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Analyzing the Impact of R&D Tax Incentive Policy on Firm Innovations in OECD Countries

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Abstract

R&D tax incentives have gained popularity among the OECD countries as a means to improve innovation. However, the impact of R&D tax incentives on innovation has not been commensurate with the tax incentives given. This study aims to analyze the role of R&D tax incentives on firm innovation. Data on innovation and government support in 16 OECD countries was drawn from the Global Economy (World Bank Data) database. Three estimation techniques, Pooled Ordinary Least Square (OLS) regression analysis, Fixed effect and Random effect models are employed in estimating the relationship between R&D tax incentives and firm innovation. The first hypothesis found that tax incentives directly improve firm innovation, hence tax incentives are a significant policy tool in OECD countries, encouraging firms to invest more in R&D activities. The second hypothesis is rejected. The third hypothesis found that R&D tax incentive is displaced by R&D intensity in full sample analysis but not in groups with high innovation performance. The study proved the importance of skilled R&D personnel in maximizing the benefit of tax credits. The capacity of R&D personnel can complement to R&D tax credit for innovation performance support schemes by the government. The study's findings indicate that while R&D tax incentives are a strong indicator of a firm's innovative activities, they tend to overshadow the R&D intensity. However, this is not observed in countries that exhibit high levels of innovation performance.

The study concludes that even though R&D tax incentives are a great predictor of firm innovation, R&D tax incentives are crowded R&D intensity but not in the case of high innovation performing countries. Policymakers should consider investing in human capital such as education and training to enhance the effectiveness of R&D tax credits in OECD countries.

Keywords
R&D tax credits, Innovation, Government policy

JEL Classification
O38, O32

Introduction

Innovation is acknowledged as an important variable input in the processes of firms and economies for growth. This recognition is reflected by a plethora of studies in the area of innovation, both at the firm level and country level (see for example Stejskal et al., 2018; Chlebovský et al., 2018; Prokop et al., 2021). At the country level, there have been an array of studies ranging from the effectiveness of fiscal incentives for R&D to the effectiveness of tax credits for innovation (Du & Li, 2018; Carvache-Franco et al., 2020). However, in recent times authors have concentrated a lot of effort on firm-level data with emphasis on fiscal incentives and how it affects firm innovation. Even though R&D tax incentives and subsidies are the most popular instrument for R&D support for government (Hall & Reenen, 2000), studies on fiscal incentive and their impact on innovation have focused extensively on R&D tax incentive and their role in firm innovation (Chen & Yang, 2019; Tian, Yu, & Ye, 2020; Ivus, Jose, & Sharma, 2021). This is probably because of the complexities that surround R&D tax incentives.

Again R&D tax incentives have gained popularity in most countries with the desire to support firm innovation, however, the success of R&D tax incentives as a driver of innovation has been mixed (Carvache-Franco et al.,2020). R&D tax incentives, unlike subsidies, by design, give the beneficiary firms the latitude to decide which research projects to invest in. The possibility of using these tax savings for activities other than R&D cannot be ignored. R&D tax incentives extended to beneficiaries are less monitored relative to other forms of government support (Guoa, Guo, & Jiang, 2016). This leaves beneficiary firms to decide how these tax savings are used relative

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to subsidies where firms are only qualified after an assessment of R&D projects (Yang, Huang, & Hou, 2012; Czmitzki, Hanel, & Rosa, 2011). This may create room for misappropriation and diversion of these tax savings to unintended investment areas. Diversions of these funds will be more pronounced in situations where there are substitutable sources of funds for R&D investment and R&D activities.

Given this context, the extant literature cites the authors’ attempt to unravel the inconsistencies in the findings on the relationship between R&D tax incentives and innovation performance (Chen & Yang, 2019; Tian, Yu, & Ye, 2020; Ivus, Jose, & Sharma, 2021). The general position of the extant literature is that R&D tax incentives enhance firm innovation. This has been the basis of policymakers and governments, especially OECD countries embracing R&D tax incentives. However, a lot remains unexplained as far as the effectiveness of R&D tax incentives is concerned. Consistent with (Mitchell, Testa, Martinez, Cunningham, & Szkuta, 2020), it has been found that despite the popularity of R&D tax incentives among OECD countries, the policy has not been very effective in enhancing firm innovation (OECD, 2020). With limited monitoring to ensure tax savings are channelled to R&D, the possibility that these tax savings are channelled to other areas of investments exists. Thus, the extant literature, in examining the effect of R&D tax incentives on innovation, fails to examine the crowding-out effect of R&D tax incentives by other forms of R&D support schemes. Moreover, the existing literature examined only the impact of R&D tax credits on firm innovation input and output. Importantly, previous literature also neglects the other factors of innovative activities which can interact with the effect of R&D tax incentives on firm innovation performance (Castellacci & Lie, 2015). This study is therefore an attempt to fill this research gap, by investigating the role of the R&D tax credit in modifying the relationship between R&D intensity and the capacity of R&D personnel in influencing innovation performance among selected OECD countries. The OECD member countries present an interesting case for the study of the effectiveness of R&D tax incentives in enhancing firm innovation. The OECD member countries predominantly employ R&D tax incentives as a means to improve firm innovation performance. The success chalked has not been commensurate with R&D tax incentives extended to firms (OECD, 2020)

This study contributes to both, theory and practice. This study contributes to the context of market failure theory. Firms may not be able to fully capture the positive externalities of innovation, in essence, R&D tax incentive is a policy tool that can address market failure by effectively lowering the cost of innovation for firms. Therefore, R&D tax incentive remains the most valuable component of a firm’s innovation strategy (Kafourosa et al., 2015; Halaskova et al., 2018). This forms the basis for R&D tax incentives as a way to enhance internal R&D. The findings of the study provide the basis to confirm or reject. The findings of the study are expected to inform policy and decision-makers on what policy direction to take to ensure enhanced innovation in firms.

The paper is structured as follows. The rest of the next section provides theoretical background. Section 3 explains the methodology. Section 4 describes the empirical results and the findings are discussed in section 5. Conclusions and limitations are offered in section 6.

Literature Review and Hypothesis

Market failure theory

The concept of market failure theory originally came from neoclassical economic theory. Market failure theory suggests when there is no efficient allocation of resources or where there is no perfect competition are not met in the free market system. In terms of innovation, the theory emphasizes the market fails to distribute resources efficiently and effectively to promote innovation in the firms. According to Martin & Scott (2000), the market mechanism cannot encourage adequate investment in the firm R&D activities due to certain conditions. Market failure has a substantial impact not only on the direction and quantity of firm innovation but also on the quality of innovative goods and services and hinders the development of new technologies (Barbaroux, 2014). Moreover, market failures can limit firms' engagement, particularly due to information and appropriability issues (Roper, 2016). In this sense, government interventions or support are required to correct these market failures, which can bring benefits to the firms as well as society. Typically, government policies or institutional arrangements can be divided into two types; direct or indirect support. Direct support comes in the form of subsidies, tax credits, and provision of public R&D resources to work with the private sector (Martin & Scott, 1998). Scholars Martin & Scott (2000) described that government policies are critical in encouraging firm R&D activities and technological development in the case of firms facing failure issues that can impede their innovation ability. Scholars keep on emphasizing that targeted government policies are required to encourage firm innovation effectively because firms can experience different types of failure based on the sectors. In this case, government policies can help bridge the gap and encourage firms to undertake innovation activities (Martin & Scott, 2000). Therefore, the aim of our study is relevant to this market failure theory approach, underlying how these fiscal incentives (R&D tax credit) can stimulate R&D activities in firms, leading to greater innovation.

Government Support for Firm Innovation

Several authors have recognized the role of government support in firm innovation (for example, Klímová, 2018; Halásková & Bednář, 2018). In a study by Du and Li (2018) for example, the authors observed that government support is a critical element of firm innovation in the Chinese economy. The motivation of the government to lend support to firms' R&D is to avoid underinvestment in R&D (Guoa, Guo, & Jiang, 2016). In a free-market system and the presence of externalities, government support for a firm's R&D is crucial to encourage firms to continue to invest in R&D. This is confirmed in a study by Szczygielski et al. (2016) who argued that market failures are bound to limit private investment in R&D making it imperative for government to intervene. It is imperative at this point to acknowledge that the literature on R&D points to two main market failures that warrant government support for firm R&D, positive spillovers of technological knowledge and capital market imperfection (Bronzini & Piselli, 2016). These imperfections, in agreement with Szczygielski et al. (2016) culminate in under-investment in R&D by the private sector if the government does not intervene (Bronzini & Piselli, 2016).

Government support for a firm's R&D has come in different forms. However, the notable ones are government subsidies and fiscal incentives (Bronzini & Piselli, 2016; Prokop & Stejskal, 2019). While subsidies are lagged, thus given after project execution and evaluation, fiscal incentives are immediate and reduce the firm's cost (Guoa, Guo, & Jiang, 2016). Thus, fiscal incentives unlike other forms of government support immediately free resources for firms to inject into their R&D activities. It can therefore be argued that tax incentives are neutral since it is not tied to any particular research projects but give firms the free hand to decide where to invest these cost savings. It has been argued that tax incentives are more favored than subsidies because of their neutrality and the fact that they reduce government influence in the decision on which projects attract funds (Kobayashi, 2014; Prokop & Stejskal, 2015). Again, the literature recognizes one important distinction between fiscal incentives and subsidies. In a study by Bronzini and Piselli (2016), the authors expressed that subsidies follow a lot of bureaucratic procedures relative to fiscal incentives which have less laborious procedures. This could mean that the fatigue associated with subsidies may make them less attractive to firms and less effective in enhancing firm innovation. Portions of the extant literature make the argument that government subsidies crowd out firms' internal R&D expenditure (Guoa, Guo, & Jiang, 2016) thereby reducing firm's innovation output. Typically, an R&D tax incentive reduces corporate income tax and or employer's social security contribution proportional to a firm's R&D efforts as a way of reducing the firm's cost and increasing R&D activities (Mohnon & Lockshin, 2011).

R&D Tax Incentive and Firm Innovation

The literature recognizes that R&D tax incentives and other forms of government support for R&D are critical inputs for a firm's innovation performance (Tian, Yu, & Ye, 2020). However, there is also a section of the R&D literature that suggests that R&D tax incentives have not been effective in ensuring innovation in firms (Mitchell et al., 2020). However, the focus of investigations on the source of R&D tax incentive ineffectiveness has focused on firm-specific and other environmental factors (Savrul & Incekara, 2015). Consideration of other factors that could explain this anomaly has been minimal. The possibility of other R&D support schemes crowding out cost savings from R&D tax incentives is yet to be investigated.

Scholars Tian et al. (2020) have shown that R&D tax incentive improves both input and output of innovation. This is confirmed by Chen and Yang (2019) who investigated R&D tax credits and firm innovation using data from China. Chen and Yang (2019) analyzed the causal effect of R&D tax credits on firm innovation and found that R&D tax credits have a significant positive effect on innovation. Firm and industrial factors account for the effectiveness of R&D tax credits (Chen & Yang, 2019). These firm and industry-specific factors may account for the differences in the study outcomes. In a study to assess the effect of India's R&D tax credit scheme, Ivus, Jose, and Sharma (2021) employed difference of difference to estimate the impact of R&D tax credit on firms that have benefited from R&D tax credit. The findings of the study confirmed Chen and Yang (2019) observation that R&D tax credit enhances innovation.

From the findings of Chen and Yang (2019), one can argue that the effect of tax credits on firms is dependent on some other variables. This is confirmed in a study conducted by Jia and Ma (2017) who revealed that institutional conditions shape the effect of R&D tax incentives on R&D activity. Thus, even though there is consensus among authors that R&D tax incentives enhance firm innovation and R&D activities, it is usually not without exceptions. The literature shows that some institutional, industry and firm-specific factors are critical to the relationship between R&D tax credit and firms' innovation outcomes (Savrul & Incekara, 2015). Thus, even though there is a consensus among authors that R&D tax incentives improve firm innovation, firm characteristics, and industrial factors may prevail especially in situations where the study involves different countries and firms in different industries with different characteristics.

Based on the review of the literature, the following hypothesis is formulated for testing:

H1: R&D tax incentives improve the innovation of firms in the selected OECD countries.

R&D Tax Incentive and R&D Intensity

The position of the R&D literature is that R&D intensity is an important determinant of firm innovation (Savrul & Incekara, 2015). It is for this reason that firms and countries are striving to increase their R&D activities as a channel to improve innovation. This amplifies the argument that technology is an important aspect of a firm's production function as against the traditional notion that only factors of production determine the growth of firms. Countries and firms that have devoted resources to improving the intensity of their R&D are expected to experience enhanced innovation (Bustinza et al., 2019).

There is a large body of literature that has revealed that R&D intensity, both at the firm and country level is important in improving firm innovation (Dong, We, Liu, & Xing, 2021). It is, however, important to recognize that the effect of R&D intensity on the innovation performance of firms has been observed to vary across firms and countries in the presence of some other factors. For example, Hsu and Hsueh (2009) as well as Savrul and Incekara, (2015) acknowledged the role of R&D intensity in the innovation of firms but added that R&D intensity could not always guarantee success in innovation. This is an indication that the chances of a high R&D intensity translating into innovation may be dependent on some other factors.

The findings of the studies that have investigated the role of R&D intensity in innovation performance are mixed. Carvache-Franco et al.,2020) for example showed a positive and significant relationship between R&D intensity and process and product innovation in Peru and Ecuador, data from Chile indicated no significant relationship. The inconsistency in the research findings in the area of R&D intensity and innovation, even though, has been thought to be explained by firm environmental factors, crowding out of R&D tax incentives by other R&D support schemes could explain why R&D Tax incentives have not been able to ensure innovation.

The study, therefore, in an attempt to determine the inconsistent relationship between R&D tax incentives and innovation performance hypothesizes the following:

H2: R&D tax incentive is displaced by increasing R&D intensity of firms among OECD countries.

The Interaction between R&D Tax Credit and Capacity of R&D Personnel to Improve Innovation

The importance of R&D tax credit in the performance of innovation has been widely researched with mixed results (Carvache-Franco et al.,2020). Whereas a chunk of empirical studies have shown that R&D tax credit is an important source of innovation performance (Du and Li, 2018; Bronzini and Piselli, 2016; Szczygielski, et al., 2016), there are pockets of studies that have shown that R&D tax credit does not improve innovation performance (Mitchell, Testa, Martinez, Cunningham, & Szkuta, 2020; OECD, 2020). These inconsistencies require an investigation into the possible modifiers in this relationship. The capacity of R&D personnel available to a country provides an important channel that could complement or otherwise R&D tax credit in influencing innovation performance. R&D expenditure has been found to correlate positively with R&D personnel (Zhu, Zhao, & Abbas, 2020). There is evidence that fiscal incentives for innovation does not increase the recruitment of R&D personnel but rather the recruitment of the number of PhD candidates (Afcha & Garcíaquevedo, 2014). This is an indication that enrolment in tertiary education forms a fertile ground for firm recruitment once firms get incentives from government. There is therefore a good reason to believe that government supports such as R&D tax effect on innovation can be modified by the pool R&D personnel available to the country. The use of tertiary school enrolment as R&D personnel capacity is well documented and has been found to be important determinant of innovation (Muhamad, Sulaiman, & Saputra, 2018). However, evidence of R&D personnel capacity moderating the relationship between R&D tax credit and innovation performance is generally perceived rather having hard core empirical support. Other studies have also highlighted that tertiary school enrolment of countries provide the needed capacity for R&D personnel for innovation performance. The importance of R&D personnel capacity in innovation performance even though, highlighted, Leibfritz and Janger (2007) showed that the capacity of R&D personnel measured by the enrolment in tertiary institutions because more important when firms are approaching the frontiers of innovation where high technology is needed. The higher the skill demand of firms and countries rise the more the success of innovation becomes more dependent on human resource with tertiary qualifications. Authors such as Krueger and Kumar (2003) and Wölfl (2005) the skill of the workforce, measured by tertiary qualification is important in determining innovation performance in the service sector and also encourages to adoption of new general purpose technologies such as ICT. The relationship between R&D tax credit and innovation performance is generally not expected to be direct without intervening variables. The effect of R&D tax credit on innovation is affected by R&D inputs including R&D personnel and their capacity. In a study by Guceri (2018), the author showed that changes in R&D tax credit to influence innovation performance works through the hiring of well-trained R&D personnel to influence innovation performance.

Based on the position of the empirical literature, the study hypothesises for testing the following:

H3: The interaction between R&D tax credit and R&D personnel capabilities of a country determines innovation performance.

Research Methodology

Consistent with the related literature (Bloom, Griffith & Reenen, 1999; Hall & Reenen, 2000; Bloom, Griffith & Reenen, 2002; Skordoulis et al., 2020; Carrasco-Carvajal et al., 2023), the current study employs inferential study design. Inferential study design is typical for studies of this nature that examine the relationship between innovation and R&D tax incentives. In this study, the relationship between the interaction between R&D tax incentive and R&D intensity as independent variables and firm innovation as a dependent variable is investigated. The study a study also investigates the role of the R&D tax credit in modifying the relationship between R&D intensity and capacity of R&D personnel in influencing innovation performance.

The study sampled sixteen OECD countries including Australia, Belgium, Czech Republic, Denmark, Finland, France, Germany, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia and Spain.

Data for the study is the panel sourced from the global economy database (World Bank Data). The data is annual and spans from 2000 to 2022. This is country-level data, which presents data on Science and Technology in the OECD member countries. The sampling is based on the availability of data on the selected variables.

Table 1. Variable and Description.

Variable	Explanation	Reference
lPATappres	Patent applications by residents	Subramanian et al. (2016)
lrd_tax	R&D tax credit	Mitchell et al. (2020)
lRDint	R&D intensity	Dong et al. (2021)
lRGDPgr	Real GDP growth	Saymeh & Orabi, (2013)
lCpinvt	Capital Investment	Farooq et al. (2024)
lGOVTspgdp	Government spending at a percentage of GDP	d'Agostino et al. (2016)
lINTupop	Internet users per population	Cui et al. (2024)
lINFtecxtox	Information technology export to total export	Fan (2021)
lHTECxp	High technology export	Sandu & Ciocanel (2014)
lGlindx	Globalisation index	Fosah et al. (2024)
lLab_Prod	Labour productivity	Yu et al. (2024)
lLAB_Prate	Labour participation rate	Lee & Parasnis (2014)
lTrd_Opness	Trade openness	Wang et al. (2024)
lPUBspedugdp	Public spending on education per GDP	Artige & Cavenaile (2023)
lTer_enrlElig	Tertiary school enrolment as a percentage of eligible people	Muhamad et al. (2018)
lwld_FDI	Percentage of world FDI	Acquah & Ibrahim (2020)

Consistent with authors such as (Chen & Yang, 2019; Ivus et al., 2021; Bergeaud & Verluise, 2024), the current study measured innovation by the number of patent applications by the European Patent Office. The R&D Tax credit, which is an incentive given by the government by way of tax reduction to firms to increase research activities (Rao, 2016; Petrin & Radicic, 2023) is used as a measure of indirect government support. This choice of R&D Tax credit as a measure of government support is inspired by studies conducted by (Jose et al., 2019 and Dimos et al., 2022). The study also used variables such as National R&D Intensity, and tertiary enrolment as a percentage of eligible people as well as economic factors as control variables. These variables are chosen in agreement with authors that have been extensively cited in the extant literature.

Three estimation technique Ordinary Least Square (OLS), panel fixed effect (FE) and random effect (RE) regression analysis are employed in estimating the relationship between variables. The choice of these estimation techniques is in tandem with the study objectives and also inspired by related studies. Such as (Chen & Gupta, 2017; Ivus et al., 2021; Dimos et al., 2022) who used regression analysis to determine whether R&D tax credit stimulates firm R&D spending.

To determine the relationship between relationship between innovation and R&D tax incentives the study estimated a general equation as follows:

$$IPATappes_{it}=\beta_0+\beta_1 lPATappres\_L1+\beta 2lRD\_tax_{it}+\beta_3\sum Con_{it}+\varepsilon_{it} \quad (1)$$

where

$\sum Con_i$ vector of control variables,

R&D Tax R&D tax credit,

ε error term and

$\beta_1 lPATappres\_L1$ lag dependent variable.

Equation (1) is estimated using OLS, fixed effect and random effect model where innovation is regressed on contemporaneous regressors and lag dependent variables. The lag dependent variable allows the study to assess the relationship within a dynamic framework. The study estimated a more realistic model especially in the context of innovation and R&D inputs that have adjustment cost.

$$IPATappes_{it}=\beta_0+\beta_1 lPATappres\_L1+\beta_2 lRD\_tax_{it}+\beta_3 lRDint+\beta_4 lRD\_tax_{it*}lRDint_{it}+\beta_5\sum Con_{it}+\varepsilon_{it} \quad (2)$$

In equation (2), the study attempts to estimate the dynamic relationship between the interaction of R&D tax credit and R&D intensity and their effect on innovation performance. The study also analysed the effect of the interaction between R&D tax credit and capacity of R&D personnel and their effect on innovation performance. This is estimated by equation 3.

$$IPATappes_{it}=\beta_0+\beta_1 lPATappres\_L1+\beta_2 lRD\_tax_{it}+\beta_3 lTer\_enrlElig_{it}+\beta_4 lRD\_tax_{it*}lTer\_enrlElig_{it}+\beta_5\sum Con_{it}+\varepsilon_{it} \quad (3)$$

Dynamic panel regression is usually unstable and therefore various techniques are employed to ensure that the model selected to test the hypothesis is stable. The model selection criteria are the explanatory power measured by the R squared and the lag dependent variable. The model with the highest coefficient of determination and a stable lag dependent variable (positive, significant and less than 1) to ensure long run convergence rather than being explosive. Again, sub sample analysis is conducted as a sensitivity test. Three sub samples based on size of patent application are used. The first sample include five countries with the highest patent application, the second is the next five countries highest patent application after the first sample and the third sample include six countries with least patent applications.

Results of the Analysis

Table A in Appendix presents a descriptive statistic of the data. The descriptive statistics show the correlation analysis as well as measures of central tendencies. The correlation analysis shows that the correlation coefficients are low and therefore there is no risk of multicollinearity in the regression analysis. The measures of central tendencies also show the means, their associated standard deviations, the maximum values of each of the variables and their minimum values.

Table 2 presents results of unit root test. This test is important to assess the stationarity of the variables to avoid spurious relationships. The results indicate that at level, variables including real GDP growth (lRGDPgr), capital investment per capita (lCpinvt), government spending as a percentage of GDP (lGOVTspgdp), internet users as a percentage of population (lINTupop), information technology export as a percentage of total goods export. Other variables that are stationary at level include globalization index (lGlindx), public spending on education as a percentage of GDP (lPUBspedugdp), tertiary school enrolment as a percentage of eligible people (lTer_enrlElig) and percentage of world FDI (lwld_FDI). All the other variables in Table 3 are not stationary at level but only stationary after first difference.

Table 2. Unit root Test.

Variable	Unit root		Remarks
	Level	First Difference	
lPATappres (Patent application)	yes	no	Stationarity
lrd_tax (R&D tax credit)	yes	no	Stationarity
lRDint (R&D intensity)	yes	no	Stationarity
lRGDPgr (Real GDP growth)	no	no	Stationarity
lCpinvt (Capital Investment)	no	no	Stationarity
lGOVTspgdp (Government spending at a percentage of GDP)	no	no	Stationarity
lINTupop (Internet users per population)	no	no	Stationarity
lINFtecxtox (Information technology export to total export)	no	no	Stationarity
lHTECxp (High technology export)	yes	no	Stationarity
lGlindx (Globalisation index)	no	no	Stationarity
lLab_Prod (Labour productivity)	yes	no	Stationarity
lLAB_Prate (Labour participation rate)	yes	no	Stationarity
lTrd_Opness (Trade openness)	yes	no	Stationarity
lPUBspedugdp (Public spending on education per GDP)	no	no	Stationarity
lTer_enrlElig (Tertiary school enrolment - percentage of eligible people)	no	no	Stationarity
lwld_FDI (Percentage of world FDI)	no	no	Stationarity
lINNdx	yes	no	Stationarity

From Table 3 the results on the effect of R&D tax credit on innovation performance are reported. The results show findings of three estimation techniques, pooled OLS, random effect model and fixed effect model. In column two, the pooled OLS shows that the lag dependent variable is significant but has a negative sign. Even though the coefficient is less than 1, the negative sign indicates that the long run effect is explosive rather than equilibrium. The coefficient of the R&D tax credit (lR&D) shows that for one per cent change in R&D tax credit leads to 0.5% change in patent count in the same direction. The R&D intensity (lR&Dint), which is the main source of innovation input of countries is not significant in the pooled OLS model. The real GDP growth rate, which is generally considered a measure of economic performance and therefore an input of innovation performance is not significant in the innovation performance model. The pooled OLS also shows that increasing government spending is inimical to innovation performance. The information technology export as a percentage of total export (lINFtecxtox) and high technology export (HTECxp) have been shown to increase with innovation performance (lPATappres). Measures of economic openness such as the globalization index (Glindx) and trade openness (DlTrd_Opness) are significant but have unexpected negative signs. Labour force productivity measured by the GDP contribution per hour worked is significant and positive. Tertiary enrolment as a percentage of eligible people which is a measure of capacity of R&D staff is significant but inversely related to innovation performance.

Column three of the study presents the random effect model in examining the effect of R&D tax credit on innovation performance. The lag dependent variable is significant, positive, and below 1. This is important to indicate that the model is a dynamic process in the relationship between R&D tax credit and innovation. In this model, just like in the case of the pooled OLS model, innovation is responsive to R&D tax credit. R&D intensity is also insignificant just like in the case of the pooled OLS. The results show that real GDP growth and capital investment per GDP are significant but carry an unexpected negative sign. Contrary to the pooled OLS, innovation performance is responsive to a change of 0.4% per 1% change in internet users as a percentage of the population in the same direction. The study showed that channels of technology transfers such as high technology exports and FDI are positive and significant. This means that technological channels transmit innovation inputs to enhance innovation performance. Economic Openness variables, just like in the case of were found to be inversely related to innovation performance in the random effect model. Labour productivity is found to be inversely related to innovation performance but public spending in education as a percentage of GDP is not important in the determination of innovation.

Table 3. R&D Tax Credit and Innovation Performance.

lPATappres Variables/Models	Pooled OLS	RE Model	FE Model
lPATappres_L1 (Patent application)	-0.000014*** (4.11e-06)	0.0000805*** (6.27e-06)	-0.000104*** (9.76e-06)
lRD_tax (R&D tax credit)	0.5075424*** (0.1424575)	0.7270057*** (0.2322873)	0.5708462*** (0.1553918)
lRDint (R&D intensity)	0.0393594 (0.1175566)	0.2095383 (0.3981821)	-0.2849291*** (0.1129232)
lRGDPgr (Real GDP growth)	-0.0229438 (0.0461027)	-0.1634233** (0.0773871)	-0.0197086 (0.0412431)
lCpinvt (Capital Investment)	-0.0212245 (0.2331132)	-0.7842839** (0.3843803)	0.0354519 (0.2521143)
lGOVTspgdp (Government spending at a % of GDP)	-0.9872197** (0.4574767)	0.3696752 (0.7753575)	-0.0499005 (0.6144853)
lINTupop (Internet users per population)	0.3967088 (0.1159469)	0.4446526** (0.192958)	0.5258874*** (0.1449765)
lINFtecxtox (Information technology export to total export)	0.0542321*** (0.0445573)	-0.0853109 (0.0754753)	0.1549317** (0.0744799)
DlHTECxp (High technology export)	0.3764911*** (0.0650529)	0.3029923*** (0.1143148)	0.1886299*** (0.0594012)
lGlindx (Globalisation index)	-2.535965** (1.173594)	-2.789369* (1.855043)	-1.96715 (1.779)
DlLab_Prod (Labour productivity)	1.047452 ** (0.2612176)	-1.080407** (0.5178461)	0.6877425*** (0.2290011)
DlLab_Prate (Labour participation rate)	-2.284248** (1.095423)	-2.038393 (1.860948)	-4.669235*** (0.9753964)
DlTrd_Opness (Trade openness)	-0.2031494 (0.2180793)	-1.024728*** (0.3721378)	-0.5645915*** (0.198206)
lPUBspedugdp (Public spending on education per GDP)	0.0223518 (0.2800781)	0.4120173 (0.4311337)	0.0197474 (0.4095542)
lTer_enrlElig (Tertiary school enrol.as % of eligible people)	-0.2425335** (0.0995914)	0.1432133 (0.164867)	-0.0096543 (0.0997781)
lwld_FDI (% of world FDI)	0.0199276 (0.0266565)	0.4638102*** (0.0444414)	0.0034185 (0.0400476)
_cons	13.79634*** (4.926341)	17.90556*** (7.258563)	7.692341 (7.968007)
R-squared Adj R-squared	0.3615 0.3233	Within = 0.0395 Between = 08143 Overall = 0.7243	Within = 0.5589 Between = 0.0929 Overall = 0.0509
Prob	0.0000	0.0000	0.0000

Note: *** p<0.01; **p<0.05; *p<0.10. Standard errors in parenthesis. All variables in logarithmic transformation.

The fixed effect model in column four shows that the lag dependent variable is significant but negative. This is explosive in the long run rather than converging at equilibrium. The results show that 1% increase R&D tax credit results lead to 0.57% increase in innovation performance. However, R&D intensity is significant but inversely related to innovation performance. The fixed effect model shows that real GDP growth, capital investment, and government spending as a percentage of GDP are not significant. Channels of technology flow into countries such as information technology export as a percentage of total export and high technology export are significant and positive indicating that knowledge spillover from other countries is contributing to innovation performance. On the contrary, the percentage of world FDI (lwld_FDI) has no effect on innovation performance. The effect of economic openness is mixed in the fixed effect model. Whereas globalization index is insignificant, trade openness is inversely related to innovation performance.

To test the study hypothesis (H1) that R&D tax credit improves innovation performance, the study relies on the random effect model. Apart from the fact that the random effect model shows a higher explanatory power (Overall R-squared of 0.7255) than the pooled OLS and the fixed effect model, the random effect model also adequately captures the dynamic process. From the random effect model, the study finds evidence that confirms the hypothesis that R&D tax credits improve innovation performance.

Table 4 presents results that test the hypothesis (H2) on the interaction between R&D tax credit and R&D intensity for innovation performance. The second column of Table 4 presents the pooled OLS. The lag dependent variable (lPATappres_L1) of the pooled OLS is significant, less than 1 but inversely related to the dependent variable. For dynamic process, it is expected that the coefficient of the lag dependent variable will be positive significant, and less than 1. However, the most important variable of focus for the hypothesis (H2) test, the interaction between R&D tax credit and R&D intensity (lRD_tax* lRDint) shows a positive and significant relationship with patent count. R&D tax credit and R&D intensity are in themselves positive and significant. Variables that indicate size of economy and spending power of the economy such as real GDP growth (lRGDPgr), and capital investment per GDP (lCpinvt) do not determine innovation performance (lPATappres). Government spending as a percentage of GDP, however, is significant but carries an unexpected negative sign. Technology drivers such as internet users per population (lINTupop) and high technology exports (DlHTECxp) are significant and positively related to innovation performance. However, this is not the case for technology drivers such as information technology exports as a percentage of total export (lINFtecxtox) and percentage of world FDI (lwld_FDI). Measures of economic openness, globalization index (lGlindx) and Trade openness (DlTrd_Opness) could not improve innovation performance. Whereas trade openness is not significant, globalization index is significant but inversely related to innovation performance. Tertiary enrolment as a percentage of eligible people as a measure of research personnel is significant but inversely related to innovation performance.

The third column tests the effect of the interaction between R&D intensity and tax credit (lRD_tax* lRDint) on innovation performance. The results show that the lag dependent variable (lPATappres_L1) is significant, positive and less than 1 reflecting the dynamic process in the model. However, the results show that the interaction between R&D tax credit and R&D intensity is not significant. The random effect model therefore finds no evidence to confirm the hypothesis (H2). It is important to note that evaluating the individual interaction terms, it is worth noting that R&D tax credit (lRd_tax) is significant and positive whereas the R&D intensity (lRDint) is insignificant. Innovation performance responsiveness to a 1% change R&D tax credit is 0.73% in the same direction. The effect of variables that explain investments and size of the economy and their effect on innovation performance is mixed. Whereas real GDP growth (lRGDPgr) and capital investment (lCpinvt) are significant and carry an unexpected negative sign government spending as a percentage of GDP (lGOVTspgdp) and public spending on education as a percentage of public spending (lPUBspedugdp) show no significant effect on innovation performance. Economic openness variables in the model, globalization index (lGlindx) and trade openness (DlTrd_Opness) have significant but negative effects on innovation performance. The control variables that transmit knowledge and technology seem to be helping improve innovation performance in the random effect model. For example, variables including internet users as a percentage of population (lINTupop), high technology export (lDHTECxp), and percentage of world's FDI (lwld_FDI) are significant and positively related to innovation performance. However, information technology export as a percentage of total goods export is not significantly related to innovation in the random effect model. The effort of labour in innovation performance is discounted. The random effect model shows that labour productivity (DlLab_Prod) is significant but inversely related to innovation performance whilst labour force participation rate of countries (DlLab_Prate) is insignificant.

Table 5 presents results that test the hypothesis (H3) that R&D Tax credit interacts with R&D personnel capacity to determine innovation performance of countries. The analysis is conducted using different estimation techniques. The second column presents a pooled OLS analysis to test the hypothesis (H3). The results show that the lag dependent variable (lPATappres_L1) is significant but has an unexpected negative sign. The variable of interest, the interaction between R&D tax credit and tertiary school enrolment as a percentage of eligible people (lRD_tax* lTer_enrlElig) is not significant in the pooled OLS analysis. However, both R&D tax credit (lRD_tax) and tertiary school enrolment as a percentage of eligible people (lTer_enrlElig) are individually significant, however, unlike the R&D tax credit that has the expected positive sign, tertiary school enrolment as a percentage of eligible people comes with a negative sign.

The result indicates that government spending and investment is not important in determining innovation performance based on the pooled OLS estimation. The real GDP growth (lRGDPgr), capital investment (lCapinvt) and public spending on education as a percentage of GDP (lPUBspedugdp) are insignificant. However, government spending as a percentage of GDP (lGOVTspgdp) is significant but inversely related with innovation performance. Economic openness also does not contribute to improving innovation performance. The results show that globalization index (Glindx) is significant but inversely related to innovation performance whilst trade openness (DlTrd_Opness) is not significantly related to innovation performance. Labour productivity (DlLab_Prod) is found to improve innovation performance but labour force participation rate (DlLab_Prate) is inversely related to innovation performance. Technology transfer channels show varied effects. The pooled OLS show that internet users as a percent of population (lINTupop) and high technology export (DlHTECxp) are positive and significantly related to innovation performance. However, information technology export as a percentage of total export (lINFtecxtox) and percentage of world's FDI (lwld_FDI) are not significantly related to innovation performance.

Table 4. Interaction between R&D Tax Credit and R&D Intensity for Innovation Performance.

lPATappres Variables/Models	Pooled OLS	RE Model	FE Model
lPATappres_L1 (Patent application)	-0.0000168*** (4.43e-06)	0.0000803*** (6.27e-06)	-0.0001031*** (9.74e-06)
lRD_tax* lRDint (Tax credit * R&D intensity)	0.3605874* (0.2188456)	-0.247866 (0.2293264)	0.3348099* (0.206679)
lRD_tax (R&D tax credit)	0.4237453*** (0.1508348)	0.7343493*** (0.2323135)	0.5138311*** (0.1588418)
lRDint (R&D intensity)	0.2876043* (0.1908685)	0.1268163 (0.4053476)	-0.193199* (0.1260016)
lRGDPgr (Real GDP growth)	-0.0333912 (0.0463907)	-0.1608941** (0.0773981)	-0.024338 (0.04121)
lCpinvt (Capital Investment)	-0.066099 (0.2339588)	-0.8073835** (0.3848531)	-0.0442194 (0.256073)
lGOVTspgdp (Government spending at a percentage of GDP)	-1.234421*** (0.4800607)	0.4591257 (0.779519)	-0.1963153 (0.619147)
lINTupop (Internet users per population)	0.3615089*** (0.1175342)	0.4478874** (0.1929204)	0.5275223 *** (0.144515)
lINFtecxtox (Information technology export to total export)	0.0246579 (0.0479046)	-0.0561876 (0.0801184)	0.1522314** (0.0742597)
DlHTECxp (High technology export)	0.37108*** (0.0649281)	0.301861*** (0.1142836)	0.1984352*** (0.0595193)
lGlindx (Globalisation index)	-2.46052** (1.170739)	-3.253267* (1.903478)	-1.632638 (1.785277)
DlLab_Prod (Labour productivity)	1.071031*** (0.2607757)	-1.028543** 0.5199022	0.6782372*** (0.2283421)
DlLab_Prate (Labour participation rate)	-2.29006** (1.091928)	-2.032771 (1.86037)	-4.572889*** (0.9740854)
DlTrd_Opness (Trade openness)	-0.1898833 (0.2175314)	-1.013522*** (0.372165)	-0.5605725*** (0.1975859)
lPUBspedugdp (Public spending on education per GDP)	-0.0879971 (0.2871035)	0.394099 (0.4313167)	0.0800201 (0.4099326)
lTer_enrlElig (Tertiary school enrolment as a percentage of eligible people)	-0.2442424** (0.0992785)	0.1332598 (0.1650722)	-0.0424835 (0.1015018)
lwld_FDI (Percentage of world FDI)	0.0270111 (0.0269169)	0.4593006*** (0.0446229)	0.0066409 (0.0399687)
_cons	14.623*** (4.936161)	19.75707*** (7.455737)	6.775618 (7.962586)
R-squared	0.3680	Within = 0.0442 Between = 0.8146 Overall = 0.7255	Within = 0.5634 Between = 0.0985 Overall = 0.0543
Adj R-squared	0.3276		
Prob	0.0000	0.0000	0.0000

Note: *** p<0.01; **p<0.05; *p<0.10. Standard errors in parenthesis. All variables in logarithmic transformation.

Third column of Table 5 presents estimation of the hypothesis (H3) that the capacity of R&D personnels of countries interact with R&D tax credit to improve innovation performance using the random effect technique. The results of the analysis show that the random effect captures the dynamic process in the relationship with a significant (1%) lag dependent variable (lPATappres_L1) which is positive and less than 1.

The variable of focus in the test of the hypothesis (H3), the interaction between R&D tax credit and tertiary school enrolment as a percentage of eligible people (lRD_tax* lTer_enrlElig) is significant and positively related to innovation performance. The responsiveness of innovation performance to a 1% increase in (lRD_tax* lTer_enrlElig) is 0.36%. This confirms the study hypothesis (H3) that R&D tax credit interacts with the capacity of R&D personnel to improve innovation performance. However, the individual interaction terms, R&D tax credit (lRD_tax) and tertiary school enrolment as a percentage of eligible people (lTer_enrlElig) are not significant in the model. R&D intensity of the economy as a measure research capacity of countries is positive and significantly related to innovation performance. Variables that measure government spendings and investments such as lRGDPgr, lCapinvt and lGOVTspgdp are not significantly related to innovation performance with exception of lPUBspedugdp which is significant but inversely related to innovation performance. Economic openness variables, lGlindx and DlTrd_Opness are significant and inversely related to innovation performance. It is important to state that in the case of globalization index a 1% increase results in more than a percentage change (6.39%) change in innovation performance in the opposite direction. Labour force, both productivity and participation rate are not important determinants of innovation in the random effect model. Technological channels show mixed results in the random effect model. Internet users per population and high technology export are positive and significantly related to innovation performance whilst factors such as information technology exports as a percentage of total exports and percentage of world's FDI are not significant.

Table 5. Interaction between R&D Tax credit and Research Personnel for Innovation Performance.

lPATappres Variables/Models	Pooled OLS	RE Model	FE Model
lPATappres_L1 (Patent application)	-0.000015*** (4.18e-06)	0.0000655*** (6.21e-06)	-0.000105*** (9.67e-06)
lRD_tax* lTer_enrlElig (Tax credit*R&D personnel)	-0.3923609 (0.3003016)	0.3645631*** (0.0538344)	0.953649*** (0.3830911)
lRD_tax (R&D tax credit)	2.212399* (1.312581)	-0.0289431 (0.2421923)	-3.609433** (1.686293)
lTer_enrlElig (Tertiary school enrolment as a percentage of eligible people)	-0.3946818*** (0.1531432)	0.1066722 (0.1526447)	0.2935799* (0.1568209)
lRDint (R&D intensity)	-0.0058688 (0.1223983)	0.7324398** (0.3764372)	-0.3129005*** (0.1123399)
lRGDPgr (Real GDP growth)	-0.0192821 (0.046127)	-0.0818083 (0.0726124)	-0.0279918 (0.0409596)
lCpinvt (Capital Investment)	0.044483 (0.2381751)	-1.331387 (0.3647224)	0.0193315 (0.2496383)
lGOVTspgdp (Government spending at a percentage of GDP)	-0.8201141* (0.4744365)	-0.4907557 (0.7285925)	-0.165773 (0.610024)
lINTupop (Internet users per population)	0.4061651*** (0.1160197)	0.5839683*** (0.1797228)	0.5536773*** (0.1439379)
lINFtecxtox (Information technology export to total export)	0.0590072 (0.0446483)	-0.0859374 (0.0698363)	0.2079695*** (0.0767405)
DlHTECxp (High technology export)	0.3706282*** (0.0651217)	0.1511543 (0.1081243)	0.2019989 (0.0590428)
lGlindx (Globalisation index)	-2.59042** (1.172784)	-6.386872*** 1.796775	-0.9583481 (1.806963)
DlLab_Prod (Labour productivity)	1.007969*** (0.2626168)	-0.6241237 (0.4838704)	0.6930266*** (0.2266857)
DlLab_Prate (Labour participation rate)	-2.437257** (1.100225)	-1.909912 (1.722016)	-4.481166*** (0.9684431)
DlTrd_Opness (Trade openness)	-0.1994946 (0.2178091)	-0.7981888** (0.3459554)	-0.581156*** (0.1963061)
lPUBspedugdp (Public spending on education per GDP)	-0.0617391 (0.2870172)	-0.6358737* (0.4278827)	0.4331382 (0.4380896)
lwld_FDI (Percentage of world FDI)	0.0124031 (0.0272371)	0.4323369*** (0.0413829)	0.0038861 (0.0396414)
_cons	14.1093*** (4.925659)	40.09159*** (7.472708)	1.464814 (8.274334)
R-squared Adj R-squared	0.3656 0.3251	Within = 0.1258 Between = 0.8539 Overall = 0.7648	Within = 0.5695 Between =0.1105 Overall = 0.0445
Prob	0.0000	0.0000	0.0000

Note: *** p<0.01; **p<0.05; *p<0.10. Standard errors in parenthesis. All variables in logarithmic transformation.

Column four of Table A in appendix presents fixed model analyses to test the hypothesis (H3) that R&D tax credit interacts with capacity of R&D personnel to improve innovation performance. The results indicate that the lag dependent variable is significant at 1% but inversely related to innovation performance. The interaction between R&D tax credit and tertiary school enrolment as a percentage of eligible people (lRD_tax* lTer_enrlElig) is significant at 1%. The results show that innovation performance is very responsive to changes in (lRD_tax* lTer_enrlElig). A percentage change in lRD_tax* lTer_enrlElig leads to a 0.95% change in innovation performance. Evidence from the fixed effect model confirms the hypothesis of the study. The individual terms in the interaction terms behave differently in the fixed effect model. R&D tax credit is significant and inversely related to innovation performance where in the case of tertiary school enrolment as a percentage of eligible people, it is significant and positively related to innovation performance. Contrary to expectation, the fixed effect model reveals that increasing R&D intensity is inimical to innovation performance. Government expenditure, size of the economy and capital investment variables such as lRGDPgr, lCpinvt, lGOVTspgdp and PUBspedugdp are not significantly related to innovation performance. Economic openness variables show mixed results. Whereas lGlindx does not affect innovation performance, DlTrd_Opness is significant but inversely related to innovation performance. Whilst Labour productivity improves innovation performance, labour force participation rate inversely affects innovation performance. Two of the technological variables, lINTupop and lINFtecxtox are positive and significantly related to innovation performance. However, DlHTECxp and lwld_FDI are not significant. Based on the R-squared and the performance of the lag dependent variable to capture the dynamic process of the model, the random effect model is the most efficient model to test the hypothesis. The study therefore shows evidence that confirms the hypothesis (H3) that R&D tax credit interacts with R&D personnels capacity to improve innovation performance.

Table B in Appendix presents a control group analysis to determine the consistency of the results with sub-sample results. The sub sample group results are presented in Table B. The second to the fourth columns present random effect analysis testing the study hypotheses. The sub samples are a group of five countries with the highest number of patent applications by residents with a group mean of 15402.96 patent applications by residents. Column 2 tests the effect of R&D tax credit on innovation performance, column three tests the effect of the interaction between R&D tax credit and R&D intensity on innovation performance whilst the fourth column tests the effect of the interaction between R&D tax credit and capacity of R&D personnel on innovation performance. In all cases, the random effect model is used. Comparing the results in column 1 with the results in Table 3 column 3 (full sample analysis of the same hypothesis using random effect model), one can conclude that the coefficients of the lag dependent variables have not changed much, and the coefficient is still significant. This is a sign that the model retained the dynamic process. R&D tax credit remains significant and positive just as in the case of the full sample analysis. However, R&D intensity is significant in the sub sample analysis contrary to the corresponding full sample analysis in Table 3. In column 3 the interaction between R&D tax credit and R&D intensity is positive and significant. This compares column 3 on Table 4 which tests the corresponding analysis for a full sample where the variable is not significant. The lag dependent variables of the two results do not change much. In both the full and sub sample, there lag dependent variable indicates model stability in time. Comparing column 4 in Table B and the results in column 3 in Table A, there is no difference between the lag dependent variable suggesting a dynamic process in both models. However, the interaction between R&D tax credit and tertiary enrolment shows marked differences. Whereas this variable is significant and positive in the full sample analysis, the corresponding sub sample analysis shows no significant relationship.

Columns 5-7 on Table B presents sub sample analysis of a group of five countries with the next highest number of patent application applications. The mean value of the patent applications for this group of countries is 1986.106. Comparing the sub sample analysis in Column 5 Table B to the corresponding analysis in Table 3 the lag dependent variable remains stable with very little change. The effect of R&D Tax credit on innovation performance remains positive and significant, however, the sub sample analysis shows a slight increase in coefficient. In column 6, comparing the lag dependent variable with the corresponding analysis in Table 4, we observe not much difference. This confirms that in both analysis the effect of the variables is in a dynamic process. The effect of the interaction between R&D tax credit and R&D intensity is significant in the sub sample but not in the full sample. In column 7 of Table B, the sub analysis focuses on testing the effect of the interaction between R&D personnel capacity and R&D tax credit on innovation performance. Comparing with Table A, we observe a lot of similarities. For example, the lag dependent variables in both cases remain significant even though in the sub sample analysis the significance is reduced to 10%. However, the interaction between R&D tax credit and tertiary enrolment shows a significant difference. Whereas in the full sample analysis the interaction term is significant, it is insignificant in the sub sample analysis.

Columns 8-10 of Table B in appendix presents sub sample analysis using a sub sample of six countries with the least patent applications. The mean patent application of these countries is 681.2933. Comparing the sub sample analysis in column 8 in Table B and the full sample analysis in Table 3 we observe both models are inconsistent to the extent that the lag dependent variable as a measure of dynamic process is significant in the case of the full sample but insignificant in the case of the sub sample. The case of inconsistency between the sub sample and the full sample runs through all the sub sample analyses in Columns 8-10 of Table B compared with their corresponding full sample analysis. The results show a marked difference in the sub sample analysis of the group of countries with least patent applications. Whereas the group of countries with the least patent applications show insignificant tertiary school enrolment, the full sample and the other sub sample analysis generally show that there is a significant relationship between tertiary school enrolment and innovation performance. It is also evident that in countries with small patent applications or lower levels of innovation performance show no sign of dynamic process in the relationship between R&D outputs and inputs.

Table B shows that as patent application levels rise the lag dependent variable is highly significant but as the levels of innovation performance fall, the level of significance drops to 5% and then turns insignificant when the level of innovation performance falls to a low mean of 681.2933. This means that when the patent application or innovation performance is high, it takes time for changes in innovation inputs to affect innovation outcomes. On the contrary at low innovation performance levels, the impact of innovation inputs becomes contemporaneous.

Discussions

The discussion of the study is presented under three themes. The first discusses the effect of R&D tax credit on innovation performance. The second is a discussion on the role of interaction between R&D tax credit and R&D intensity in influencing innovation performance. In the last section of the discussions, the study presents the role of interaction between R&D tax credit and the capacity of R&D personnel in influencing innovation performance.

5.1 Effect of R&D tax credit on Innovation Performance

In results of the study find evidence to confirm the hypothesis that R&D tax incentives improve the innovation of firms in the selected OECD countries. The study has shown that the response of innovation performance for 1% change in tax credit is 0.727%. This shows that the position by a section of the literature that suggests that R&D tax credit is not responsible for innovation performance (Mitchell et al., 2020) has been discounted by the findings of the study. Rather the findings have given credence to studies by authors including Tian, Yu and Ye (2020) who have shown empirically that R&D tax credit is an important component factor in explaining innovation performance. In this study, we take note of the findings of other authors such as Mitchell et al. (2020) who showed that R&D Tax credit is an important input in the innovation process. Our findings respond to this by analysing a resampled data based on size of innovation performance. We have been able to prove that the effectiveness of R&D tax credit could be a function of the innovation performance level. In this study, we have shown that extreme levels of innovation performance are not ideal for the effectiveness of R&D tax credit. Chen and Yang (2019) showed that the effectiveness of R&D tax credit is influenced by firms and industrial factors. In this study we have shown that R&D tax credit is more effective when innovation performance is hovering around 1986 patent applications, but the effectiveness of R&D reduces as it deviates to extreme levels of innovation performance. Our results have also shown that the effect of R&D tax credit is more of a dynamic than a static process. The R&D tax credit and the other R&D inputs of innovation generally affect innovation in time rather than contemporaneously. It is however, important to state that in this study, we have also shown that in some instances there are contemporaneous effects of R&D inputs and this phenomenon is usually associated with countries with high economic growth rates and low innovation performance. Consistent with Jia and Ma (2017) and Savrul and Incekara (2015), we have shown that even though R&D tax credit is critical to innovation performance, some other factors such as the level of innovation performance is an important in determining its effectiveness.

5.2 Effect of the interaction between R&D tax credit and R&D intensity on Innovation Performance

The findings of the study have shown that the effect of the interaction between R&D tax credit and R&D intensity on innovation performance is a variant of the chosen estimation strategy. Even though the Pooled OLS and fixed effect models show that the interaction between R&D tax credit and R&D intensity has a positive effect on innovation performance, the random effect model finds no significant relationship. In this study, however, the model selection criteria used rejects both the pooled OLS and the fixed effect model. The study, therefore, based on the random effect model, finds no evidence in support of the hypothesis that the interaction between R&D tax credit and R&D intensity affects innovation performance. The findings of the study agree with Chen and Yang, (2019) who make the argument that firm and industrial factors are important in explaining why R&D input may or may not improve innovation performance. In this study even though the full sample analysis finds no evidence to support the hypothesis that the interaction between R&D tax credit and R&D intensity improves innovation performance based on the random effect analysis, the sub sample analysis finds evidence to support the hypothesis for countries with high innovation performance. Another important aspect of the study findings is that the effect of the interaction between R&D tax credit and R&D intensity on innovation performance is a dynamic process and not a static process. This means that the effect of the interaction term on innovation performance occurs in time. There is therefore some sluggishness in the effect of the interaction between R&D tax credit and R&D intensity on innovation performance. However, even in the dynamic effect, the interaction between R&D tax credit and R&D intensity is more effective in economies with high innovation performance. The findings of the current study are therefore in sync with the position of authors such as Jia and Ma (2017) and Savrul and Incekara (2015) the effect of innovation inputs on innovation performance is not automatic but it requires the presence of some other favourable factors such as a high level of innovation performance. What is also important to highlight is that one of the important sources or reasons for the inability of the interaction between R&D intensity and R&D tax credit to improve innovation performance in the random effect analysis is that R&D intensity is not significantly related to innovation performance. This is an indication that R&D capacity measured by R&D intensity is important for collaboration between internal R&D resources and external R&D inputs. We state in this paper therefore that firms for lack of sufficient internal R&D resources, in the face of R&D tax credit substitute R&D tax credit for internal R&D intensity.

5.3 Effect of the interaction between R&D tax credit and R&D Personnel capacity on Innovation Performance

The capacity of R&D personnel of a country is a function of the number of people with tertiary education. R&D personnels are considered the brain that translates all R&D inputs into innovation. Countries with R&D personnels with the capacity to translate innovation inputs into innovation outcomes are more likely to experience enhanced innovation performance. In this study, we have shown empirically that the hypothesis that the interaction between the capacity of R&D personnel and R&D tax credit enhances innovation performance is confirmed. This agrees with the empirical literature that suggests that both R&D tax credit and the capacity of R&D personnel are important determinants of innovation performance. If R&D tax credit which frees resources to firms in terms of cost savings after tax for R&D activities are considered part of firm R&D expenditure, it brings to fore the position of Afcha and Garcíaquevedo (2014) that tax credit enhances the chances of recruiting PhD graduates as a means to boost innovation performance. We state that improved R&D tax credits have different channels of improving innovation performance. One of the important channels is the R&D personnel recruited. From the findings of the current study, it is our position that R&D tax credit works to improve innovation performance through recruiting highly qualified R&D staff with tertiary education. It is important to understand the working of innovation that it is a risky enterprise for firms. There government incentive such as tax credit serves as a risk reduction strategy that allows firms to invest in areas they may not have invested such as recruiting highly qualified R&D staff. This position is inspired by the findings of the study which in itself confirms the positive correlation between R&D tax credit and recruitment of PhD graduates for R&D observed by Zhu, Zhao, and Abbas (2020). This study agrees very much with the findings of Leibfritz and Janger (2007) who observed that the capacity of R&D staff becomes more critical for innovation performance when high technology is involved. We have also shown that the innovation performance is responsive to the combinatorial effect of R&D tax credit and the capacity of R&D personnel, the response sluggish and fairly inelastic with an elasticity of 0.36%.

Table 6 shows the confirmation of the hypotheses.

Table 6. Confirmation of hypotheses.

Hypotheses Statements	Accept/Rejected
H1: R&D tax incentives improve the innovation of firms in the selected OECD countries.	Accepted
H2: R&D tax incentive is displaced by increasing R&D intensity of firms among OECD countries.	Rejected
H3: The interaction between R&D tax credit and R&D personnel capabilities of a country determines innovation performance.	Accepted

Conclusions

In this study, we have investigated the role of R&D tax credit in innovation performance of selected OECD countries. Three main channels through which R&D affects innovation performance, direct channels, through R&D intensity of the countries, and R&D personnel capacity. The investigations were conducted using three estimation strategies, pooled OLS, random effect model, and fixed effect model. Using the explanatory power and ability of models to capture the desired dynamic process that characterises innovation activities, the random effect model was found to be the ideal model for efficient analysis. It is concluded based on the findings of the study that the effect of R&D tax credit cannot be generalised as some specific factor unique to a country or the innovation process can make a big difference. In this study, we conclude that the size or level of innovation performance and the channel are important to how effective R&D tax credits affect innovation performance. Lower levels of innovation performance are associated with a more contemporaneous effect of innovation inputs with much greater effect size than when innovation performance is high. There is generally sluggish response of innovation performance to changes in R&D tax credit and the extent of this drag and the effect on innovation is determined by several factors but notable among them is the variables through which the R&D tax credit affects innovation performance. Innovation is most responsive to R&D tax credit at an elasticity coefficient of 0.72% and the interaction between R&D tax credit and R&D personnels capacity at an elasticity coefficient of 0.36%. Innovation performance is not responsive to the interaction between R&D tax credit and R&D intensity at full sample analysis but shows evidence of responsiveness in the case of large patent countries but with reduced effect for low patent application countries.

The study findings imply that for policy purposes, R&D tax credit as a means of improving innovation should be determined in consonance with variables such as the capacity of R&D personnel and not just the size of R&D intensity. This is important because just considering the size of R&D intensity blurs issues of quality such as the calibre of people forming the R&D personnels to drive innovation activities. This is more important when high technology is involved in driving innovation of a country. Moreover, Policymakers should consider targeted specific types of firms, which are more likely to benefit from R&D tax credits (Falck et al., 2023). Continuously, balancing direct and indirect support should be considered, which means creating a more effective combination of tax incentives and direct funding, which can lead to the most beneficial results to encourage innovation (Appelt et al., 2020). In addition, R&D personnel capacity is an important factor of policy, therefore, investment in human capital should be considered.

It is recommended that future studies on the effect of R&D tax incentives on innovation consider using a more embracing measure of innovation or use several of the measures of innovation. This is to address the problem of defects in measuring innovation. It is also recommended for future studies to consider the effect of R&D tax incentives on the various types of innovation such as process, product, market, and organizational innovation. The possibility exists that the behavior of these innovation variables about R&D tax incentives will differ.

The findings of the study make clear that some other government R&D support schemes crowd out R&D tax incentives. However, the specific support schemes are beyond the scope of the study. It is recommended for future studies to determine the specific schemes that crowd out R&D tax incentives. Finally, long-term effects of R&D tax credits on innovation and the role of other mediating factors could be explored.

References

Acquah, A. M., & Ibrahim, M. (2020). Foreign direct investment, economic growth and financial sector development in Africa. *Journal of Sustainable Finance & Investment*, *10*(4), 315-334.

Afcha, S., & Garcíaquevedo, J. (2014). The impact of R&D subsidies on R&D employment composition. *Industrial and Corporate Change, 25*(6), 955–975.

Appelt, S., Bajgar, M., Criscuolo, C., & Galindo-Rueda, F. (2020). *The Effects of R&D Tax Incentives and Their Role in the Innovation Policy Mix Findings from the OECD MicroBeRD Project, 2016-19*. OECD Publishing.

Artige, L., & Cavenaile, L. (2023). Public education expenditures, growth and income inequality. *Journal of Economic Theory*, *209*, 105622.

Barbaroux, P. (2014). From market failures to market opportunities: managing innovation under asymmetric information. *Journal of Innovation and Entrepreneurship*, 3(1).

Bloom, N., Griffith, R., & Reenen, V. (2002). Do R&D tax credit Work. *Journal of Public Economics*, 85, 1-31.

Bronzini, R., & Piselli, P. (2016). The impact of R&D subsidies on firm innovation. *Research Policy*, 45, 442-457.

Bustinza, O., Gomes, E., Vendrell-Herrero, F., & Baines, T. (2019). Product-Service Innovation and Performance: The role of Collaborative Partnership and R&D Intensity. *R&D Management*, 49(1), 33-45.

Carrasco-Carvajal, O., García-Pérez-de-Lema, D., & Castillo-Vergara, M. (2023). Impact of innovation strategy, absorptive capacity, and open innovation on SME performance: A Chilean case study. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(2), 100065.

Carvache-Franco, O. G.-C., Guim-Bustos, P., Carvache-Franco, M., & Carvache-Franco, M. (2020). Effect of R&D intensity on the innovative performance of manufacturing companies: Evidence from Ecuador, Peru and Chile. *International Journal of Innovation Science*, 12(5).

Castellacci, F., & Lie, C. M. (2015). Do the effects of R&D tax credits vary across industries? A meta-regression analysis. *Research Policy*, *44*(4), 819-832.

Chen, L., & Yang, W. (2019). R&D Tax Credit and Firm Innovation: Evidence from China. *Technological Forecasting and Social Change*, 146, 233-241.

Chen, Y., & Puttitanum, T. (2005). Intellectual Property Right and Innovation in Developing Countries. *Journal of Development Economics*, 78(2), 474-493.

Chlebovsky, V., Schuller, D., & Skapa, S. (2018). Are Product Innnovation-Oriented Firms Prepared for Effective Product Customisation. *Scientific Papers of University of Pardubice, Faculty of Economics and Administration. Series D*, 44(1).

Cui, Y., Zhao, Q., Glauben, T., & Si, W. (2024). The impact of Internet access on household dietary quality: Evidence from rural China. *Journal of Integrative Agriculture*, *23*(2), 374-383.

Czmitzki, D., Hanel, P., & Rosa, J. (2011). Evaluating the Impact of R&D tax credits on Innovation: A Microeconometric Study on Canadian Firms. *Research Policy*, 40(2), 217-229.

d'Agostino, G., Dunne, J. P., & Pieroni, L. (2016). Government spending, corruption and economic growth. *World development*, *84*, 190-205.

Dimos, C., Pugh, G., Hisarciklilar, M., Talam, E., & Jackson, I. (2022). The relative effectiveness of R&D tax credits and R&D subsidies: A comparative meta-regression analysis. *Technovation*, 115, 102450.

Dong, Y., We, Z., Liu, T., & Xing, X. (2021). The Impact of R&D Intensity on the Innovation Performance of Artificial Intelligence Enterprises- Based on the Moderating Effect of Patent Portfolio. *Sustainability*, 328, 1-17.

Du, W., & Li, M. (2018). Government support and innovation for new energy firms in China. *Applied Economics*, 51(25), 2754-2763.

Falck, O., Kerkhof, A., & Pfaffl, C. (2023). Taxation and innovation: How R&D tax credit schemes foster innovation in the private sector. *EconPol Forum*, 24(4), 61-66.

Fan, P. (2021). Export Technological Sophistication of China: Measurement and Impact Factor. *Discrete Dynamics in Nature and Society*, *2021*, 1-9.

Farooq, U., Wen, J., Tabash, M. I., & Fadoul, M. (2024). Environmental regulations and capital investment: Does green innovation allow to grow?. *International Review of Economics & Finance*, *89*, 878-893.

Fosah, M. S. G., Mama, N., Dinga, G. D., & Nchofoung, T. N. (2023). The effect of globalisation on Sub-Saharan Africa's development thrives. *Research in Globalization*, *7*, 100149.

Guoa, D., Guo, Y., & Jiang, K. (2016). Government-subsidized R&D and firm innovation: Evidence from China. *Research Policy*,

45, 1129-1144.
Halaskova, M., & Bednar, P. (2018). Public Research and Development in European Union Countries-Evaluation Based on Selected Indicators. *Scientific Papers of the University of Pardubice. Series D. Faculty of Economics and Administration*, 43.
Halaskova, M., Halaskova, R., & Prokop, V. (2018). Evaluation of efficiency in selected areas of public services in European Union countries. *Sustainability*, 10(12), 4592.
Hall, B., & Reenen, J. (2000). How effective are fiscal incentives for R&D? A review of the evidence. *Research Policy*, 29, 449–469.
Hsu, F., & Hsueh, C. (2009). Measuring relative efficiency of government-sponsored R&D projects: A three-stage approach. *Evaluation and program planning*, 32, 178–186.
Huang, K. F., Lin, K. H., Wu, L. Y., & Yu, P. H. (2015). Absorptive capacity and autonomous R&D climate roles in firm innovation. *Journal of Business Research*, 68(1), 87-94.
Ivus, O., Jose, M., & Sharma, R. (2021). R&D tax credit and innovation: Evidence from private firms in India. *Research Policy*, 50, 1-16.
Jia, J., & Ma, G. (2017). Do R&D tax incentives work? Firm Level Evidence from China. *China Economic Review*, 46, 50-66.
Kafourosa, M., Wangb, C., Piperopoulosa, P., & Zhang, M. (2015). Academic collaborations and firm innovation performance in China: The role of region-specific institutions. *Research Policy*, 44, 803–817.
Klimova, V. (2018). How Do Regions use Indirect R&D Support for their Innovation Activities? *Scientific Papers University of Pardubice. Series D. Faculty of Economics and Administration*, 42(1), 104-115.
Kobayashi, Y. (2014). Effect of R&D Tax Credit on SMEs in Japan: A Microeconomic Analysis focused on Liquidity Constraints. *Small Business Economics*, 42, 311-327.
Lee, G. H., & Parasnis, J. (2014). Discouraged workers in developed countries and added workers in developing countries? Unemployment rate and labour force participation. *Economic Modelling*, *41*, 90-98.
Li, H., Ru, S., & Shi, V. Z. (2021). The Effect of Government Subsidy Policy for Foreign Capital R&D from the Perspective of Global Supply Chain: An Empirical Analysis with Time Lag and Propensity Score Matching. *Sustainability*, 13(15), 1-12.
Martin, S., & Scott, J. (1998). Market failures and the Design of Innovation Policy. Report prepared for the Working Group on Technology and Innovation Policy, Division of Science and Technology, OECD.
Martin, S., & Scott, J. T. (2000). The nature of innovation market failure and the design of public support for private innovation. *Research policy*, *29*(4-5), 437-447.
Mitchell, J., Testa, G., Martinez, M., Cunningham, P., & Szkuta, K. (2020). Tax incentives for R&D: Supporting Innovative Scale Set-Up? *Research Evaluation*, 29(2), 121–134.
Mohnon, P., & Lockshin, B. (2011). What does it take to make R&D tax Incentive Policy to be Effective. In: V. Ghosal, Reforming Rules and Regulations, Laws Institutions and Implementation, pp. 1-43. London, England: The MIT Press.
Muhamad, S., Sulaiman, N. F., & Saputra, J. (2018). The role of human capital and innovation capacity on economic growth in ASEAN-3. *Juornal Ekonomi Malaysia, 52*(1), 281-294.
OECD (2020). The effects of R&D tax incentives and their role in the innovation policy mix: Findings from the OECD microBeRD project, 2016-19. OECD Publishing. Retrived October 20, 2021, from OECD Science, Technology and Industry Policy Papers, No. 92.
Park, H., Park, J., Lee, S., & Hahn, H. (2021). A Study on the Impact on the Impact of R&D Intensity on Business Performance: Evidence from South Korea. *Journal of Open Innovation: Technology, Market and Complexity*, 7(2), 1-12.
Prokop, V., & Stejskal, J. (2015). Impacts of local planning to competitiveness index change–using approximate initial analysis to the Czech regions. *WSEAS Transactions on Business and Economics*, 12(1), 279-288.
Prokop, V., & Stejskal, J. (2019). Different influence of cooperation and public funding on innovation activities within German industries. *Journal of Business Economics and Management*, 20(2), 384-397.
Prokop, V., Kotkova Striteska, M., & Stejskal, J. (2021). Fostering Czech firms' innovation performance through efficient cooperation. *Oeconomia Copernicana*, 12(3), 671-700.
Sandu, S., & Ciocanel, B. (2014). Impact of R&D and innovation on high-tech export. *Procedia Economics and finance*, *15*, 80-90.
Savrul, M., & Incekara, A. (2015). The Effect of R&D Intensity on Innovation Performance: A Country Level Evaluation. *Procedia - Social and Behavioral Sciences*, 210, 388-396.
Saymeh, A. A., & & Orabi, M. M. (2013). The effect of interest rate, inflation rate, GDP, on real economic growth rate in Jordan. *Asian Economic and financial review, 3*(3), 341.
Skordoulis, M., Ntanos, S., Kyriakopoulos, G. L., Arabatzis, G., Galatsidas, S., & Chalikias, M. (2020). Environmental innovation, open innovation dynamics and competitive advantage of medium and large-sized firms. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 195.
Stejskal, J., Hájek, P., & Prokop, V. (2018). Collaboration and innovation models in information and communication creative industries–the case of Germany. *Journal of Information and Communication Technology*, 17(2), 191–208.
Subramanian, A. M., Choi, Y. R., Lee, S. H., & Hang, C. C. (2016). Linking technological and educational level diversities to innovation performance. *The Journal of Technology Transfer, 41*, 182-204.
Szczygielski, K., Grabowski, W., Pamukcuc, M., & Tandogan, V. (2016). Does government support for private innovation matter? Firm-level evidence from two catching-up countries. *Research Policy*, 46, 219-237.
Teslenko, V., Melnikov, R., & Bazin, D. (2021). Evaluation of the Impact of Human Capital on Innovation Activities in Russian Region. *Regional Studies, Regional Science*, 8(1), 109-126.
Tian, B., Yu, S., & Ye, J. (2020). Tax Incentive, R&D Investment and Firm Innovation: Evidence from China. *Journal of Asian Economics*, 71, 1-14.
Wang, Q., Zhang, F., & Li, R. (2024). Free trade and carbon emissions revisited: the asymmetric impacts of trade diversification and trade openness. *Sustainable Development*, *32*(1), 876-901.

Yang, C. H., Huang, C. H., & Hou, T. C. T. (2012). Tax incentives and R&D activity: Firm-level evidence from Taiwan. *Research Policy*, 41(9), 1578-1588.

Yu, X., Dilanchiev, A., & Bibi, S. (2024). Enhancing labor productivity as a key strategy for fostering green economic growth and resource efficiency. *Heliyon*, *10*(3).

Zhu, H., Zhao, S., & Abbas, A. (2020). Relationship between R&D grants, R&D investment, andinnovation performance: The moderating effect of absorptivecapacity. *Journal of Public Affairs, 20*(1), 1-10.

Appendices

Table A. Descriptive Statistic.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.RGDPgr	1.00																	
2.Cpinvt	0.34	1.00																
3.GOVTsp	-0.30	-0.08	1.00															
4.INTup	-0.17	-0.16	0.40	1.00														
5.INNdx	-0.05	0.08	0.36	0.25	1.00													
6.R&Dint	-0.21	-0.03	0.58	0.51	0.52	1.00												
7.INFtecx	0.01	0.06	0.07	0.06	-0.02	-0.01	1.00											
8.HTECxp	-0.10	-0.17	0.15	0.10	0.08	0.37	0.03	1.00										
9.PATapp	-0.11	-0.20	-0.07	0.03	0.18	0.33	-0.02	0.90	1.00									
10.PUBse	-0.17	-0.05	0.68	0.34	0.36	0.54	0.06	0.39	-0.19	1.00								
11.Glindx	-0.23	-0.14	0.59	0.68	0.36	0.65	0.09	0.30	0.23	0.37	1.00							
12.Labpr	-0.19	-0.04	0.54	0.50	0.33	0.59	0.07	-0.30	0.22	0.55	0.72	1.00						
13.LabP	0.05	0.17	0.21	0.38	0.14	0.24	-0.05	-0.05	-0.12	0.36	0.17	0.25	1.00					
14.Trdop	0.17	0.06	0.08	0.22	-0.01	-0.08	0.13	-0.11	-0.26	-0.08	0.15	-0.16	0.00	1.00				
15.Pseps	0.24	0.15	-0.08	-0.13	0.06	-006	-0.01	-0.42	-0.41	0.26	-0.37	-0.22	0.40	0.00	1.00			
16.Tenel	-0.03	0.02	0.15	0.37	0.21	0.21	0.03	-0.50	-0.49	0.35	0.05	0.11	0.26	-0.11	0.44	1.00		
17.PwFDI	-0.01	-0.06	0.06	-0.01	-0.02	0.08	-0.04	0.33	0.27	-0.08	0.17	0.18	0.00	-0.87	-0.11	-0.19	1.00	
18.RDtax	-0.15	-0.02	0.36	0.29	0.21	0.41	0.01	0.20	0.18	0.35	0.39	0.60	0.19	-0.16	-0.13	0.11	0.06	1.00
Obs	368	368	368	368	368	368	366	368	368	363	362	368	368	368	368	368	368	368
Mean	2.05	23.04	20.69	68.46	49.16	1.78	91.23	33749	5689	5.308	83.32	78.85	59.12	96.99	11.48	69.93	1.60	0.71
Std.dev	3.04	3.56	2.52	22.62	7.34	0.77	1635	51649	11362	1.09	4.75	23.71	4.43	40.46	2.01	19.53	4.04	0.43
Min	-14.84	12.66	16.3	6.43	24.66	0.45	0.74	961.34	62	3.52	65.57	31.38	48.13	37.01	7.1	4.99	-39.17	0.21
Max	11.11	33.05	27.93	99	63.4	3.73	31294	223370	51736	8.56	91.31	176.88	67.46	204.12	19.18	119	23.98	6.88

Table B. Control group analysis.

lPATappres Variables/Models	Countries with the highest Patent Applications. Mean of 15,402.96			Countries with mid Patent Applications. Mean of 1986.106			Countries with low Patent Applications. Mean of 681.2933		
lPATappres_L1	0.0000138*** (4.47e-06)	0.0000104*** 4.79e-06	0.0000246*** (3.99e-06)	0.0000321** (0.0000167)	0.0000456*** 0.0000138	0.0000309* 0.0000175	0.0000169 0.0000381	0.0000158 (0.0000385)	4.04e-06 (0.0000388)
(lRD_tax* lRDint)		0.5294661* 0.2945699			-1.878029*** (0.3152075)			0.1028126 (0.3653364)	
(lRD_tax*lTer_enrlElig)			0.5387883 (0.6073038)			0.1487158 0.5985026			2.801325** (1.164787)
lRD_tax	0.4541647** (0.187409)	1.052514** (0.2136138)	-1.7161 (2.606754)	0.989252*** (0.0986858)	1.703582*** 0.1442324	0.3188905 2.708182	2.050841*** (0.4229013)	2.123885*** (0.4980801)	-10.20763** (4.832311)
lRDint	1.095694*** (0.2153921)	- 0.0923231*** (0.0362885)	1.257114*** (0.3569454)	-0.0193154 (0.0656418)	-0.0732641 (0.0540952)	-0.0338636 (0.1636144)	0.8353149*** (0.1675937)	0.8753542*** (0.2205084)	1.407971*** (0.2570476)
lTer_enrlElig	- 0.1822194*** (0.0692166)	- 0.2090644*** (0.0698256)	-0.0106488 (0.1469722)	0.0714532 (0.0666736)	0.0700281 (0.0541708)	0.1391757 (0.2780386)	-2.354039*** (0.429686)	-2.358683*** (0.4322413)	0.5077908 (1.204684)
lRGDPgr	- 0.0946395*** (0.0368009)	- 0.0923231*** (0.0362885)	- 0.1012736*** (0.0399347)	0.0485861* (0.0262574)	0.0367652* (0.0214254)	0.046382* (0.0272394)	-0.0173061 (0.0978683)	-0.0181346 (0.0984226)	-.006358 (0.0951535)
lCpinvt	-0.2118626 (0.2953441)	-0.3132832 (0.2964667)	-0.1442159 (0.3248402)	- 0.8458485*** (0.2224045)	-0.6781121*** (0.182877)	-0.8417247*** (0.228684)	0.034495 (0.4071294)	0.0038741 (0.4234697)	-0.2387249 (0.4431539)
lGOVTspgdp	0.3606006 (0.8026933)	0.1411671 (0.8003813)	0.6664754 (0.8944766)	-1.247736*** (0.4361155)	-0.8173306** (0.3616196)	-01.212415*** (0.4760165)	-0.2863429 (1.116383)	-0.3936692 (1.185238)	-0.6675733 (1.184537)
lINTupop	0.238774* (0.1347017)	0.338228** (0.1438125)	0.1405369 (0.1557511)	0.2657867** (0.1107402)	0.1644154* (0.0915677)	0.242472* (0.134329)	0.6193634*** (0.2427284)	0.6215427*** (0.2441168)	0.3380862 (0.2561578)
lINFtecxtox	0.4523498*** (0.09168)	0.4465813*** (0.0904032)	0.3905314*** (0.1006982)	-0.0350952 (0.0522931)	0.0332291 (0.0440069)	-0.0380379 (0.0511247)	-0.1070504 (0.1195731)	-0.1015904 (0.1217522)	-0.0059767 (0.1239491)
DlHTECxp	0.0929851 (0.1003148)	0.1436269 (0.1027921)	0.1640909* (0.1074584)	0.2856547*** (0.0638098)	0.2511974*** (0.0521651)	0.2905556*** (0.0654895)	-0.1725894* (0.1180679)	-0.1722394* (0.11869)	-0.0816784 (0.1206327)
lGlindx	-3.542442* (2.113555)	-5.803391** 2.43318	-1.486099 (2.437157)	1.186204 (1.792157)	0.5379261 (1.460134)	1.218202 (1.822603)	2.308288 (2.872087)	2.134428 (2.952423)	-0.7325879 (0.7058078)

DlLab_Prod	-0.3651849 (0.4276718)	0.3517493 (0.5802725)	-1.000409* (0.6306702)	-1.376522*** (0.2278139)	-0.996604*** (0.1957678)	-1.372998*** (0.2419703)	-0.7279739 (0.6991942)	-0.6842107 (0.7198377)	-0.7325879 (0.7058078)
DlLab_Prate	-5.025196*** (0.8349237)	-4.280133*** 0.9212967	-4.672389*** (0.936025)	2.15995*** (0.8384551)	1.657283** (0.6864241)	2.279962*** (0.8618129)	-1.425758 (2.047495)	-1.43128 (2.058263)	-3.008029 (2.136687)
DlTrd_Opness	0.0843698 (0.351322)	0.1965249 (0.3517891)	0.2147688 (0.3881625)	- 0.6799874*** (0.2480234)	-0.5835846*** (0.2021601)	-0.6851113*** (0.2523106)	-0.527202 (0.398217)	-0.5463344 (0.4060254)	-0.5278822 (0.3905759)
lPUBspedugdp	-1.404777** (0.6311861)	-1.701191*** 0.6434937	-1.012652 (0.7989155)	-0.4753255** (0.2329819)	-0.116669 (0.198632)	-0.4625573* (0.2410747)	-1.029546 (0.8021935)	-1.061033 (0.814101)	-1.107515 (0.7962567)
lwld_FDI	-0.0454838 (0.0389716)	-0.0607706* (0.0393351)	-0.0052405 (0.0430196)	-0.0023335 (0.0237401)	-0.0044723 (0.0192914)	-0.000923 (0.0239119)	-0.0624226 (0.0801498)	-0.0643082 (0.0808458)	-0.0582801 (0.0783767)
_cons	44.32384*** (7.770183)	48.47313*** 7.997555	34.47343 (8.068816)	5.917304 (8.345115)	6.898286 (6.782154)	4.885174 (9.104307)	18.58024 (15.73505)	19.74653 (16.35101)	14.59657 (15.38021)
Within	0.3817	0.3877	0.3880	0.7906	0.8600	0.7912	0.3426	0.3436	0.3653
Between	0.9989	0.9989	0.9986	0.9940	0.9994	0.9934	0.9509	0.9508	0.9607
Overall	0.9628	0.9644	0.9575	0.8914	0.9294	0.8913	0.7077	0.7079	0.7273
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000