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The Global Effects of R&D Tax Incentives: Evidence from Micro-Data

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Abstract

Recent years have seen an unprecedented increase in the provision of R&D tax incentives. A growing empirical literature suggests that R&D tax incentives are instrumental in raising domestic R&D activity. In policy debates this finding is often interpreted to lend support to the notion that R&D tax incentives increase national welfare by internalizing knowledge spillovers to other agents in the economy and raising inefficiently low R&D levels. Our paper stresses that much of the observed increase in R&D activities in response to R&D tax incentives is in fact related to R&D activities that are attracted from abroad. Using unique panel data on R&D activities of European multinational firms, we test for a potential impact of both, R&D tax incentives in the affiliate's host country and R&D tax incentives at other locations of the multinational group. In line with theoretical predictions, we find a positive impact of domestic R&D subsidies and a negative one for foreign subsidies provided at other group locations. Quantitatively, the findings suggest that around 80% of the observed increase in R&D activities is related to relocations of R&D across country borders.

Keywords R&D, multinational firms, tax incentives

JEL Classification H2, H7

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1 Introduction

Recent decades have seen an unprecedented increase in the prevalence of tax incentives for research and development (R&D). 27 OECD countries offered preferential tax treatment of R&D expenditures in 2013, while less than half of these countries had implemented R&D incentive scheme 20 years ago ((OECD, 2013, p. 1)).

The main theoretical justification for providing R&D subsidies to the private sector is related to positive externalities, in particular knowledge spillovers, which are not internalized by the individual firm (see Arrow (1962) for the seminal work). In line with this notion, a growing literature reports evidence that the social returns to R&D substantially outweigh the private returns (see e.g. Schankerman (1981), Jaffe (1988), Griliches and Mairesse (1991), Mohnen (1990), Griliches (1992)).¹

Whether R&D tax incentives are instrumental in raising inefficiently low R&D levels and internalizing benefits related to knowledge spillovers is ultimately an empirical question. If the effect of R&D tax incentives on firm behaviour is small, the incentives may just generate windfall gains to the corporate sector. Existing empirical studies have assessed this question by identifying own-price elasticities of R&D investment, which capture the effect of the domestic R&D user costs of capital on R&D spending in the private sector, commonly finding large and significant effects (see e.g. Bloom, Griffith, and van Reenen (2002)). In the policy arena, these findings are often interpreted to lend support to the notion that R&D tax incentives are instrumental in raising inefficiently low innovation levels.

This interpretation may be heavily misleading. Among other things, activities related to R&D are observed to be increasingly mobile across countries (see e.g. Bloom and Griffith (2001) and Abramovsky, Griffith, Macartney, and Miller (2008)). Governments may thus strategically compete for mobile R&D investments, implying that increases in R&D investments in one country in response to generous R&D subsidies may come at the expense of neighbouring jurisdictions that lose out in R&D activity. As governments do not take the fiscal externality on other countries into account, international competition may lead to a race-to-the-top of R&D tax incentives and imply

¹See also Hall (1996) and Hall, Mairesse, and Mohnen (2010) for a further discussion, especially on the measurement problems related to the private and social rates of return of R&D investment. Most studies focus on knowledge spillovers in specific countries or regions. However, there is a small but growing strand of literature covering international knowledge spillovers. Coe and Helpman (1995), for example, find evidence that the influence of R&D on productivity growth is not just depending on the domestic level of R&D capital but also on R&D of the trading partners.

that subsidies are set inefficiently high from a global perspective. Moreover, if R&D tax incentives fails to raise global R&D activity, their social desirability is strongly called into question.

The purpose of our paper is to empirically assess whether responses of national private sector R&D to R&D tax incentives reflect a genuine increase in R&D activities or beggar-thy-neighbor policies that attract mobile R&D from abroad. To do so, we use a unique panel data set that links information on multinational firms in Europe with data on patent applications drawn from the European Patent Office (EPO). The firm level data is obtained from the Amadeus data base provided by Bureau van Dijk which offers detailed balance sheet information on firms in Europe. The data furthermore includes information on ownership connections and thus allows to identify whether firms are part of a multinational group and determine the group structures. Our main analysis focuses on multinational entities in the nine-year period between 1998 and 2006. Innovative activity of the affiliates in our data set is proxied by the number of granted patent applications to the EPO. As previous evidence suggests that patents strongly differ in their level of innovativeness and industrial value (see e.g. Hall, Mairesse, and Mohnen (2010) for a survey), we furthermore construct a quality-adjusted count of patent applications of our sample firms which acknowledges potential quality differences based on the value-correlates family size, the number of forward citations and the number of industry classes on the patent.

The firm-level data is furthermore augmented by country-level information. Most importantly, we add data on tax allowances and tax subsidies provided in our European sample countries. Precisely, for each country-year-cell, we construct the so-called B-index which models the minimum pre-tax profit required for an R&D investment to break-even, accounting for the R&D tax credit and allowance provisions as well as the host country's corporate income tax rate. The empirical analysis regresses the number of (quality-adjusted) patent applications of our sample affiliates on the B-index in the affiliate's host country and the average B-index at other locations of the multinational group, controlling for observed and unobserved heterogeneity across firms and host countries. While a significant impact of the domestic B-index may reflect that new R&D activities are triggered by an increase in the generosity of R&D subsidies, it may equally reflect that R&D activities are attracted from abroad. A positive response of R&D activities to the average B-index at foreign group locations is in turn only consistent with the notion of internationally mobile R&D that responds to locational tax incentives.

In line with previous papers, our results suggest significant own-price elasticities of

R&D activities. Quantitatively, an increase in tax subsidies that trigger a reduction in R&D investment cost by 10% raises the number of (quality-adjusted) patent counts by around 5%, suggesting that domestic R&D subsidies are instrumental in fostering the level of innovative activity. Augmenting the model specifications by a regressor for the average B-index of other affiliates in the same multinational group offers two insights: firstly, we find the elasticity of corporate R&D activities to the domestic user costs of capital to increase significantly in absolute terms (by around one third), suggesting that ignoring average R&D user costs in neighbouring jurisdictions implies an omitted variable bias and underestimates the effect of interest in absolute terms. This is in line with intuition since international competition suggests a positive correlation between R&D tax subsidies chosen by neighbouring countries. Increases in the generosity of R&D tax incentives may thus not only raise domestic innovative activity, but may equally trigger a policy response of neighbours which then equally increase R&D subsidies. If the latter absorbs some R&D investment but is disregarded in the empirical model, this results in a downward bias of the own-price elasticity of R&D in absolute terms.

As a second insight, the estimations suggest that increases in tax subsidies at foreign locations of the multinational group equally exert a significant impact on the affiliate's R&D activities. Precisely, a reduction in foreign R&D costs by 10% is found to decrease the affiliate's innovative activity by around 6% (while reductions in domestic R&D costs raise innovative activity as measured by the number of patent counts by around 7%). Consequently, the results suggest that a large fraction of the observed own-price elasticities of R&D investment, reported in this and in prior work, reflects beggar-thy-neighbor strategies and investment that is attracted from foreign sources. This finding has important welfare implications. First of all, it suggests that the global response of R&D activities to tax incentives is weak, suggesting that public R&D subsidies are hardly effective in raising aggregate global R&D investment. In the contrary, the results point to strong international competition for mobile R&D. This calls the effectiveness of the policy instrument strongly into question. In any case, decentralised policy choices turn out to be suboptimal from a global perspective, which supports ideas for an international coordination of policies related to the subsidisation of R&D.

Our paper relates to a growing empirical literature that aims to assess the impact of R&D subsidies on domestic R&D expenditures. Early papers for the US provide evidence for a significant effect, commonly reporting quantitatively large R&D price elasticities of at least unity (see e.g. Hall (1993), Hines (1994), Baily and Lawrence (1992) and Mamuneas and Nadiri (1996)). Bloom, Griffith, and van Reenen (2002)

calculate the tax-adjusted cost of investing in R&D across a panel of nine OECD countries over nineteen years. Specifying a dynamic model with manufacturing sector business enterprise R&D intensity as the dependent variable, they find a negative long run elasticity with respect to the user cost of R&D. Similar findings have recently been reported in Corchuelo and Martinez-Ros (2009), Czarnitzki, Hanel, and Rosa (2011), Mairesse and Mulkey (2011), Bond and Guceri (2012), Lokshin and Mohnen (2012) and Guceri (2013) whose empirical identification strategy relies on changes in R&D tax incentives scheme in Canada, France, the Netherlands, Spain and the UK, which are exploited as natural experiments.

None of the described papers, however, assesses whether the observed responsiveness of R&D activities to tax incentives reflects a genuine increase in the (global) resources allocated to R&D activities or whether R&D activities are attracted from foreign countries. Two exceptions are Bloom and Griffith (2001) and Wilson (2009). Both papers use aggregate data to determine the effect of domestic and foreign user costs of R&D capital on R&D spending. Bloom and Griffith (2001) use panel data for the countries of Australia, Canada, France, Germany, Italy, Japan, the UK and the USA between 1979 to 1997. In line with intuition, they find a significantly negative effect of domestic user costs of capital on R&D spending and a positive one for the foreign user costs of capital which are constructed based on FDI weights. In absolute terms, the foreign effect is three times larger than the domestic effect, pointing to the importance of competition effects related to the international mobility of R&D. Wilson (2009) uses data on R&D spending and R&D tax incentives at the US state level between 1981 and 2004 to identify the impact of domestic and foreign user costs of capital on the level of private sector R&D. He reports an in-state user cost elasticity of around -2.5 and an out-of-state user cost elasticity of $+2.7$.

Our paper offers several advantages relative to these two existing studies. Firstly, our empirical identification strategy relies on micro data and is thus less likely to be prone to simultaneity bias. In particular, governments' R&D tax incentives are plausibly exogenous to the individual firms' R&D decision. Our data furthermore allows to control for observed and unobserved characteristics of multinational groups, which adds further credibility to the identification approach. Using micro data further offers to test for potential heterogeneity in the effect of interest across firms. Moreover, our study allows to assess effects related to *national* R&D tax subsidies. Wilson (2009) in turn focuses on R&D tax subsidies at the US state level. His results do not automatically carry over to the international level as R&D investments are likely much more mobile subnationally than internationally. Our study fills this gap and presents evidence that

the interjurisdictional competition effects are still important for R&D tax incentives chosen at the national level.

The remainder of the paper is structured as follows: Section 2 describes our data. Sections 3 and 4 present the estimation approach and the empirical results. Section 5 concludes.

2 Data

As sketched in the introductory section, our empirical analysis intends to assess the impact of R&D incentives on corporate R&D activities. The analysis draws on rich firm level data as well as information on corporate patent applications to proxy for firms' innovative activities.

Patent Data

Precisely, we exploit information on the universe of patent applications to the European Patent Office which is drawn from the Worldwide Patent Statistical Database PATSTAT (version October 2012). While the information on patent applications dates back to 1978, our analysis is restricted to the interval between 1998 and 2006 as we lack concise R&D tax incentive information for earlier years (see below). Note that firms may file for patent protection in the member states of the European Patent Office either at the EPO or at the respective national offices. Filing directly at the EPO offers several advantages. First and foremost, filing for patent application involves non-negligible costs (see e.g. Helfgott (1993)) and thus filing at EPO is cheaper than filing for patent protection at several national offices. Moreover, the decision to further the application to other countries can be delayed. PATSTAT contains detailed information on the patent applications. In particular, the data includes information on the host countries of the patent applicant and the patent inventor as well as information on the application filing date as well as if and when patent protection has been granted, the technology classes stated on the patent and patent citations.

Construction of Composite Quality Index

Previous research has shown that the value of patents is highly skewed and dispersed (Schankerman and A.Pakes (1986), Harhoff, Narin, and Vopel (1999) and Graevenitz, Wagner, and Harhoff (2008) among others). Using simple patent counts to proxy for corporate innovative activities may thus be an imprecise measure. To account for that, we exploit the information in PATSTAT to construct quality-adjusted patent counts

which acknowledged potential differences in the underlying industrial and innovative value of the technologies protected by the patent applications in our data.

Precisely, we follow previous research (i.e. Lanjouw and Schankerman (2004) and Hall, Thoma, and Torrisi (2007)) and exploit information on the family size of the patent, the number of forward citations and the number of industry classes on the patent to proxy for its value.

The family size captures the number of patent offices in which the firm files for patent protection.² The rationale for using a patent's family size as a proxy for its value is that filing for patent protection involves considerable costs, e.g. costs for patent attorneys, filing fees at the patent offices and the costs for translation of documents (see Helfgott (1993), Lerner (1994) and Harhoff, Scherer, and Vopel (2003)). Note that the PATSTAT data includes information on patent applications to all (major) patent offices worldwide and allows to identify priority filings to a patent application and thus identify all patent offices where an applicant filed for patent protection for a technology. For the analysis to come, we used the INPADOC definition of a patent's family size in PATSTAT.

Furthermore, we use the patent's number of the forward citations within the five year period from its publication date as a proxy for its industrial value (see Hall et al.(2007)). Forward citations have an important legal function in the sense that they limit the scope of property rights which are awarded to a patent. In the case of EPO patents, inventors are not required to cite prior technology used in the development of their patent but the references are added by patent examiners. On the one hand, this implies that not necessarily all innovations which draw on an existing patent in fact acknowledge the reference. On the other hand, an external patent examiner has the benefit of following a consistent and objective patent citation practice. We consider forward citations to be a particularly strong indicator for the level of innovativeness and knowledge value related to a patent as it indicates whether the technology is the basis for future inventions.³

As suggested by previous research, the third indicator used to proxy for patent

²The definition of the family size of patents differs across papers (Martinez (2010)) and may also include related patents to the original patent. For our analysis, we use the INPADOC definition of a patent's family size provided in PATSTAT.

³On top, previous research has proposed to use information on patent renewal data or backward citations to proxy for patent value (Lanjouw, Pakes, and Putnam (1998)). As the results for the latter two proxies have been mixed (see Harhoff, Narin, and Vopel (1999)), we disregard them in the analysis to come.

quality is the number of technology classes (Lerner (1994)). Each patent is assigned to one or more technology classes. PATSTAT uses the eight digit IPC (International Patent Classes) classification which is matched with the OST35 classification⁴ to assign industry classes to each patent.

We use factor analysis to determine a composite quality index which accounts for the three value proxies described above. The underlying assumption of the factor model is that the variation in the quality indicators consist of a quality related and an idiosyncratic component. It exploits that variation in the patent quality induces variation common to all individual indicators. This leads to patent quality estimates conditional on the indicators (see the appendix and Hall et al.(2007) and Lanjouw and Schankerman(2004) for further details).

Firm Level Information

The described data on patent applications is linked to firm level data contained in the Amadeus data base provided by Bureau van Dijk. Precisely, the name of the patent applicant in the PATSTAT data is matched with the name in the Amadeus data using standard name matching procedures.⁵ Matching rates are high and in line with previous matching efforts (see Thoma et al. (2010)) for details.

The Amadeus data comprises rich unconsolidated accounting and profit and loss information for firms in Europe. The data available to us spans the time period between 1998 and 2006 and is available as an unbalanced panel. One main benefit of the data is that includes detailed ownership information and thus allows to identify whether firms belong to multinational corporations. We will, in the following, restrict our data to affiliates (subsidiaries or parents) which are part of a multinational group, in the sense that they are either owned by a foreign parent with an ownership share of 50% or more or that they own a subsidiary in a foreign country with an ownership share of 50% or more or their ultimate parent owns a majority-held subsidiary in a foreign country. For these affiliates, the data allows us to determine the precise structure of their multinational group, i.e. to determine the home country and all host countries of the multinational group.

We will use the patent data described above to determine the number of patent counts for our sample affiliates per year. In doing so, we only account for patents that were invented in the applicant's host country as we intend to proxy for the innovative

⁴This technology classification is jointly constructed by the Fraunhofer Institute for Systems and Innovation Research Karlsruhe and the Observatoire des Sciences et des Technique (OST) Paris.

⁵We are very grateful to Grid Thoma for providing us with this data.

activity of the firm (this is the case for the large majority, around 90%, of the patents).⁶ The quality-adjusted count measure is constructed based on the rationale that patent applications whose composite quality index derived in the factor model corresponds to the average quality of patents in the same industry-year cell are assigned a count of 1. If the composite quality index indicates a quality larger than the average in the patent's industry-year cell, the patent is assigned a 'count'-value of $1 + \frac{c-\bar{c}}{\bar{c}}$, where c indicates the composite quality index from the factor model for the considered patent and \bar{c} represents the average quality index for patents in the same industry and application year. Thus, consider a patent with a quality index of 7 which belongs to an industry-year cell with an average patent quality of 5. The quality-adjusted count for this patent thus sums to $1+0.40 = 1.4$, indicating that the determined patent quality indicates that the patent is 40% more valuable than other comparable patents filed during the same year in the particular industry. Analogously, if the patent quality index read 3 only, the quality adjusted patent count would read $1 - 0.4 = 0.6$, indicating that the patent is 40% less valuable than other comparable patents. Note that this construction implicitly accounts for the fact that patent value varies significantly across industries and across time. We thus implicitly follow the existing literature and use quality measures which control for technology and year fixed effects (i.e. account for deviations from the average patent quality in a technology class at a given point in time). Note that the analysis is restricted to multinational groups that undertake significant R&D activities in Europe, in the sense that at least three group affiliates have filed for at least one patent application within our sample period.⁷ Descriptive Statistics for the quality variables are depicted in Table 1 and indicate that the number of patent counts as well as the number of quality adjusted patent counts varies significantly across affiliates and over time. Affiliates in our data on average file for 2.1 patent applications per year. The distribution is highly skewed though, with sum affiliates filing several hundred

⁶Note that multinational firms may set up structures which geographically split the location of the patent applicant (which is commonly also the patent owner, see e.g. Quick and Day (2004)) and the inventor of the technology. The multinational group may e.g. set up contract research agreements, where an affiliate contracts out research to an R&D unit in another country. The finances the project and bears its risk. Consequently, while the R&D unit earns a small fixed mark up on its costs, residual income accrue with the financing affiliate that is the owner of the technology and entitled to file for patent protection. Further note that while patent applications can be filed by corporates for technologies owned by the firm, the inventor on the patent is necessarily an individual person. Thus, the link between PATSTAT and Amadeus was implemented based on the name of the patent applicant. If the technology inventor is located in a different country than the patent applicant, the data does not allow to achieve between the inventor and a firm in Amadeus.

⁷Note that this assumption is not decisive for our results though.

patent applications (maximum: 760) per year, while others file none (see Table 1 for details). Interestingly, the quality adjusted patent count is somewhat smaller, likely reflecting the well-known skewed value-distribution of corporate patents.

The Value of R&D Tax Incentives: Construction of the B-Index

To measure the generosity of a country’s R&D tax treatment, we follow the previous literature and subsume information on R&D tax incentives in a so-called B-index. It was first introduced by Warda (1983). The B-index B_{kt} for country k in period t is defined as

$$B_{kt} = \frac{1 - Z_{kt} \cdot \tau_{kt}}{1 - \tau_{kt}} \quad (1)$$

where τ_{kt} indicates the corporate tax rate of country k at time t and Z_{kt} measures the generosity of the deductibility of R&D expenditures from the corporate tax base, accounting for R&D tax allowances, tax credits and current tax expenditures. The numerator of the B-index thus captures the marginal cost of a 1 EUR investment in research and development in a certain country after taxes. The numerator reflects the after-tax cost of one unit of expenditure in R&D and the B-index consequently captures the minimum pre-tax earnings required for the project to break even and to go ahead. If investment in R&D can be fully deducted in the fiscal year, Z_{kt} and consequently also the B-index have a value of one. More generous R&D tax credits and tax allowances reduce the B-Index below 1. The lower the B-index, the smaller the required pre-tax return for an R&D investment project to break even and the more attractive the tax incentive scheme. Our data comprises information for the B-index in our sample countries between 1998 and 2006.⁸ As indicated in Table 1, the index exhibits a considerable cross-sectional and longitudinal variation.

Construction of the Foreign B-Index

As sketched above, the aim of our analysis is not only to determine the effect of domestic R&D tax incentives, but also to assess whether changes in R&D tax incentives provided in neighbouring countries impact on the innovative activity of multinational affiliates. Precisely, we exploit the ownership data which allows to identify the location of multinational groups in Europe.⁹ For every affiliate in our data set we thus construct a variable which captures changes in the generosity of other potential R&D hosting

⁸We are grateful to Christof Ernst and Christoph Spengel for providing us with this data. See Ernst and Spengel (2011) for further details.

⁹Note that the Amadeus data is restricted to European countries and thus we do not account for potential host locations of multinational groups outside Europe.

affiliates (subsidiaries or parents) within the multinational group.¹⁰ The average index is defined as

$$AVGB_{it} = \frac{1}{n-1} \sum_{j \in M(i) - \{i\}} W_{ijt} B_{jt}$$

where $M(i)$ is the set of all n affiliates in the same multinational group as firm i and B_{jt} indicates the B-index in the host countries of affiliates j in time period t that belong to the same MNE as firm i . In general, we employ the mean of the B-index of all potential R&D hosting affiliates (except of firm i) to measure the entire attractiveness of R&D investments in the multinational. W_{ijt} depicts a weighting matrix. In the analysis to come, we will use uniform weighting schemes and size weighted averages (by total assets and sales respectively).¹¹

Other Control Variables

We furthermore augment our data by control variables for the country's economic development as measured by the average GDP per capita as well as the country's attractiveness in terms of access to labor markets for high-skilled workers and government infrastructure provision as measured by enrolment rates in tertiary education and R&D spending relative to GDP. We furthermore account for the country's attractiveness for inward FDI by including a control variable for inward FDI flows. All variables are obtained from the World Bank's World Development Indicator Database. We furthermore add information on the quality of governance institutions as contained in the World Governance Indicators database. Descriptive statistics for the control variables is included in Table 1.

3 Estimation Strategy

The empirical analysis intends to identify the effect of R&D tax incentives on the R&D activity of multinational firms. We estimate a regression model of the following form

$$\log PAT_{ikt} = \beta_0 + \beta_1 B_{kt} + \beta_2 AVGB_{it} + \gamma_1 X_{it} + \rho_t + \phi_i + \epsilon_{it} \quad (2)$$

¹⁰Analogously to our main analysis, all affiliates which file for at least one patent application at EPO during our sample period are defined to be potential R&D hosting affiliates.

¹¹For the calculation of the size weighted averages, we assign the average size of the set of foreign affiliates, as measured by total assets and sales respectively, to those foreign affiliates for which size information is missing, to avoid that these affiliates are disregarded in the calculation of the size-weighted averages.

where PAT_{ikt} denotes the number of (quality-adjusted) patent applications of firm i located in country k in period t as defined above. Due to the strongly skewed distribution of the number of patent applications, we use the logarithm of the (quality-adjusted) patent count as dependent variable in our baseline specifications (but will also present robustness checks with the level version) B_{kt} and $AVGB_{it}$ depict the B-index in affiliate i 's host country k and the average B-index at other affiliates which belong to the same multinational group as defined above. If firms are indeed responsive to R&D tax incentives, we expect that reductions in R&D costs as measured by a decrease of the B-index raise the affiliate's number of (quality-adjusted) patent applications, and thus $\beta_1 < 0$. As described in the introductory section, a negative β_1 may be driven by two mechanisms: firstly, R&D tax incentives may lead to a genuine increase in the number of R&D projects undertaken at an affiliate (and within an MNE) by lowering project costs. Secondly, more generous R&D tax incentives in the affiliate's host country may, however, also imply that R&D is attracted from other locations of the multinational group (leaving the overall R&D activity of the MNE unaffected). To disentangle the two effects, we augment the specification by information on the average B-index at other group affiliates $AVGB_{it}$. If R&D is internationally mobile across borders, we expect $\beta_2 > 0$, as more generous R&D tax incentives at other locations within the multinational group and the associated reduction in the foreign B-index are expected to lower innovative activity at the considered affiliate and thus the number of (quality-adjusted) patent applications. Note that the ratio $\beta_2/|\beta_1|$ allows to determine which fraction of the effect of R&D tax incentives on domestic R&D is related to activity that is attracted from abroad.

To control for time constant heterogeneity across affiliates, host countries and multinational groups, the model furthermore accounts for a full set of affiliate fixed effects.¹² Additionally, we include a full set of time fixed effects ρ_t to account for common shocks to all patent applicants over time. The vector X_{it} includes the time-varying host country controls described above. We furthermore calculate the mean of the country controls for all other countries where other affiliates of the MNE are located (using the analogous methodology and weighting schemes as for the calculation of $AVGB_{it}$ in the previous section) to acknowledge that the strategic decision where within the group to locate R&D activities may also be determined by the level of development, access to labor markets and openness of host countries of foreign group affiliates. Finally, ϵ_{it}

¹²Note that one shortcoming of the Amadeus data is that information on ownership connections is available in cross-sectional format for the last reported data only. Thus including affiliate fixed effects nests country fixed effects.

depicts the idiosyncratic error term.

Note that, as sketched in the introductory section, previous papers have largely focused on estimating models which account for the effect of direct host country tax incentives but disregards R&D tax incentives of neighbouring jurisdictions. If governments compete for mobile R&D by strategically setting R&D tax incentives, this likely leads to biased estimates if tax incentives of neighbouring jurisdictions are not taken into account. To see this, consider that the affiliate's host country increases the generosity of its R&D tax incentives. This is expected to raise innovative activity at affiliates in the country as described above. But neighbouring governments have an incentive to respond to the change in R&D tax incentives by equally raising the generosity of R&D subsidies. This triggers, in turn, an outflow of mobile R&D, which is not accounted for in models that neglect to model neighbouring jurisdictions tax incentives. Consequently, the coefficient estimate for the responsiveness of R&D to R&D costs is biased towards zero and underestimated in absolute terms.

4 Results

The results are reported in Tables 2 and 5. Heteroskedasticity robust standard errors that account for clusters at the country-year level are reported in parentheses below the coefficient estimates. All specifications account for a full set of firm fixed effects to absorb time constant heterogeneity across entities and a full set of year fixed effects to account for common shocks to our sample firms over time. Specifications (1) and (2) in Table 2 regress the natural logarithm of the quality-adjusted and normal patent counts per affiliate-year on the domestic R&D costs as measured by the B-index as well as basic country-level controls (the country's GDP per capita and tertiary enrolment rates). The findings confirm our theoretical expectations and indicate a significantly negative effect. Quantitatively, a reduction in R&D costs by 10% is found to raise the number of (quality-adjusted) patent applications by 4.1% and 5.0% respectively. These estimates are in line with prior findings in the literature.

Note that, interestingly, the coefficient estimates hardly differ between the specifications which employ the quality-adjusted patent counts and the normal patent counts as dependent variable to proxy for R&D investment activity, with a slightly smaller estimate in the specification which employs the quality-adjusted counts as dependent variable. First and foremost, the quality-adjusted patent count is expected to offer a more precise measure for the R&D activities undertaken at an affiliate. Moreover, if

R&D tax incentives trigger new marginal investment projects, they are expected to exhibit lower average quality. The latter notion is in line with the smaller point estimate in Specification (1) although the coefficient estimates in the two regressions do not statistically differ from each other. The qualitative and quantitative result furthermore turns out to be robust against including further control variables for the host country's access to high-skilled labor markets and common public support for R&D activity as well as information for the countries' openness (see Specifications (3) to (6)).

Specifications (1) and (2) of Table 3 reestimate the baseline model by augmenting the set of regressors by the foreign B-index, i.e. the weighted average R&D costs at other host locations of the multinational group as well as basic country-level controls (the country's GDP per capita and tertiary enrolment rates) for foreign group locations. The results offer two insights: firstly, in line with the expectations formulated above, the coefficient estimate for the domestic B-index increase relative to the baseline specifications in Table 2, suggesting that disregarding R&D tax incentives provided by neighbouring jurisdictions leads to an underestimation of the effect of domestic R&D costs on corporate R&D activity. Precisely, the specifications suggest that a reduction in domestic R&D costs by 10% raises the number of (quality-adjusted) patent applications by 7.2% and 8.6% respectively. Secondly, the findings furthermore also suggest that the number of (quality-adjusted) patent applications is, however, equally strongly affected by the foreign R&D user costs, i.e. by the average B-index at other locations of the multinational group. Quantitatively, the findings indicate that a reduction in the foreign B-index by 10% reduces R&D activities by 6.0 and 6.8% respectively. Following our reasoning above, this suggests that much of the observed own-price elasticity of R&D activities actually reflects that generous R&D tax subsidies and resulting low R&D user costs attract R&D investment from foreign locations, rather than genuinely expanding overall R&D investments of the group. A Wald-test which assesses the null hypothesis that the sum of the coefficient estimates of the domestic and foreign B-index is equal to zero cannot be rejected at conventional significance levels for all specifications.

This result again turns out to be robust to the inclusion of additional control variables for the host and foreign countries' R&D expenditures and FDI inflows in Specifications (3) to (6). Note that the control variables show the expected signs. The host country's GDP per capita, public R&D expenditures and FDI inflows tend to raise corporate R&D activity, while increases in the analogous controls for the foreign affiliate locations of the multinational group tend to weakly reduce it (effects only turn out statistically significant for the GDP per capita variable).

Table 4 reestimates the baseline model using the number of (quality-adjusted) patent counts as the dependent variable. Specifications (1) to (4) estimate standard fixed effects OLS models, whereas Specifications (5) to (8) acknowledge the count nature of the data and estimate poisson models which account for affiliate fixed effects. The general pattern of the results remains unchanged in all specifications. Specification (3) suggests that a reduction in the user costs of capital by 10% raises the number of quality-adjusted patents by 7.1, while an analogous reduction in the foreign user costs at other affiliate locations leads to drop in the number of quality-adjusted patent applications by 7.0. The findings thus again suggest that corporate responses to tax subsidies largely reflect the international relocation of R&D activity rather than the genuine increase of R&D undertaken by the multinational group.

In Table 5 we run a jackknife analysis for our baseline analysis, assessing whether the determined effects are driven by particular countries in our data. The analysis suggests that this is not the case. In the contrary, the effect turns out to be very stable across specifications.

5 Conclusion

The purpose of this paper was to assess the impact of R&D tax subsidies on R&D activity in the host country as well as in neighbouring jurisdictions. Previous papers have presented compelling evidence which suggests that R&D tax credits and tax allowances exert a significantly and quantitatively large impact on host country R&D spending.

To assess the welfare consequences of the policy instruments, it is decisive to understand whether this positive effect reflects that R&D activities are genuinely expanded in response to an increase in the generosity of R&D tax credits and tax allowances or whether the instruments just attract mobile R&D from abroad. In the latter case, global R&D activities would remain unaltered by the policies, implying that the instruments are not well targeted to internalize knowledge spillovers and raise inefficiently low R&D levels in the private sector.

We address this question using unique panel data on multinational firms in Europe. R&D activities are proxied by the quality-adjusted number of patent applications of these affiliates to the European Patent Office and R&D tax subsidies are modelled by a classic user costs of capital approach. In line with previous studies, our findings suggest that tax subsidies that lead to a drop in the user costs of capital significantly

raise R&D activities. The quantitative estimate is in the range of prior studies and implies that a decrease in the user cost of capital by 10% raises R&D activities by around 5%.

The innovation of our paper is to stress that multinational R&D activities are also significantly affected by R&D tax subsidies at foreign locations of the multinational group. One insight from these specifications is that adding information on foreign R&D user costs at other locations of the multinational firm to the estimation model significantly increases the estimates for the direct effect of the host country's tax subsidy on R&D activities in absolute terms (by around one third), suggesting that prior studies which ignore this information suffer from an omitted variable bias and underestimate the true effect of R&D tax incentives on R&D activity in the private sector.

The second insight from these specifications is that the effect of foreign R&D user costs on R&D activities in the host country is quantitatively large. While we estimate own R&D price elasticities of around -0.7 , the elasticity with respect to the foreign R&D user costs is up to 0.6. The estimates thus suggest that a large fraction of the observed sensitivity of R&D activities to governmental subsidies reflects R&D activities that are attracted from abroad, suggesting that the incentives scheme do not exert a large positive impact on global R&D. In the contrary, the policy instruments appear to serve as competitive instruments mainly to attract mobile R&D from other countries, thus engaging in beggar-thy-neighbor policies. From a global perspective, R&D tax subsidies are thus inefficiently high.

These insights have important implications for economic policy. First of all, the desirability of R&D tax credits and allowances is called into question as our estimates suggest that the genuine increase in global R&D induced by the instruments is small. The elasticity of global R&D to the incentives may be as small as 0.1, i.e. suggesting that a 10% drop in the user costs of capital increases global R&D by 1%. Moreover, the estimates suggest that R&D tax incentives attract R&D activities from abroad, implying that governments have an incentive to engage in international detrimental competition. Policy coordination of R&D subsidy schemes, e.g. at the level of the European Union, may significantly increase aggregate welfare.

Table 1: Summary statistics

variable	obs.	mean	sd	min	max
patents	16644	2.141	18.192	0.000	760.000
quality adjusted patents	16644	1.354	10.272	0.000	342.187
log patents	16644	0.406	0.763	0.000	6.635
log quality adjusted patents	16644	0.304	0.650	0.000	5.838
B index	16644	0.980	0.094	0.428	1.048
average B index	16644	0.977	0.079	0.428	1.044
log gdp p.c.	16644	10.289	0.238	8.421	11.408
average log gdp p.c.	16644	10.308	0.221	9.215	11.198
R&D expenditures	16644	2.200	0.691	0.551	4.130
average R&D expenditures	16644	2.252	0.549	0.861	4.130
FDI inflow	16644	3.969	4.404	-3.598	74.711
average FDI inflow	16644	4.001	3.838	-3.598	38.312
log total enrollment rate science	16644	11.876	1.029	5.421	12.812
average log total enrollment rate science	16644	11.933	0.897	8.222	12.812
year	16644	2002.668	2.410	1998.000	2006.000

Notes:

The quality adjusted patent use the constructed composite quality index as a weight. The B index measures the tax generosity towards R&D in a country. The average B index is the index for the corresponding affiliates of our observations. The GDP p.c. and the average GDP p.c. depict the gross domestic product of the corresponding countries measured in US dollar. The R&D expenditures and the average R&D expenditures, the FDI inflow as well as the average FDI inflow are measured in US dollar and taken from the World Development Indicators. The total enrollment rates in science have the same source.

Table 2: Direct Effect of R&D Tax Incentives

	(1)	(2)	(3)	(4)	(5)	(6)
	log q.a. patents	log patents	log q.a. patents	log patents	log q.a. patents	log patents
B index	-0.405** (0.147)	-0.498** (0.182)	-0.416** (0.147)	-0.510** (0.182)	-0.338* (0.139)	-0.468** (0.174)
log gdp p.c.	0.0543 (0.129)	0.496** (0.156)	0.110 (0.127)	0.555*** (0.155)	0.120 (0.125)	0.553*** (0.152)
log total enrollment rate science	0.0583 (0.0487)	0.0166 (0.0581)	0.0405 (0.0482)	-0.00249 (0.0579)	0.0774 (0.0510)	0.0242 (0.0599)
R&D expenditures			0.147*** (0.0400)	0.158*** (0.0478)	0.128** (0.0401)	0.134** (0.0478)
FDI inflow					0.00328** (0.00115)	0.00165 (0.00126)
constant	-0.905 (1.391)	-4.715** (1.652)	-1.556 (1.391)	-5.414** (1.653)	-2.075 (1.357)	-5.676*** (1.612)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.0707	0.119	0.0716	0.119	0.0724	0.119
N_clust	2486	2486	2486	2486	2513	2513
N	16644	16644	16644	16644	17197	17197

Standard errors in parentheses

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes:

The standard errors are clustered on the country-year level. The observational unit is the affiliate. The dependent variable is the number of successful patent applications of the affiliate per year. All specifications include a full set of year fixed effects.

Table 3: Baseline Regression: Direct & Indirect Effect of R&D Tax Incentives

	(1)	(2)	(3)	(4)	(5)	(6)
	log q.a. patents	log patents	log q.a. patents	log patents	log q.a. patents	log patents
B index	-0.722*** (0.207)	-0.861*** (0.255)	-0.722*** (0.210)	-0.866*** (0.257)	-0.648** (0.205)	-0.815** (0.254)
average B index	0.596* (0.267)	0.678* (0.327)	0.576* (0.275)	0.674* (0.335)	0.532 ⁺ (0.272)	0.621 ⁺ (0.333)
log gdp p.c.	0.312 ⁺ (0.172)	0.759*** (0.204)	0.359* (0.171)	0.819*** (0.204)	0.348* (0.171)	0.810*** (0.204)
average gdp p.c.	-0.474* (0.230)	-0.487 ⁺ (0.276)	-0.464* (0.231)	-0.506 ⁺ (0.281)	-0.444 ⁺ (0.231)	-0.495 ⁺ (0.281)
log total enrollment rate science	0.0696 (0.0501)	0.0268 (0.0597)	0.0523 (0.0499)	0.00573 (0.0598)	0.0876 ⁺ (0.0521)	0.0246 (0.0617)
average log total enrollment rate science	-0.0266 (0.0184)	-0.0243 (0.0250)	-0.0269 (0.0184)	-0.0249 (0.0248)	-0.0270 (0.0183)	-0.0259 (0.0248)
R&D expenditures			0.144** (0.0528)	0.177** (0.0639)	0.151** (0.0533)	0.182** (0.0644)
average R&D expenditures			-0.00629 (0.0675)	-0.0517 (0.0841)	-0.0112 (0.0677)	-0.0538 (0.0842)
FDI inflow					0.00458** (0.00163)	0.00312 ⁺ (0.00173)
average FDI inflow					-0.00266 (0.00166)	-0.00279 (0.00187)
constant	1.479 (1.818)	-2.278 (2.206)	0.829 (1.855)	-2.701 (2.267)	0.299 (1.852)	-2.935 (2.264)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.0720	0.119	0.0728	0.120	0.0734	0.120
N_clust	2486	2486	2486	2486	2486	2486
N	16644	16644	16644	16644	16644	16644

Standard errors in parentheses

⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes:

Heteroskedasticity robust standard errors are clustered on the country-year level. The observational unit is the affiliate. The dependent variable is the number of successful patent applications of the affiliate per year either in normal counts or quality adjusted. The average B index for the other host countries is total-asset weighted. The specifications (1) and (2) are the baseline regressions where as the specifications (3) to (6) add additional control variables on the country level. All specifications include a full set of year fixed effects.

Table 4: Robustness Check: Fixed Effect Model & ML Poisson Model

	OLS				ML-Poisson			
	(1) q.a. patents	(2) patents	(3) q.a. patents	(4) patents	(5) q.a. patents	(6) patents	(7) q.a. patents	(8) patents
main								
B index	-7.208** (2.337)	-13.35** (5.085)	-7.156** (2.410)	-13.49** (5.215)	-4.066* (1.816)	-3.223** (1.078)	-4.294* (1.981)	-3.190** (1.063)
average B index	7.026* (2.943)	12.06+ (7.011)	6.797* (3.097)	12.32+ (7.315)	3.924+ (2.107)	2.698* (1.064)	3.796+ (2.219)	2.578* (1.092)
log gdp p.c.	1.838 (2.602)	10.21 (7.495)	1.929 (2.631)	10.94 (7.563)	-2.311+ (1.212)	-0.544 (0.700)	-2.482 (1.599)	-0.271 (0.686)
average gdp p.c.	0.228 (5.665)	0.509 (13.46)	0.518 (5.539)	-0.147 (13.44)	-1.458 (1.074)	-0.971+ (0.535)	-0.753 (1.176)	-0.899 (0.584)
log total enrollment rate science	0.133 (0.422)	-1.380+ (0.758)	0.0879 (0.429)	-1.614* (0.800)	0.977* (0.482)	1.008* (0.407)	1.045+ (0.535)	0.899* (0.376)
average log total enrollment rate science	-0.236 (0.271)	-0.691 (0.613)	-0.233 (0.270)	-0.704 (0.607)	0.0881 (0.0794)	-0.0309 (0.0513)	0.0882 (0.0812)	-0.00457 (0.0572)
R&D expenditures			0.361 (0.672)	1.988* (0.874)			-0.472 (0.560)	0.373 (0.254)
average R&D expenditures			0.361 (1.196)	-1.213 (1.637)			0.978 (1.092)	0.0724 (0.366)
constant	-18.37 (39.79)	-81.62 (84.97)	-23.23 (37.66)	-80.96 (82.07)				
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2-a	0.00994	0.0174	0.00991	0.0175				
N-clust	2486	2486	2486	2486				
N	16644	16644	16644	16644	14781	14781	14781	14781

Standard errors in parentheses

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes:

Heteroskedasticity robust standard errors are clustered on the country-year level. The observational unit is the affiliate. The dependent variable is the number of successful patent applications of the affiliate per year either in normal counts or quality adjusted. The average B index for the other host countries is total-asset weighted. The specifications (1) and (2) as well as (5) and (6) are the baseline regressions for the OLS fixed effects model respectively the ML Poisson model. The specifications (3), (4) and (7), (8) add additional control variables on country level. All specifications include a full set of year fixed effects.

Table 5: Robustness check: Jackknife estimations

	mean/min	max	mean/min	max	mean/min	max	mean/min	max	mean/min	max	mean/min	max
B index	-0.719	-	-0.718	-0.975	-0.857	-1.014	-0.843	-0.805	-0.718	-0.975	-0.843	-0.805
average B index	-0.528	-1.019	-0.517	-0.580	-0.570	-1.014	-0.441	-0.532	-0.517	-0.580	-0.441	-0.532
log total enrollment rate science	0.595	0.319	0.574	0.678	0.673	0.389	0.529	0.618	0.574	0.678	0.389	0.618
average log total enrollment rate science	0.791	0.102	0.763	0.858	0.860	0.084	0.732	0.795	0.763	0.858	0.084	0.795
log gdp p.c.	0.067	0.036	0.051	0.027	0.006	0.084	0.085	0.024	0.051	0.027	0.084	0.024
average log total enrollment rate science	0.036	0.102	0.021	-0.040	-0.025	0.084	0.045	-0.032	0.036	0.102	0.045	-0.032
log gdp p.c.	-0.027	-0.006	-0.027	-0.024	-0.025	-0.005	-0.027	-0.026	-0.027	-0.006	-0.005	-0.026
average log gdp p.c.	-0.034	-0.006	-0.035	-0.033	-0.033	-0.005	-0.035	-0.035	-0.034	-0.006	-0.005	-0.035
R&D expenditures	0.312	0.406	0.361	0.753	0.816	0.349	0.808	0.312	0.361	0.753	0.349	0.808
average R&D expenditures	0.193	0.470	0.282	0.505	0.597	0.868	0.260	0.594	0.193	0.470	0.868	0.260
FDI inflow	-0.470	-0.288	-0.460	-0.487	-0.504	-0.271	-0.440	-0.494	-0.470	-0.288	-0.271	-0.494
average FDI inflow	-0.582	-0.288	-0.577	-0.609	-0.642	-0.271	-0.551	-0.627	-0.582	-0.288	-0.271	-0.627
Countries	18	18	18	18	18	18	18	18	18	18	18	18

6 Appendix: Construction of Patent Quality

This appendix provides further information on the construction of the patent quality index used in this study to capture the earnings potential of an invention. The methodology follows Hall et al. (2007) and Lanjouw and Schankerman (2004). The data we use in our estimations is obtained from Grid Thoma.

Previous studies document evidence that patent value strongly varies across patent applications (e.g. Harhoff et al. (1999)). While in the past many different indicators have been used to measure patent value, more recent literature suggests to combine several indicators within a composite measure (see Lanjouw and Schankerman (2004)) by means of factor analysis. Factor analysis allows to filter out idiosyncratic shocks contained in each single indicator to retain only a common shock that influences all included factors. The so obtained common factor is then used in the empirical analysis as the composite quality index. A main underlying assumption to factor analysis is that the variance in each indicator may be traced back to a common factor that influences all indicators and an idiosyncratic component which is independent of the other indicators and may only impact one indicator. The general factor model is denoted

$$y_{ki} = \alpha_k v_i + \beta X_i + \epsilon_{ki} \tag{3}$$

where y_{ki} is the observation of the k 'th patent indicator for the i 'th patent, v_i is the common factor (here: patent quality) that is assumed to be normally distributed, α_k is the factor loading obtained and X_i is any control variable. The factor loading determines the impact of the common factor on the patent indicators. Taken together, the common factor multiplied with the corresponding factor loadings is the common component K . Estimating the common factor is a minimization problem of the idiosyncratic term, where a linear combination of the indicators that explains as much as possible the total variance of each indicator has to be identified. The common factor v , however, is unobservable and therefore, no unique solution to the problem exists. To extract the common factor, principal components analysis is used. By means of principal components analysis, the data on y_{ki} is used to determine the first V eigenvalues and eigenvectors from the variance-covariance matrix. The common component is defined as $K = XVV'$, where $V = [p_1, \dots, p_v]$ and p_i is the eigenvector corresponding to the i 'th largest ($i = 1, \dots, Q$) eigenvalue of the covariance matrix of X . After having extracted the common component only the idiosyncratic term ϵ_{ki} remains.

The indicators we include in the analysis are family size, forward citations and technological classes. The common factor influences all three separate indicators of patent

quality and eventually will be our multidimensional quality measure. The data we use to determine the common factor is information on the total number of patents granted at the EPO. The *family size* of a patent covers all countries where patent protection is sought. When applying for patent protection at the EPO directly, the patentee may select the countries where the intellectual property right should be protected. These will be the countries where the patentee wants to use the patent in the production process and where the products are ultimately sold to the consumer. Since the cost for patent application increases in the number of countries where protection is sought, a firm will only apply in several countries if it expects the profits to outweigh the cost. Consequently, the size of a patent's family can be interpreted as an indicator of the patent's quality and its future earnings potential. For the construction of the measure, note that PATSTAT also contains information on patent applications to the US patent office and all other major national patent offices. This information is used to identify equivalent applications filed outside of the EPO at an earlier time (priority applications). In a first step, all priorities for the EPO patents were identified. In a second step, all applications that report the EPO application as a priority were identified. After removing any double counting, the number of patent applications plus the patents from step 1 constitute the size of the patent family. Furthermore, *forward citations* provide information about how often a patent has been cited by following patent applications. The citations are an instrument to determine the scope of the patent right relative to prior art in the field. Therefore all necessary citations are added to the application by the patent examiner during the filing process. On the one hand, this implies that not necessarily all innovations which draw on an existing patent in fact acknowledge the reference. On the other hand, an external patent examiner has the benefit of following a consistent and objective patent citation practice. The number of forward citations provides some information on the importance of the invention for future research in the field and hence, will be another indicator of quality of a patent. When constructing the number of forward citations, we only include citations within a 5-year-interval after the application date. Last, we include the number of *technological classes* in the composite quality index which have been shown by previous research to be an indicator of technological quality (see Lerner (1994)). This is a measure of the scope of application of the respective technology. The technological classes are listed in the patent document and are eight digit codes of the International Patent Classification (IPC) system.

In a previous step to the principal components analysis, the separate quality indicators are regressed on the year of application and the main technology class in a

three stage least squares estimation procedure to filter out any trends in time or industry. The residuals from this first step are then used to estimate the factor model by maximum likelihood estimation, assuming that the common component v is normally distributed. See also Lanjouw and Schankerman (2004) and Hall et al. (2007) for a thorough discussion of the theoretical framework and the estimation procedure of the factor model.

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