)	(0.009)	(0.010)	(0.01)	(0.007)	(0.01)	(0.009)	(0.012)	(0.016)
GovernmentR&D	**0.159**	0.271	0.121	0.143	0.162	0.218	-0.08	0.099	0.223	0.205
	(0.180)	(0.793)	(0.155)	(0.178)	(0.178)	(0.160)	(0.141)	(0.167)	(0.204)	(0.216)
TradeOpenness	**0.030**	0.928**	0.002	0.048	0.033	0.031	0.053	0.059	0.204	0.543*
	(0.098)	(0.4)	(0.098)	(0.096)	(0.098)	(0.104)	(0.087)	(0.096)	(0.129)	(0.286)
StockMarketCoV	**-0.026**	-0.017	-0.057							
	(0.046)	(0.065)	(0.049)							
LogGDPpercapCoV	**-0.142***	-0.289***	-0.125***	-0.28***	-0.121***		-0.126***	-0.139***	-0.157***	0.091
	(0.040)	(0.08)	(0.04)	(0.108)	(0.043)		(0.036)	(0.044)	(0.046)	0.11
InterestRateCoV	**-0.01***	-0.015***	-0.009***	-0.118**	-0.01**		-0.011***	-0.009***	-0.011***	-0.143
	(0.003)	(0.004)	(0.003)	(0.052)	(0.005)		(0.002)	(0.003)	(0.003)	(0.103)
StateFragility	**-0.023***	-0.048**	-0.026**	-0.032***	-0.025**	-0.02**	-0.056***	-0.025***	-0.023**	
	(0.009)	(0.016)	(0.01)	(0.011)	(0.012)	(0.008)	(0.014)	(0.009)	(0.011)	
LogGDPpercapitaCoV_sq				0.173*						
				(0.100)						
InterestRateCoV_sq				0.077*						
				(0.042)						
LogGDPpercapitaCoV_nonlin					-0.157					
					(0.313)					
InterestRateCoV_nonlin					0.001**					
					(0.00)					
StateFragility_nonlin					-0.00					
					(0.001)					

LogGDPpercap_StDev						-1.057**				
						(0.429)				
InterestRate_StDev						-0.003**				
						(0.001)				
PoliticalConstraints							-0.434***			1.75
							(0.121)			(1.09)
StateFragility *PoliticalConstraints							0.061***			
							(0.019)			
ExchangeRate								-0.00		
								(0.00)		
ExchangeRateEMU								-0.039		
								(0.025)		
ExchangeRateCoV								-0.029		
								(0.085)		
ExchangeRateCovEMU								0.042		
								(0.092)		
Democracy									-0.003	
									(0.013)	
HighTechExports									-0.002	
									(0.004)	
TaxRevenue									0.009	
									(0.006)	
FinancialDevelopment										0.145*
										(0.083)
FinancialDevelopmentCoV										0.132
										(0.348)
Obs.	284	341	284	259	278	252	275	284	268	248
R^2	0.38	0.15	0.42	0.39	0.36	0.35	0.35	0.37	0.4	0.22
N. country	44	47	44	44	44	44	44	44	44	16
Wald-F	10	1.4	11	10.5	8.6	8.6	10	8.3	4	59.3
Hansen-J	0.13	0.08	0.49	0.35	0.42	0.16	0.24	0.17	0.09	0.12

Heteroskedasticity-robust standard errors in brackets. Significance levels: ***$p<0.01$ **$p<0.05$ *$p<0.1$. Column (1) corresponds to the benchmark model in column (10) of Table 2. In (2), external instruments are used. In (3), time dummies are added. In (4) and (5), non-linearities are modelled. In (6), new political instability measures are included. In (7), the coefficient of variation is substituted by the standard deviation. In (8), the exchange rate and its volatility are added. In (9), three additional regressors are included. In column (10), the benchmark specification in (1) is estimated in an OECD country panel.

fact that rule of law loses significance, while trade openness gains with a positive and significant coefficient. A summary of the first stage regression statistics is presented in Table B1 of Appendix B below. While all F-tests, but the government R&D regression one, point towards the significance of the excluded instruments; the Angrist-Pischke multivariate F-test indicates there may be a problem of weak identification in both the trade openness and government R&D reduced form regressions. As it is well known, weak identification decreases considerably the explanatory power of 2SLS. Therefore, because the Hansen-J statistics in column (1) indicates that the exclusion restrictions are valid when internal instruments are used, the specification where internal rather than external instruments are used remains our preferred specification.

Next, in column (3), time dummies are added to control for any time effects which may be common across countries. All results carry over with no significant variation. Because no time dummy is significant, they are all dropped from any subsequent estimation.[25] I turn, now, to the analysis of potential non-linearities. The impact of volatility on investment has been suggested to exhibit threshold effects. Sarkar (2000), in particular, argued that a positive relationship occurs at low uncertainty levels, and that this switches to a negative relationship only when uncertainty rises beyond a criticalthreshold. To test this hypothesis, non-linearity effects have been modeled into the benchmark specification with the inclusion of quadratic terms in column (4), and, in column (5), with the inclusion of interaction terms.[26]

In column (4), quadratic terms for both real and monetary volatility are included, which indicate that as either volatility dimension increases, aggregate private R&D spending decreases at a decreasing rate.[27] Thus, unlike Sarkar, I find that the impact of volatility on business R&D is negative, albeit decreasingly so for higher values of volatility. The rest of the results in this regression carry over from previous specifications. In (5), another type of non-linearity is examined. Specifically, I test whether the impact of instability varies according to the phase of the business cycle.

[25] The time dummies coefficients are not reported in the table for reasons of space.

[26] Note that the volatility of stock market capitalisation has been dropped in column (4) to (10), due to its insignificance throughout the estimation set of Table 2 and in (2) and (3) of Table 3.

[27] Note that a quadratic term of the StateFragility index is not included due to the ordinal nature of this variable

To do this, I create a measure of GDP deviation from its mean,[28] and interact it with each volatility indicator. The interaction terms will indicate whether any difference exists between the impact of volatility during a recession and its impact during an expansion.

My results indicate that a discernible differential in impact only exists for the monetary volatility component. Specifically, as the phase of the cycle improves, volatility in the interest rate becomes less of a hindrance to private R&D spending. This result is line with the claim made by the body of microeconometric literature reported above that uncertainty has less of a negative effect when credit constraint are not as binding (Aghion and Saint Paul, 1998; Rafferty and Funk, 2008; Aghion et al., 2008; Bohva-Padilla et al., 2009). If such 'credit constraint' effect is the prevailing dynamic underlying different investment responses along the business cycle, then this may account for the failure to identify a similar impact in the case of real and political instability. Moreover, uncertainty in GDP per capita and state effectiveness levels is less observable than fluctuations in the official lending interest rate. For this reason, the aggregate spending adjustment to real or political instability may be not as correlated or synchronised to the phase of the cycle as it is the case of interest rate variations. No other change takes place with regards to all other results.

Next, in column (6) and (7), I test the robustness of the volatility impacts uncovered so far to variations in the way instability is measured, or variations in the channel through which the impact takes place. In particular, in column (6), I use the standard deviation of both (log) GDP per capita and interest rate instead of their coefficient of variation. A great part of the literature agrees on the coefficient of variation being a more robust indicator of volatility than the standard deviation. Mobarak (2005) and Klomp and de Haan (2009) argue that the latter is an absolute measure of variation and it is very sensitive to noise in the data. The normalisation involved in the coefficient of variation, instead, makes it a relative measure of variation. In this respect, Klomp and de Haan (2009) show that the coefficient of variation allows to appropriately control for co-movements of similar countries, due, for example, to the effect of common business cycle patterns. Nonetheless, some shortcomings still persist

[28] The mean of (log) GDP per capita is calculated across the entire 1994-2008 time window. For each country, this is then subtracted from each year's realised (log) GDP per capita value.

in this measure. For example, for mean values close to zero, the coefficient of variation will approach infinity and be sensitive to small changes in the mean.

Therefore, the robustness of the findings based on the coefficient of variation measures will be tested against those obtained using the standard deviation. All basic results remain identical in (6). Real and monetary instability have the same qualitative impact, but the coefficient magnitudes need re-interpreting. In this sample, the coefficient of real volatility indicates that a 0.01 of standard deviation increase in (log) GDP per capita leads to a 0.05% point decrease in Business R&D. While two standard deviations increase in the real interest rate generates a 0.006% point decrease.[29]

In column (7), I verify the robustness of the institutional instability indicator by adding a measure of political constraints and an interaction between state fragility and political constraints. This is done in order to test under what specific conditions institutional instability produces negative changes in the level of aggregate private innovation spending. In particular, Henisz (2002) has constructed and used the 'Political Constraint' variable to show that constraints on the ease of policy shifts in any given country are conducive to infrastructural investment, and specifically to innovative investment. The index scores are derived from a simple spatial model and theoretically range from 0 to 1, with higher scores indicating more political constraint and thus less feasibility of policy change. The idea is that, when any political actor can easily influence policy change, the resulting institutional framework will be more unstable. The political constraint measure is included in the model together with StateFragility and an interaction between the two.

The impact of state fragility remains negative; however its magnitude has now increased. Unlike Henisz (2002), higher political constraints appear to hinder private R&D spending in this sample. This seemingly contradictory result can however be reconciled if one considers that a slow pace of policy change is negatively correlated to innovation when the former proxies for a conservative societal structure, or a malfunctioning National System of Innovation (see Lundvall, 1992, for more details

[29] In calculating such impacts, I standardise by considering a change of half of the observed standard deviation (i.e. 0.1 for the standard deviation of (log) GDP per capita, and 2 for the standard deviation of the interest rate, see Table 1).

on this point in the context of the National Innovation System literature). On the other hand, however, the interaction term between institutional instability and the political constraints index has a positive sign. This indicates that, given a negative impact of state fragility on business innovation, increased political constraints mitigate such negative impact, by limiting the extent to which instability can produce abrupt policy shift.

Column (8) and (9) carry out some further robustness checks, via the inclusion of additional right hand side variables. As pointed out by Serven (2003), fluctuations in the nominal exchange rate can affect the export/import incentives of firms. In column (8), this international dimension is brought into the picture by adding the exchange rate level among the explanatory variables. At the same time, the coefficient of variation of the official exchange rate is also included to control for the effect of recurrent fluctuations in its level. Two additional terms are also constructed, by interacting a dummy variable (EMU), with both the exchange rate level and its volatility. EMU takes the value of 1 for those countries which joined the European Monetary Union (EMU), and only in the year they switched currency regime.

When the exchange rate is interacted with EMU, the interaction term controls for the structural break taking place when the euro currency regime is adopted, by correcting for the switch in measurement units.[30] Instead, the interaction term between the volatility of the exchange rate and EMU is used to capture the increased exchange rate stability which followed the adoption of the common currency by the Euro Zone economies. While all previous results remain identical, none of the four variables introduced to model the international dimension enters the regression significant. While this result contradicts Serven (2003), it is not an uncommon finding in the literature. In fact, the evidence on the relationship between exchange rate regimes and firms' exports is rather inconclusive (see Wang and Barrett, 2007, for a review).

Moving now to column (9) of Table 4, I present the set of results deriving from the inclusion of a number of additional regressors. Democracy takes values from 10 (very democratic countries) to 0 (autocratic regimes). *HighTechExports* refers to the amount

---

[30] Most EMU countries in my sample joined the currency union in 1999; the rest between 2001 and 2007. When the switch takes place, LCU denominated exchange rates turn to euro denominations. The EMU dummy takes into account the break to avoid biasing the estimation.

of high-tech exports to GDP and it has been instrumented with its first and second lag to account for its likely endogeneity. *TaxRevenue* refers to the level of overall fiscal imposition to GDP. None of these variables enters the regression significantly, but once again, neither the significance nor the qualitative impact of all other variables has been altered by the inclusion of these new covariates. Note, however, that both the F-stat and the Hansen-J statistic deteriorate sharply in this specification. Such change is attributable to the inclusion of *HighTechExports* among the endogenous variables and of its lags in the instrumentation set, which has weakened the identification strategy.

In the last robustness test of column (10), I restrict the estimation sample to OECD countries only. This is done, first of all, because instability levels can be expected to be lower in these countries during the time span considered. At the same, a larger proportion of firms in high-income countries is likely to exhibit lower financial constraints and to have access to better developed financial markets. The combination of all such factors may result in an improved ability of the private sector to cope with volatility.[31] Thanks to the wider data coverage, the reduced panel is formed by fewer countries (17) but it covers a longer time period of 28 years, from 1981 to 2008, with a total sample size of 246 observations.

The results shown in column (10) lend some support to the hypothesis mentioned above. In fact, in this sample, the evidence on the impact of real, monetary, political and financial instability is inconclusive.[32] On the other hand, both the level of aggregate GDP per capita and the level of financial development are positive predictors of private R&D spending.[33] In addition, trade openness also appears to have a positive impact on Business R&D in this sample, (significant at the 10% level). This result is in line with the theoretical (Porter, 1990; Lundvall, 1992; Nelson, 1993) and empirical findings (Smolny, 2003; Sameti et al., 2010; Wang, 2010) of a number of studies, which show how international openness is likely to result in a positive impact on technological progress, due to increased external exposure and interaction.

---

[31] Or even in its capacity to benefit from such fluctuations. As put forward by Schumpeter-inspired creative destruction theories (Hall, 1991; Saint-Paul, 1993).

[32] Note that the 'StateFragility' measure could not be used in this sample due to its time coverage (earliest data period is 1994). Therefore Henisz's Political Constraint Index is used instead.

[33] Note that, in this sample, due to the data availability restrictions for the 1980s, stock market capitalisation has been substituted by a measure of private credit by commercial banks as a proxy for financial development.

Finally, an interesting finding of this specification is the negative relationship linking Business R&D to the index of property rights protection. However, this result should not be seen as surprising, given that the protection standards of both physical and intellectual property rights enforced in this sample of OECD economies is already very high. The result may rather indicate that there exists a certain threshold past which stricter enforcement levels can prove detrimental to innovation incentives and diffusion. Such argument is supported by various theoretical and empirical studies (Furukawa, 2007; Murray and Stern, 2007; Bessen and Maskin, 2009; Gangopadhyaya and Mondal, 2012), which show that the relationship between property rights protection and innovation exhibits an inverted-U pattern, in which too weak or too high enforcement levels are detrimental to the pace of innovation.

5. Conclusions

This paper has studied the impact of macro-institutional instability on private innovative investment. The underlying motivation for investigating such relationship lies in the consideration that innovation is crucial to growth and development. Yet, its long maturity horizon coupled with its high-budget nature make it an intrinsically riskier type of investment. The empirical analysis has therefore sought to clarify the relationship between various dimensions of volatility and aggregate private R&D spending in unstable macro-institutional environments.

On the one hand, an important limitation of this study lies in its overlooking of those forms of incremental, small-scale, grassroots or non-industrial innovation, for which aggregate secondary data does not exist. On the other, the contribution of the paper has been threefold. Firstly, the literature on the impact of instability on private R&D spending focuses mainly on first moment effects, by relating recessions to innovation incentives. Such focus has been here expanded to cover second moment fluctuations, that is, it has been extended to the role of overall volatility. Secondly, a macroeconometric approach has been adopted to complement the firm-based evidence already available in the literature. While such approach has its limitation, it has helped uncover the aggregate dynamics underlying movements in national levels of private R&D investment in unstable environments.

Finally, the analysis has disentangled the specific impact of a number of co-existing instability dimensions. In particular, the econometric findings suggested three channels through which macro-institutional volatility negatively affects business R&D investment, that is, political, real and monetary volatility. Such impact has been shown to exhibit non-linearities and to be larger for higher values of the real and monetary volatility dimensions. In addition, the negative effect of monetary instability appears to be mitigated during expansionary phases, in the sample considered. Lastly, the evidence on financial and international volatility is inconclusive.

The indirect policy implication deriving from the results here presented points towards the desirability of safeguarding stable macroeconomic and institutional environments if encouraging private innovation engagement is a priority. Considerations regarding the most appropriate policy tools are beyond the scope of this paper. However, an interesting avenue for further research seems to be the investigation of the role that targeted counter-cyclical policy interventions and firm subsidisation may play in preserving private profitability horizons and incentives.

Appendix A: Data and Country Appendix

Table A1. Data Sources

BusinessR&D	R&D spending by the private sector (%GDP)	OECD-MSTI Database UNESCO - Stats.uis RICYT.org
GovernmentR&D	R&D spending by the public sector (%GDP)	OECD-MSTI Database UNESCO - Stats.uis RICYT.org
LogGDPpercapita	Log(Total Output / Population)	World Bank-WDI
InterestRate	Real interest rate based on lending rate charged to businesses by commercial banks (3 months-1 year)	Own calculation. Raw data from World Bank-WDI
Balance	Overall Deficit/Surlpus (%GDP)	IMF -Government Finance Statistics
PropertyRights	0-10 Index where 10 indicates the highest level of rule of law enforcement	Economic Freedom of the World – Area 2: Legal System and Property Rights
TradeOpenness	(Exports + Imports) / GDP	World Bank-WDI
StockMarket	Value of listed shares to GDP, calculated using the deflation:$\{(0.5)*[F_t/P_{et}+F_{t-1}/P_{et-1}]\}/(GDP_t/P_{at})$, where F is stock market capitalization, P_e is end-of period CPI, and P_a is average annual CPI	Database on Financial Development and Structure (Beck et al. 2000)
StateFragility	The Index scores countries on effectiveness and legitimacy in four dimensions: security, political, economic, and social. Scores are 0-25 where 0 indicates very stable countries	POLITY IV Dataset
PoliticalConstraints	The index measures the feasibility of policy change It ranges from 0-1, with higher scores indicating more political constraint	Henisz' Political Constraints Index III Dataset
ExchangeRate	Nominal Exchange Rate (LCU per US$)	World Bank-WDI IMF–International Financial Statistics
Democracy	The index ranges from -10 to 10, where -10 is the score given to authoritarian regimes	POLITY IV Dataset
HighTechExports	High-Tech Exports/ Tot Manufacturing Exp	World Bank-WDI
TaxRevenue	Tot Tax Revenue / GDP	IMF- Governance Finance Statistics

FinancialDeveleopment	Private credit by deposit money banks and other financial institutions to GDP, calculated using the deflation:$\{(0.5)*[F_t/P_{et}+F_{t-1}/P_{et-1}]\}/(GDP_t/P_{at})$ where F is stock market capitalization, P_e is end-of period CPI, and P_a is average annual CPI	Database on Financial Development and Structure (Beck et al. 2009)
InfantMortality	Infant Mortality Rate per 1000 live births	World Bank - WDI
LifeExpectancy	Adjusted Life Expectancy at birth	World Bank - WDI

Table A2. Country List

Argentina	Cyprus*	Ireland*†	Mongolia	Slovak Rep*
Australia†	Czech Rep*	Israel*†	Netherlands*†	Slovenia*
Austria*†	Denmark*†	Italy*†	Norway†	South Africa
Belgium*†	Estonia*	Japan†	Panama	Spain**
Bolivia	Finland *†	Korea Rep*†	Paraguay	Thailand
Brazil	France**	Kuwait	Philippines	Uganda
Bulgaria	Germany*†	Latvia*	Poland*	Ukraine
Canada*†	Hungary*	Lithuania	Portugal*†	United Kingdom*†
Chile	Iceland*†	Malaysia	Romania	United States*†
China	India	Malta*	Russia	Uruguay
Colombia	Iran	Mexico	Singapore*	Venezuela

*High-Income countries (ATLAS classification) *†OECD countries included in the robustness analysis panel †OECD countries appearing in the robustness analysis panel only.

Appendix B: Technical Appendix

B1. First Stage results

Table b1. Summary of Results for 1st Stage Regressions

	F-test of excluded Ivs	Angrist-Pischke Weak Identification test	Underidentification test
LogGDPpercapita	63.53***	24.15	59.68***
LogGDPpercapita* HighIncome	49.17***	31.13	76.92***
GovernmentR&D	4.65***	4.12	10.19***
TradeOpenness	14.45***	5.47	13.52***
Obs.	341	341	341
Stock-Yogo weak identification crit. value (5%)		18.37	

Notes: first-stage test statistics are heteroskedasticity-robust

B2. Notes on the Construction of the Volatility Measures

The Coefficient of Variation is a normalized measure of dispersion of a variable's distribution over a certain time period. It is calculated as the ratio of the standard deviation to the mean of a series.

(1) $$v = \left({}^{\sigma}/_{\mu} \right)$$

where the standard deviation is calculated as follows

(2) $$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2}$$

In this paper, a two year rolling window is utilised to calculate both the mean and the standard deviation of (log) GDP per capita, real interest rate and stock market capitalisation. Thus real, monetary and financial volatility, in this context, is defined as the ratio of the standard deviation to the mean of the rolling window. A backward looking strategy has been used in constructing such window, to reflect the type of knowledge agents might have of volatility at time *t*. The latter is typically attained by comparing the volatility levels prevailed at time *t-1* with those of time *t*. For example, to obtain the real volatility of the year 2001, the standard deviation and mean of (log) GDP per capita are first calculated over the 2000-2001 period and then their ratio is multiplied by 100. Likewise, to obtain the coefficient of variation of GDP per capita in 2002, values from the years 2001 and 2002 are used to calculate both standard deviation and mean. Please note that, because of the log transformation with which GDP per capita appears in the regressions, the coefficient magnitude of real volatility is not comparable to that of the other volatility measures. To restore visual comparability, the coefficient of variation of GDP per capita has been multiplied by 100. Its quantitative interpretation will however also be in percentage change terms.

B3. Notes on the Constructions of the R&D Dataset

See Appendix B of Chapter 1

Chapter 3: Macroeconomic Volatility, Institutional Instability, and the Skill Premium

1. Introduction

An extensive literature exists surrounding the role of innovation for growth, and the interaction between skilled labour and productive capital (Romer, 1990; Grossman and Helpman 1991a; Aghion and Howitt, 1992; Grossmann, 2007). In this literature, skilled labour is shown to be key to the growth process, as its existence complements and augments the productivity of innovative capital. For a skilled workforce to exist, however, some level of skill premium - defined as the difference between skilled and unskilled wages - must be in place. This acts as an incentive inducing individuals to acquire the necessary level of skills (Kimura and Yasui, 2007; Agénor and Canuto, 2012). Failure to allow the skill premium to take shape will likely lead to lower levels of human capital accumulation and brain drain, which, ultimately, slow down the pace of both innovation and development (Docquier et al., 2010; and Di Maria and Lazarova, 2012). The scope of this paper is to analyse the impact of macroeconomic and political instability on the unskilled to skilled wage differential; in light of the importance that a stable macro-political environment has for the skill premium formation.

In practice, instability can affect both of the main determinants of skilled wages: the demand for skilled labour and its productivity. With regards to the first, the literature has extensively shown that macro-institutional instability lowers the incentives to innovate faced by entrepreneurs (Isham and Kaufmann, 1999; Rafferty, 2003; Rafferty and Funk, 2008; Aghion *et al.*, 2008; Bohva-Padilla *et al.*, 2009, Aghion et al., 2010). It follows that an innovative investment reduction translates into lower skilled labour's employment and retribution (Spagat, 1995; Goolsbee, 1998; Rodrik, 1999).

On the other hand, the productivity of skilled labour can be lowered by instability either directly or indirectly. For example, social unrest can directly affect and disrupt the continuity of education attendance as well as education quality (see Rubio, 1998 and Hofstetter, 1998). A fragmented or stagnating political environment can instead hinder the pace of reforms, slow down change and innovation and as a result fail to recognise and upgrade the status of researchers and scientists. In addition, the productivity of skilled labour can decrease, indirectly, as a consequence of reduced productivity of the tangible and intangible capital skilled labour works with (Olson et al., 2000; Fosu, 2002).[34] Instability in the productive environment is likely to result in working capital loss or investment discontinuation.

To see why this is the case, consider that innovative investment entails higher than average set-up costs and longer maturity horizons. These two characteristics make it inherently risky and create a range of inaction in the presence of uncertainty (Bernanke, 1980). Moreover, uncertainty often leads governments to pursue sub-optimal short-term policies, which translate into high probability of policy reversal (Rodrik, 1989; Fanelli and Frenkel, 1995; Guillaumont et al., 1999). In other words, volatile and mixed signals sent by institutions with regards to property right enforcement, fiscal and monetary policy objectives, incentive and tax regimes, can lead to misallocation of private investment efforts (Aryeetey, 1994; Alesina et al., 1996; Isham and Kaufmann, 1999; Fosu, 2003). If all these elements shift the investment composition towards less risky, short-term projects, lower levels of innovation will result in decreased overall productivity of tangible and intangible capital. And, as a result of the complementarity existing between skilled labour and productive capital (Griliches, 1969; Mincer, 1985; Krusell et al., 2000; Lindquist, 2004), skilled labour's productivity will also decrease, together with its marginal wage. In this respect, Mincer (1985) argues that, as the ratio of 'new' capital per worker increases so does the skill premium, as a reflection of capital-skill complementarity.

The literature on the skill premium, as proxied by the differential between skilled and unskilled wages, has focused in the past mainly on factors and variables altering the distributional structure of wages. Such factors include trade composition effects (Parteka, 2010), the strength of the labour unions (Kraft, 1994; Ziliak et al., 1999), the cyclicality of output (Nissim, 1984; Keane and Prasad, 1993; Kraft, 1994), and the skill-capital complementarity (Krusell et al., 2000; Lindquist, 2004). While, most of these factors are included in our empirical model as determinants of the wage ratio, a rather limited number of studies exists which examines the impact of instability on the skill premium.

[34] Tangible capital refers to physical capital, e.g. machinery. Intangible capital defines non-physical capital, e.g. software

Importantly, all these studies only consider such effect in an indirect way. For example, in Mincer (1985), the focus is not on instability per se, but rather on the interdependency between economic growth and human capital. Mincer argues that it is innovative investment that drives the wage differential in favour of skilled wages, so that only innovative societies can maintain high skill premia. On the other hand, while more openly referring to the negative relationship between macro-political instability and the wage differential, Spagat (1995) retains a purely theoretical focus in his analysis. Finally, Isham and Kaufman (1999) use a micro-dataset to explore the relationship between the quality of the macro-institutional environment and input factor productivity. They argue that political volatility and lack of timely policy adjustment considerably lower input factor productivity.

The present study can be viewed as an attempt to fill a gap in the existing empirical literature on the link between macro-political instability and the skill premium. Our findings offer support to the view that unstable environments result in relatively lower skilled wages, that is, in a lower skill premium. Because a low skill premium can ultimately represent a disincentive to human capital accumulation and encourage brain drain, this study highlights the importance of a stable macro-political environment for the promotion of knowledge-based development.

The rest of the paper is structured as follows: the model and data are presented in the next section. The results followed by the robustness analysis appear in Sections 3 and 4. Section 5 summarises the main findings, outlines some policy implications and draws some conclusions. Finally, all data sources and the list of country appearing in our sample, as well as some technical notes, are contained in Appendix A and B.

2. Model and Data

The panel of data we use for this analysis includes 449 observations in total, when the benchmark specification outlined in equation (1) is estimated. The sample contains 69 countries, representing all levels of economic development, and covers 20 years from 1983 to 2002.[35] The regression specification is as follows:

[35] A list of the countries and all data sources appears in Appendix A.

$$(1) \qquad y_{it} = a_i + \sum_{j=1}^{m} \beta_j X_{j,i} + \sum_{l=1}^{n} \theta_l \text{Instability}_{l,it} + \varepsilon_{it}$$

The dependent variable, y, represents the skill premium, measured as the ratio of unskilled wage rates to skilled wage rates. The source of the raw occupational wage data measured in $US is the 2004 ILO October Inquiry database, which Freeman and Oostendorp (OWW, 2004) have normalised using country-specific calibration. The normalised data refers to average monthly wage rates and is recorded for a number of occupations. We use the normalised data as a base to create the mean ratio of unskilled to skilled wages. For each year, occupation data is averaged at the country level to calculate mean wage rates. The detailed procedure implemented to transform the original OWW micro-dataset into a macro-dataset of aggregate mean ratios is described in detail in Appendix B. The summary statistics (Table 1) indicate that the mean wage ratio in the sample considered is 0.568. In other words, on average, unskilled wages are slightly more than half the size of skilled wages.

The vector of controls $\{X_{j,it}\}_{j=1}^{m}$ broadly reflects the choice of wage-ratio determinants found in the literature. It includes GDP per capita in log-form to control for the level of development, and an interaction between GDP and an HI dummy. This dummy takes the value of one for countries defined as high income economies by the World Bank's Atlas classification system, and the interaction is used to verify whether in developed countries the skill premium is more prominent. An indicator of brain drain of the skilled population aged 25 and above is included to verify whether the emigration of skilled workforce leads to a scarcity premium for the skilled people who are left in the home country. The brain drain measure is defined as the share of 25 and over tertiary educated population leaving the country to six pre-defined developed country destinations. The average years of tertiary education are included to account for the higher salary level usually associated with additional years of education. An index of worker rights protection proxies for the strength of trade and labour unions. Finally, we use the share of high-tech exports to assess the wage distribution effects of trade composition: higher technological content of exports should indicate greater need for skilled workforce and possibly higher skill premia (Parteka, 2011).

With regards to the variables of interest in this study, the $\{Instability_{l,it}\}_{l=1}^{n}$vector in equation (1) has two dimensions: output and institutional/political instability. Output instability is measured as the coefficient of variation of (log)GDP per capita. The politico-institutional instability is proxied by a measure of internal armed conflict and by parliamentary fractionalisation. Conflict is used to represent contexts where socio-political unrest takes the form of openly conflicting factions. Parliamentary fractionalisation, instead, considers the ease by which the political system is operating. This is measured by the probability that two deputies within the parliament belong to different party-groups. Because none of the developed countries in our sample experienced internal armed conflict during the time span considered, the political fragmentation variable seems more appropriate in their case. As illustrated in the summary statistics table (Table 1), conflict is measured on a 0-3 scale, with 3 indicating situations of open armed civil war. Political Fragmentation takes up probability values between 0 and a maximum of 0.92.

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
(Mean)WageRatio	0.568	0.206	0.164	1.74
(Median)WageRatio	0.584	0.219	0.112	1.56
GDPpercapita	11274	11056	142.4	38390
BrainDrain	0.114	0.149	0.001	0.888
AvrageTertiaryEduc	0.493	.364	0.005	1.68
WorkerRights	1.38	0.654	0	2
HighTechExports	0.074	0.093	0	0.635
PoliticalFractional	0.611	0.213	0	0.921
Democracy	3.85	1.84	1	18
Conflict	0.298	0.831	0	3
GdppercapitaCoV	0.023	0.016	0	0.088
GovernmFractional	0.266	0.271	0	0.892
BattleRelatedDeaths	0.349	1.43	0	16
GDPpercapitaStDev	213.9	244.1	0.01	1349
EthnoReligiousFractional	0.298	0.235	0.002	0.93
CulturalFractional	0.238	0.19	0	0.733
CompletedTertiaryEduc	6.2	8.56	0.699	77.5

Note, however, that the results generated by this variable should be interpreted with caution, since, in principle, zero values of political fragmentation can be the result of dictatorship. This would be the case if, for example, the probability of finding two deputies of different parties was zero because parties are not allowed to exist. To correct for this, we take explicitly into account the type of institutional background with the inclusion of an additional variable, Democracy, which measures on a 1-18 scale the degree of checks and balances enforcement. In this way, once the political regime effect is dealt with, the residual impact can be attributed to political fragmentation.

The model is estimated using GMM dynamic panel data techniques. In particular, the System-GMM estimator developed by Arellano and Bover (1995) is adopted. This technique solves contemporaneously for a number of issues arising in the data, namely, the presence of county fixed effects, endogeneity of the right hand side regressors and reverse causality. The System-GMM approach is preferred to the Difference-GMM (Arellano and Bond, 1991), because the latter solves the endogeneity problem by instrumenting the differenced endogenous variables with their available lags in levels. However, lagged levels are weak instruments for first-differences if the series are very persistent (Blundell and Bond, 1998), which is most likely the case for institutional variables, such as the ones employed in this analysis (Klomp and de Haan, 2009).

Under an additional set of assumptions, the System-GMM estimator can overcome these problems and increase efficiency. To be more specific, if the assumption that the regressors' first-differences are not correlated with the country effects holds, lagged values of the first-differences can be used as instruments in the equation in levels. The estimation will then combine the set of moment conditions available for the first-differenced equation with the additional moment conditions available for the level equation. To avoid dynamic panel bias, we instrument for all variables which are not strictly exogenous. These include all the right hand side variables in (1), as well as in the other robustness regression specifications. In this respect, Hayakawa (2007) shows that the System-GMM estimator is less biased than the Difference-GMM, even though the latter uses more instruments.

In fact, the validity of the described instrumentation strategy relies on a number of assumptions. Broadly speaking, more instruments convey additional useful information. However, too many instruments can result in over-fitting of the instrumented variables, thereby biasing the results towards those obtained by OLS (Roodman, 2009). To avoid this, each regression is estimated with the instrument lag interval that maximises the trade-off between the total number of instruments used and the resulting degree of overidentification. In addition, in a number of sensitivity tests, the benchmark instrument set is replaced by different lag interval sets. Furthermore, two specification tests are used to confirm the validity of the instrumentation strategy: the Hansen (1982) J-test of overidentifying restrictions, which assesses the exogeneity of the excluded instruments; and the Arellano Bond (1991) test, which is informative of the presence of serial correlation in the error term.

3. Results

Before describing the results, note that at the bottom of each table the second-order error serial correlation test is reported. In each instance, the presence of serially correlated errors is rejected at any meaningful level of significance. In addition, the lag interval used for each regression is always specified along with the Hansen J-statistic for the overidentification test of the instruments. In all cases, the null hypothesis that the chosen set of instruments is uncorrelated with the error term cannot be rejected. Finally, note that dynamic panel data methods have been originally designed to estimate micro-panels where typically the number of observations are larger than that macro-panels work with. The panel considered in this analysis is relatively large in macroeconomic terms, nonetheless, the 'small panel' correction has been applied.

Turning now to the results, Table 2 presents, first, a regression specification where only the control variables identified in vector $\{X_{j,it}\}_{j=1}^{m}$ are included. Subsequently, the macro-political instability indicators are added one at a time in columns (2)-(4), and, finally, all at the same time in column (5), which presents the benchmark specification in its most inclusive form. Starting with column (1), the reduced form specification is estimated to check the validity of the chosen wage ratio determinants before the instability components are added. In this specification, as development increases, so do wages of unskilled workers, which can be viewed to represent the increased scope for redistribution that richer societies commit to. At the same time, however, the negative coefficient exhibited by the interaction term between GDP and HI suggests that, in richer societies, such effect is mitigated insofar as higher skill premiums are offered. In other words, while low-skill wages increase with overall development in general, in higher income societies such positive impact is quantitatively smaller due to the existence of higher skill premia.

Brain drain has a negative effect on the wage ratio, indicating that the retribution of skilled individuals who are left in their country of origin is higher. In particular, a 1% point increase in the proportion of skilled individuals leaving the country leads to an increase of about 1% point in the skill premium. This may be capturing a scarcity premium effect. That is, the fewer the skilled individuals available in a given country, the higher the demand per individual and, as a result, the retribution. Alternatively, it may be capturing some positive externality produced by the brain drain. For example, brain drain can encourage outflows of FDI and transfer of knowledge by enhancing network effects; or it can foster human capital accumulation in the country of origin, via an 'emulation' effect (Docquier et al., 2010; Beine et al., 2011). Our robustness analysis will, however, reveal that when the scarcity premium effect is explicitly controlled for, the impact of brain drain on the skill premium turns negative. This is in line with part of the literature and the claim that skilled emigration leads to countries' inability to keep pace with technological progress (Docquier et al., 2010; Di Maria and Lazarova, 2012).

Table 2: Benchmark Regressions

	System GMM				
Wage Ratio	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
LogGDPpercapita	0.089***	0.08***	0.08***	0.08***	0.07***
	(0.009)	(0.001)	(0.001)	(0.002)	(0.003)
LogGDPpercapita*	-0.029***	-0.026***	-0.024***	-0.025***	-0.018***
HighIncome	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
BrainDrain	-0.98***	-1.24***	-0.8***	-0.61***	-1.2***
	(0.019)	(0.013)	(0.01)	(0.024)	(0.046)
AverageTertiaryEduc	-0.043***	-0.0123***	-0.063***	-0.034***	-0.11***
	(0.002)	(0.006)	(0.003)	(0.007)	(0.017)
WorkerRights	0.062***	0.01***	0.087***	0.01***	0.11***
	(0.004)	(0.001)	(0.001)	(0.004)	(0.005)
HighTechExports	-0.002	-0.054***	-0.004	0.016	-0.02
	(0.009)	(0.01)	(0.015)	(0.015)	(0.04)
Democracy		-0.005***			-0.001*
		(0.000)			(0.001)
PoliticalFractional		0.021***			0.215***
		(0.002)			(0.01)
Conflict			0.037***		0.08***
			(0.002)		(0.004)
LogGDPpercapitaCoV				0.012***	0.01***
				(0.000)	(0.000)
Obs.	475	449	472	472	449
Countries	72	69	72	72	69
AR (2)	0.22	0.16	0.18	0.16	0.13
Hansen J	0.64	0.4	0.65	0.55	0.35

Significance level: ***p<0.01, **p<0.05, *p<0.1. In column (1), lags 2-12 are used; in (2) lags 2-8 are used; in (3) and (4), lags 2-10 are used; in (5), lags 2-6 are used. Column (5) is the benchmark regression specification.

Coming to the average level of tertiary education, its impact is, as expected, that of increasing the skill premium. To the contrary, an increase in the coefficient of worker rights protection raises unskilled wages. Such finding is supported by Ziliak et al. (1999) and Kraft (1994). It could be explained by the fact that the wages of unskilled workers are lower, but, while skilled personnel is more likely to experience wage increases as a result of rising underlying productivity, unskilled workers are more likely to unite to achieve most of their pay rise. Finally, there is no evidence that the composition of trade, represented by high-tech exports, bears any explanatory power for the wage ratio determination.

Columns (2)-(4) include the institutional and macroeconomic instability variables one at a time. As explained above, political fragmentation is measured as the probability that two deputies in the parliament pertain to two different party groups. This measurement hides the possibility that very low fragmentation probabilities are the result of authoritarian regimes that forbid the existence of political parties. To control for this explicitly, when PoliticalFractional is included, Democracy is included at the same time. Political fragmentation appears with a positive coefficient. This indicates that disrupted dialogue and slower pace of reforms, caused by political fragmentation, hinder the formation of skilled premia. In fact, it is likely that lack of swift political responses to signals emerging from society slow down innovation rates and technological progress. Instead, Democracy has a negative, albeit small, coefficient, suggesting that once the presence and strength of worker rights protection is controlled for, more democratic societies lead to a higher skill premium (Feng, 2001).

In column (3), Conflict, too, appears to lower the skill premium. All types of social unrest carry the risk of physical damage, as well as the risk of damage to productive equipment. The first will likely lead to disruption in the quality of education and in the continuity of its acquisition. While, the second will decrease innovative investment levels (see Rubio, 1998; Hofstetter,1998; for a similar point). On top of this, as pointed out by Goolsbee (1998) and Guellec and Van Pottelsberghe de la Potterie (2003), low levels of innovative investment result in lower demand for skilled workforce, which drives their wages down. All such factors, combined, hinder human capital accumulation and the pace of innovation, resulting in lower skill premia.

In column (4), output volatility is added to the model. The use of GDP volatility, proxying for aggregate output uncertainty, is well documented in the literature (Aizenman and Marion, 1993; Price, 1995). In addition, GDP volatility has been used in the literature to assess the effects of output cyclicality on the skilled-to-unskilled wage ratio (Nissim, 1984; Keane and Prasad, 1993). Because aggregate volatility discourages innovative investment (Price, 1995; Aghion et al., 2008) and skilled labour is complementary to capital-intensive technologies (Krusell et al., 2000), the skill premium is likely to fall with aggregate output volatility, as confirmed by the results reported in Table 2.

Finally, in column (5), no significant change affects the main results, with the exception of an increased coefficient magnitude for brain drain, average tertiary education, and worker rights protection. All the findings identified in columns (2)-(4) as to the effects of instability carry over to the benchmark specification in column (5), where all instability measures are included at the same time. To quantify the negative impact of political instability and real volatility, consider that a 20 percentage points increase in the probability of finding two deputies of different parties in the parliament decreases the skill premium by approximately 4 percentage points. Further to this, moving from a situation of no internal conflict to one of minor armed conflict decreases the skilled premium by slightly more than 8 percentage points. Finally, a 0.015 standard deviation increase in the coefficient of variation of GDP per capita leads to a 0.015 percentage point decrease in the skill premium.

4. Robustness Analysis

The sensitivity analysis tests the robustness of the results obtained thus far. This is done, in Table 3, by estimating the model with different instrument lag structures and by testing the sensitivity of the dependent variable to a different measure: the median wage ratio. In Table 4, additional control variables are included in the benchmark model, while in Table 5 all the instability variables are substituted by other proxies.

In Table 3 below, column (1) repeats the benchmark specification to facilitate comparison. In this, the instrumentation set goes from lag 2 to lag 6. In columns (2) and (3), different lag structures are applied: 2 to 5 lags in column (2), and 2 to 7 lags in column (3). All results carry over with no significant difference, apart from two elements: in (2), the average years of tertiary education lose significance, and, in (3), the coefficient magnitude of output volatility is somewhat reduced.

Table 3: Testing Instrument Lag Structure and Changing Dependent Variable Definition

	System GMM			
Wage Ratio	**(1)**	**(2)**	**(3)**	**(4)**
LogGDPperccapita	0.07***	0.07***	0.063***	0.08***
	(0.003)	(0.006)	(0.003)	(0.003)
LogGDPpercapita* HighIncome	-0.018***	-0.015***	-0.016***	-0.021***
	(0.001)	(0.003)	(0.001)	(0.001)
BrainDrain	-1.2***	-1.32***	-1.08***	-1.13***
	(0.046)	(0.26)	(0.02)	(0.046)
AverageTertiaryEduc	-0.11***	-0.056	-0.14***	-0.19***
	(0.017)	(0.044)	(0.014)	(0.017)
WorkerRights	0.11***	0.117***	0.127***	0.126***
	(0.005)	(0.009)	(0.002)	(0.003)
HighTechExports	-0.02	-0.16	-0.018	-0.016***
	(0.04)	(0.11)	(0.02)	(0.033)
Democracy	-0.001*	0.001	0.0005	-0.004***
	(0.001)	(0.003)	(0.000)	(0.000)
PoliticalFractional	0.215***	0.16***	0.19***	0.14***
	(0.01)	(0.035)	(0.005)	(0.012)
Conflict	0.08***	0.08***	0.073***	0.08***
	(0.004)	(0.01)	(0.001)	(0.006)
LogGDPpercapitaCoV	0.01***	0.013***	0.001***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	449	449	449	446
Countries	69	69	69	68
AR (2)	0.13	0.12	0.13	0.08
Hansen-*J*	0.35	0.35	0.77	0.45

Significance level: ***p<0.01, **p<0.05, *p<0.1. In column (1), lags 2-6 are used; in (2), lags 2-5 are used; in (3), lags 2-7 are used; in (4), lags 2-6 are used. Column (1) is the benchmark regression specification, with the median wage ratio substituting the mean wage ratio.

In column (4), we change the measure of the dependent variable to the median wage ratio instead of its mean.[36] Once again results remain broadly stable, with the magnitude of both political fragmentation and output volatility being somewhat reduced; and high-tech exports acquiring explanatory power and taking up a negative sign. This trade composition effect is supported by Parteka (2011), but, despite its significance, the magnitude of the coefficient suggests that, in practice, the share of high-tech exports has very limited influence on the wage ratio.

[36] This robustness check is meant to address the unbalanced structure of the raw wage data used to calculate the unskilled-to-skilled wage ratio. For a technical description, refer to Appendix B.

In Table 4 below, column (1) reports once again the benchmark specification to facilitate comparison. In columns (2) and (3), the benchmark regression is re-estimated changing the way the coefficient of variation of aggregate output is measured. More specifically, instead of using a two year rolling window to calculate the coefficient of variation, a fifteen year window in used in column (2) and a ten year window is used in column (3). All results carry over from the previous specification, but the impact magnitude of real volatility increases when the coefficient of variation is measured over a longer time-span.

Moving to the next columns, two additional indicators of instability are added in (4) and (5). The first is a measure of ethno-religious fragmentation and the second is a measure of cultural fragmentation. For the purpose of this analysis, they are two conceptually similar variables. They are included to control for instability that may come from social fragmentation, but that does not culminate in open armed confrontation, and, as such, is therefore not captured by Conflict.

While the impact of ethno-religious fragmentation appears to be insignificantly different from zero, increasing levels of cultural fragmentation are found to decrease the skill premium.[37] This finding is in line with the results of Aisen and Vega (2011) and Alesina (1996), who show that social instability and social discontent caused by inequality lead to uncertainty, which hinders investment and growth. In turn, lack of investment, especially in innovation, means lower demand for skills (Goolsbee, 1998; Guellec and Van Pottelsberghe de la Potterie, 2003) and a low skill premium. Once again the results for most of the other covariates carry over from the benchmark regression. The only differences worth mentioning are found in (3), where the magnitude of the worker rights protection, political fragmentation and armed conflict have slightly declined, while the magnitude of output volatility has risen.

Moving to column (6) of Table 4, some interesting changes are brought about by the inclusion of CompletedTertiaryEduc. To construct this variable, we use Barro and Lee (2011)'s data on the percentage of primary, secondary and tertiary schooling attained in the 25 and over population. Specifically, we build a ratio of the percentage of 25 and over population who has completed primary and secondary education, over the percentage that has completed tertiary education. While the average tertiary

[37] Cultural Fragmentation takes values between 0 and 1.

education variable already used in the regressions aims to control for the average level and/or quality of educational attainment in a given country, CompletedTertiaryEduc controls for a supply side effect. That is, it controls for the composition of the education qualifications in the population and the impact the latter has on the wage differential. On the one hand, the variable's specific impact on the wage ratio is in practice very small. Its negative sign indicates that the lower the share of tertiary graduates in the population the higher the skill premium, thus signalling the existence of a scarcity premium effect.

Table 4: Changing CoV Measurement and Controlling for Additional Variables

	System GMM					
Wage Ratio	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
LogGDPpercapita	0.07***	0.069***	0.069***	0.06***	0.068***	0.066***
	(0.003)	(0.002)	(0.001)	(0.006)	(0.003)	(0.005)
LogGDPpercapita*	-0.018***	-0.019***	-0.018***	-0.011**	-0.013***	-0.018***
HighIncome	(0.001)	(0.001)	(0.001)	(0.005)	(0.002)	(0.003)
BrainDrain	-1.2***	-1.37***	-1.67***	-1.14***	-1.12***	1.03***
	(0.046)	(0.037)	(0.09)	(0.04)	(0.03)	(0.27)
AverageTertiaryEduc	-0.11***	-0.14***	-0.17***	-0.12***	-0.14***	-0.06
	(0.017)	(0.02)	(0.02)	(0.022)	(0.014)	(0.06)
WorkerRights	0.11***	0.089***	0.12***	0.11***	0.01***	0.08***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.003)	(0.02)
HighTechExports	-0.02	-0.033**	-0.119**	-0.015	-0.0003	-0.187**
	(0.04)	(0.016)	(0.016)	(0.041)	(0.025)	(0.072)
Democracy	-0.001*	-0.006***	-0.006***	-0.001	-0.004***	0.003***
	(0.001)	(0.0008)	(0.0008)	(0.001)	(0.000)	(0.000)
PoliticalFractional	0.215***	0.297***	0.299***	0.213***	0.187***	0.095***
	(0.01)	(0.011)	(0.017)	(0.008)	(0.004)	(0.02)
Conflict	0.08***	0.069***	0.099***	0.084***	0.069***	0.056***
	(0.004)	(0.004)	(0.006)	(0.003)	(0.007)	(0.006)
LogGDPpercapitaCoV	0.01***	0.028***	0.094***	0.008***	0.12***	0.018***
	(0.000)	(0.006)	(0.005)	(0.000)	(0.003)	(0.000)
EthnoReligiousFractional				0.13		
				(0.1)		
CulturalFractional					0.19***	
					(0.08)	
CompletedTertiatyEduc						-0.024***
						(0.03)
Obs.	449	449	449	445	449	329
Countries	69	69	69	66	69	51
AR (2)	0.13	0.16	0.12	0.14	0.14	0.15
Hansen_*J*	0.35	0.52	0.77	0.45	0.45	0.64

Significance level: ***p<0.01, **p<0.05, *p<0.1. In columns (1)-(5), lags 2-6 are used; in (6), lags 2-4 are used. Column (1) is the benchmark specification.

On the other hand, some covariates adjust to the inclusion of this labour force supply side variable. Specifically, the average years of tertiary education now lose explanatory power, indicating that the education composition effect prevails over the average education level effect. Also, the share of high-tech exports turns significant, suggesting that the skill premium is positively related to a trade composition which favours high-tech exports. More interestingly, Democracy turns positive, indicating that the wage ratio increases in favour of unskilled wages in democratic settings. This suggests that the negative effect of democracy found in the previous part of the analysis is mediated through workforce supply side effects. To be more specific, it may be the case that there is a higher supply of skilled people in democracies, which leads to advantageous network effects. But, once we control for that, the residual impact of Democracy is positive, implying a relative increase in unskilled occupations' retributions. This finding is in line with Rodrik (1999)'s results.

Similarly, in all previous regressions, BrainDrain appeared with a negative sign, indicating that, as skilled people in the economy emigrate and the ones who stay become scarcer, the skill premium for the latter increases. However, once the unskilled to skilled composition of the labour supply is controlled for explicitly, the 'net' effect of brain drain is that of decreasing skilled wages (Docquier et al., 2010). This can be due to network effects (e.g. skilled workers are weaker when their number in the economy decreases), or it could be due to production side dynamics. Notably, as innovative investment lags behind due to brain drain, demand for skilled workforce declines, leading to a lower skill premium. In this sense, Acemoglu (1998) showed that if more workers with the same level of skills coexist, in the short-run this may depress individual returns, but in the medium-run skill-complementary innovative investment is fostered, and returns will increase as demand for skills outstrips supply. The dynamics unveiled by this coefficient estimate picture quite well the so called 'standing on shoulders' effect (see Agénor and Canuto, 2012, for a similar point).

Turning now to Table 5, note that typically institutional indicators can have multiple measurement specifications, but nonetheless capture the same underlying fundamental variable, such as democracy or instability. Thus, it is recommended that more than one variable specification is used, to avoid bias or ad hoc results when estimating the impact of institutional covariates (De Haan, 2007). This is why, in Table 5, the whole set of instability indicators is replaced. Again, the new variables are added one at a time first, in columns (2)-(4), and then jointly in column (5).

Column (1) reports the benchmark regression to facilitate comparison. The results remain fairly stable across regressions with regards to the significance and sign of the control variables. The magnitude of the estimates, however, changes in a few instances: the impact of the level of development fluctuates in magnitude, while that of the development interaction term increases; the impact of brain drain, average tertiary education, and worker rights protection drops, while that of high-tech exports gains explanatory power at the 10% level in columns (2) and (4), and at the 5% level in columns (3) and (5).

Table 5: Substituting the Measures of Instability

	System GMM						
Wage Ratio	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
LogGDPpercapita	0.07***	0.086***	0.088***	0.069***	0.069***	0.062***	0.069***
	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)
LogGDPpercapita*	-0.018***	-0.028***	-0.028***	-0.026***	-0.027***	-0.026***	-0.026***
HighIncome	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)
BrainDrain	-1.2***	-0.99***	-0.98***	-0.64***	-0.855***	-0.775***	-0.836***
	(0.046)	(0.01)	(0.007)	(0.023)	(0.02)	(0.05)	(0.028)
AverageTertiaryEduc	-0.11***	-0.061***	-0.056***	-0.03***	-0.022***	-0.009	-0.005
	(0.017)	(0.002)	(0.004)	(0.007)	(0.008)	(0.015)	(0.01)
WorkerRights	0.11***	0.086***	0.075***	0.1***	0.087***	0.092***	0.084***
	(0.005)	(0.001)	(0.000)	(0.003)	(0.002)	(0.007)	(0.002)
HighTechExports	-0.02	-0.037*	-0.019**	-0.039*	-0.042**	-0.073	-0.1
	(0.04)	(0.02)	(0.007)	(0.02)	(0.02)	(0.1)	(0.018)
Democracy	-0.001*						
	(0.001)						
PoliticalFractional	0.215***						
	(0.01)						
Conflict	0.08***						
	(0.004)						
LogGDPpercapitaCoV	0.01***						
	(0.000)						
GovernmFractional		0.038***			0.027***	0.065***	0.03***
		(0.001)			(0.004)	(0.01)	(0.002)
BattleRelatedDeaths			0.004***		0.003***	0.004***	0.004***
			(0.000)		(0.000)	(0.000)	(0.000)
LogGDPpercapStDev				0.13***	0.02***	0.026***	0.018***
				(0.000)	(0.000)	(0.000)	(0.000)
Obs.	449	469	475	475	469	469	469
Countries	69	71	72	72	71	71	71
AR (2)	0.13	0.19	0.2	0.16	0.17	0.16	0.18
Hansen J	0.35	0.75	0.58	0.51	0.68	0.71	0.86

Notes: Significance level: ***p<0.01, **p<0.05, *p<0.1. In column (1), lags 2-6 are used; in columns (2)-(4), lags 2-10 are used; in (5), lags 2-7 are used; in (6), lags 2-6 are used; in (7), lags 2-8 are used. Column (1) is the benchmark specification.

Democracy has been dropped from this set of results because political fragmentation is substituted by government fractionalisation. The latter refers to the probability that two deputies in the government cabinet (and not in the whole parliament) pertain to different parties. While the sample Spearman correlation between PoliticalFractional and GovernmFractional is 0.72, the main difference is that a majority government may be formed by one party only. Therefore, the remarks relative to dictatorial regimes biasing the coefficient interpretation of PoliticalFractional no longer apply, and the inclusion of Democracy is no longer necessary.

In column (2), government fragmentation is estimated on its own. The coefficient is significant and its sign is positive, indicating that an increase in the probability that two deputies in the government cabinet belong to different parties leads to lower skill premium levels.[38] Thus, similar considerations to the ones made when PoliticalFractional was interpreted apply in this case as well. In this respect, Aisen and Vega (2011) show that political instability, proxied by the number of government cabinet changes in a year, negatively affects growth by reducing the productivity of human and physical capital.

Conflict is substituted in, column (3), by a measure of battle related deaths. The sample Spearman correlation coefficient between these two variables is 0.98, and the coefficient of BattleRelatedDeaths indicates that more battle related deaths lead to a decrease in the skill premium. Finally, the volatility of output is measured in column (4) by the standard deviation of GDP per capita instead of its coefficient of variation. Output volatility has a higher effect on the skill premium when entering the regression on its own, but, even when combined with the other instability indicators, in column (5), it suggests that increasing output volatility decreases the skill premium. Lastly, columns (6) and (7) test the robustness of the instrument lag set used in the regression specification presented in column (5). In particular, while the benchmark instrumentation set uses lags 2 to 7, column (6) uses 2 to 6 lags and column (7) 2 to 8 lags. Nonetheless, the core results remain substantially unaffected.

5. Conclusions

This study has sought to uncover the channels through which instability in the macroeconomic and institutional environment is detrimental to the skill premium formation. It has been shown that both output volatility and political instability

[38] This value goes down to about 0.03% points in column (5), where all the new instability indicators are estimated jointly.

diminish the magnitude of the skill premium In particular, it has been argued that the skilled premium decreases in the presence of internal armed conflict, of higher parliamentary or governmental fractionalisation, and of more volatile aggregate output. A number of mechanisms have been suggested as potentially underlying these negative relationships. These mechanisms negatively impact on one or both of the main determinants of skilled wages, that is, demand for skilled labour and skilled labour's productivity. Decreasing levels of either will result in a reduction of the skill premium.

Specifically, it has been argued that instability lowers the productivity of human capital both directly and indirectly. Productivity is directly affected when the education quality, the continuity of education acquisition, or the on-the-job performance of skilled individuals is hampered by unstable environments. Human capital productivity is also indirectly affected when the productivity of the tangible and intangible capital skilled labour works with is disrupted. In this regard, the literature has shown that instability lowers firms' incentives to engage in costly and risky innovation projects. We have argued that, as a consequence of scarce innovation and slow technological progress, the demand as well as the retribution of skilled labour falls. As a result, the wage premium in favour of skilled occupations is reduced.

The results have been shown to be robust to a number of sensitivity tests conducted to verify the validity of both the methodological specification and the underlying economic theory. In sum, the findings of this study reveal the importance of stable environments, especially when considering that the existence of a skill premium is fundamental to human capital accumulation incentives. And that, in turn, human capital accumulation is crucial to foster innovation-led and self-sustainable growth.

Appendix A: Data Sources and Country List

Table A1. Data Sources

Wage Ratio	Mean value of unskilled (pimary + secondary education occupations) wages over skilled (tertiary education occupations) wages	Author's own calculation. Raw data is from OWW (Freeman & Oostendorp, 2012) and ILO October Inquiry (2004)
GDP per capita	GDP/midyear population. Data are in constant 2000 US$	World Development Indicators (2012)
Brain Drain	Ratio of number of skilled (i.e. post-secondary certificate) emigrants aged 25+ to the six major receiving countries over number of skilled natives (residents + emigrants) aged 25+	Defoort (2006)
AverageTertiaryEduc	Average years of tertiary schooling attained in the 25+ population	Author's own calculation. Raw data is from the Barro & Lee Dataset (2011)
CompletedTertiaryEduc	% of primary + secondary schooling attained in the 25+ population divided by % of tertiary schooling attained in the 25+ population.	Author's own calculation. Raw data is from the Barro&Lee Dataset (2011)
HighTechExports	Share of High-Tech exports (% GDP)	Own calculation. Raw data on high-tech exports as a % of tot manufacturing exports is from World Bank-WDI (2010)
WorkerRights	Worker's rights are: (0) Severely restricted (1) Somewhat restricted (2) Fully protected	Cingranelli & Richards – Human Rights Dataset (2010)
Democracy	Index of Political plurality which measures the degree to which checks and balances are imposed on institutional decision-making , 0 indicates low levels of checks, and 18 indicates high levels	Database of Political Institutions (Beck et al., 2010)
PoliticalFractional	Probability that two randomly chosen deputies in the parliament belong to different parties.	Database of Political Institutions (Beck et al. 2010)
Conflict	Conflicts between government and internal opposition groups (no	UCDP/PRIO Armed Conflict Dataset

	intervention from abroad): (0)No internal conflict (1)Internal minor armed conflict (2)Internal intermediate armed conflict (3)Internal war	(version 3-2005)
GovernmentFractional	Probability that two randomly chosen deputies in the government will be from different parties	Database of Political Institutions (Beck et al., 2010)
BattleRelatedDeaths	All military and civilian deaths (per 10,000 inhabitants) happened during battlefield fighting, guerrilla, bombardments, etc.	World Development Indicators (2012)
EthnoReligiousFractional	Probability that two randomly selected people from a given country will belong to different ethno-religious groups. The variable ranges from 0 (perfectly homogeneous) to 1 (highly fragmented)	Fearon (2003)
CulturalFracional	Structural distance between the languages spoken by different groups in a country. If the groups speak unrelated languages, their cultural diversity index will be the same as the level of *EthnoReligFract*. The more similar the languages they speak the more the index is reduced below the level of ethno-religious fractionalization. The variable ranges from 0 (homogeneous) to 1 (highly fragmented)	Fearon (2003)
LogGdppercapitaCoV	Coefficient of Variation of (Log)GDPper capita	Author's own calculation. Raw data is from WDI (2012)
LogGdppercapitaStDev	Standard Deviation of (Log)GDPper capita	Author's own calculation. Raw data is from WDI (2012)

Table A3. Country List

Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Belize, Bolivia, Cambodia, Canada, Centr. African Rep., China, Colombia, Costa Rica, Croatia, Cyprus, Czech Rep., Cote d'Ivoire, Estonia, Finland, Gabon, Germany, Guyana, Honduras, Hungary, Iceland, India, Japan, Kyrgizstan, South Korea, Latvia, Lithuania, Malawi, Mauritius, Mexico, Mongolia, Moldova, New Zealand, Nicaragua, Norway, Perù, The Philippines, Poland, Portugal, Papua New Guinea, Romania, Singapore, Slovak Rep., Slovenia, Sri Lanka, Sudan, Sweden, Switzerland, Thailand, Togo, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, Venezuela, Zambia.

Appendix B: Technical Notes

B1. Construction of Dependent Variable

We use the 2004 'OWW' dataset by Freeman and Oostendorp to generate a mean ratio of unskilled to skilled wages. To do so, all occupations recorded in the 'OWW' dataset have been re-coded according to the average level of education needed to enter a determined profession. Occupations associated with primary, or secondary qualifications at most, are coded as unskilled, while those that need a tertiary qualification are coded as skilled. To assign the education level to the selected occupations, we follow Freeman and Oostendorp (2001) as well as Chor (2001). Both the actual duties involved in each occupation and the skill level of such duties have been standardised in the OWW dataset by Freeman and Oostendorp. The standardisation procedure ensures that the same occupation coding can be assigned to different countries while retaining comparability (for full details of the country-specific calibration and standardisation procedure, see Freeman and Oostendorp, 2001).

Such considerations also extend to the time dimension. In other words, occupation contents and skill levels are harmonised both across countries and over time. On the other hand, however, the limitation of the approach we are following is that we cannot take into account any formal variation with regard to official qualifications needed for specific occupations. More specifically, the minimum qualification required to be employed in a certain occupation may rise from secondary to tertiary schooling from one decade to another within the same country. With the available information, unfortunately, it is impossible to account for such shift, and it is therefore necessary to acknowledge such limitation in the data.

Occupational observations in the OWW dataset are recorded as a micro-dataset, where occupational wage data appears every year on a country-by-country basis. To transform this panel into a macro-dataset, we construct two aggregated averages: one is calculated across all occupations coded as unskilled, the other across all occupations coded as skilled. The aggregated averages are calculated in this way for each year from 1983 to 2002 by country. In short, the 'OWW' dataset is transformed twice, as follows:

$$\frac{\frac{1}{N}\sum_{t=1}^{N}(\gamma_{i,\,t} \;+\; \delta_{i,\,t})}{\frac{1}{N}\sum_{t=1}^{N}\mu_{i,\,t}}$$

The first time it is collapsed into a panel that every year has two observations only per country: one for the mean average of unskilled occupations and one for the mean average of skilled occupations. The second transformation creates the ratio of the two and results in an aggregated macro-dataset where every country has a wage differential time series from 1983 to 2002. This procedure has been repeated, in the sensitivity analysis, with the median average of both sets of occupations instead of the mean. This is done for robustness reasons: in fact, the raw data presents multiple and repeated gaps throughout the cross-sectional time series. Country-specific factors that affect the wage of a specific occupation (or groups of occupations) could bias the mean averages. This would happen if the occupations for which the biased data is recorded appeared in some countries only, and were missing in others. The resulting average calculated across the set of existing occupational data could thus inflate and misrepresent the true skill premium in country A when compared to country B. While we acknowledge the fact that it is impossible to entirely correct for this source of bias, we try to minimise the latter, by estimating the benchmark regression first on the mean ratio and then on the median ratio.

B2. Coefficient of Variation

see Appendix B of Chapter 2

CONCLUSIONS

This thesis is a collection of essays on innovation, human capital, and economic instability. The investigation has, on the one hand, modeled the innovation process in order to understand its internal dynamics, and, on the other, contributed to uncovering the consequences of disruptions to the technological development path. The former task has involved the non-parametric estimation of an innovation input-output equation. While, in the latter, economic volatility and political instability were brought into the picture to analyse how business funded R&D investment and human capital formation decisions were affected by its occurrence.

The non-parametric analysis of the innovation input-output equation has uncovered marked non-linearities in the innovation process, with critical mass effects taking place at the initial phases of technological development, and diminishing marginal returns for higher R&D expenditure values. This pattern, which characterises the patent- total R&D spending relation, is shown to be driven by the business funded component. Public R&D investment is instead found to follow a linear and positive pattern of contribution to national patenting.

Furthermore, the findings suggest that political, real and monetary volatility lower the R&D investment funded by the business sector. Such impact is shown to exhibit non-linearities: on the one hand, the impact is larger for higher values of the real and monetary volatility dimensions; on the other, the negative effect of monetary instability appears to be mitigated during expansionary phases. Instead, the evidence on financial and international volatility is inconclusive. With respect to the skill premium, this is lowered by volatile aggregate output, institutional instability, and armed conflict. These occurrences, in fact, lower both the demand for skilled labour, and its productivity, which are both determinants of skilled wages.

These results have a number of policy implications. Firstly, revealing non-linearities in the innovation accumulation path amounts to emphasising the existence of threshold points. More specifically, it has been shown that, for low levels of aggregate innovation spending, innovation output levels represented by patent applications are not affected. That is, too low innovative investment levels do not translate in any detectable innovative output. Only after a certain threshold value of aggregate spending is past, will a patent response appear. Various forms of disaggregation helped to qualify the nature of such threshold effects, and, on top of that, to uncover compositional effects.

In particular, a sample split suggested that the critical mass effect is driven by developing countries. Indeed, no delayed onset of returns is detected when the response function of OECD countries' patents is considered. This result represents the first policy implication: due to the existence of a critical mass effect for low levels of innovative investment, developing countries need to reach this minimum threshold before positive returns to their R&D spending materialise. A further policy implication comes from the analysis of a new disaggregation. In fact, when the private and public components of aggregate R&D are divided and analysed separately, a potential for interactions and complementarities between the two different R&D spending sources appears.

Specifically, private R&D investment was shown to suffer from a delayed onset of positive returns and subsequent diminishing marginal returns to accumulation. This pattern was found to drive the functional form of aggregate R&D spending. To the contrary, public R&D was shown to contribute positively and linearly to patenting. In this setting, a compensating role for increased public R&D spending may arise. In other words, in less technologically advanced countries, the overall level of innovative investment is likely to stand below the critical mass threshold. Similarly, private R&D spending is likely too low due to imperfect appropriability. Moreover, private R&D, too, is shown to exhibit initial critical mass effects. Instead, increasing the level of public R&D could push the innovation accumulation beyond the initial threshold and trigger positive returns to R&D spending.

The second type of non-linearity uncovered in chapter one reflects the existence of diminishing returns to the accumulation of aggregate R&D investment. Because such pattern is again driven by the business funded innovation component, a complementary role of public R&D stands out. More specifically, in technologically advanced countries, where R&D spending reaches its highest values, shifting part of such R&D expenditure from the private to the public sector could counteract diminishing returns at the margin.

Once the existence of such threshold effects is uncovered, the importance of stable macroeconomic and institutional environments attracts even more emphasis. We have shown, in fact, that the investment decisions behind both ‘drivers of growth’ are sensitive to instability in a number of economic indicators. Specifically, the signals coming from the real, monetary, and political sectors of an economy influence the R&D spending funded by the private sector. If the latter stays low as a consequence of pervasive instability in the surrounding environment, economies may lag behind and remain trapped in technological underdevelopment. This, in turn, may influence and reflect on the second driver of growth, that is, human capital formation.

In fact, human capital accumulation, too, is shown to be affected by instability in the political and real sectors. Such effect is mediated through the skill premium formation and through the interaction between the latter and the economy’s level of R&D investment. Specifically, when R&D spending stays low due to the disruption in the profitability environment caused by instability, a number of related consequences materialises. First of all, less innovative investment translates in lower demand for skilled workforce. It also results in lower levels of technological development, which in turn imply lower productivity of skilled labourers. Because, as mentioned previously, demand for and productivity of skilled workforce are the main determinants of skilled wages, low levels of either will result in reduced skilled premia. As the incentive to accumulate human capital is driven by the wage premium skilled workers can aspire to, the lower such premium, the less human capital will be accumulated.

These considerations emphasise the chain effect that unstable environments can trigger, and highlight the impact this can have on economic development, once the incentives behind the accumulation path of both drivers of growth is disrupted. When linking such effect to the existence of critical mass and composition effects, it is possible, on the one hand, to gauge the extent of the complexity involved in the technological development process. On the other hand, it is possible to appreciate the role that public involvement in the innovation process may play. Such involvement may be both direct, in terms of a complementary contribution to aggregate innovation creation, and indirect, by way of ensuring stable macro-institutional environments.

Bibliography

Abel, A.B. (1983) 'Optimal Investment under Uncertainty'. *American Economic* Review, 73: 228-33.

Acemoglu, D. (1998). 'Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality'. *The Quarterly Journal of Economics*, 113(4): 1055-89.

Acemoglu,D. and Zilibotti, F.(2001) 'Productivity Differences' *Quarterly Journal of Economics*,116:563-606.

Adam, C. and Bevan, D. (2005). 'Fiscal Deficits and Growth in Developing Countries'. *Journal of Public Economics*, 89: 571-97.

Agénor, P. and Canuto, O. (2012) 'Middle-income Growth Traps'. World Bank Policy Research Working Paper Series no. 6210.

Agénor, P. and Neanidis, K. (2010). 'Innovation, Public Capital and Growth'. CGBCR Discussion Paper Series No. 135.

Aghion, P., Angeletos, G., Banerjee, A. and Manova, K. (2010) 'Volatility and Growth: Credit Constraints and the Composition of Investment'. *Journal of Monetary Economics,* vol. 57(3): 246-265.

Aghion, P., Askenazy, P., Berman, N., Cette, G., Eymard, L. (2008) 'Credit Constraints and the Cyclicality of R&D Investment: Evidence from France', *Journal of the European Economic Association*, 10(5): 1001-1024.

Aghion, P. and Howitt, P. (1992). 'A Model of Growth through Creative Distruction'. *Econometrica*, 60(2): 323-351.

Aghion, P. and Saint-Paul, G. (1998) 'Virtues of Bad Times, Interactions between Productivity Growth and Economic Fluctuations', *Macroeconomic Dynamics*, 2: 322-344.

Ahamada, I. and Flachaire, E. (2010). 'Non-Parametric Econometrics'. Oxford University Press.

Aisen, A. and Vega, F. (2011). 'How Does Political Instability Affect Economic Growth?'. IMF Working Paper Series no. 11/12.

Alesina, A. (1996). 'Income Distribution, Political Instability, and Investment'. *European Economic Review*, 40(6): 1203-1228.

Alesina, A., Ozler, S., Roubini, N., Swagel, P. (1996). 'Political Instability and Economic Growth'. *Journal of Economic June*. 1:189-211.

Arellano, M. and Bond, S. (1991). 'Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equation'. *Review of Economic Studies*, 58(2): 277-97.

Arellano, M. and O. Bover. (1995). 'Another Look at the Instrumental Variable Estimation of Error-Components Models.' *Journal of Econometrics*, 68(1): 29-52.

Arrow, K. (1962) 'Economic Welfare and the Allocation of Resources for Invention'. In Nelson. R. "The Rate and Direction of Inventive Activity', Princeton University Press, p.609-626

Aryeetey, E. (1994). 'Private Investment under Uncertainty in Ghana'. *World Development*, 22(8): 1211-1221.

Baltagi, B., (2005) 'Econometric Analysis of Panel Data'. 3rd ed. New York: Wiley.

Barrett, C., Sherlund, S. and Adesina, A. (2006) 'Macroeconomic Shocks, Human Capital and Productive Efficiency: Evidence from West African Rice Farmers'. *Journal of African Economies*, 15(3): 343-72.

Barro, R. (1991) 'Economic Growth in a Cross Section of Countries' *Quarterly Journal of Economics,* 106:407- 443.

Beck, T.; Demirgüç-Kunt, A. and Levine, R. (2000). 'A New Database on Financial Development and Structure'. *World Bank Economic Review* 14: 597-605.

Becker, B. and Pain, N. (2008) 'What Determines Industrial R&D Investment in UK?' *The Manchester School*, 76 (1): 66–87.

Beine, M., Docquier, F. and Oden-Defoort, C. (2011). 'A Panel Data Analysis of the Brain Gain'. *World Development,* 39(4): 523-532.

Bernanke, B. (1983) 'Irreversibility, Uncertainty and Cyclical Investment'. *The Quarterly Journal of Economics*, 98(1): 85-106.

Bessen, J. and Maskin, E. (2009). 'Sequential Innovation, Patents, and Imitation' *Rand Journal of Economics*, 40 (4): 611–635.

Blundell, R. and Bond, S. (1998). 'Initial Conditions and Moment Restrictions in Dynamic Panel Data Models'. *Journal of Econometrics*, 87(1): 115-143.

Blundell, R.; Griffith, R.; Van Reenen, J. (1995). 'Dynamic Count Data Models of Technological Innovation'. *The Economic Journal*, 105(429): 333-344.

Bohva-Padilla, S., Damijan, J.P. and Konings, J. (2009). 'Financial Constraints and the Cyclicality of R&D Investment: Evidence from Slovenia'. KU Leuven, LICOS - Discussion paper series 239: 1-17.

Bose, N.; Holman, G., and Neanidis, K. (2007). 'The Optimal Public Expenditure Financing Policy: does the Level of Economic Development Matter?'. *Economic Inquiry*, 45(3): 433-452.

Bottazzi, L. and Peri, G. (2005). 'The International Dynamics of R&D and Innovation in the Short and in the Long Run'. NBER Working Paper no. 11524.

Bound, J.; Cummins, C.; Griliches, Z.; Hall, B. and Jaffe, A. (1984). 'Who Does R&D and Who Patents?'. in Griliches (ed.) 'R&D, Patents, and Productivity', University of Chicago Press.

Chor, H. (2001). 'Skilled and Unskilled Wages in a Globalising World, 1968-1998'.

Coe, D.; Helpman, E. and Hoffmaister, A. (2009). 'International R&D Spillovers and Institutions'. *European Economic Review*, 53: 723-41.

Cohen, W. and Levinthal, D. (1989). 'Absorptive Capacity: A New Perspective on Learning and Innovation'. *Administrative Science Quarterly*, 35(1):128-52.

David, P.; Hall, B.; Toole, A. (2000). 'Is public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence' *Research Policy*, 29: 497:529.

De Haan, J. (2007). 'Political Institutions and Economic Growth Reconsidered'. *Public Choice*, 131: 281-292.

De Hoyos, R. and Sarafidis, V. (2006). 'Testing for Cross-Sectional Dependence in Panel-Data Models'. *The Stata Journal*, vol 6(4): 482-496.

De Rassenfosse, G.; Dernis, H.; Guellec, D.; Picci, L. and van Pottelsberghe de la Potterie, B. (2013). 'The Worldwide Count of Priority Patents: a New Indicator of Inventive Activity'. *Research Policy*, 42: 720-737.

Dehn, J. (2000). 'Private Investment in Developing Countries: The Effects of Commodity Shocks and Uncertainty'. CSAE Working Paper Series, no. 11.

Di Maria, C. and Lazarova, E. (2012). 'Migration, Human Capital Formation, and Growth: an Empirical Investigation'. *World Development*, 40(55): 938-955.

Docquier, F., Marchiori, L. and Shen, W. (2010) 'Brain Drain in Globalisation: A General Equilibrium Analysis from the Sending Countries' Perspective'. CEPR Working Paper no. 7682.

Escaleras, M. and Thomakos, D. (2008). 'Exchange Rate Uncertainty, Sociopolitical Instability and Private Investment: Empirical Evidence from Latin America". *Review of Development Economics,* 12 (2): 372-385.

Fan, J. and Gijbels, I. (1995). 'Adaptive Order Polynomial Fitting: Bandwidth Robustification and Bias Reduction'. *Journal of Computational and Graphical Statistics*, 4(3): 213–227.

Fan, J. and Gijbels, I. (1996). 'Local Polynomial Modelling and its Applications'. Chapman & Hall.

Fanelli, J. and Frenkel, R. (1995). 'Micro-macro Interaction in Economic Development'. *UNCTAD Review,* pp. 129-154.

Fisher, S.(1993) 'The Role of Macroeconomic Factors in Growth' *Journal of Monetary Economics*, 32: 485-512.

Fosu, A. (1992) 'Political Instability and Economic Growth: Evidence from Sub-Saharan Africa'. *Economic Development and Cultural Change*, 4(4): 829-841.

Fosu, A. (2002). 'Political Instability and Economic Growth'. *American Journal of Economics and Sociology*, 61(1): 329-348.

Fosu, A. (2003) 'Political Instability and Export Performance in Sub-Saharan Africa'. *The Journal of Development Studies*, 39(4): 68-82.

Freeman, R. and Oostendordp, R. (2001). 'The Occupational Wages around the World data file'. *International Labour Review*,140 (4).

Furman, J.; Porter, M. and Stern, S. (2002). 'The Determinants of National Innovative Capacity'. *Research Policy*, 31: 899–933.

Furukawa, Y. (2010) 'Intellectual property protection and innovation: an inverted-U relationship' *Economics Letters*, 109 (2): 99–101.

Gangopadhyaya, K. Mondal, D. (2012). 'Does Stronger Protection of Intellectual Property Stimulate Innovation?' *Economics Letters*, 116:80-82.

Goel, R. and Ram, R. (1999). 'Variations in the Effect of Uncertainty on Different Types of Investment: An Empirical Investigation'. *Australian Economic Papers* 38: 481–492.

Goolsbee, A. (1998). 'Does Government R&D Policy Mainly Benefit Scientists and Engineers?'. *American Economic Review*, 88(2): 298-302.

Greenwood, J. and Smith, B. (1997). 'Financial Markets in Development, and the Development of Financial Markets'. *Journal of Economic Dynamics and Controls*, (21):145-181.

Griffith, R.; Redding, S.; Van Reenen, J. (1999). 'Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries'. Review of Economics and Statistics, 86(4):883-95.

Griliches, Z. (1969). 'Capital-Skill Complementarity'. *Review of Economic and Statistics*, 51: 465-478.

Griliches, Z. (1979). 'Issues in Assessing the Contribution of R&D to Productivity Growth'. *The Bell Journal of Economics*, 10(1): 92-116.

Griliches, Z. (1980). 'Returns to R&D Investment in the Private Sector'. In 'New Developments in Productivity Measurement', Kendrick, J. and Vaccara, B., (NBER) UMI eds.

Grossman, G. and Helpman, E. (1991a). 'Quality Ladders in the Theory of Growth'. *Review of Economic Studies*, 58(1): 43-61.

Grossman, G. and Helpman, E. (1991b). '*Innovation and Growth in the Global Economy*'. MIT Press.

Grossmann, V. (1997). 'How to Promote R&D-based Growth? Public Education Expenditure on Scientists and Engineers versus R&D Subsidies'. *Journal of Macroeconomics*, 29(4): 891-911.

Guellec, D. and Van Pottelsberghe De La Potterie, B. (2003). 'The Impact of Public R&D Expenditure on Business R&D'. *Economics of Innovation and New Technology*, 12(3): 225-43.

Guo, J. and Trivedi, K. (2002). 'Flexible Parametric Models for Long-Tailed Patent Count Distributions'. *Oxford Bulletin of Economics and Statistics*, 64(63): 63-82.

Gurmu, S. and Pérez-Sebastián, F. (2008). 'Patents, R&D and Lag Effects: Evidence from Flexible Methods for Count Panel Data on Manufacturing Firms'. *Empirical Economics*, 35: 507-526.

Hall, B. Griliches, Z. and Hausman, J. (1986). 'Patents and R&D: Is There a Lag?'. *International Economic* Review, 27(2): 265-283.

Hall, B.; Mairesse, J. and Mohnen, P. (2010). 'Measuring the Returns to R&D'. Ch. 24, Vol.2, in 'Handbooks in Economics'.

Hall, R. (1991). 'Recession as Reorganization'. NBER Macroeconomics Annual.

Hansen, J. (1982). 'Large Sample Properties of Generalised Methods of Moments Estimators'. *Econometrica*, 50:1029-54.

Härdle, W. and Mammen, E. (1993). 'Comparing Nonparametric versus Parametric Regression Fits', *Annals of Statistics*, 21: 1926-1947.

Harrell, F. (2001). 'Regression Modelling Strategies with Applications to Linear Models, Logistic Regression and Survival Analysis'. New York: Springer-Verlag.

Hartman, R. (1972). 'The Effects of Price and Cost Uncertainty on Investment' *Journal of Economic Theory*, 5:258–266.

Hausman, J.; Hall, B.; Griliches, Z. (1984). 'Econometric Models for Count Data with an Application to the Patents-R&D Relationship'. *Econometrica*, 52(4): 909-38.

Hayakawa, K. (2007). 'Small Sample Bias Properties of the System GMM Estimator in Dynamic Panel Data Models". *Economics Letters,* 95(1): 32–38.

Hayashi, F. (2000). 'Econometrics'. NJ: Princeton University Press.

Henisz, W. (2002). 'The Institutional Environment for Infrastructure Investment'. *Industrial and Corporate Change,* 11(2): 355-89.

Higino Schneider, P. (2005) 'International Trade, Economic Growth and Intellectual Property Rights: A Panel data Study of Developed and Developing Countries*', Journal of Development Economics*, 78:529-547.

Hu, M. and Mathews, J. (2005a). 'National Innovative Capacity in East Asia'. *Research Policy,* 34(9): 1322–49.

Hu, M. and Mathews, J. (2005b). 'China's National Innovative Capacity'. *Research Policy,* 37(9).

Isham, J. and Kaufmann, D. (1999) 'The Forgotten Rationale for Policy Reforms: The Productivity of Investment Projects'. *Quarterly Journal of Economics*, 114 (1): 149-184.

Jones, C. (1995). 'R&D Based Models of Economic Growth'. *Journalof Political Economy*, 103: 739-84.

Katz J. (1987) 'Technology Generation in Latin American Manufacturing Industries'. The Macmillan Press.

Keane, M. and Prasad, E. (1993) 'Skill Levels and the Cyclical Variability of Employment, Hours, and Wages'. *IMF Staff Papers*, 40(4): 711-743.

Kimura, M. and Yasui, D. (2007). 'Occupational Choice, Educational Attainment, and Fertility'. *Economics Letters*, 94: 228-234.

Kleibergen, F. and Paap, R. (2006). 'Generalized Reduced Rank tests Using the Singular Value Decomposition'. *Journal of Econometrics*, 133(1): 97-126.

Klomp, J. and de Haan, J. (2009). 'Political Institutions and Economic Volatility'. *European Journal of Political Economy,* 25: 311-326.

Kraft, K. (1994) 'Wage Differentials between Skilled and Unskilled Workers'. *Weltwirtschaftliches Archiv*, 130(2): 329-49.

Krusell, P., Ohnanian, L., Rios-Rll, J., Violante, G. (2000) 'Capital-skill Complementarity and Inequality: A Macroeconomic Analysis'. *Econometrica,* 68(5): 1029-1053.

Levine, R. and Zervos, S. (1996) 'Stock Market Development and Long-Run Growth' *The World Bank Economic Review*, 10(2): 323-339.

Lewbel. A. (1997). 'Constructing Instruments for Regressions with Measurement Error when no Additional Data are Available, with an Application to Patents and R&D'. *Econometrica*, 65(5): 1201-1213.

Lin, C.; Lin, P.; and Song, F. (2010). 'Property Rights Protection and Corporate R&D: Evidence from China' *Journal of Development Economics*, 93:49-62.

Lindquist, M. (2004) 'Capital–Skill Complementarity and Inequality over the Business Cycle'. *Review of Economic Dynamics*, 3(7): 5195-40.

Lucas, R. (1988). 'On the Mechanics of Economic Development'. *Journal of Monetary Economics*, 22: 3-42.

Lundvall, B-A. (1992). 'National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning'. London: Pinter Publishers.

Mankiw, G., Romer, D., Weil D. (1992). 'A Contribution to the Empirics of Economic Growth". *Quarterly Journal of Economics*, 107: 407-437.

Mincer, J. (1995). 'Economic Development, Growth of Human Capital, and the Dynamics of the Wage Structure'. *Journal of Economic Growth* 1(1): 29-48.

Mobarak, A. (2005). 'Democracy, Volatility and Economic Development'. *The Review of Economics and Statistics*, 87(2): 348-361.

Montalvo, J. (1997). 'GMM Estimation of Count-Panel-Data Models with Fixed Effects and Predetermined Instruments'. *Journal of Business and Economics Statistics*, 15(1): 82-89.

Murray, F., and Stern, S. (2007) 'Do Formal Intellectual Property Rights Hinder the Free Flow of Scientific Knowledge? An Empirical Test of the Anti-Commons Hypothesis' *Journal of Economic Behavior and Organization*, 63: 648–687.

Neanidis, K. and Savva, C. (2010). 'Macroeconomic Uncertainty, Inflation and Growth: Regime - dependent Effects in the G7'. *Journal of Macroeconomics*, 35: 81-92.

Nelson, R. (1993). 'National Innovation Systems. A Comparative Analysis'. Oxford University Press.

Newey, W., Powell, J. and Vella, F. (1999). 'Non-parametric Estimation of Triangular Simultaneous Equation Models'. *Econometrica*, 67: 565-604.

Nissim, J. (1984) 'An Examination of the Differential Patterns in the Cyclical Behaviour of the Employment, Hours and Wages of Labour of Different Skills: British Mechanical Engineering, 1963-1978' *Economica*, 51: 423-436.

OECD (2010). 'Measuring Innovation: A New Perspective', OECD Publications.

Olson, M.; Sarna, N.; Swamy, V. (2000). 'Governance and Growth: A Simple Hypothesis Explaining Cross-Country Differences in Productivity Growth'. *Public Choice*, 102:341-364.

Pakes, A. and Griliches, Z. (1980). 'Patents and R&D at the Firm Level: A First Look'. NBER Working Paper Series no. 0561.

Parteka, A. (2011). 'Skilled-Unskilled Wage Gap and Returns to Education in the Enlarged EU - Sectoral Analysis Based on the Experience of EU-15 Countries and Five New Member States'. CERGE-EI, Prague.

Perez, C. and L. Soete (1988). 'Catching Up in Technology: Entry Barriers and Windows of Opportunity', in G. Dosi, C. Freeman, R.R. Nelson, G. Silverberg and L. Soete (eds) 'Technical Change and Economic Theory', London: Pinter, pp.458-79.

Pesaran, M. (2004). 'General Diagnostic Tests for Cross-Section Dependence in Panels' CESifo Working Papepr Series no. 1229.

Pindyck, R. and Solimano, A. (1993) 'Economic Instability and Aggregate Investment'. NBER Working Paper Series no. 4380.

Porter, M. (1990). 'The Competitive Advantage of Nations.. Free Press, New York.

Rafferty, M. (2003). 'Do Business Cycles Influence Long-run Growth? The effect of Aggregate Demand on Firm Financed R&D Expenditures'. *Eastern Economic Journal*, 29 (4): 607-618.

Rafferty, M. and Funk, M. (2008). 'Asymmetric Effects of the Business Cycle on Firm-Financed R&D'. *Economics of Innovation and New Technology,* 17(5): 497-510.

Robinson, P. (1988). 'Root-N Consistent Semiparametric Regression'. *Econometrica*, 56(4): 931–54.

Rodriguez-Pose, A. and Bilbao-Osorio, B. (2004) 'From R&D to Innovation and Growth in the EU'. *Growth and Change*, 35(4): 434-55

Rodrik, D. (1989). 'Policy Uncertainty and Private Investment in Developing Countries'. *Journal of Development Economics*, 36(2): 229-242.

Rodrik, D. (1999). 'Democracies Pay Higher Wages'. *The Quarterly Journal of Economics*, 114(3): 707-738.

Romer, P. (1990). 'Endogenous Technological Change'. J*ournal of Political Economy*, 98(5): 71-102.

Roodman, D. (2006). 'How to Do xtabond2: An Introduction to Difference and System GMM in Stata'. Centre for Global Development Working Paper Series n.103.

Roodman, D. (2009). 'A Note on the Theme of Too Many Instruments'. *Oxford Bulletin of Economics and Statistics*, 71(1): 135-158.

Ruppert, D., Sheather, S. and Wand, M. (1995). 'An Effective Bandwidth Selector for Local Least Squares Regression'. *Journal of the American Statistical Association*, 90(432): 1257–1270.

Saint-Paul, G. (1993) 'Productivity Growth and the Structure and of the Business Cycle', *European Economic Review,* 37*:*861-90.

Sameti, M., Ranjbar, H., Anoushesh, S. (2010). 'Determinants of R&D Investment: Evidence from OECD countries'. *The Knowledge Economy,* (3):35-42.

Sanyal, P. (2003). 'Understanding Patents: the Role of R&D Funding sources and the Patent Office'. *Economics of Innovation and New Technology*, 12(6):507-529.

Sarkar, S. (2000) 'On the Investment-Uncertainty Relationship in a Real Options Model'. *Journal of Economic Dynamics and Controls*, 24(2): 219-225.

Serven, L. (2003). 'Real-Exchange-Rate Uncertainty and Private Investment in LDCs'. *The Review of Economics and Statistics*, 85(1): 212–218.

Smolny, W. (2003). 'Determinants of Innovation Behaviour and Investment Estimates for West German Manufacturing Firms'. *Economics of Innovation and New Technology,* 12(5):449–463.

Spagat, M. (1995). 'Human Capital, Instability and Foreign Investment in Transition Economies'. *Economics of Planning*, 8: 185-203.

Ulku, H. (2007). 'R&D, Innovation and Output: Evidence from OECD and non-OECD Countries'. *Applied Economics*, 39: 291-307.

Varsakelis, N. (2001). 'The impact of Patent Protection, Economy Openness and National Culture on R&D Investment: a Cross-Country Empirical Investigation'. *Research Policy*, 30: 1059-1068.

Verardi, V. and Debarsy, N. (2012) 'Semipar: Stata Module to Compute Robinson's (1988) Semiparametric Regression Estimator'. *The Stata Journal* (forthcoming).

Wand, M. and Jones, M. (1995). 'Kernel Smoothing'. Chapman & Hall.

Wang, E. (2010) 'Determinants of R&D Investment: The Extreme-Bounds-Analysis approach applied to 26 OECD countries'. *Research Policy*, 39 (1): 103-116.

Wang, K. and Barrett, C. (2007). 'Estimating the Effects of Exchange Rate Volatility on Exports Volumes'. *Journal of Agricultural and Resource Economics,* 32(2): 225-255.

Yang, G. and Maskus, K. (2001) ‘Intellectual Property Rights and Licensing: An Econometric Investigation’. *Review of World Economics*, 137(1): 58-79.

Ziliak, J., Wilson, B., Stone, J., (1999) ‘Spatial Dynamics and Heterogeneity in the Cyclicality of Real Wage’. *Review of Economics and Statistics*, 81(2): 227-236.