Internal and External Effects of R&D Subsidies and Fiscal Incentives.
Empirical Evidence Using Spatial Dynamic Panel Models

Benjamin Montmartin* and Marcos Herrera†

GREDEG Working Paper No. 2014-09

Abstract

Most studies evaluating the macroeconomic effects of financial support policies on business-funded R&D use econometric methods that do not consider the existence of spatial effects, and generate biased estimates. In this paper, we discus and address this problem using spatial dynamic panel data methods. This allow us to provide new insights on the internal (in-country) and external (out-of-country) effects of both Research and Development (R&D) subsidies and fiscal incentives. We use a database of 25 OECD countries for the period 1990-2009. In relation to internal effects, for both instruments, we find a non-linear relationship between their effect on private R&D and their level (suggesting the possibility of leveraging and crowding-out effects). We also find a substitution effect between the R&D subsidies and fiscal incentives implemented within a country. Concerning the spatial component, we find evidence of positive spatial spillovers among private R&D investments. However, our results suggest the existence of competition/substitution effects between national R&D policies.

Keywords: Direct and Indirect support, Business-funded R&D, Complementarity, Dynamic spatial panel data.

JEL Classification: H25, O31, O38.

*Corresponding author; University of Nice Sophia-Antipolis; Nice, F-06000, France; CNRS, GREDEG UMR 7321, Valbonne, F-06560, e-mail: benjamin.montmartin@unice.fr

†CONICET - IELDE, National University of Salta; Av. Bolivia 5150 (A4408FVY), Salta, Argentina; email: mherreragomez@gmail.com.

1 Introduction

The European Commission has set an R&D investment objective for the "2020 European Strategy"[1] at 3% of GDP, two-thirds of which should be financed by the private sector. In 2012, the EU's R&D investment is estimated at 2.06% of GDP, financed 55% by the private sector (source: Eurostat). Thus, the public sector investment objective (0.93% vs 1%) has almost been achieved but, the private sector contribution is lagging (1.13% vs 2%). The rationale for these objectives and public support for private R&D, is the common belief that R&D specificities generate numerous market failures[2] leading to a sub-optimal equilibrium and private under-investment in R&D.

A growing literature[3] discusses and evaluates the capacity of financial support policies to increase private investment in R&D through two main instruments: tax incentives (indirect support) and direct subsidies (direct support). This topic is especially important in a context of public budget pressure that requires all public expenditure to be justified and effective. In the context of financial support for R&D, although most macroeconometric studies provide evidence on the effectiveness of such measures to increase private investment in R&D, some basic questions remain unaddressed. These are related to crowding-out effects and distortions between firms and sectors that can be generated by direct and indirect support. In an empirical context, while the cost of financial support for R&D has increased significantly in European countries, the evolution of privately financed R&D has been relatively flat.[4] Also, in EU countries with the highest level of private investment in R&D (Denmark, Germany, Finland, Sweden) support for R&D - either, direct (subsidies) or indirect (fiscal incentives) - is less than the EU and OECD averages.

The economic literature distinguishes tax incentives and direct subsidies according to their design, timing, cost and potential welfare impact. Obviously, the main difference between direct and indirect support is that the former typically allows firms to choose projects, while the latter usually is related to a public authority project choice. Concerning timing, R&D subsidies do not always require an initial R&D investment from the firm, and thus can be used to finance a current R&D project. However, to benefit from fiscal incentives firms must first conduct and finance R&D. In relation to relative cost, it is often argued that direct support implies heavier administrative costs than indirect support, and in terms of welfare impact, many economists highlight the risk that indirect support favors projects with high private returns not high social returns while direct support seems to be linked to projects with considerable social returns.[5] Table 1 presents an overall view of the main advantages and disadvantages of each instrument in terms of its cost, efficiency and welfare impact.

The extensive empirical literature evaluating the impact of financial support on private investment in R&D mostly (1) evaluates the capacity of a specific measure to increase private R&D investment and (2) is at a microeconomic level. Only four studies analyze the impact of both direct and indirect support at the macroeconomic level.[6] However, macroeconomic investigation of financial support would seem very useful in many respects: to evaluate the global effect of R&D policies, to discuss the complementarity of instruments and the pertinence of the policy mix, and to understand their cross-border effects. The small number of macroeconometric works mean much remains to be done.

[1]The objectives set by "2020 European Strategy" are the same as those in the Lisbon agenda (2000) for R&D. For further information see: $http://ec.europa.eu/europe2020/index_en.htm$.

[2]Such as knowledge spillovers, surplus appropriability problems, duplications, etc.

[3]See reviews by David *et al.* (2000), Hall and Van Reenen (2000), Lentille and Mairesse (2009) and Lokshin and Mohnen (2009).

[4]Privately financed R&D increased from 1.03% of GDP in 1999 to 1.13% in 2012.

[5]Altough the allocations made by public authorities are often questioned for their efficiency.

[6]Guellec and Van Pottelsberghe de la Potterie (2003), Shin (2006), Falk (2006) and Montmartin (2013).

Table 1: Advantages and Disadvantages of Support

	Advantages	Disadvantages
Direct support	• Adapted to target upon activities and projects where there is a significant gap between private and social returns to R&D. • Theoretically, competition between firms ensures that public funds are used for the best R&D projects. • May be used to reduce the effects of economic cycles on firms' R&D investments. • May encourage cooperation and the transfers of technology thereby reinforcing knowledge externalities • Allows the verification of costs entailed by measures. • May enhance the reputation of firms who have received financing thereby reducing their capital cost (SMEs).	• High administrative costs for both firms and public authorities. • Impossible to put into practice for a large number of projects. • Causes distortions on the markets for the allocation of resources between different R&D fields and firms. • Project selection tends to reward lobbies. The pressure related to the result objectives of the established policies entails the risk of projects being selected due to their high success potential, i.e., projects with high private productivity carried out without any public funding. • Numerous potential eviction sources, due to the fact that direct measures are targeted and affect returns to R&D.
Indirect support	• Measures are more neutral as they encourage investment in R&D for all firms, particularly SMEs (although specific sectors may also be targeted). • The firms themselves decide which projects they wish to invest in. • Reduces the risk of public markets being rigged. • Does not require a specific budget line as the cost is only expressed in terms of a loss of financial income. • Implementation and management costs are relatively low (although they are tempered by the OECD). • Financial measures reduce the cost of R&D directly which theoretically reduces the potential eviction sources.	• It is difficult to control the cost of financial measures. • The effects are limited for firms who do make sufficient profit or which invest heavily in R&D (large companies) because they do not reap the maximum benefit from the financial measures. • Non-neglect able risk of eviction as these measures can reduce the cost of projects which would have been carried through anyway (particularly in the case of a large tax credit). • Financial incentives favour R&D projects with the highest short-term productivity. Hence, projects with high social returns to R&D will not be favoured by this type of measure. • Few knowledge externalities are generated as the firms choose the projects and cooperation is rarely a factor for eligibility.

Notes: Adapted of Carvalho (2011).

The literature mostly ignores the possibility of an external (out-of-country) impact of R&D policies, i.e, a country's R&D investment is considered only to be affected by the home country environment and R&D policies. However, Tobler's (1970, p.234) first law of geography reminds us that "everything is related to everything else, but near things are more related than distant things", i.e, a country's R&D investment may well be affected by the environment and policy decisions of other countries (and vice-versa). Distance is understood as proximity, not necessarily geographical distance, such as the intensity of trade or scientific collaboration for instance. Given the nature of knowledge creating activities and the existence of localized knowledge externalities, it might be expected that private R&D investment in country i could be affected by private R&D intensity and the R&D policy incentives of other countries.

The main objective of this paper is to investigate more comprehensively the global effects of direct and indirect support policies by considering both temporal and spatial dependence of R&D activities.

Although temporal dependence[7] has been modeled in previous works, spatial dependence has been ignored. The presence of spatial dynamics in panel data models generates important spatial spillovers effects that condition the standard results. We provide new empirical evidence based on data for 25 OECD countries in the period 1990-2009. In terms of internal effects, we show that, for both instruments, there exists a non-linear relationship between their effect on the business-funded R&D intensity and their level of use. This suggest the possibility of both leveraging and crowding-out effects of these policies according to their exploitation by countries. The spatial component of our work provides evidence that business-funded R&D intensity generates positive spatial spillovers. However, the fact that policies implemented by neighboring countries (in terms of scientific cooperation) have the opposite impact to national policies highlights a positive external effect of R&D subsidies and a negative external effect of fiscal incentives. In other words, it seems that R&D policies implemented by different countries are substitutes.

The paper is organized as follows. In section 2, we present the theoretical macroeconomic effects of financial support policies; section 3 investigates and briefly reviews the empirical literature on these effects. Section 4 develops dynamic panel data models and extensions that introduce spatial effects. Section 5 presents the empirical methodology applied to the dataset of 25 OECD countries observed during 20 years, and the results of different specification including a variety of spatial effects. Section 6 concludes the paper.

2 Theoretical and empirical analysis of the effects of direct and indirect support at the macroeconomic level

2.1 A simple framework of private R&D investment

David *et al.* (2000, p.502) observed that the economic literature is "predominantly inductive in its approach to considering the effects of government R&D funding upon the level of business R&D investment behavior", and this observation remains relevant even with the emergence of a microeconomic literature (Inci, 2009; Klette and Moen, 2011; and Takalo *et al.*, 2013). The conceptual framework developed by David *et al.* (2000) based on the seminal work of Howe and McFetridge (1976), provides interesting elements to assess the effect of different R&D financial support policies at the macroeconomic level. This framework is the principal theoretical reference for several macroeconometric works.[8]

The framework proposed by David *et al.* (2000) treats the firm's R&D decision as an asset acquisition decision, and assumes that at each time in point, an array of potential R&D investments projects or a "technological innovation possibility set" is available to the firm. Each project is perfectly divisible and firms are able to evaluate the associated (internal) rate of return (which allow firms to compare and rank the profitability of each projects). Based on these assumptions, each firm will rank projects in descending order of anticipated yield, thereby forming a continuous and continuously differentiable marginal rate of return (MRR) schedule. Obviously, firms also face a marginal cost of funds (MCF) schedule, which reflects the opportunity cost of investment funds at different levels of R&D investment. David *et al.* (2000) propose a simplified schema to represent the MRR and MCC curves:

$$MRR = f(r, x), \quad MCC = g(r, z),$$

where r represents the level of R&D expenditure and x and z represent vectors of the "shift variables" that determine the distribution of project rates of return and the associated marginal cost of capital. In the David

[7]The introduction of temporal dependence in empirical works is related to the strong adjustments costs of R&D investment that do not allow firms to react fully to environmental changes within a period.

[8]See Guellec and Van Pottelsberghe (2003), Shin (2006), Falk (2006), Cerulli (2010) or Montmartin (2013).

et al.'s scheme the x-variables refers to - (1) the technological opportunities, (2) the state of demand in its potential market, and (3) the appropriability of innovation benefits. Correspondingly, the z-variables refers to - (1) financial support policies: direct subsidies, fiscal incentives and other support, (2) macroeconomic conditions affecting the internal cost of funds, (3) bond market conditions affecting the external cost of funds, and (4) the availability of external sources of funds. Considering that firms are profit maximizers, the level of R&D expenditure can be assumed to proceed to the point at which the MRR to R&D equals the MCF.

2.2 On the internal (in-country) effect of R&D financial support

The first side of the internal effect: the individual effect of each instrument

Using David *et al.*'s (2000) simple framework and assuming the absence of externalities, it is straightforward to see that direct subsidies or fiscal incentives will directly reduce the marginal cost of capital and increase the global amount of private investment in R&D. But obviously, the macroeconomic effect of financial support for R&D will also be the result of the interplay among different externalities within the country. David *et al.* (2000) highlight and discuss several of these.

On the positive side, it can be argued that subsidized (directly or not) R&D activity generates learning and training effects for subsidized firms that are willing to increase their efficiency by conducting their own R&D programs. Public support available for durable research equipment or other R&D fixed costs can help firms to conduct successive own R&D projects at lower incremental costs which will increase the expected internal rates of return on its R&D investments. Direct support can also generate another positive externality for subsidized firms if taken as a positive signal of future product demand. However, although these positive effects can reinforce the macroeconomic effects of financial support for R&D, there are some negative effects. The first concerns the individual behavior of firms in terms of their exploitation of support. It is possible that part of support might be used to finance R&D projects that would have been financed anyway, or might not be used to increase R&D expenditure. Here, we refer to the possibility that these policy instruments can be (partial) substitutes for private R&D funding. The second effect refers to the distortions between firms and industries generated by policy instruments. Although these measures may encourage firms and sectors that benefit from them to increase their R&D investments, they can create distortions *vis à vis* the firms and sectors that do not (or only very slightly) increase their R&D investments, and may even reduce investment.[9] The third problem refers to the influence of this support on the price of R&D inputs which are extremely inelastic over the short and medium terms. We could expect significant R&D policies to increase demand for R&D inputs (and especially labor which is strongly inelastic) implying an increase in R&D costs, thereby reducing the profitability of R&D investment.

Two natural questions arise from these diverse sources of externalities. The first is whether the positive externalities are higher than the negative externalities, and the second is whether these effects are of the same magnitude in relation to direct and indirect support. The first question requires empirical work; the second can draw on existing theory. Fundamentally, direct support generates more distortions than indirect support (due to the base of application of these measures). Consequently, it is more likely to generate (compared on a same amount basis) higher complementary but also more crowding-out effects than indirect support. On the negative side, the "crowding-out" effects of indirect support should be less important than the crowding-out effects of direct support because indirect support means that: (1) firms should invest before receiving the tax subsidies (less potential substitution effect) and (2) distortion effects between firms and industries should be low if these measures apply to all sectors/and firms (which is not the case for direct

[9] E.g, subsidized firms may have a higher probability of quickly and successfully commercializing innovations which may reduce the productivity expected from the R&D projects of non-subsidized firms.

support). On the positive side, the "complementary" effects of direct support should be more important than the complementary effects of indirect support because direct support means: (1) that firms can more easily cover the initial fixed costs of R&D (by receiving cash-in advance or sharing the cost burden), (2) that signaling effects are more important due to the selective process, and (3) greater cooperation and knowledge transfer.

The second side of the internal effect: the externalities between instruments

So far, we have discussed the potential individual externalities that direct and indirect support generate. Another important aspect related to the macroeconomic impact of R&D policies is taking account of the potential interaction between each instruments. In the introduction to this paper, we mentioned the numerous differences between direct and indirect support. We would expect that such differences in design and timing would create complementarity effects because direct and indirect support target different firms or at least different projects due to different incentive mechanisms. Such idea is supported by Busom *et al.* (2012) who show that some characteristics of firms determine their uses of each instrument. Busom *et al.* argue that generally tax incentives are used more by large firms or historic R&D performers, while SMEs (small and medium-sized enterprises) with financial constraint and no history of performing R&D are more likely to use R&D subsidies.

If the idea of complementarity between different instruments is rational, the idea of substituability is similary possible. Indeed, taking into account the high administrative costs related to applying for a grant or the possibility of grant allocation bias towards top R&D performers, it is easy to see that both types of support mainly benefit large firms. Lokshin and Mohnen (2009) note that, tax credits seem more effective at increasing SMEs' investment in R&D compared to large firms' R&D investment. Thus, it is possible to that R&D policies are not complementary to increased private investment in R&D but rather are substitutes because they increase crowding-out effects. Even if we assume that both supports are not used by same firms, we can imagine that an increase in indirect support might displace the incentives to apply for a public grant, and therefore reduce the quality of grant awarded firms and the effectiveness of the policy.

2.3 On the external (out-of-the country) effect of R&D direct subsidies and fiscal incentives

In the previous subsection, we suggested some theoretical elements related to the internal effects of both types of support. Obviously, given the specificities of R&D activities, it is straightforward to consider the possibility of external effects of private R&D support. We define the external effects of R&D subsidies and tax incentives as the total macroeconomic effect that the R&D subsidies and tax incentives of other countries generate for a specific country.

The traditional economic literature on fiscal competition (Tiebout, 1956; Musgrave, 1959; Oates, 1972) provides interesting elements to asses the potential external effects that fiscal incentives (and to some extent direct support) can generate. Indeed, the main conclusion of this literature is that coordination among jurisdictions in the definition of fiscal policies is desirable when they concern activities that exceed the bounds of individual jurisdictions' interests because they generate important externalities. The idea is that if governments non-cooperatively set levels of tax rates, they will not internalize the existence of externalities and will choose a non-optimal tax rate. This idea seems plausible if R&D activities are implicated. Indeed, we can envisage potential tax competition among countries to attract R&D investments and new knowledge as the result of the strategic choice of governments or fiscal optimization by private firms. These assumptions seem more likely since several indicators suggest that the organization of R&D activities is increasingly rationalized and internationalized (Kulhmann and Meyer-Krahmer, 2001). If we assume that mobility of R&D investment although not perfect is at least possible between "neighboring" countries, then we can also assume that the level of R&D fiscal incentives in a country i generates a negative externality for private investment in R&D in (at least) neighboring countries. If such negative externalities exists, then non-cooperative governments are likely to choose higher tax incentives compared to the level that a social planner would choose.

Obviously, this idea of R&D competition among countries can be extended to direct subsidies, and generate inefficient levels of direct support. But, in the case where such competition effects would be marginal, we can also imagine the potential existence of complementarity rather than substituability between R&D policies implemented by different jurisdictions. Similar to internal externalities, we can suppose that direct support implemented by a government can directly benefit firms located in other jurisdictions (via grant programs based on cooperation with foreign firms) or indirectly benefit them via a second order external effect. The learning and training effects that increase subsidized firms' R&D efficiency, in turn can generate a positive external effect for the foreign firms that cooperate with subsidized firms. Obviously, on the assumption of no knowledge capital mobility, such first and second order positive externalities can also be generated by indirect support measures, especially for multinational firms.

3 Empirical estimates of internal and external effects of direct and indirect support

3.1 The empirical estimates of the first side of internal effect

The individual effect of direct support

Before discussing the macroeconomic studies evaluating the effects of direct support on business-funded R&D, we need to introduce the notion of additionality and substitutability for this R&D policy instrument. Since direct support is accounted for in publicly financed R&D, the elasticity of business-funded R&D with respect to direct support measures directly the net effect of these measures. Consequently, a positive (negative) elasticity refers to the notion of additionality (substitutability). An absence of significance or an elasticity closer to 0 means that we have a "neutral" effect of direct support on business-funded R&D. Table 2 presents the empirical models used to estimate the impact of direct support on private investment in R&D. These evolved over time from the static (taking no account of the adjustment process related to firms' investments in R&D) to the dynamic model. Nevertheless, this important difference seems not to influence the results. Overall, the macroeconomic studies highlight one core result: there is not substitutability effect of direct support on private investment in R&D. The main difference is related to the existence of a leveraging (or additionality) effect of this policy instrument. Indeed, among the nine papers evaluating this effect, four find a neutral (or insignificant) effect, three find a leveraging effect, and two report contrasting results (depending on the country studied). Consequently, it is not obvious to decide which assumption, between neutral and leveraging effect, should be retained.

There are many elements that might explain these contrasting results. One is that the effects presented in Section 2 are not accounted for in the same manner in all studies. In Capron and Van Pottelsberghe de la Potterie's study, country data are based on aggregating sectoral data, to evaluate the extent of the sectoral distortions caused by direct support. The comparison between weighted[10] and unweighted marginal effects highlight significant negative distortions between industries due to direct support. Indeed, the unweighted effect is lower than the weighted effect for all countries studied. Another theoretical explanation is provided

[10] After estimating the marginal effects for each industry, they weight these effects using the direct national subsidies allocated to each industry. Thus, for each country, we obtain the weighted average of the marginal effects of each industry.

by David and Hall (2000) who suggest that most macroeconomic studies do not take into account the impact of direct support on the cost of R&D inputs. Goolsbee (1998) uses American data and, shows that an increase in direct subsidies has a significant effect on the salary rises of both engineers and researchers. According to Golsbee, studies that not take this price-effect into account overestimate the effect of direct support by 30% to 50%. Wolff and Reinthaler's (2008) study carried out on a panel of 15 OECD countries between 1981 and 2002 seems to corroborate this idea. Indeed, they demonstrate that the coefficient of direct support is much larger if the dependent variable is private R&D investment rather than number of researchers. In the same vein, we note that macroeconomic studies using a relative measure of direct support (Falk, 2006; and Montmartin, 2013) find a neutral or insignificant effect. These last elements together with the contrasting empirical evidence provided by microeconomic studies[11] reinforces the idea that direct support does not generate leveraging effect on private investment in R&D..

The individual effect of indirect support

We first introduce the notion of additionality and substitutability for this R&D policy instrument. Since fiscal incentives are accounted for in privately financed R&D, the elasticity of business-funded R&D with respect to indirect support does not directly measure the net effect of fiscal incentives. Indeed, in order to assess the net effect of this policy instrument, which economists call the "bang for the buck" (BFTB), we need to take account of the cost (in terms of fiscal revenue lost to the public authority). If the BFTB is higher than 1, this means that $1 of revenue lost generates more than $1 of R&D investment, i.e, indirect support has an additionality effect on private investment in R&D. Nevertheless, measuring this net effect at the macroeconomic level has been impossible due to the unavailability of sufficient time series data on the macroeconomic cost of indirect support. Consequently, macroeconomic studies often evaluate the elasticity of private R&D investment to the user cost of R&D (which is influenced by the tax incentives). Although this elasticity is an imperfect measure of the BFTB, economists generally agree that an elasticity higher (lower) than 1 gives a positive (negative) indication concerning the capacity of indirect support to generate an additionality effect on private investment in R&D.

There are few empirical studies that evaluate the macroeconomic effect of indirect support on the private investment in R&D. This is obviously because these instruments are more recent than R&D subsidies - no significant fiscal measures were implemented before the 1980s. On the whole, macroeconomic studies evaluating the effect of indirect support provide more controversial results than those evaluating direct support. All studies show that indirect support significantly influences private investment in R&D,[12] and the estimated elasticities are relatively heterogeneous. Based on our survey, four of the six macroeconomic studies considered, report long-run elasticity of private R&D with respect to indirect support higher than 1, suggesting an additionality effect. Note however that in two cases the elasticity is very close to 1 (and not always significant). The other two studies report different results. The study by Shin (2006) on Korea reports a long-run elasticity slightly lower than 1, while the study by Guellec and Van Pottelsberghe de la Potterie (2003) reports a long-run elasticity much lower than 1. We think this latter result might be partially explained by the specification and estimation methods used. Indeed, Guellec and Van Pottelsberghe de la Potterie (2003) is the only paper to use a non-GMM (Generalised Method of Moments) estimator on a first-difference AR(1) model. GMM estimators may not be the best estimators when the sample size ratio N/T tends to 1 and the persistence of R&D data over time suggest the need to work on first-difference. Given the problems related to measurement of tax incentives at the macroeconomic level and the heterogeneity

[11] According to Capron and Van Pottelsberghe de la Potterie (1997) and David and Hall (2000) half of microeconomic studies reviewed report additionality effect of direct support and half report a substitutability effect.

[12] Which is not surprising in the sense that, as already mentioned, the effect of tax incentives is entirely accounted for in private R&D investment (in contrast, only substituability or additionality effects are accounted for in direct support).

of empirical results, it is difficult to draw conclusions about the capacity of indirect support to generate a leverage effect on private investment in R&D.

The empirical estimates of the second side of internal effect and external effects

Although these concepts are not new in the theoretical literature, they have received very little attention in empirical studies. These effects are of prime importance to assess the net efficiency of financial support for private R&D at the macroeconomic level.

Table 2 shows that only two papers try to measure the presence of internal complementarity between instruments at the macroeconomic level. Both study OECD countries in different time periods and conclude that within a jurisdiction (here a country), direct and indirect support are substitutes stimulating private investment in R&D. In other words, it appears that if a country raises the level of indirect support, it decreases the incentive effects of direct support and vice-versa. This very interesting fact for countries using both instruments has very little theoretical foundation so far. Some elements (already discussed) can be advanced to explain such inter-effects but do not constitutes a satisfactory rationales for their existence.

Concerning the external effects of R&D policies, only two papers provide interesting results. The first, from Wilson (2009), evaluates the sensitivity of firms' R&D investment located in one American state, to in-state and out-of-state tax credits (from neighboring states). His results show that if firms react positively to in-state tax credit, they also react negatively to the out-of state tax credits. More precisely, this reaction is estimated to be of the same magnitude, implying a zero effect of these "local" tax credits at the macroeconomic level. Using OECD country data, Montmartin (2013) reports an absence of influence of out-of-country financial support on private R&D investment in the focal country. This suggests that out-of-country policies do not influence the effects of the in-country financial support for private R&D. Consequently, the author concludes that there is an absence of a significant external effect of financial support at country level. Note that, these two conflicting results are obtained at different geographical levels. Therefore, they may suggest that the existence of an external complementarity or substituability depends on the geographical unit retained. A simple explanation might be the geographical limits to firms' capacity to react to R&D incentives. Indeed, it is evident that it is easier for firms to change their location within one country than between countries.

Table 2: Empirical Review

Author(s)/year	Dimension of Data	Econometric model and estimator	Short-term elasticity (*marginal effect) to direct support (Long-term)	Short-term elasticity to indirect support (Long-term)	Internal complementarity of financial support	External complementarity of financial support	Other significant variables
Levy and Terleckyj (1983)	US aggregate time series (1949-1981)	Static model GLS estimator	*Strongly significant	No studied	No studied	No studied	Not indicated
Lichtenberg (1987)	US aggregate time series (1956-1983)	Static model GLS estimator	[0.045; 0.122]	No studied	No studied	No studied	Not indicated
Levy (1990)	9 OECD countries (1963-1984)	Static model FGLS estimator	*Negative for 2 countries and positive for 5 countries (1)	No studied	No studied	No studied	Not indicated
Capron and Van Pottelsbeerghe de la Potterie (1997)	7 OECD countries (1973-1990)	AR(1) model IV estimator (2SLS)	*Negative for 3 countries and positive for 1 country	No studied	No studied	No studied	Total sales (+)
Bloom *et al.* (2002)	9 OECD countries (1979-1997)	AR(1) model IV estimator (2SLS)	No studied	-0.144* (-1.08*)	No studied	No studied	No other variables are significant
Guellec and Van Pottelsbeerghe de la Potterie (2003)	17 OECD countries (1983-1996)	First difference AR(1) model IV estimator (3SLS)	0.072* (0.078*)	-0.281* (-0.306*)	Direct support is substitute to indirect support	No studied	Valued added (+), Public R&D (except Higher education (-))
Falk (2006)	21 OECD countries (1975-2002), five year average, unbalanced panel	First difference AR(1) model GMM estimators	0.03 (0.13)	-0.24* (-1.04*)	No studied	No studied	Public R&D (Higher education only (+)), patent protection (+)
Shin (2006)	Korea aggregate time series (1982-2002)	AR(1) model GMM estimators	0.111* (0.134*)	-0.271* (-0.899*)	No studied	No studied	Real interest rate (-), GDP (+), public R&D (+)
Wolff and Reinthaler (2008)	15 OECD countries (1981-2004), unbalanced	AR(1) model CLSDV estimator	0.22 (3.14)	No studied	No studied	No studied	No other variables are significant
Wilson (2009)	51 US states (1981-2004)	AR(1) model LSDV and CLSDV estimator	No studied	-1.41* (-2.34*)	No studied	Tax credit of state i is substitute to tax credit of other state $j \neq i$ at the country level	State GDP (+), Federal R&D (-), National GDP (-).
Montmartin (2013)	25 OECD countries (1990-2007), unbalanced	AR(1) model CLSDV estimator	-0.07 (-0.805)	0.114* (-1.31*)	Direct support is substitute to indirect support	No significant impact of direct and indirect support of country $j \neq i$ on country i.	Interest rate (-)

Notes: (1) The estimates reported for Levy (1990) are taken from Capron (1992).* significance is at least at 10%

4 Dynamic panel data models

The empirical R&D literature focuses on a set of dynamic panel data models. In this section we present the models that we run for our empirical estimations, from a naive dynamic pooled data model to a dynamic spatial general model. We denote by i the spatial unit (in our case, country) and by n the total number of countries ($i = 1, 2, \dots, n$). The time unit is denoted by t and T denotes the total number of observations in the temporal dimension ($t = 1, 2, \dots, T$). A simple panel data model, *dynamic pooled*, is considered in vector form for spatial units at time t:

$$y_t = \tau y_{t-1} + x_t \beta + \varepsilon_t, \tag{1}$$

with $\varepsilon_t \sim \mathcal{N}\left(0, \sigma_\varepsilon^2 I_n\right)$ and:

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ \vdots \\ y_{nt} \end{bmatrix}; \; x_t = \begin{bmatrix} 1 & x_{21t} & \cdots & x_{k1t} \\ 1 & x_{22t} & \cdots & x_{k2t} \\ 1 & x_{23t} & \cdots & x_{k3t} \\ \vdots & \vdots & \cdots & \vdots \\ 1 & x_{2nt} & \cdots & x_{knt} \end{bmatrix}; \; \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_k \end{bmatrix},$$

which imposes homogeneity on the intercept and slope coefficients across all countries. The y_{t-1} vector denotes the temporally lagged dependent variable and captures the inertia present in the time series. Estimation of this model can be carried out by either ordinary least square (OLS) or maximum likelihood (ML). The estimators obtained with these methods are biased but consistent with T.

The principal criticism of the *dynamic pooled model* is that it does not account for temporal and cross-section heterogeneity. Cross-section units probably differ in relation to their background variables, time-invariant variables that do affect the dependent variable. Examples of such variables are difference in the percentages of urban/rural areas, poverty rate, rights and values in labor market, crime, religion, etc. These variables are usually time-invariant and space-specific, which also are difficult to measure. Similarly, it is possible to justify the inclusion of time-period specific effects based on the idea that they control for all spatial-invariant variables whose omission could bias the time-series estimations (Hsiao, 2003).

Model (1) can be relaxed to take account of such spatial-specific and time-period specific effects transforming the model in the following way:

$$y_t = \tau y_{t-1} + x_t \beta + \mu + \eta_t \iota_n + \varepsilon_t, \tag{2}$$

with $\varepsilon_t \sim \mathcal{N}\left(0, \sigma_\varepsilon^2 I_n\right)$ and $\mu^{'} = [\mu_1, \mu_2, \dots, \mu_n]$, ι_n a $(n \times 1)$ vector.

Model (2) captures cross-section (or spatial) heterogeneity among countries, μ_i $(i = 1, 2, \dots, n)$, and time-period heterogeneity η_t. The spatial-specific effects can be treated as fixed effects or random effects. In the fixed effects model, a dummy variable is introduced for each spatial unit, in the random effects model, μ_i is treated as a random variable i.i.d. with zero mean and variance σ_μ^2. Following the spatial literature, we take this individual effect as fixed effects in all the models (for more details of the discussion on these methods in spatial panel data, see Elhorst 2012).

The panel data literature extensively discusses this model compared to its static version, i.e, when $\tau = 0$ (see Hsiao, 2003; Baltagi, 2005). Estimation of the fixed effects in static panel model is based on eliminating the intercept β_1 and the dummy variable μ_i from the regression equation (called *demeaning* procedure).

The slope coefficient β (without the intercept) in the demeaning equation can be estimated by OLS, and it is known as the Least Square Dummy Variable (LSDV) estimator. Thereafter, the intercept β_1 and dummy variables μ_i can be recovered (Baltagi, 2005). However, when $\tau \neq 0$ we introduce a temporally lagged dependent variable into the model, the OLS estimator of the slope coefficients in the demeaned equation is inconsistent if T is fixed, regardless of the size of n. The problem with the demeaning technique, known as *Nickell's bias*, is that it creates a correlation of order $(1/T)$ between the demeaned lagged variable, y_{it-1} (after the demeaning), and the demeaned error term (Nickell, 1981; Hsiao, 2003).

The econometric literature has developed a number of consistent estimators which use methods with instrumental variables (Anderson and Hsiao, 1982) and GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). The instrumental variables estimator suggested by Anderson and Hsiao (1982) estimates a model in first differences as an instrument the dependent variable lagged by two periods. We can distinguish between two types of GMM estimator for the dynamic panel data model, i.e, the first differences GMM estimator and the system GMM estimator. The first one procedure uses lagged variables in level as instruments, whereas the second procedure uses a system of equations in both first differences and level.

Another procedure that can be used to estimate a dynamic panel data model is to bias-correct the LSDV estimator, obtaining the corrected least square dummy variable, CLSDV (Kiviet, 1995; Kiviet, 1999; Bun and Kiviet, 2003). The advantage of this method is twofold, on the one hand the LSDV estimator often has smaller variance than others, and on the other hand, correcting the LSDV estimator's bias allows us to provide a consistent estimation for all panel sizes. Elhorst (2008) shows that the CLSDV estimator of τ and β can be obtained by maximizing the log-likelihood function of the model, conditional upon the first observation, with respect to τ, β and σ^2_ε.

Other alternative methods apply an ML procedure based on the unconditional likelihood function of the model (Hsiao *et al.*, 2002). Regression models that include temporally lagged variables are often estimated conditional upon the first observations. However, if the data generating process is stationary, the initial values provide an important information about this process (Nerlove, 1999). Then, taking into account the density function of the first observation of each time-series, the unconditional likelihood function is obtained.

So far, we have discussed two of the problems inherent in modeling panel data: temporal dependence (through consideration of serially lagged dependent variable), and the unobservable cross-section effects (through fixed effects). However, we need also to include the spatial dependence among countries at each point in time. This dependence can be introduced into model (2) obtaining the so-called dynamic spatial panel data models, which mainly adopt four forms: (a) spatially lagged dependent variable as an explicative variable, Wy_t; (b) spatially lagged error term, Wu_t; (c) spatially lagged explanatory variables and (d) time-spatial lagged dependent variable as an explicative variable, Wy_{t-1}. These different forms to introduce spatial dependence generate new models.

The first model, the so-called the dynamic spatial lag model (*dynSLM*), is defined as:

$$y_t = \tau y_{t-1} + \rho W y_t + x_t\beta + \mu + \eta_t \iota_n + \varepsilon_t, \tag{3}$$

with $\varepsilon_t \sim \mathcal{N}\left(0, \sigma^2_\varepsilon I_n\right)$. The parameter ρ captures the contemporaneous spatial dependence of the endogenous variable. The term W is the spatial weight matrix. The spatial weight is an $n \times n$ positive matrix, pre-specified by the researcher, and describes the arrangement of the cross-sectional units in the sample (Anselin, 1988). The elements of W, w_{ij}, are non-zero when i and j are hypothesized to be neighbors, and zero otherwise. By convention, the diagonal elements w_{ii} are equal to zero, i.e, the self-neighbor relation is excluded. Also, the inclusion of time lagged variable with the spatial endogenous variable, Wy_t, generates the possibility of spatial effects in short-run and long-run.

If we introduce a spatially autoregressive process into the error term, we obtain the dynamic spatial error model (*dynSEM*) defined as:

$$\begin{aligned} y_t &= \tau y_{t-1} + x_t\beta + \mu + \eta_t \iota_n + u_t, \\ u_t &= \lambda W u_t + \varepsilon_t, \end{aligned} \tag{4}$$

with $\varepsilon_t \sim \mathcal{N}\left(0, \sigma_\varepsilon^2 I_n\right)$. This model can only take spatial dependence as a nuisance parameter, λ, to correct the standard errors.

The combination of *dynSLM* with spatially lagged explanatory variables produces the dynamic spatial Durbin model (*dynSDM*) defined as:

$$y_t = \tau y_{t-1} + \rho W y_t + x_t\beta + W x_t\theta + \mu + \eta_t \iota_n + \varepsilon_t. \tag{5}$$

The *dynSDM* model introduces spatial effects in the explanatory variables in order to take account of spatial local dependence. Also, the inclusion of a spatial endogenous variable, Wy_t, produces a contemporaneous global dependence in all countries. Finally, the inclusion of time lagged variable allow us to obtain short and long term effects.

An important model, the so-called generally Spatial Dynamic Panel Data (*SDPD*), introduces more complex dynamic effects in the following way:

$$y_t = \tau y_{t-1} + \delta W y_{t-1} + \rho W y_t + x_t\beta + W x_t\theta + \mu + \eta_t \iota_n + \varepsilon_t, \tag{6}$$

In equation (6) we have a new parameter, δ, that captures the response of the dependent variable lagged in both space and time, Wy_{t-1}. The importance of this model is based on the following restrictions:

$$\begin{aligned} \delta &= -\tau\rho \\ \theta &= -\beta\rho \end{aligned} \tag{7}$$

Introducing these restrictions into equation (6), we obtain:

$$\begin{aligned} y_t &= \tau y_{t-1} + (-\tau\rho) W y_{t-1} + \rho W y_t + x_t\beta + W x_t (-\rho\beta) + u_t, \\ &= \tau y_{t-1} - \tau\rho W y_{t-1} + \rho W y_t + x_t\beta - \rho W x_t\beta + u_t, \\ &= (I_n - \rho W) \tau y_{t-1} + (I_n - \rho W) x_t\beta + u_t, \\ (I_n + \rho W) y_t &= (I_n - \rho W) \tau y_{t-1} + (I_n - \rho W) x_t\beta + u_t \\ y_t &= \tau y_{t-1} + x_t\beta + (I_n - \rho W)^{-1} u_t \end{aligned} \tag{8}$$

The last equation (8) presents a similar specification to the dynamic spatial error model (4), changing the parameter ρ by λ. Then, it is easy to test whether the *SDPD* model (6) can be reduced to model (4). Knowing this, we can apply a post-estimation Wald test or LR test of dynamic common factor where the null hypothesis represents $H_0:$ *dynSEM* and the alternative hypothesis, $H_1:$ *SDPD*, equation (6).

To estimate the dynamic spatial panel data models, there are different alternatives that extend the conditional or unconditional Maximum Likelihood procedures. To estimate the *SDPD*, Yu *et al.* (2008) consider the log-likelihood function of equation (6), taking account of the endogeneity of the Wy_t in the Jacobian term. The estimator that is derived from this log-likelihood function is called the Quasi Maximum Likelihood (QML); 'quasi' refers to the fact that the error terms are not assumed to be normally distributed.

Yu *et al.* (2008) show that the QML estimator is biased and propose a bias-corrected QML. Alternatively, Elhorst (2010) suggests a different procedure, ML-based estimators taking account of the initial condition. The ML estimator has a similar performance of bias-corrected QML in terms of bias and root mean squared error when T is equal to or greater than 15. The dynamic spatial error model can be estimated following the procedure proposed by Elhorst (2005) under ML estimation extended to include spatial and time-period fixed effects.

Some empirical studies that introduces spatial weights use point estimates of one or more spatial models to test the hypothesis about the importance of spillover effects. However, LeSage and Pace (2009) point out that this could lead to erroneous conclusions, and it is necessary take account of the partial derivative of the impact from changes to the explanatory variables to interpret correctly the different model specifications.

The relevance of spatial spillovers comes from the presence of Wy as an explanatory variable. Under a cross-section Durbin model, $y = \rho W y + x\beta + W x\theta + \varepsilon$, the matrix of partial derivatives of y with respect to the $k-th$ explanatory variable of x in unit 1 up to unit n can be represented as:

$$
\begin{aligned}
\begin{bmatrix} \frac{\partial y}{\partial x_{1k}} & \cdots & \frac{\partial y}{\partial x_{nk}} \end{bmatrix} &= \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial x_{1k}} & \cdots & \frac{\partial y_n}{\partial x_{1k}} \end{bmatrix}, \\
&= (I_n - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_k & \cdots & w_{2n}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdots & \beta_k \end{bmatrix}, \\
&= (I_n - \rho W)^{-1} \left[\beta_k I_n + \theta_k W\right], \qquad (9)
\end{aligned}
$$

where w_{ij} is the $(i, j) - th$ element of W, β_k is the $k - th$ element of the vector β, and θ_k is the $k - th$ element of the vector θ.

The expression in (9) is the total effect and it can be broken down into direct and indirect effects. The *direct effect* captures the effect in own country of the unit change in explanatory variable. Since this effect is particular to each country, LeSage and Pace (2009) propose to report this effect by the average of the diagonal elements of $(I_n - \rho W)^{-1}[\beta_k I_n]$. The *indirect effect*, known as spatial spillover, is reported as the average of the row sums of non-diagonal elements of the matrix $(I_n - \rho W)^{-1}[\theta_k W]$. The significance of these effects can be obtained using Monte Carlo simulation of shocks in the error term.

The direct and indirect effects can be easily extended to dynamic panel data, for example, assuming estimation of SDPD. The advantage of using a temporal dynamic is that we can obtain the direct and indirect spatial effects in the short- and long-runs (in the case of Durbin model, these effects are similar to SDPD assuming $\delta = 0$). To obtain the short-run effects we ignore τ and δ. The matrix of partial derivatives of y with respect to the $k-th$ explanatory variable of x in unit 1 up to unit n at a particular point in time can be seen as:

$$
\begin{bmatrix} \frac{\partial y}{\partial x_{1k}} & \cdots & \frac{\partial y}{\partial x_{nk}} \end{bmatrix}_t = (I_n - \rho W)^{-1} \left[\beta_k I_n + \theta_k W\right]. \qquad (10)
$$

To obtain the long-run effects we assume that $y_t = y_{t-1} = y^*$ and $W y_t = W y_{t-1} = W y^*$:

$$
\begin{bmatrix} \frac{\partial y}{\partial x_{1k}} & \cdots & \frac{\partial y}{\partial x_{nk}} \end{bmatrix}_t = \left[(1-\tau) I_n - (\rho + \delta) W\right]^{-1} \left[\beta_k I_n + \theta_k W\right]. \qquad (11)
$$

The results reported in (10) and (11) can be used to determine *short-run and long-run direct effects*, and *short-run and long-run indirect effects* (spatial spillover). For more details see Debarsy *et al.* (2012).

5 Empirical methodology

5.1 Data and descriptive statistics

The dataset comprises information on 25 OECD countries[13] over a time period of 20 years from 1990 to 2009, yielding a total of 500 observations (see Tables 3 and 4 for details). Most of data are from the OECD and the IMF, apart from the B-index which were gathered from Thomson's (2009) paper which proposes B-index values for 25 OECD countries. The B-index is a famous general measure of countries' R&D tax generosity. Detailed information on this indicator can be found in Appendix A. We use two datasets to construct the spatial weights. The first is the OECD's STAN on bilateral trade (aggregation of all industry sectors) for four years: 1995, 2000, 2005, and 2008. The second is the OECD's REGPAT on collaboration based on international patent applications (Patent Cooperation Treaty, PCT); in this case, we have annual data for the whole study period.

Since our panel data has about the 6% of missing observations, we have an unbalanced data set. Normally, missing values are not a problem for panel data estimations using traditional techniques but spatial econometrics need balanced panel data in order to take account of spatial dependence at each temporal point. Spatial econometrics assumes a connected matrix between all cross-section units, and missing data in any year means this condition in not satisfied. A strategy to avoid this problem is to use a multiple imputation technique (Rubin, 1987) and to replace the missing values by multiple sets of plausible values. We apply this technique to obtain a full balanced set of panel data.[14] Our results do not change significantly compared to the original data. Table 3 presents the basic statistics after multiple imputation.

Table 3: Summary Statistics (pooled)

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
$Dirdefi$ (% GDP)	500	0.96	0.66	0.004	2.96
$Credit$ (% GDP)	500	94.20	49.64	10.93	235.93
$Interetlt$	500	7.95	6.73	1.00	66.94
$Dirdpub$ (% GDP)	500	0.67	0.25	0.016	1.34
Sub (% BERD)	500	8.28	7.92	0.053	94.40
$Bindex$	500	0.94	0.11	0.57	1.08

Notes: See Table B.1 in Appendix B.

Table 3 shows that average business-funded R&D intensity ($Dirdefi$) is 0.96% with a maximum of 2.93% for Sweden in 2001, and a minimum of 0.04% for Mexico in 1990. R&D expenditure by the public sector in terms of GDP ($Dirdpub$) are 0.67% on average with a maximum of 1.34% for Sweden in 2009 and 0.01% for Mexico in 1990.

Table 4 shows the evolution of variables using the four-year averages. Growth of business-funded R&D intensity reaches a maximum in 2006-2009. Direct subsidy rate is measured as government funded expenditure on R&D in the business sector as a percentage of business expenditure in R&D (BERD) is decreasing in all periods from 10% to reach a minimum value of 6.9% in the period 2006-2009.

[13] Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Korea, Germany, Finland, France, Greece, Hungary, Ireland, Italy, Japan, Mexico, Norway, New-Zealand, Netherlands, Poland, Portugla, Spain, United Kingdom, United-States and Sweden

[14] We assume an autoregressive process for each country separately, i.e, the missing values are dependent on the values in the dataset (NMAR, not missing randomly).

Table 4: Summary Statistics. Evolution over Time

Variable	**1990-1993**	**1994-1997**	**1998-2001**	**2002-2005**	**2006-2009**
Dirdefi (% GDP)	0.83	0.87	0.97	1.02	1.11
Credit (% GDP)	73.98	76.62	90.19	103.87	126.34
Interetlt	13.28	10.41	6.79	4.69	4.57
Dirdpub (% GDP)	0.59	0.63	0.66	0.71	0.76
Sub (% BERD)	10.01	9.25	7.42	7.01	6.91
Bindex	0.98	0.97	0.96	0.91	0.88

Notes: See Table B.1 in Appendix B.

In order to properly specify the models described in Section 3, we begin with a pre-estimation analysis of the data. Table 5 shows the common tests for unit roots in heterogeneous panel data. As we can see, practically all series (using logarithm transformation) are integrated of the order 1. An exception is *Dirdpub* where the IPS and ADF tests reject the null hypothesis of unit root but Pesaran's (2007) CADF test can not reject that the series has a unit root. As a consequence of these results, the variables for all panel data models will be the first differences of the logarithm, i.e, we will explain the results in terms of growth rate.

Other preliminary results are the average cross-section correlation coefficients and a test for cross-section dependence. Using the Pesaran (2004) CD test, we detect cross-section dependence in all variables. The analysis of cross-section correlation suggests important dependence among the variables (Table 6).

Table 5: Unit Root Test to Variables in Logarithm.

Method		$H_0: I(1)$ $H_1: I(0)$		$H_0: I(2)$ $H_1: I(1)$		Conclusion
Unit root specific for each country		Statistic	p-value	Statistic	p-value	
Dirdefi (% GPD)	IPS W-stat	−1.16	0.13	−7.06	0.00	$I(1)$
	ADF: Fischer χ^2	0.17	0.43	4.79	0.00	$I(1)$
	Pesaran's CADF test	2.86	0.99	−1.92	0.03	$I(1)$
Credit (% GDP)	IPS W-stat	−0.89	0.19	−8.74	0.00	$I(1)$
	ADF: Fischer χ^2	−1.49	0.93	3.79	0.00	$I(1)$
	Pesaran's CADF test	−1.16	0.12	−4.93	0.00	$I(1)$
Interetl	IPS W-stat	1.52	0.93	−9.32	0.00	$I(1)$
	ADF: Fischer χ^2	−0.54	0.71	7.09	0.00	$I(1)$
	Pesaran's CADF test	−0.71	0.24	−3.93	0.00	$I(1)$
Dirdpub (% GDP)	IPS W-stat	−3.44	0.00	−	−	$I(0)$
	ADF: Fischer χ^2	9.63	0.00	−	−	$I(0)$
	Pesaran's CADF test	0.12	0.55	−4.89	0.00	$I(1)$
Sub (% BERD)	IPS W-stat	−1.18	0.12	−11.90	0.00	$I(1)$
	ADF: Fischer χ^2	−0.78	0.78	4.01	0.00	$I(1)$
	Pesaran's CADF test	0.89	0.81	−4.70	0.00	$I(1)$
Bindex	IPS W-stat	0.59	0.72	−12.97	0.00	$I(1)$
	ADF: Fischer χ^2	−1.52	0.94	3.30	0.00	$I(1)$
	Pesaran's CADF test	−0.89	0.19	−5.43	0.00	$I(1)$

Notes: IPS (Im, Pesaran and Shin,2003). For Pesaran (2007) test we report the standardized Z-tbar statistic and its p-value. The tests to $H_0: I(1)$ included a constant and trend. The tests to $H_0: I(2)$ included a constant.

Table 6: Average Cross-section Correlation to Variables in Logarithm.

Variable	CD-Test		corr.	abs (corr.)
	Statistic	p-value		
$Dirdefi$ (% GDP)	16.44	0.00	0.21	0.51
$Credit$ (% GDP)	31.76	0.00	0.42	0.65
$Interetl$	65.23	0.00	0.86	0.86
$Dirdpub$ (% GDP)	23.72	0.00	0.31	0.46
Sub	7.32	0.00	0.10	0.49
$Bindex$	16.98	0.00	0.23	0.46

Notes: The results are based on CD test (Pesaran, 2004).

5.2 Dynamic panel model without spatial effects

Table 7 presents the estimations of the basic specification using two potential unbiased types of estimator (GMM and CLSDV). The two GMM and the three CLSDV estimators provide estimated values for the time lag coefficient (τ) which are in the bounds of the true value of τ (given by OLS and LSDV estimates, for further details see Bond, 2002). Nevertheless, due to the size of our sample, the asymptotic properties of the estimators and the time lag estimates, we are more confident about the CLSDV results (Judson and Owen, 1999). These first estimations highlight the fact that (the growth rate of) private R&D intensity appears relatively persistent over time. Indeed, the speed at which the growth rate of private R&D intensity adjusts to changes is estimated at around 60% which implies that the long-run[15] effect of exogenous variables should be slightly less than twice their short run-effect.

Table 7: Dynamic Panel Models Without Spatial Effects

VARIABLE	OLS	LSDV	GMM(AB)	GMM(BB)	CLSDV(AH)	CLSDV(AB)	CLSDV(BB)
$\Delta ldirdefi_{-1}$	0.472***	0.366***	0.373***	0.366***	0.421***	0.423***	0.430***
$\Delta lcredit$	0.041	0.048	0.024	0.034	0.047	0.047	0.046
$\Delta interetlt$	−0.004	−0.005***	−0.007***	−0.007**	−0.005***	−0.005***	−0.005***
$\Delta lsub$	−0.042	−0.043***	−0.042***	−0.024***	−0.043***	−0.044***	−0.045***
$\Delta ldirpub_{-1}$	0.235*	0.254*	0.316***	0.339***	0.244***	0.242***	0.241***
$\Delta lbindex_{-1}$	−0.205*	−0.193***	−0.195***	−0.150**	−0.196***	−0.196***	−0.197***
$constant$	−0.012	−0.011	−0.037**	−0.039**			
$R-squared$	0.407	0.330					

Notes: *, ** and *** denotes significance at 10%, 5% and 1%. Dependent variable is log Dirdefi %GDP (in first difference). Terms Δ and l denotes first diff. and log. All tests are based in robust std. errors. Time effects are include but not reported. AB: Arellano-Bond, AH: Anderson-Hsiao and BB: Blundell-Bond.

We first concentrate on the impact of the "control variables" which are nominal long term interest rate, public R&D intensity, and credit to the private sector. The nominal interest rate negatively affects private R&D intensity. The estimated coefficient implies that an increase of 100bp in the nominal interest rate reduces the growth of private R&D intensity by approximately 1pp in the long-run implying a long-run elasticity of about -1. The impact of credit granted to the private sector does not seem to have a significant effect on private R&D intensity. We think that this result is related to the fact that this variable includes all credits delivered to the private sector and not only those related to R&D. Nevertheless, these first estimates

[15] Long-run effects are calculated as the ratio between short-run effects (i.e. estimated $\beta-$coefficients) and the 1 minus estimated $\tau-$coefficient.

indicate that the private R&D intensity is strongly influenced by the unfolding financial conditions. Our last control variable is public R&D investment in terms of GDP. Using a time lag in order to account for intertemporal knowledge spillovers between public and private R&D, our results show a significant positive effect of public R&D intensity. The long-run elasticity of public R&D intensity to private R&D intensity is estimated at around 0.45. This result highlights strong positive inter-temporal knowledge externalities between both R&D sectors. This last result is in line with Guellec and Van Pottelsberghe de la Potterie (2003).

Returning to our core interest, i.e, the effect of R&D policy variables, all public policy variables affect private R&D intensity significantly. An important point of the estimation in Table 7 is the suggestion of a clearly opposite effect between direct and indirect support. Indeed, while an increase in direct support negatively influences private R&D intensity, the effect is reversed for indirect support. More precisely, the long-run elasticity of private R&D intensity to direct support is estimated at around -0.07. In other words, if the direct subsidy rate increases by 1%, then the private R&D intensity decreases by 0.07% in the long-run. This result highlights a slight crowding-out effect of direct support on private R&D intensity. Concerning indirect support, the long-run elasticity of private R&D intensity to the B-index is estimated at around -0.32. That is, if the growth rate of indirect subsidy rate increases by 1% (which translates into a decrease of the B-index), then private R&D intensity will increase by 0.32% in the long-run. This result clearly highlights a positive effect of indirect support on the private R&D intensity. Nevertheless, this positive effect does not means that fiscal incentives generate a leveraging effect,[16] it tells us only that if there is a crowding-out effect of indirect support, it is only partial.

Our results concerning indirect support are in line with those in Guellec and Van Pottelsberghe de la Potterie (2003), and, in some sense, with those obtained by Falk (2006). However, our results for direct support contrast with the existing literature (which highlights either a significant positive effect or a neutral effect). This difference is mainly explained by the relative measure of direct support used in this paper. As Goolsbee (1998) and Wolff and Reinthaler (2008) point out, it is necessary in macroeconomic studies to use a relative measure for direct support in order to control for the price-effect on R&D inputs which seems to be very important and causes an upward skew in estimations of the coefficient of direct support. This idea is reinforced when we analyze the specification and variables used in previous studies. Guellec and Van Pottelsberghe de la Potterie (2003) explain the amount of private R&D by the amount of direct support and find a strong positive effect of direct support. Falk (2006) explains private R&D intensity by "direct subsidy intensity" (amount of direct support/GDP) and finds a neutral effect of direct support. Thus, our negative effect could be simply due to the fact that unlike Falk (2006), we use different relative measures for private R&D (private R&D intensity) and for direct support (amount of direct support/ amount of private R&D executed) which is likely to take better account of the aforementioned price-effect.

Non-linear effects of direct and indirect support

So far, we have only considered the possibility of a linear effect between private R&D intensity and R&D public support. It might be that the capacity of each policy to increase private R&D intensity is non-linear with its level of use, i.e, rate of subsidy. We therefore test the following relationships:

$$\begin{aligned} \beta_{\Delta lsub} &= \beta_1 sub + \beta_2 sub^2, \\ \beta_{\Delta lbindex} &= \beta_1 bindex + \beta_2 bindex^2. \end{aligned}$$

[16] Because we cannot evaluate the marginal effect of fiscal incentives using the B-index.

The first two and last two columns in the Table 8 report GMM and CLSDV estimates of the model with non-linear effect of both direct and indirect support.

Table 8: Dynamic Panel Model Without Spatial Effects. Alternative Specifications.

VARIABLE	MODEL 1		MODEL 2		MODEL 3	
	GMM	CLSDV	GMM	CLSDV	GMM	CLSDV
$\Delta ldirdefi_{-1}$	0.352^{***}	0.405^{***}	0.367^{***}	0.418^{***}	0.360^{***}	0.410^{***}
$\Delta lcredit$	0.023	0.040	0.026	0.047	0.027	0.040
$\Delta interetlt$	-0.008^{***}	-0.007^{***}	-0.007^{***}	-0.005^{**}	-0.009^{***}	-0.007^{***}
$\Delta lsub$			-0.034^{***}	-0.037^{***}		
$\Delta lsub \times sub$	-1.124^{***}	-1.058^{***}			-0.996^{***}	-0.974^{***}
$\Delta lsub \times sub^2$	4.455^{***}	4.016^{***}			3.973^{***}	3.755^{***}
$\Delta ldirpub_{-1}$	0.292^{***}	0.239^{***}	0.308^{***}	0.234^{***}	0.287^{***}	0.232^{***}
$\Delta lbindex_{-1}$			-0.250^{***}	-0.246^{***}		
$\Delta lbindex_{-1} \times lbindex$	-1.304	-1.173^{*}			-3.773^{***}	-3.176^{***}
$\Delta lbindex_{-1} \times lbindex^2$	1.435	1.244			4.635^{***}	3.819^{***}
$\Delta interact$			0.593^{***}	0.581^{***}	1.100^{***}	1.020^{***}
$constant$	-0.030^{**}		-0.037^{**}		-0.032^{**}	

Notes: *, ** and *** denotes significance at 10%, 5% and 1%. Dep. variable is log Dirdefi %GDP (first difference). Terms Δ and l denotes first diff. and log. All tests are based on robust std. errors. Time effects are included but not reported.

Concerning R&D subsidies, our results clearly highlight the existence of a convex relationship between private R&D elasticity with respect to direct support and direct subsidy rate.

Figure 1:Impact of Direct Subsidies according to the Level of Subsidization

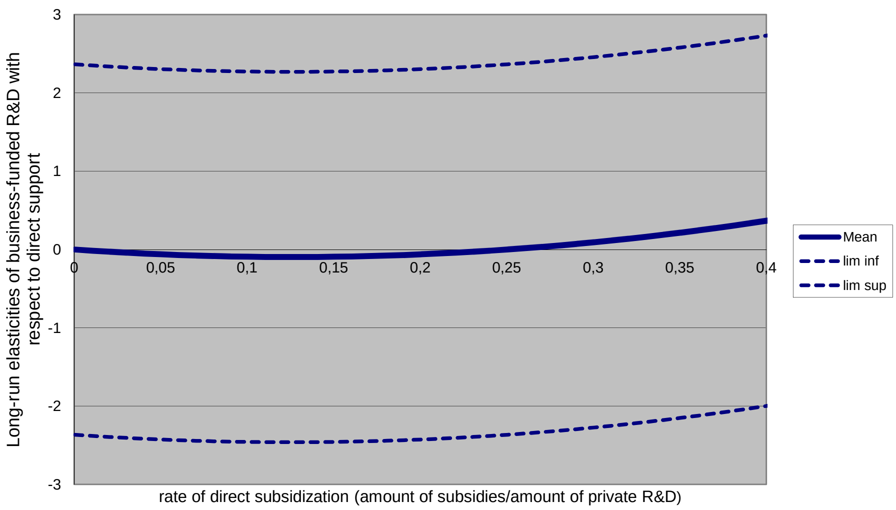

Figure 1 reports the long-run elasticity of business-funded R&D intensity with respect to the direct subsidy rate[17]. Our results suggest that, on average, the elasticity decreases with the subsidy rate up to a threshold of 13%, then increases with the subsidy rate and becomes positive above a threshold of approximately 26%. This highlights that the leveraging or crowding-out effect of direct subsidies depends fundamentally on the level of use of this policy. Nevertheless, the empirical distribution of subsidies is

[17]The figure is based on the estimates of Model 3 CLSDV in Table 8. The confidence intervals are constructed assuming the lagged estimated value as constant and the standard errors are created using each variance and covariance between the estimated coefficients of $\Delta lsub \times sub$ and $\Delta lsub \times sub^2$

concentrated between 4.19% (Q1) and 10.27% (Q3), suggesting that for most OECD countries, R&D subsidies generate a partial crowding-out effect on business-funded R&D intensity.

In relation to indirect support, our results show the existence of a convex relationship between private R&D elasticity with respect to indirect support and the indirect/fiscal subsidy rate (by considering that $1 - Bindex$ is a measure of the fiscal subsidy rate). However, in contrast to direct support, for the empirical values of the B-index, we have only the increasing part of the convex function.

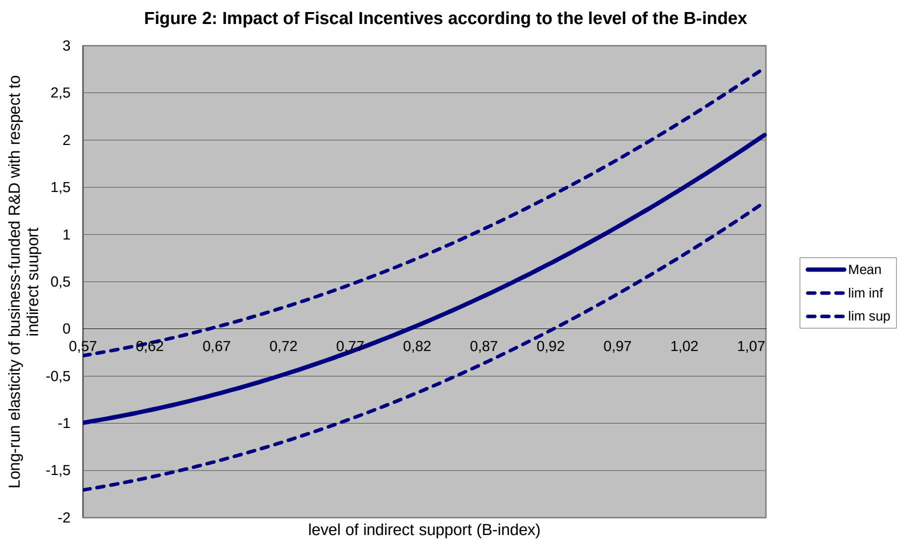

Figure 2 reports the long-run elasticities of business-funded R&D intensity with respect to the B-index[18]. It shows that private R&D elasticity with respect to indirect support decreases with the fiscal subsidy rate. For high values of the B-index (low fiscal subsidy rate), the elasticity is positive, highlighting a negative effect of fiscal incentives on business-funded R&D. Figure 2 highlights the fact that, on average, fiscal incentives generate a positive effect on business-funded R&D if the indirect subsidy rate is higher than 18% $(1 - 0,82)$. In the same vein, fiscal incentives generate a leveraging effect (elasticity higher than -1) only for high fiscal subsidization rates (higher than 43%). Nevertheless, the empirical distribution of the B-index is concentrated between 0.9 (Q1) and 1.02 (Q3), suggesting that for most OECD countries, fiscal incentives reduce the business-funded R&D intensity.

Externalities between direct and indirect support

Another important question for public authorities that rely on a combination of direct and indirect support, is related to their complementarity for increasing private investment in R&D. The results in Guellec and Van Pottelsberghe de la Potterie (2003) show that direct and indirect measures substitute for each other since it appears that an increase in either direct or indirect measures diminishes the positive effect of the other upon private investment in R&D. In order to investigate this further, we extend the basic model by integrating a crossed variable of both direct and indirect support which we call *interact* $(\Delta lbindex_{-1} \times \Delta lsub)$. The estimation results are presented in the last four columns in Table 8. They confirm the results in Guellec and Van Pottelsberghe de la Potterie (2003) and show that direct and indirect support are substitutes for

[18] The figure is based on the estimates of Model 3 CLSDV in Table 8. The confidence interval are constructed assuming the lagged estimated value as constant and the standard errors are created using each variance and the covariance between the estimated coefficients of $\Delta lbindex \times bindex$ and $\Delta lbindex \times bindex^2$

boosting the intensity of private R&D. In our case, however, the estimated coefficient of direct support is negative (whereas it is positive in Guellec and Van Pottelsberghe, 2003). Hence, an increase in the dynamic of fiscal subsidization implies that the windfall effect of direct support will also increase and that an increase in direct support will reduce the positive effect of indirect support.

The last two columns in Table 8 report the estimates simultaneously integrating the presence of a non-linear effect of public support for R&D and the presence of spillovers between direct and indirect support. These results are interesting for public policy makers. All the policy variables are strongly significant and validate our assumption about non-linear effects and interdependence between R&D policy instruments. As a consequence, the substitution effect between direct and indirect support seems not to be negative from a policy mix perspective. Indeed, since most countries have set direct R&D subsidy rates below 26% implying a crowding-out effect of direct support, then a decrease in the R&D subsidy rate will increase the positive effect of indirect support on private R&D intensity while reducing the cost of the policy mix. In other words, our results suggest that substitution of direct support for indirect support will likely increase the effectiveness of the policy mix on the private R&D investment intensity.

5.3 The introduction of spatial effects

A problem with the results presented so far is that they implicitly assume that a country's R&D investment is influenced only by its own policy mix. Given the nature of knowledge creating activities, the geography of innovation, and the growing internationalization of R&D activities, we might assume that the private R&D intensity of a country i could be impacted by the private R&D intensity of its neighbors and their R&D policy incentives. To test this assumption, we extend the previous models and report estimates of the spatial Durbin version of models presented in Table 8.

We introduce spatial dependence using two alternative criteria. The first uses the idea of proximity between countries based on strength of bilateral trade, and each weight is formed by defining the relation between two countries i and j in the following way:

$$w_{ij} = \frac{1}{2T} \sum_{t \in T} \left(\frac{export_{ij,t}}{\sum\limits_j export_{ij,t}} + \frac{import_{ij,t}}{\sum\limits_j import_{ij,t}} \right), \tag{12}$$

where $export_{ij,t}$ represents the total amount of country i's exports towards country j (at time t), and $import_{ij,t}$ represents the amount of country i's imports from country j during that same period. The proximity between two countries is measured by the average of their bilateral commercial relations of all T periods.

The second criterion considers the intensity of technological relationships. To construct these weights, we use collaboration data from international patent applications (Patent Cooperation Treaty, PCT). The intensity of technological collaboration between two countries i and j can be defined as:

$$w_{ij} = \frac{\frac{1}{T} \sum\limits_{t \in T} p_{ij,t}}{\sum\limits_j \left[\frac{1}{T} \sum\limits_{t \in T} p_{ij,t} \right]}, \tag{13}$$

where $p_{ij,t}$ represents the number of collaborations between the countries i and j during the period t for PCT patent applications. Thus, the proximity between two countries is measured by the relative average intensity of their collaboration for international patent applications during T periods.

To break down the connection between all countries and to avoid possible endogeneity issue of W, we apply a binary transformation of the weights. For each criterion, we apply the following condition:

$$w_{ij} = \begin{cases} 1 \quad if \quad \sum_j w_{ij}^o \leq 0.75 \\ 0 \quad otherwise \end{cases},$$

where w_{ij}^o is the ordered weight in descending form, for the $i - th$ country. This transformation allows us to reduce the connectivity of the matrices into an average of six neighbours for bilateral trade and around four neighbours for patent collaboration relationships. Finally, we apply row normalization of the spatial weight matrix.

Using these two spatial weight matrices, we estimate the dynamic Spatial Durbin Model. The results are presented in Table 9. Before discussing the results of the dynamic Spatial Durbin model, we refer to the possibility of introducing spatial dependence using other models, $dynSEM$ and $SDPD$. Table B.2 in Appendix B presents the estimation results of these models. The common factor test indicates that the $SDPD$ model is preferred to $dynSEM$ model. Also, in the $SDPD$ model, the parameter of Wy_{-1} is not significant in all cases, so the $SDPD$ can be reduced to the $dynSDM$ model.

The estimates in Table 9 report the existence of positive spatial dependence between OECD countries in terms of private R&D intensity. This result is explained in the literature as depending on the localized nature of knowledge externalities induced by the "tacit" character of scientific knowledge which requires more face-to-face interactions. Our results report that spatial dependence is more than two times higher based on scientific collaboration intensity compared to bilateral trade intensity which confirms the intuition that scientific collaboration generates significant positive externalities that increases the productivity of private R&D. This first element highlights the need to take account of spatial dependence even at the OECD country level. Looking at the results of the two weight models, we prefer the estimates using the "patent" spatial weight matrix because they fit the data better (lower AIC), however both models provide similar core results. The results for direct effects are presented in Table 10. The indirect or spillover effects are presented in Table 11. In both tables, we obtained the significance of short-run effect using Monte Carlo simulations. In the cases of long-run effects, we apply the calculation given by the equation (11).

Results for direct effects

We begin our analysis by comparing the direct effects obtained with and without inclusion of spatial dependence (Tables 8 and 10). Tables 8 and 9 show that the speed of adjustment of private R&D intensity is estimated to be slightly higher when we introduce spatial dependence at around 65% (against an estimate of 59-64%) implying a lower gap between short- and long-run effects. Note that, the sign of estimated coefficients is the same in Tables 8 and 10 and that overall there is not a huge difference in their values. Nevertheless, the long-run elasticities of private R&D intensity with respect to each significant variable[19] is (slightly) lower when spatial dependence is included.

[19] Interest rate, public R&D intensity, direct support and indirect support.

Table 9: Dynamic Spatial Durbin Models.

VARIABLE	*dynSDM* 1		*dynSDM* 2		*dynSDM* 3	
	W (trade)	**W (patent)**	**W (trade)**	**W (patent)**	**W (trade)**	**W (patent)**
MAIN EFFECTS						
$\Delta ldirdefi_{-1}$	0.338***	0.345***	0.348***	0.353***	0.343***	0.340***
$\Delta lcredit$	0.052	0.058	0.059	0.059	0.053	0.059
$\Delta interetlt$	−0.007***	−0.007***	−0.005***	−0.005***	−0.007***	−0.007***
$\Delta lsub$			−0.034***	−0.035***		
$\Delta lsub \times sub$	−1.048***	−1.001***			−0.974***	−0.921***
$\Delta lsub \times sub^2$	3.995***	3.902***			3.739***	3.562***
$\Delta ldirpub_{-1}$	0.249*	0.245**	0.247*	0.242**	0.241*	0.236**
$\Delta lbindex_{-1}$			−0.246***	−0.255***		
$\Delta lbindex_{-1} \times bindex$	−0.967	−1.109			−3.198***	−3.252***
$\Delta lbindex_{-1} \times bindex^2$	0.969	1.158			3.840***	3.903***
$\Delta interact$			0.623***	0.574***	1.066***	1.062***
SPATIAL EFFECTS						
$W\Delta ldirdefi$	0.122**	0.257**	0.165**	0.314**	0.150**	0.262**
$W\Delta lcredit$	0.221	0.207	0.249	0.196	0.219	0.193
$W\Delta interetlt$	0.012	−0.047*	0.011	−0.053**	0.007	−0.055**
$W\Delta lsub$			0.006	0.068		
$W\Delta lsub \times sub$	−0.028	−2.319			0.078	−0.704
$W\Delta lsub \times sub^2$	0.609	39.804			−0.021	28.370
$W\Delta ldirpub_{-1}$	−0.037	0.163	−0.030	0.112	−0.043	0.093
$W\Delta lbindex_{-1}$			−0.053	1.077**		
$W\Delta lbindex_{-1} \times bindex$	−0.040	1.736			−2.775	−0.285
$W\Delta lbindex_{-1} \times bindex^2$	0.157	−2.345			3.438	1.968
$W\Delta interact$			0.508	15.547***	1.168	14.989***
AIC	−1075	−1080	−1078	−1088	−1087	−1100

Notes: *, ** and *** denotes significance at 10%, 5% and 1%. Dependent variable is log Dirdefi %GDP (in first difference). Terms Δ and l denotes first diff. and log. All tests are based on robust std. errors. Time effects are included but not reported. AIC: Akaike's inf. crit.

Concerning public R&D support, this implies that ignoring spatial dependence tends to overestimate the positive effect of indirect support and the negative effect of direct support (between 1% and 7% for indirect support and between 5% and 15% for direct support). Consequently, overall, the direct effects estimated by the Spatial Durbin Models are in line with those provided by non-spatial model and confirm all the previous results including (1) a positive influence of fiscal incentives and a negative influence of direct subsidies,[20] (2) the fact the influence of both types of support follow a non-linear relationhip with their level of use, and (3) these two instruments are substitutes to increase private R&D intensity.

[20] Recall previous remarks on the leveraging effect of both types of support.

Table 10: Short- and Long-terms of Direct Effects. Spatial Durbin Models

VARIABLE	$dynSDM$ 1		$dynSDM$ 2		$dynSDM$ 3	
	W (trade)	**W (patent)**	**W (trade)**	**W (patent)**	**W (trade)**	**W (patent)**
SHORT RUN						
$\Delta lcredit$	0.053	0.057	0.058	0.058	0.053	0.059
$\Delta interetlt$	-0.007^{***}	-0.006^{***}	-0.005^{***}	-0.004^{***}	-0.008^{***}	-0.006^{***}
$\Delta lsub$			-0.033^{***}	-0.035^{***}		
$\Delta lsub \times sub$	-1.023^{***}	-0.934^{***}			-0.969^{***}	-0.903^{***}
$\Delta lsub \times sub^2$	3.934^{***}	3.138^{***}			3.733^{***}	3.086^{***}
$\Delta ldirpub_{-1}$	0.256^{**}	0.249^{**}	0.253^{*}	0.247^{**}	0.249^{**}	0.241^{**}
$\Delta lbindex_{-1}$			-0.239^{***}	-0.271^{***}		
$\Delta lbindex_{-1} \times bindex$	-0.841	-1.002			-3.105^{***}	-3.168^{***}
$\Delta lbindex_{-1} \times bindex^2$	0.806	1.024			3.719^{**}	3.772^{***}
$\Delta interact$			0.585^{***}	0.216	1.034^{***}	0.808^{***}
LONG RUN						
$\Delta lcredit$	0.080	0.087	0.089	0.090	0.080	0.090
$\Delta interetlt$	-0.010	-0.009	-0.008	-0.006	-0.011	-0.009
$\Delta lsub$			-0.051	-0.054		
$\Delta lsub \times sub$	-1.545	-1.426			-1.475	-1.368
$\Delta lsub \times sub^2$	5.941	4.789			5.679	4.675
$\Delta ldirpub_{-1}$	0.387	0.379	0.389	0.382	0.379	0.365
$\Delta lbindex_{-1}$			-0.367	-0.420		
$\Delta lbindex_{-1} \times lbindex$	-1.270	-1.528			-4.723	-4.801
$\Delta lbindex_{-1} \times lbindex^2$	1.216	1.563			5.657	5.715
$\Delta interact$			0.897	0.335	1.572	1.225

Notes: *, ** and *** denotes significance at 10%, 5% and 1%. Dependent variable is log Dirdefi %GDP (in first difference). Terms Δ and l denotes first diff. and log.

Results for indirect effects

Altough numerous direct effects are significant, the estimates reported in Table 11 highlight that few exogenous variables in neighboring countries directly influence private R&D intensity in the focal country. Concentrating on the estimates using the "patent" spatial weight matrix, we observe that only three indirect effects are significant (and only two at the 5% level). The first is related to the difference in the long-run nominal interest rate. Our spatial model estimates that an increase of 100bp of the long-run nominal interest rate in all neighboring regions reduces growth of private R&D intensity in the focal country by approximately 3pp in the short-run. This implies that financial conditions in other countries more strongly influence the private investment intensity in the home country than do home national financial conditions. Many elements can explain these results. Here, we concentrate on one potential explanation. Currently, in the world, multinational companies are responsible for more than 90% of private R&D investment in the world (source: EU Industrial R&D investment Scoreboard 2013).

Table 11: Short- and Long-terms of Indirect Effects. Spatial Durbin Models

VARIABLE	$dynSDM$ 1		$dynSDM$ 2		$dynSDM$ 3	
	W (trade)	**W (patent)**	**W (trade)**	**W (patent)**	**W (trade)**	**W (patent)**
			SHORT RUN			
$W\Delta lcredit$	0.180	0.137	0.201	0.119	0.181	0.127
$W\Delta interetlt$	0.012^{*}	-0.035^{*}	0.011	-0.038^{*}	0.009	-0.041^{*}
$W\Delta lsub$			0.013	0.053		
$W\Delta lsub \times sub$	0.088	-1.774			0.352	-0.551
$W\Delta lsub \times sub^2$	0.164	30.625			-1.100	22.392
$W\Delta ldirpub_{-1}$	-0.067	0.078	-0.072	0.021	-0.074	0.031
$W\Delta lbindex_{-1}$			0.019	0.896^{**}		
$W\Delta lbindex_{-1} \times bindex$	-0.298	1.258			-2.481	-0.447
$W\Delta lbindex_{-1} \times bindex^2$	0.543	-1.699			2.994	0.603
$W\Delta interact$			0.352	11.758^{***}	0.988	10.743^{***}
			LONG RUN			
$W\Delta lcredit$	0.271	0.209	0.309	0.184	0.275	0.192
$W\Delta interetlt$	0.018	-0.054	0.017	-0.059	0.013	-0.061
$W\Delta lsub$			0.020	0.082		
$W\Delta lsub \times sub$	0.133	-2.707			0.536	-0.834
$W\Delta lsub \times sub^2$	0.248	46.734			-1.674	33.929
$W\Delta ldirpub_{-1}$	-0.102	0.118	-0.110	0.032	-0.112	0.047
$W\Delta lbindex_{-1}$			0.030	1.385		
$W\Delta lbindex_{-1} \times lbindex$	-0.451	1.920			-3.774	0.678
$W\Delta lbindex_{-1} \times lbindex^2$	0.820	-2.592			4.555	0.914
$W\Delta interact$			0.541	18.183	1.503	16.279

Notes: *, ** and *** denotes significance at 10%, 5% and 1%. Dependent variable is log Dirdefi %GDP (in first difference). Terms Δ and l denotes first diff. and log.

These companies develop global strategies for their R&D activities which are undertaken in different countries. In a context of increasing financial market integration, we can think that private investment in R&D of these companies (and hence global investment in R&D) is more sensitive to global financial market conditions rather than the conditions in one specific country. Our assumption seems plausible since our data show a positive correlation between the first difference of the long-run nominal interest rate and its spatial-lag counterpart ($corr = 0.2825$).

The second significant indirect effect is related to the level of fiscal incentives in neighboring countries in long run. In the fifth column of Table 11, we estimate that an increase in fiscal incentives of 1% (a decrease in the B-index of 1%) in all neighboring regions decreases private R&D intensity in the focal country of approximately 1.35% in the long-run. This indirect effect is clearly higher than its direct counterpart and has the opposite sign implying a negative (direct+indirect) total effect of indirect support. Obviously, some caution is needed in interpreting this result but it nevertheless tends to confirm our assumption of fiscal competition/optimization. It is also in line with the results in Wilson (2009) showing the ineffectiveness of local tax credits in United States at the macroeconomic level, to increase private investment in R&D. It is interesting to note that the opposite applies to direct support (but the indirect effect is not significant). Indeed, the indirect effects reported in Table 11 show that an increase in direct support in all neighboring regions increases private R&D intensity in the focal country and overcomes the negative direct effect of national R&D subsidies implying a positive (but insignificant) total effect of direct support.

The last significant indirect effect is related to the spatial lag of the interact variable[21]. We notice that this variable $W\Delta interact$ does not correspond to the crossed variable of the spatial lag of each support ($W\Delta interact \neq W\Delta lbindex_{-1} \times W\Delta lsub$). This implies that we cannot interpret this variable directly in terms of substituability between direct and indirect support implemented in neighboring countries. Nevertheless, we can deduct some elements from the correlation between $W\Delta interact$ and $W\Delta lbindex_{-1} \times W\Delta lsub$ which is 0.6334. As the coefficients of $W\Delta interact$, $W\Delta lbindex_{-1}$ and $W\Delta lsub$ are all positive, this reflects complementarity among both direct and indirect support from neighboring countries in terms of their influence on own country R&D intensity. In other words, if neighboring countries increase their level of direct support, it increase the negative impact of indirect support from neighboring countries on own country R&D intensity.

These comments highlight the importance of taking account of the spatial dependence to assess the macroeconomic effect of R&D policies. Indeed, without that we only consider internal/direct effect of policies whereas it seems that external/indirect effects could be at least as large.

6 Conclusions

This paper provides new empirical evidence on the macroeconomic effects of R&D subsidies and fiscal incentives on business-funded R&D intensity using a database of 25 OECD countries over the period 1990-2009. We developed theoretical concepts and discussed empirical results in order to determine the core functional relationships to investigate. This first step highlighted that the empirical literature does fully answer questions related to (1) the internal impact of public support for R&D, (2) the externalities between direct and indirect support, (3) the external effects of these policies. The second step focused on appropriate econometric methods to test these elements. More precisely, we developed dynamic spatial panel models.

In terms of internal (in-country) effects, our results show that tax incentives increase business-funded R&D intensity while the reverse applies to R&D subsidies. However this difference does not imply that subsidies are less efficient than fiscal incentives for increasing business-funded R&D. R&D subsidies are deducted in business-funded R&D accounting but not fiscal incentives, and overall, our results point more to a small crowding-out effect for both types of support. A clearer result is found for the shape of the impact of R&D subsidies and fiscal incentives. We show that there is a convex relationship between the effect of each instrument on business-funded R&D intensity and level of use of each instrument. In other words, the existence of a leveraging or a crowding-out effect for both types of policies is directly related to the direct and indirect subsidy rate (the amount of direct and indirect support received for each $ spent on R&D). In relation to the externalities between R&D subsidies and fiscal incentives, our results are in line with previous studies. We find that within a country, R&D subsidies and fiscal incentives are substitutes for stimulating business-funded R&D intensity. This invalidates the common assumption of complementarity of these two policies in terms of incentives and firm's use.

The most important and new contribution of this paper is its consideration of potential external effects of R&D policies and more generally of spatial dependence between private R&D activities in the OECD countries. Our results highlight significant and positive spatial dependence in terms of business-funded R&D intensity suggesting the existence of strong spillovers between private R&D firms. In terms of the external effects of public support, our estimates highlight the possibility of a substitution effect between in-country and out-of-country R&D policies. In other words, the effects of national R&D policies on national business-funded R&D intensity can be nullified by the effects of external R&D policies. More specifically, there is a substitution effect between internal and external fiscal incentives whereas this substitution effect is present

[21] i.e the spatial lag of the crossed variable of direct and indirect support.

but not significant in the case of direct subsidies. This demonstrates the importance of taking account of spatial dependence of public policies to assess their macroeconomic effects. Focusing only on internal effects could potentially lead empiricists to conclude the opposite to what is the true impact of R&D policies.

A direct implication of these findings is the need for international coordination in the definition of R&D support policies in order to optimize their global impact and internalize the effects of spatial dependence. Indeed, our results suggest that the total (internal and external) elasticity of private R&D intensity with respect to direct support is (at least) less negative than its internal counterpart. The total (internal and external) elasticity of private R&D intensity with respect to indirect support is clearly less positive than its internal counterpart. In other words, if governments do not take account of spatial interdependencies in the definition of R&D policies, they will likely favor indirect support compared to direct even if, in the long-run, this choice will not be the most effective. Looking at the reality and the tendency of governments to substitute direct subsidies for fiscal incentives, this implication is significant.

References

[1] Anderson T. and Hsiao C. (1982), "Formulation and Estimation of Dynamic Models Using Panel Data", *Journal of Econometrics*, 18, p. 570-606.

[2] Anselin L. (1988), *Spatial Econometrics: Methods and Models*. Kluwer Academic, Dordrecht.

[3] Arellano M. and Bond S. (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies*, 58, p. 277-297.

[4] Arellano M. and Bover O. (1995), "Another Look at the Instrumental Variable Estimation of Error-components Models", *Journal of Econometrics*, 68, p. 29-51.

[5] Baltagi B. (2005), *Econometric Analysis of Panel Data*, 3rd edition. John Wiley & Sons.

[6] Bérubé C. and Mohnen P. (2009), "Are Firms that Received R&D Subsidies More Innovative?", *Canadian Journal of Economics*, 42(1), p. 206-225.

[7] Bond S., Hoeffler A. and Temple J. (2001), "GMM Estimation of Empirical Growth Models", Economics Papers N2001-W21, *University of Oxford*.

[8] Bond S. (2002), "Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice", *Portuguese Economic Journal*, 1, p. 141-162.

[9] Bloom N., Griffith R. and Van Reenen J. (2002), "Do R&D Tax Credit Works? Evidence From a Panel of Countries 1979-1997", *Journal of Public Economics*, 85, p. 1-31.

[10] Blundell R. and Bond S. (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models", *Journal of Econometrics*, 97, p. 115-143.

[11] Bun M. and Carre M. (2005), "Bias-corrected Estimation in Dynamic Panel Data Models", *Journal of Business and Economic Statistics*, 23(2), p. 200-210.

[12] Bun M. and Kiviet J. (2003), "On the Diminishing Returns of Higher Order Terms in Asymptotic Expansions of Bias", *Economics Letters*, 79, p. 145-152.

[13] Busom I., Corchuelo B. and Martínez Ros E. (2012), "Tax Incentives or Subsidies for R&D?", Working Paper n2012-056, UNU-MERIT.

[14] Capron H. (1992), "Economic Quantitative Methods for the Evaluation of the Impact of R&D Programmes. A State-of-the-art", Monitor-Spear Series, European Community Commission, Brussels.

[15] Capron H. and Van Pottelsberghe de la Potterie B. (1997), "Public Support to Business R&D: A Survey and Some New Quantitative Evidence", *Policy Evaluation in Innovation and Technology*, OECD.

[16] Carvalho A. (2011), " Why are Tax Incentives Increasingly Used to Promote Private R&D?", CEFAGE-UE Working Paper, *Universidade de Evora*.

[17] Cerulli G. (2010), "Modelling and Measuring the Effect of Public Subsidies on Business R&D: A Critical Review of the Econometric Literature", *Economic Record*, 86(274), p. 421-449.

[18] David P., Hall B. and Toole A. (2000), "Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence", *Research Policy*, 29, p. 497-529.

[19] David P. and Hall B. (2000), "Heart of Darkness: Modeling Public-private Funding Interactions Inside the R&D Black Box", *Research Policy*, 29, p. 1165-1183.

[20] Debarsy N., Ertur C. and LeSage J. (2012), "Interpreting Dynamic Space-time Panel Data Models", Statistical Methodology, 9, p. 158-171.

[21] Elhorst J. P. (2003), "Specification and Estimation of Spatial Panel Data Models", *International Regional Science Review*, 26, p. 244-268.

[22] Elhorst J. P. (2005), "Unconditional Maximum Likelihood Estimation of Linear and Log-linear Dynamic Models for Spatial Panels", *Geographical Analysis*, 37, p. 62-83.

[23] Elhorst J. P. (2008), "Estimation of Dynamic Panels with Endogenous Interaction Effects", *II World Conference of the Spatial Econometrics Association*, New York.

[24] Elhorst J. P. (2010), "Dynamic Panels with Endogenous Interaction Effects when T is Small", *Regional Science and Urban Economics*, 40, p. 272-282.

[25] Elhorst J. P. (2012), "Dynamic Spatial Panels: Models, Methods, and Inferences", *Journal of Geographical Systems*, 14, p. 5-28.

[26] Falk M. (2006), "What Drives Business Research and Development (R&D) Intensity across Organisation for Economic Co-operation and Development (OECD) Countries?", *Applied Economics*, 38, p. 533-547.

[27] Goolsbee A. (1998), "Does Government R&D Policy Mainly Benefit Scientists and Engineers?", *National Bureau of Economic Research*, Working Paper No. 6532.

[28] 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, p. 225-243.

[29] Hall B. and Van Reenen J. (2000), "How Effective are Fiscal Incentives for R&D? A Review of the Evidence", *Research Policy*, 29, p. 449-469.

[30] Hall B. (2011), "The Internationalization of R&D", working paper N49, UNU-MERIT, *United Nations University.*

[31] Hsiao C. (2003), *Analysis of Panel Data*, 2nd edition, Cambridge University Press, Cambridge.

[32] Hsiao C., Pesaran M. and Tahmiscioglu A. (2002), "Maximum Likelihood Estimation of Fixed Effects Dynamic Panel Data Models Covering Short Time Periods", *Journal of Econometrics*, 109, p. 107-150.

[33] Howe, J. and McFetridge, D. (1976), "The determinants of R&D expenditures ", *Canadian Journal of Economics*, 9, p. 57-71.

[34] Im K., Pesaran H. and Shin Y. (2003), "Testing for Unit Roots in Heterogeneous Panels", *Journal of Econometrics*, 115, p. 53-74.

[35] Inci E. (2009), "R&D Tax Incentives: A Reappraisal", *International Tax and Public Finance*, 16(6), p. 797-821.

[36] Judson R. and Owen A. (1999), "Estimating Dynamic Panel Data Models: A Guide for Macroeconomists", *Economics Letters*, 65, p. 9-15.

[37] Kiviet J. (1995), "On bias, inconsistency, and efficiency of various estimators in dynamic panel data model", *Journal of Econometrics*, 68, p. 53-78.

[38] Kiviet, J.F. (1999), "Expectation of Expansions for Estimators in a Dynamic Panel Data Model: Some Results for Weakly Exogenous Regressors", in C. Hsiao, K. Lahiri, L-F Lee and M.H. Pesaran (eds.), *Analysis of Panel Data and Limited Dependent Variables*, Cambridge University Press, Cambridge.

[39] Klette J. and Moen J. (2011), "R&D investment responses to R&D subsidies: A theoretical analysis and a microeconometric study", Working Paper1500-4066, Institutt for Foretaksøkonomi.

[40] Kuhlmann S. and Meyer-Krahmer F. (2001), "Internationalisation of Innovation, Interdependence, and Innovation Policy for Sustainable Development", in G.P. Sweeney (Ed.) *Innovation, Economic Progress and Quality of Life*, Cheltenham, p. 86-110.

[41] Lee L and Yu J. (2010), "Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects", *Journal of Econometrics*, 154, p. 165-185.

[42] Lentile D. and Mairesse J. (2009), "A Policy to Boost R&D: Does the R&D Tax Credit Work?", *EIB PAPERS*, 14, p. 143-169.

[43] LeSage J and Pace R (2009), *Introduction to Spatial Econometrics*, CRC Press Taylor & Francis Group, Boca Raton.

[44] Levy D. (1990), "Estimating the Impact of Government R&D", *Economics Letters*, 32(2), p. 169-173.

[45] Levy D. and Terleckyj N. (1983), "Effects of Government R&D on Private R&D Investment and Productivity: A Macroeconomic Analysis", *Bell Journal of Economics*, 14(4), p. 551-561.

[46] Lichtenberg F.R. (1987), "The Effect of Government Funding on Private Industrial Reserach and Development: A Re-assessment", *Journal of Industrial Economics*, 36, p. 97-104.

[47] Lichtenberg F.R. (1988), "The Private R&D Investment Response to Federal Design and Technical Competitions", *American Economic Review*, 78, p. 550-559.

[48] Lokshin B. and Mohnen P. (2009), "What does it Take for an R&D Tax Incentive Policy to be Effective?", working paper for the CEPR project Science, Innovation, Firms and markets in a Globalized World (SCI-FI GLOW).

[49] McFetridge D.G and Warda J. (1983), "Canadian Tax Incentive: Their Adequacy and Impact", Canadian Tax Paper 70, *Canadian Tax Foundation.*

[50] Montmartin B. (2013), "Intensité de l'Investissement Privé en R&D dans les Pays de l'OCDE: Impact et Complémentarité des Aides Financières à la R&D ", *La Revue Economique*, vol.64(3), p. 541-550.

[51] Musgrave R. (1959), *The Theory of Public Finance*, New York, Mc Graw Hill.

[52] Nerlove M. (1999), "Properties of Alternative Estimators of Dynamic Panel Models: An Empirical Analysis of Cross-country Data for the Study of Economic Growth", in Hsiao C, Lahiri K, Lee LF, Pesaran MH (eds) *Analysis of Panels and Limited Dependent Variable Models.* Cambridge University Press, Cambridge, p. 136-170.

[53] Nickell S. (1981), "Biases in Dynamic Models with Fixed Effects", *Econometrica*, 49, p. 1417-1426.

[54] Oates W. (1972), *Fiscal Federalism*, New York, Harcourt, Brace, Jovanovitch.

[55] Pesaran H. (2004), "General Diagnostic Tests for Cross Section Dependence in Panels", *IZA* Discussion Paper 1240.

[56] Pesaran H. (2007), "A Simple Panel Unit Root Test in the Presence of Cross-section Dependence", *Journal of Econometrics*, 22 (2), p. 265-312.

[57] Rubin D. (1987), *Multiple Imputation for Nonresponse in Surveys*, New York, Wiley.

[58] Shin T. (2006), "Behavioural Additionality of Public R&D Funding in Korea", in OECD, *Government R&D Funding and Company Behaviour: Measuring Behavioural Additionality*, chap. 9, p. 167-180.

[59] Takalo T., Tanayama T. and Toivanen O. (2013), "Estimating the benefits of targeted R&D subsidies", *The Review of Economics and Statistics*, 95(1), p. 255-272.

[60] Thomson R. (2009), "Tax Policy and the Globalisation of R&D", *Australian National University*, Working Paper 3.

[61] Tiebout (1956), "A Pure Theory of Local Expenditure", *The Journal of Political Economy*, 64(5), p. 416-424.

[62] Tobler W. (1970), "A Computer Movie Simulating Urban Growth in the Detroit Region", *Economic Geography*, 46, p. 234-240.

[63] Warda J. (2001), "Measuring the Value of R&D Tax Treatment in OECD Countries" in *OECD STI Review*, 27, Special Issue on New Science and Technology Indicators, p. 185- 211.

[64] Warda J. (2005), "Measuring the Value of R&D Tax Provisions: A Primer on the Bindex for Analysis and Comparisons", paper prepared for The OMC Working Group on *Design and evaluation of fiscal measures to promote business research, development and innovation.*

[65] Warda J. (2006), "Tax Treatment of Business Investments in Intellectual Assets: An International Comparison", STI Working Paper 4, *DSTI OECD.*

[66] Wilson D. (2009), "Beggar thy Neighbor? The In-state, Out-of-state, and Aaggregate Effects of R&D Tax Credits", *The Review of Economics and Statistics*, 91(2), p. 431-436.

[67] Wolff G. and Reinthaler V. (2008), "The Effectiveness of Subsidies Revisited: Accounting for Wage and Employment Effects in Business R&D", *Research Policy*, 37, p. 1403-1412.

[68] Yu J., de Jong R. and Lee L. (2008), "Quasi-maximum Likelihood Estimators for Spatial Dynamic Panel Data with Fixed Effects when Both n and T are Large", *Journal of Econometrics*, 146(1), p. 118-134.

Appendix A: The B-index, a relevant indicator for comparing the generosity of tax systems

The B-index is a synthetic measure of the generosity of the tax system for R&D developed by McFetridge and Warda (1983). Its simplicity makes it the reference index for making international comparisons of tax systems. This index measures the present value of pre-tax income required to cover the initial cost of R&D investment and corporate income tax. Mathematically, the B-index is equal to the cost, after tax incentives, of a dollar's investment in R&D divided by 1 minus the tax rate on profits:

$$\text{B-index} = \frac{1-\tau z}{1-\tau},$$

where τ is the corporate tax rate and z is the present value of deductible R&D expenditure. Consequently, $(1-\tau z)$ represents the after-tax cost per dollar of R&D expenditure. In an economy in which there are no taxes ($\tau = 0$), the value of the B-index will be 1. Another situation where the B-index can be equal to 1 is the case where all R&D expenditure are fully deductible in a current year ($z = 1$) and are taxed at the same tax rate. For example, if $\tau = 0.3$ and $z = 1$ then the B-index is equal to $B = (1-0.3)/(1-0.3) = 1$. The B-index will vary from 1 only when R&D expenditure are not fully deductible ($z < 1$) or are more than fully deductible ($z > 1$), and/or where there exist allowances or tax credits for R&D that reduce the after-tax cost of an R&D project (that is, the after-tax cost of one dollar of expenditure on R&D). Thus, the lower a country's B-Index the more generous its tax system towards R&D will be. We need also to precise that the B-index is often use to determine the ficsal (or indirect) R&D subsidiization rate (by using the following formula: indirect subsidization rate $= 1 - B - index$).

1. ***Some examples and implications of the B-index***

   - Deductibility of R&D expenditure

   Assume that R&D expenditure are partially deductible in the current year ($z < 1$). In this case, the present value of pre-tax income required to cover the initial cost of R&D investment and corporate income tax will be higher than 1. Consequently, the value of the B-index is higher than 1 ($B > 1$) and reflects a less attractive tax treatment for R&D than the case where R&D expenditure are fully deductible (which is the benchmark of the B-index model). When R&D expenditure are more than fully deductible ($z > 1$), the B-index is a decreasing function of the corporate tax rate. In other words, the lower the corporate tax rate the higher the B-index will be. Consequently, the marginal effect of a more favorable deductibility on the B-index decreases with the corporate tax rate.

   - A volume tax credit

   Assume a volume tax credit of 10%, a fully deductible R&D expenditure and a corporate tax rate of 50%. If the tax credit is not taxable, the B-index is given by $B = (1-0.5-0.1)/(1-0.5) = 0.8$. In this case, the B-index is a decreasing function of the corporate tax rate. If the tax credit is taxable, then the B-index is given by $B = (1-0.5)(1-0.1)/(1-0.5) = 0.9$ whatever the level of corporate tax rate. Consequently, when the tax credit is not taxable, a decrease of the corporate tax rate reduces the marginal effect of the tax credit on the B-index whereas when it is not taxable, the variation of the corporate tax rate has no impact on the marginal effect of the tax credit on the B-index.

   The generalized formula for the B-index with a volume tax credit is the following:

$$\text{B-index} = \frac{1 - \tau z - cz}{1 - \tau}, \qquad \text{not taxable case,}$$
$$\text{B-index} = \frac{1 - \tau z - cz(1 - \tau)}{1 - \tau}, \quad \text{taxable case,}$$

where c represents the rate of the tax credit.

- The incremental tax credit

An incremental tax credit also reduces the B-index. In order to give a general measure of the impact of an incremental tax credit on the B-index, the model assume that R&D expenditure are constant in real terms over time. Under this assumption, an incremental tax credit represents a tax gain resulting from the investment of one dollar in R&D at time t minus the present value of the tax gain lost (n periods) related to the investment at time t. Consequently, the effect of an incremental tax credit is increasing with the period used as basis (t) and with the discount rate (r). The generalized formula for the B-index with an incremental tax credit is given by:

$$\text{B-index} = \frac{1 - \tau z - cz(1/n)(1 - (1 + r) - n)}{1 - \tau}, \qquad \text{not taxable case,}$$
$$\text{B-index} = \frac{1 - \tau z - cz(1 - \tau)(1/n)(1 - (1 + r) - n)}{1 - \tau}, \quad \text{taxable case.}$$

The simplicity of the B-index model allows the differenciation of R&D expenditure components. Usually, we distinguish the current expenditure from the expenditure related to the acquisition of fixed assets due to different tax treatment. The standard assumption[22] concerning the distribution of R&D expenditure is the following: 90% are current expenditure (which two thirds consist of salaries) and 10% are fixed assets (half for equipment and machines and half for buildings).

As shown by Thomson (2009) and Mohnen et Lokshin (2009), the B-index is a linear function of the user cost of capital à la Jorgenson (1963):

$$u_R = P_R(r + \delta)B,$$

where P_R is a price index for R&D inputs (labor, equipment, machine, building), r is the real interest rate, δ is the depreciation rate of the stock of knowledge and B is the B-index. As we can see, the B-index is the fiscal component of the user cost of R&D. Therefore, the elasticity to the B-index can be interpreted in the same way that the elasticity to the user cost of R&D, other things being equal.

2. ***Limitations of the B-index and its calculation by Thomson (2009)***

An important limitation of the B-index is to only consider the impact of tax incentives on the corporate taxable income. Thus, a large number of tax characteristics that affect investment decisions in R&D are excluded from the calculation of the B-index. For example, taxes on income, consumption taxes, property taxes, payroll taxes and capital taxes are excluded.

Remember that the B-index model measures the potential generosity of the tax system so that he assumes an absence of tax exhaustion. This implies that the model does not distinguish between refundable and non-refundable provisions. Similary, the model assumes that firms have sufficient

[22] See Mcfetridge et Warda (1983), Bloom et al. (2002) or Thomson (2009).

taxable income to take advantage of all tax incentives so that some dynamic aspects of these measures such as retroactive or deferred provisions do not affect the value of the B-index.

Another important assumption of the B-index model is to ignore the limits of fiscal measures. Of course, in reality, the tax measures are often "capped and floored".

The B-index measure used in this paper is taken from Thomson (2009). It is built on standard assumptions of McFetridge and Warda (1983) previously explained. We refer the reader to the Thomson's article (2009) for details on the composition of R&D expenditure and the formulas used to calculate the effect of tax incentives. Obviously, the measure does not incorporate any other forms of financial support for R&D (grants, loans,...). Specific measures concerning collaboration in R&D with universities or those only applicable to SMEs are not included as well as policies of local and regional authorities. Indeed, it is not possible to model all of these measures in an index whose goal is to allow international comparisons.

Appendix B. Definition of variables and the Common factor test

Table B.1: Definition of Variables.

Variable name	**Definition of the variable**	**Data Source**
Dirdefi	R&D expenditures funded by the private sector as a percentage of GDP.	OECD
Credit	Domestic credit to private sector as a percentage of GDP.	IMF
Interetlt	Long-term nominal interest rate in percentage point.	IMF
Dirdpub	R&D expenditures executed by the public sector as a percentage of GDP.	OECD
Sub	Corresponds to the ratio of Government funded expenditures on R&D in the business sector divided by business expenditures in R&D (BERD) private sector.	OECD
Bindex	B-index for the large company group.	Thomson (2009) OECD

Table B.2: Dynamic Common Factor using W(patent).

VARIABLE	MODEL 1		MODEL 2		MODEL 3	
	SDPD	dynSEM	SDPD	dynSEM	SDPD	dynSEM
MAIN EFFECTS						
$\Delta ldirdefi_{-1}$	0.406^{***}	0.406^{***}	0.416^{***}	0.522^{***}	0.397^{***}	0.417^{***}
$\Delta lcredit$	0.050^{*}	0.036	0.051^{*}	0.028	0.052^{*}	0.035
$\Delta interetlt$	-0.008^{***}	-0.007^{***}	-0.006^{***}	-0.007^{**}	-0.008^{***}	-0.008^{***}
$\Delta lsub$			-0.037^{***}	-0.042^{**}		
$\Delta lsub \times sub$	-1.048^{***}	-1.073^{***}			-0.968^{***}	-0.992^{***}
$\Delta lsub \times sub^2$	4.148^{***}	4.037^{***}			3.798^{***}	3.773^{***}
$\Delta ldirpub_{-1}$	0.239^{***}	0.233^{***}	0.236^{***}	0.214^{***}	0.230^{***}	0.226^{***}
$\Delta lbindex_{-1}$			-0.248^{***}	-0.255^{**}		
$\Delta lbindex_{-1} \times bindex$	-1.276	-1.159			-3.365^{***}	-3.162^{***}
$\Delta lbindex_{-1} \times bindex^2$	1.395	1.395			4.068^{***}	3.782^{***}
$\Delta interact$			0.524^{**}	0.546	1.038^{***}	1.019^{***}
SPATIAL EFFECTS						
$W\Delta ldirdefi_{-1}$	-0.407		-0.377		-0.399	
$W\Delta ldirdefi$	0.229^{*}		0.123		0.205^{*}	
$W\Delta lcredit$	0.210^{*}		0.197^{*}		0.196^{*}	
$W\Delta interetlt$	-0.046		-0.052^{*}		-0.054^{**}	
$W\Delta lsub$			0.074			
$W\Delta lsub \times sub$	-2.578				-0.894	
$W\Delta lsub \times sub^2$	44.367				32.074	
$W\Delta ldirpub_{-1}$	0.123		0.359		0.054	
$W\Delta lbindex_{-1}$			2.404^{***}			
$W\Delta lbindex_{-1} \times bindex$	2.953				0.926	
$W\Delta lbindex_{-1} \times bindex^2$	-3.486				0.917	
$W\Delta interact$			16.772^{***}		15.705^{***}	
$Werror$		-0.033		-0.033		-0.036
Common Factor test	85.18		62.03		94.46	
(*p value*)	(0.00)		(0.00)		(0.00)	

Notes: *, ** and *** denotes significance at 10%, 5% and 1%. Dependent variable is log Dirdefi %GDP (in first difference). Terms Δ and l denotes first diff. and log. Time effects are included but not reported. Common factor test using LR. The conclusions not change if we use W trade.